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Chapter One

Discount Retailers and Sales Tax Collections: Accounting for Competitive and Spatial Aspects

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Discount Retailers and Sales Tax Collections:
Accounting for Competitive and Spatial Aspects

Abstract

The impact of discount retailers on tax revenues, wages, and locally-owned businesses has been the topic of much recent debate. This study analyzes the effect of three major discount retailers – Wal-Mart, KMart, and Target - on total sales tax collections and regional sales tax pull, incorporating an increasingly popular local revenue option – local option sales taxes. The empirical analysis first tests for the potential endogeneity between location choice and community growth, which could bias estimates of interest. Next, a two-stage, fixed-effects estimation is performed on county and municipal-level panel data for the State of New York. Consistent with previous research, the findings suggest that the presence of a discount retailer is positively related to a municipality's sales tax collections and negatively related to collections of a competing retailer's community. The implication for rural communities and their relative proximity to the big three discount retailers is also analyzed.

I. Introduction

Retail business activity is a major contributor to the overall economic prosperity of a community. It produces jobs and a viable tax base for funding public goods. In particular, local option sales taxes (LOSTs) imposed on retail business activity occurring within local jurisdictions are becoming increasingly important sources of tax revenues. Because LOST revenues capture the bulk of retail activity occurring within a jurisdiction, they are a good indicator of a community's economic health. This analysis investigates the empirical relationship between major discount retailers and sales tax collections in a regional context that accounts for competitive and spatial aspects.

This study is particularly relevant for current policy-making given the increased use of LOST revenues as an alternative to increased property taxes, as well as the proliferation of large discount retailers across the country. Because they are interdependent, understanding the interaction between LOST revenues and big box discount retailers in a spatial context is important for taxpayers/public service users as well as investors in big box entities.

The analysis makes several contributions. It adds to the small body of literature analyzing the role that large discount retailers play in a regional economy. Table 1 identifies seven important previous studies that explicitly consider discount retailers. Only two investigate impacts across communities with and without a discount retailer. Stone (1995), in particular, found that in Iowa towns a new Wal-Mart store with $20 million yearly revenues results in the loss of $12 million dollars of sales for small businesses within the community. Stone also found the impact on surrounding communities to vary with their relative size to the Wal-Mart community: those of equal or smaller size often experience large sales losses while only larger towns could experience continued growth in most retail sectors.

Similar to Stone, virtually all studies of this type analyze the effect of just Wal-Mart. In contrast, this study deals with the combined effect from the three largest discount retailers: Wal-Mart, KMart, and Target. Considering the competitive environment of regional retail sales markets is an important contribution of this study.

Another contribution comes from using a large, diverse data set of counties and communities in New York State. Except for Stone (1995) who uses cross-section, time-series data at the community level for the state of Iowa, the majority of previous studies are conducted at the county level. Similar to previous studies, spatial aspects are included to analyze effects on neighboring communities. The retail market areas, usually defined in terms of driving distance, are also measured using driving time. Basker (2005) points out that the sub-county level effect of discount retailers on tax revenues has not yet been explored. Taking another departure from existing literature, the analysis explicitly accounts for LOST policy by including LOST tax rates, which is important due to within-community and cross-border tax rate elasticities.

Another important contribution is the investigation of the potential endogeneity of a discount retailer's location choice with previous economic growth trends. The endogeneity test suggests that location choice of the big three discount retailers is not driven by community-specific per-capita income and sales tax growth rates.

Finally, the econometric analysis employs a two-stage, fixed effect model to exploit the panel data. Consistent with previous research, the findings suggest that the presence of a discount retailer is positively related to a municipality's sales tax collections and negatively related to collections of a competitor's community. A discount retailer opening in a new community is associated with an increase of $329,972 in yearly sales tax collections, while a competitor within 20 miles decreases a community's pull on regional sales tax collections by 3%.

II. Literature Overview

Discount retailers and their impact on tax revenues, wages, and locally-owned businesses have been the topic of much recent debate. With an increase in public sentiment toward supporting locally owned business, discount retailers with economies of scale, ability to cut costs, and high level of efficiency are seen as a direct threat to smaller community establishments.

The impact of discount retailers on employment has specifically been the subject of media attention. With Wal-Mart, KMart, and Target together accounting for over 5,600 retail stores and over 1.59 million employees in the United States, discount retailers are unable to be ignored and are a large force in retail activity and employment within communities. Clearly, they will reallocate the labor force within a community, but it is unclear whether more net jobs are created or destroyed by the location of a "big box" retailer within a community.

Studying these mass discount merchandisers has proven difficult and previous studies offer conflicting evidence concerning the above issues. This analysis aims to quantify the impact of a discount retailer on both a county and community level in terms of their specific effect on sales tax collections. This is the first known study to look at this particular aspect.

One of the discount retailers included in this analysis, Wal-Mart, has been the subject of particular recent media attention. Critics contend that by cutting costs the flight of U.S. jobs overseas has been accelerated and Wal-Mart itself has admitted that a full-time worker may not be able to support a family. Wal-Mart pays its grocery workers an estimated $10 less per hour in wages and benefits than other nationwide supermarkets. Only 48% of employees choose to enroll in the health insurance the company offers (Goldman and Cleeland 2003).

Wal-Mart supporters respond with figures claiming that the 48% of employees covered by their health insurance plan is above the 44% national retail sector average. Additionally, 2/3 of its management started as hourly associates. They contend that Wal-Mart provides a career ladder otherwise nonexistent for some citizens. Some U.S. economists contend that by cutting costs, Wal-Mart has not only helped its own bottom line and consumers (groceries are 17% to 39% cheaper at Wal-Mart than at competing grocers), but helped hold down inflation for the entire country. McKinsey Global Institute estimated that between 1995 and 1999, 4% of the growth in U.S. productivity was due to Wal-Mart's efficiency alone, while no other single company had a measurable impact (Goldman and Cleeland 2003).

These issues are also debated at the global level, as many of Wal-Mart's suppliers are companies outside of the United States. Wal-Mart is the most powerful corporate citizen in Bangladesh even though there are no Wal-Mart stores in the country (Cleeland, Ititani, and Marshall 2003). Wal-Mart is so important to the economies of some developing nations that these countries send delegates to Bentonville, Arkansas (where Wal-Mart's headquarters are located) as if it were a nation of its own.

Sales tax collections are but one of the ways in which discount retailers affect a community. By no means will the results of this analysis decide whether these large retailers are "good for" or "bad for" a community overall. It will quantify how the low prices vs. high volume of these retailers affect sales tax revenues for the communities in which they operate.

Why would discount retailers affect sales tax collections? By attracting customers both inside and outside the community with low prices and a large selection of merchandise, discount retailers can be a valuable addition to a community's tax base and its pull on regional sales tax collections.

A measure of a municipality's success is the "pull factor" introduced by Stone in 1995. A pull factor represents a county or community's share of regional sales tax collections. When a pull factor is less than one, the interpretation is that the community is selling to less than the full size of the community. If a pull factor is greater than one, the community is capturing some of the retail market from its neighbors. Stone found that an average Wal-Mart city's regional sales pull factor had increased by 5.6% within 5 years of Wal-Mart's opening. Gruidl and Andrianacos (1994) found similar results, with a Wal-Mart increasing pull factors by 3%. Eathington and Swenson (2002) found that for non-metro areas the presence of a Wal-Mart was more important than population when determining changes in the share of regional sales.

Stone also found that a Wal-Mart store has a negative impact on retail sales in surrounding communities. He found that stores within 20 miles of a Wal-Mart saw their sales decrease by 25% within 5 years of Wal-Mart's opening, with rural businesses exhibiting the largest losses. Snodgrass and Otto (1990) came to a similar conclusion.

Specifically, the distance between a rural community and alternative shopping locations plays an important role. Supporting this contention, Gruidl and Andrianacos (1994) find that better access to highways weakens rural trade. This is in addition to their finding that retail trade, in general, shifted away from rural areas in the 1980's.

Chervin, Edmiston, and Murray (2001) conclude that substantial erosion of the local sales tax bases (inferred from per capita sales) occurs in communities without expanded shopping facilities as consumers take advantage of this alternative in other jurisdictions. This erosion of the tax base decreases a community's ability to collect tax revenues sufficient to fund the desired level of public goods and services. Harris and Shonkwiler (1997) propose that the economic strength of rural communities can be enhanced by the creation of expanded retail facilities.

LOST Popularity

Another increasingly popular option for local sales tax revenues are local option sales taxes (LOSTs). Not only do LOSTs help alleviate the issue presented above, they are also a popular alternative to increasing property taxes. As Lewis (2001) pointed out, municipalities have been increasingly attempting to diversify their revenue base, due to the unpopularity of the property tax coming in the form of a lump-sum payment. In contrast, a sales tax is paid over time. Jung (2001) found that communities imposing LOST had lower property taxes and were more likely to increase their general expenditures.

In the pursuit of new or increased revenue sources some communities establish land uses (zoning ordinances) based on the net tax revenues they will generate for the city. This process was termed land fiscalization by Kotin and Peiser (1997).   Lewis (2001) found that sales tax revenues are the leading motivation for land use decisions and that, specifically, retail development is the most favored land use.

Schrag (1998) contends that through land fiscalization, municipalities court relatively low-paying retail businesses (i.e. discount retailers) to locate within their community. They choose these companies over other potentialemployers, even those which can offer better jobs to the community residents, such as those in manufacturing. The preference for retailers is driven by the desire to maximize sales tax revenue.

The focus on retail development poses several problems. The attempts made by local officials to be overly generous regarding retail development zones implies that other land uses, such as housing, will be underzoned. Some argue that current zoning practices in suburban areas lead to the exclusion of minority and poorer residents. Others argue that current land use regulations restrict the rights of property owners and disrupt real estate markets, making quality housing less affordable. Almost all of the literature in this area agree that current zoning to encourage retail development excludes multi-family housing (Flesichmann 1989).

Additionally, as Lewis (2001) points out, municipal policy makers' attempts to attract retail development are often in vain. A retail tax base, or retail activity on the consumer level, is not going to just occur within a community based on local government incentives for retailers (rerouting traffic, etc.) or their land use decisions. Retailers are more likely to select given locations regardless of local government intervention. The problem that lies therein is the relatively fixed amount of regional retail sales.

Therefore, local governments are left to compete for tax revenues to provide public goods efficiently, in an effort to attract new residents and retain the existing. This problem of interjurisdictional competition, where residents "vote with their feet" in terms of which towns they choose to live in and shop in, leads to local governments fighting for their share, or more than their share, of the regional sales tax base.

Chervin, Edmiston, and Murray (2001) contest that an important trend that has likely affected the interjurisdictional migration of the sales tax base among communities is the rapid growth of large retailers, discounters, and shopping malls.

Figure 1 helps clarify how the above literature is connected. Discount retailers, the subject of this analysis, play an important role in local and regional economies. This analysis aims to specifically look into the role of discount retailers in rural areas.

As rural areas struggle to find tax revenues, recent studies point out that the local option sales tax has become a popular option (Rogers 2004), as have land fiscalization policies (Lewis 2001). Discount retailers have often been found to lie at the heart of interjurisdictional competition for tax revenues, due to their effect on sales tax collections.

This analysis incorporates issues from several of these literature areas, specifically discount retailers and their effect on a local economy in general, local option sales taxes, and the effect of both in rural areas.

III. Overview of Big Three Discount Retailers and LOST in New York

Big Three in New York Communities

Focusing on the State of New York offers advantages. The number of discount retailers operating within its borders is one of the highest in the nation. Additionally, New York State tracks sales taxes by point of collection, even at the local level.[1] There is special focus on rural areas which are often ignored, mostly due to lack of community level data, and New York State has one of the highest numbers of citizens living in rural areas.[2] The analysis will highlight the impact on rural communities when a large discount retailer opens.

The period 1990-2002 was chosen for the study based on tax data availability. In 2002, New York State had the following breakdown of discount retailers: Wal-Mart and K-Mart were almost even with 84 and 82 stores, respectively, while Target operated 36 stores.

There are 1294 municipalities in the State of New York.[3] Availability of sales tax collection data excluded some communities from this study. Sales tax revenues were obtained for each community from the New York State Office of the State Comptroller for the period 1990-2002. 273 communities listed on the Report of Government Finance

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[1] Most states do not track sales taxes by point of collection at the local level.

[2] A rural area is defined as an area with a population density less than 1,000 persons per square mile (U.S. Census), not included in a Metropolitan Statistical Area (Office of Management and Budget), or having an urban-influence code between 4 and 9 (U.S. Department of Agriculture).

[3] All incorporated communities, those with a tax-collecting local government, are characterized as a city, a town, or a village in New York State. Communities have been classified as such according to historical factors, as with other older states. Cities and towns are independent areas, while villages are, often densely populated, areas within a town. Although one community may be separated into both a city and a village (such as Batavia, NY) or a city and a town (such as Binghamton, NY), and thus reported separately on the New York State Special Report of Government Finances, for the purpose of this analysis it makes sense to count both together as one economic municipality, summing their revenues and expenditures. Therefore, although there are a total of 1525 separate reporting municipalities, only 1294 of them appear as separate "dots on a map."

never reported any sales tax collections during this 13-year period and were thus omitted. Another 371 were also omitted due to missing data.[4] This brings the total number of New York communities included in the study to 650. Over the 13-year period, this accounts for 8,450 time-series, cross-sectional community-level observations. Of these 650 towns, 74 have one or more discount retailers in operation during at least a portion of the study period. For the county-level analysis, the 5 counties which include New York City are omitted.[5] The remaining 57 counties are included, accounting for 741 time-series, cross-sectional county-level observations.

LOST policy in New York

New York State currently imposes a 4.25% sales tax.[6,7] State policy determines the extent of autonomy granted to local jurisdictions regarding LOST. All counties and communities are authorized to impose LOST, but the aggregate rate is not to exceed 4% for any municipality.[8]

The 5 counties that comprise New York City determine their LOST rates collectively as a city. In 2005, only 1 of the 57 remaining counties does not impose a LOST. Only one county imposes the maximum rate of 4% (Albany). 57% impose a 3.5% rate and 34% impose a rate of 3%. 24 communities impose LOST, although a total

[4] There is no systematic reason for missing data.
[5] New York City, and the counties it comprises, are omitted because they are not representative of an average city or counties in New York State. They are economically and geographically different from the rest of the State.
[6] .25% expires at the end of May 2005
[7] States neighboring New York do not impose LOST
[8] Sales taxes in New York are determined by New York State Consolidated Law Services, Article 28, Section 1101 et seq. The values for tax rates used in this analysis were acquired from New York State Department of Taxation and Finance Publication 718-A.

of 36 have utilized it at some point since the statewide institution of sales taxes in 1965. 58% of the communities currently imposing LOSTs impose a rate of 1.5%.

A special vote can eliminate the 4% maximum county/community rate. For example, Nassau and Suffolk counties themselves impose a 4.25% rate. This also implies that a county imposing a high rate doesn't necessarily infringe, at least legally, on the ability of the communities within its bordersto impose at the municipal level. The community of Fulton imposes a 4% rate in addition to the 3% imposed by its county and the 4.25% state rate.

By studying New York State, this analysis further enhances ideas presented by Stone in the most closely related study. LOST policy in Iowa, the focus of Stone's analysis, allows LOST within part or all of a county jurisdiction with voting held on a county-wide level. New York LOST policy allows for voting and imposition at both the county and municipal level. Therefore, a study of cross tax elasticities between the county and municipal rates can be performed here, which was not possible with Stone's analysis.

Rogers (2005) contends that establishing a connection between local policy choices and community network characteristics is a potentially important aspect policy analysis, especially for rural communities.

Retail Market Areas

Following the typical approach, a twenty-mile radius was drawn around each discount retailer town to find all the communities in the retail market area (Stone 2001). A large percentage of the 650 communities in the study were within 20 miles of a discount retailer for most of the study period. Figure 2 shows the decrease in the number of communities outside the market area of a discount retailer and the increase in those near more retailers over the study period.

The number of communities within 20 miles of 5-9 discount retailers has increased dramatically over the sample period, from roughly 60 communities to nearly 200. Although most of the communities were within 20 miles of 1-4 discount retailers, the number of communities in this group fell by 120 over the sample period. 1995 appears to be a significant year. The number of communities with 0 discount retailers within 20 miles tapers off, as no stores were opened in "new" areas after 1995. Instead, discount retailers seem to be opening more stores in areas already serviced by discount retailers, as the number of communities within 20 miles of 14+ discount retailers increases.

IV. Empirical Specification

Endogeneity Test

The relationship of interest is that between total sales tax collections[9] and the number of discount retailers that exist within proximity. If discount retailers base their location decisions on an existing trend in sales tax collections, the empirical analysis would be undermined. The resulting estimates would not be informative about the impact of discount retailers on retail sales tax collections due to the endogeneity of locational choice to the dependent variable of interest.

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[9] $SalesTaxCollections = RetailSales * (StateSalesTaxRate + CountySalesTaxRate + LocalSalesTaxRate)$
Data obtained from New York State Comptroller.

To address this issue, an endogeneity test similar to that of Hicks and Wilburn (2001) and Franklin (2001) is performed. First, the income and sales tax collection growth rates for towns with no discount retailers and those with discount retailers were compared for the period of time covered in the study. They were virtually the same. [10]

Second, a logit model was constructed with a dummy variable for the decision to locate (1) or decision not to locate (0) in community *i* in year *t* as the dependent variable. This was tested on a constant and the one and two-year lagged income and sales tax collection growth rates.[11] Results are reported in Table 3. Neither coefficient estimate was significant in any of the specifications, suggesting that income and sales tax collection growth and lagged growth measures have no significant effect on the decision to enter a market area.[12] Hicks and Wilburn (2001) suggest that discount retailers location decisions depend more on rival locations. In any case, endogeneity bias of the focal relationship does not appear to be a concern.[13]

Fixed-Effect Specification

An estimation utilizing sales tax collections or a related measure would need to capture effects that are both time-specific, such as sales tax rates and income, and time

[10] Sales tax collection one and two-year lagged growth rates were 9.62% and 9.82% (no discount retailer) and 8.14% and 8.67 (with discount retailers). Income growth rates were 3.28% and 3.39% (no discount retailer) and 4.04% and 4.11% (with discount retailers).

[11] Results are reported assuming a normal distribution. Results were robust assuming binomial or negative binomial distributions.

[12] Longer lag periods could be explored to determine whether a "pre-program dip" exists. (Heckman and Smith 1999)

[13] A test was also performed to account for the possibility of sales tax rates being endogenous to sales tax collection growth. Table 4 reports the results of this test. There was no statistically significant relationship between the sales tax rate on the municipal level, county level, or the two combined and sales tax collection growth over the past three years.

invariant, such as the area of the county or community. A model similar to the following could be used.

$$y_{it} = \alpha + \sum_{c=1}^{k_1} \beta_c C_{c,it} + \sum_{d=1}^{k_2} \gamma_d U_{d,i} + \varepsilon_{it} \qquad \textbf{(1)}$$
$$i = 1,\ldots,N \quad ,$$
$$t = 1,\ldots,T$$

where y is estimated separately as either annual sales tax collections in real dollars[14] or the pull factor for a county or community i in time t.[15] Following Stone (1995), Harris and Shonkwiler (1997), and others, the pull factor (PF) is calculated as

[PF_{it}] = per capita sales tax collections$_{it}$ / regional per capita sales tax collections$_{it}$.

Region is defined as contiguous counties for the county-level analysis and the sum of all communities within the county and contiguous counties for the community-level analysis.[16] C_{it} is a vector of k_1 county or community variables that vary over time and place; U_i is a vector of k_2 county or community-specific variables that are invariant over time. T is the total number of time periods and N is the total number of communities or counties.

An estimation such as this including many county or community-specific variables has an error structure containing a fixed, county or community-specific term, $\varepsilon_{it} = \lambda_i + \upsilon_{it}$. To account for this, the following fixed effects model is used,

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[14] The dependent variable sales tax collections is expressed in levels because it is assumed that policy makers at the community level are most concerned with real dollar values. Further analysis will consider sales tax collections per capita and the log percentage change in sales tax collections. The pull factor measure currently gives insight into per capita effects.

[15] Basker (2005) tests for unit roots in county-level employment data by running a Dickey-Fuller test on each county series separately. Following Basker, a Dickey-Fuller test was run separately on each county sales tax collections series. By construction, a 5% or less rejection rate is expected at the 95% confidence level if the series contains unit roots. The rejection rate was 16% for these series suggesting that county-level sales tax collection data does not contain unit roots.

[16] Region is defined as it is above as a starting point. Later results consider an alternative region definition, the Bureau of Economic Analysis's Economic Areas.

$$
\begin{aligned}
& y_{it} = \alpha + \sum_{c=1}^{k_1} \beta_c C_{c,it} + \sum_{d=1}^{k_2} \gamma_d U_{d,i} + \lambda_i + v_{it} \\
& i = 1,\ldots,N \qquad\qquad\qquad\qquad\qquad\qquad . \quad \mathbf{(2)} \\
& t = 1,\ldots,T
\end{aligned}
$$

The equation cannot be estimated in the form outlined by equation **(2)**, as the time invariant variables in the vector U_i can't be separated from the community-specific error, λ_i. Therefore, equation **(2)** is estimated as

$$
\begin{aligned}
& y_{it} = \alpha + \sum_{c=1}^{k_1} \beta_c C_{c,it} + \lambda_i * + v_{it} \\
& i = 1,\ldots,N \qquad\qquad\qquad\qquad \mathbf{(3),} \\
& t = 1,\ldots,T
\end{aligned}
$$

$$
\text{where} \quad
\begin{aligned}
& \lambda_i * = \tau + \sum_{d=1}^{k_2} \gamma_d U_{d,i} + \lambda_i \qquad \mathbf{(4)}. \\
& i = 1,\ldots,N
\end{aligned}
$$

Equation **(3)** is estimated in Stage One. In Stage Two, the estimated coefficients for the county or community fixed effects, $\lambda_i *$, are used as the dependent variable in an estimation on U_i, the vector of k_2 time invariant variables.[17] This specification provides insight into the effect of both the time-changing and time-unchanging county and community-specific variables on sales tax collections and sales tax pull factors.[18]

Variables included in vector C_{it} and U_i for both the county and community-level analyses are outlined below. *C* indicates county and *M* indicates municipal.

[17] Similar to that outlined by Hsiao (1986).
[18] Descriptive statistics for these variables can be found in Table 2.

Time Variant Factors:

$$C_{C\,t} = f\,(\,BIG3_C\,,\,POP_C\,,\,CORATE_C\,,\,REC_C\,,\,HWMILES_C\,,\,URATE_C\,,\,INCOME_C\,,\,EST_C\,)$$

$$C_{M\,t} = f\,(\,POP_M\,,\,MRATE_M\,,\,CORATE_C\,,\,REC_M\,,\,HWMILES_M\,,\,INCOME_C\,)$$

Time Invariant Factors:

$$U_C = f\,(\,AREA_C\,,\,COL_C\,,\,AIR_C\,,\,UINF_C\,,\,TYPE_C\,)$$

$$U_M = f\,(\,AREA_M\,,\,COL_M\,,\,AIR_M\,,\,UINF_C\,,\,TYPE_C\,)$$

Data Description and Sources

- *Y* = sales tax collections or sales tax pull factors, *MRATE* = municipal sales tax rate, CORATE = county sales tax rate, REC = municipal recreational expenses, and *AREA* = land area, in square miles

  (county and municipal data; Source: New York State Comptroller)

- *BIG3* = number of the big three discount retailers, by county and municipal location

  (Source: corporate websites / calls to the individual stores)

- *POP* = population, *INC* = per capita income in real dollars, and *URATE* = annual unemployment rate, *(county and municipal data; Source: author estimation based on decennial U.S. Census values)*

- *HWMILES* = total local and state-owned highway miles within the jurisdiction

  (county and municipal data; Source: New York State Department of Transportation)

- *EST* = number of retail establishments

  (county data; Source: County Business Patterns)

- *COL* = number of colleges and *AIR* = number of airports

  (county and municipal data; Source: www.epodunk.com)

- *UINF* = urban influence code dummy variables and *TYPE* = typology code dummy variables

  (county level data; Source: Economic Research Service/U.S. Department of Agriculture)

These variables were chosen based on previous research dealing with sales tax collections. Snodgrass and Otto (1990), for example, used the municipal sales tax rate, income, population, retail employment, and other community attributes when modeling sales tax revenue. Gruidl and Andrianacos (1994) used income, the unemployment rate, the number of retail establishments, and the numbers of discount retailers to model pull factors.

The estimated coefficient on population *(POP)* is expected to have a positive sign. It is assumed that as more people live in a community, sales will increase and sales tax collections and pull factors will increase. County per capita income *(INC)* is expected to be positively related to sales tax collections and pull factors. As residents have higher incomes, we would expect them to spend more. Similarly, the estimated coefficient on the unemployment rate *(URATE)* is expected to have a negative effect. Including variables such as per capita income and the unemployment rate also act as additional controls for macroeconomic fluctuations during this time period (Chervin, Edmiston, and Murray, 2000).

Municipal and county retail sales tax rates *(MRATE, CORATE)* have ambiguous relationships with sales tax collections. They could have a positive effect on tax revenues, since as the tax rate increases, tax revenues could also increase. This would be consistent with Snodgrass and Otto (1990). On the other hand, if tax rates in a community are too high, consumers may choose to make their purchases in a community with a lower tax rate, thus decreasing tax revenues. This would also cause a negative effect on pull factors.[19]

Recreational spending *(REC)* is expected to have a positive estimated coefficient, as this would indicate a tourist area. Land area *(AREA)* and the number of colleges *(COL)* and airports *(AIR)* are also expected to be positively related. Several outcomes exist for the highway miles *(HWMILES)* relationship. For those communities without discount retailers, more highway miles would allow easier access to other areas with a discount retailer, having a negative effect on sales tax collections. For those communities with a discount retailer, more highway miles could facilitate patronage from neighboring community citizens (producing a positive effect on sales tax collections) or they can allow easier access to competitor stores (producing a negative effect).

The effect on sales tax collections and pull factors based on the area's classification as a metro area, or its proximity to a metro area, are captured by the urban influence code *(UINF)*.[20] A lower value represents a more urban area, while a higher value represents a rural area. Therefore, a negative estimated coefficient sign would mean that a more rural area would be expected to have lower tax collections and less pull, while the opposite exists for an urban area (as in Stone 1995). We could expect a negative sign if rural areas are associated with relatively less businesses and less spending in terms of population. We would expect a positive estimated coefficient if, as

[19] Often referred to as "the border city problem." See Fisher (1980)
[20] See Appendix Tables E.1 and E.2 for a full description urban influence and typology codes

Lewis (2001) stated, urban centers are attracting an increasingly unfavorable proportion of regional sales tax revenues.

Three county typology code *(TYPE)* dummies represent whether the county has been designated as dependent on manufacturing *(MANF)*, services *(SERV)*, or federal or state government *(FSGOV)*. The two remaining dummy variables indicate whether the county has been designated as a population loss county *(POPLOSS)* or a housing stress county *(HOUSE)*. Negative estimated coefficients are expected for each of these dummy variables.

Lastly, the impact of the number of retail establishments *(EST)* is also ambiguous. A positive coefficient would suggest that more businesses mean more sales and more tax revenues. An alternative explanation suggests either inefficiency in the retail sector or that there is an optimal number of retail establishments for a given level of population and exceeding that level simply leads to increased competition and prices so low that tax revenues decrease.

V. Results

County-Level Analysis

Table 5 presents the results for the county-level analysis. In stage one, the coefficient for the variable of interest, the number of discount retailers, is highly positive and significant in both cases, supporting the opinion that discount retailers play a large role in local and regional economies. The estimated coefficient for the *BIG3* variable suggests that the presence of an additional discount retailer itself, as well as the rest of the retail outlets it attracts through its role as an anchor store, increases predicted sales tax collections at the county level by $10,093,260[21], which represents 20% of the overall county mean. Each additional retailer increases the county's share of regional sales tax collections by an estimated 1.7%.

The tax policy implication given the estimated coefficient of the county tax rate variable is that consumers are still on the left-hand side of a sales tax Laffer curve. This is consistent with Snodgrass and Otto (1990). The results suggest that an increase in county tax rates will increase sales tax collections, as well as be positively related to a county's pull on regional sales tax collections over time. However, given the magnitude of the estimated coefficient ($3,889,791), increasing the county tax rate by 1% has less of an effect on sales tax collections than the presence of an additional discount retailer.

As expected, the estimated coefficients for population, recreational expenditures, and income are positive and significant in at least one of the specifications. The presence of a college has a small, yet unexpected, negative estimated coefficient in the collections estimation. Highway miles are positively associated with sales tax collections and sales tax pull factors, perhaps due to providing better access to a county's retail outlets.[22]

In both estimations, the negative coefficient for the number of retail establishments suggests that increased competition decreases a county's sales tax collections and sales tax pull factors. In stage two, the estimated coefficient for urban influence codes is negative for sales tax collections, suggesting that more influence from an urban area increases sales tax collections. The estimated coefficient for designation as a housing distress county is also negative. However, both estimated effects would have little impact.

[21] Stone (1995) states that an average Wal-Mart store is expected to have yearly sales of $20,000,000.
[22] Another possible explanation could be that highways are built in counties and communities where the bulk of retail activity exists. Potential endogeneity will be explored in future analysis.

Community-Level Analysis

The analysis is first performed for all communities. Then, to account for potential unobserved variable bias, three separate estimations are performed. The three groups include communities that (i) did not have a discount retailer, (ii) had a discount retailer, and (iii) did not have a discount retailer at the beginning of the sample period but gained one throughout. Additionally, the variables *20MILES*, representing the number of discount retailers outside the community but within a 20-mile radius, and *20MINS*, representing the number of discount retailers outside the community but within a 20-minute drive, are added to each estimation separately.

As stated earlier, previous literature uses drive distance to define market areas. Drive time is also considered because it can be assumed that consumers also care about minimizing costs associated with travel and time.[23] The impact of a discount retailer outside a community greatly depends on the road network between the two. The travel and time costs are highly different if there are 15 miles of unimpeded highway versus 15 miles of crowded city streets or a body of water. The results are reported in Table 6 for all communities, Table 7 for communities with a discount retailer, Table 8 for communities without a discount retailer, and Table 9 for communities that experienced the opening of a discount retailer for the first time during the sample period.

The results show again that discount retailers increase sales tax collections. In the estimation for communities that did not have a discount retailer at the beginning of the sample period but did at the end, hereafter referred to as those with "changing status", the opening of a store is associated with an increase in sales tax collections of $329,972,

[23] Drive time is calculated using the software Microsoft Office Streets and Trips.

which is 12.5% of the mean for this subsample.[24] *BIG3* is also positively associated with pull factors. It is estimated that communities in general with discount retailers are able to capture an additional 1.79% of the regional sales tax collections. Those with changing status were estimated to have increased their pull on regional sales tax collections by 3.645%. [25]

A higher county sales tax rate is predicted to increase tax collections and pull factors in communities, as in the county-level analysis. Although the county sales tax rate coefficient is not statistically significant in the overall community analysis, its estimated coefficient is positive in the remaining estimations. The county tax rate also has a positive estimated coefficient in the pull factor estimation for communities with changing status. However, for communities without a discount retailer, higher county tax rates are negatively associated with the share of regional collections over time, indicating that without extensive shopping facilities, consumers are more likely to be deterred by a higher sales tax rate.

Interestingly, the municipal sales tax rate estimated coefficient is significant in only the estimation for communities with changing status. In general, this is consistent with Wong's (1996) finding that the municipal tax rate is not related to retail sales per capita. It also indicates that the only communities that have been able to truly use municipal sales taxes (LOST) as an expanded source of revenue are those that recently had new discount retailer stores open their doors.[26,27]

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[24] *BIG3* was omitted from the "with" estimation to make this estimation more comparable to the "without" estimation.

[25] The difference between the two could be attributed to the attractiveness of shopping in a "new" store. Additionally, most of the openings during the sample period were Wal-Mart store openings. Wal-Mart is the largest of the three retailers included in this analysis.

[26] Again, endogeneity of sales tax rates may be an issue here. Mu and Rogers (2005) analyze the relationship between LOST and fiscal decentralization. They address the endogeneity issue of whether

There is a clear distinction between communities with and without a discount retailer for the variables representing highway miles and the number of discount retailers nearby (in terms of both drive distance and travel time). For communities with a discount retailer, proximity of competitors and highway miles are negatively related to tax collections but the effect on pull factors is unclear. The opposite is true for communities without a discount retailer – highway miles are positively associated with tax revenues but negatively associated with pull factors. Discount retailer proximity is positively associated with both sales tax collections and pull factors.

A possible explanation for this outcome could be that especially in more rural areas, which in New York are virtually the only places without a discount retailer[28], having a discount retailer nearby or within reasonable driving distance could make living there much more attractive to potential residents. Attracting more residents could offset the decrease in sales tax collections due to a large competitor being close by.

As expected, *POP* and *INCOME* have positive estimated coefficients in essentially each estimation, for both outcome measures. Different from the county-level analysis, recreational expenditures now have a negative coefficient with respect to sales tax collections, with the exception of the estimation for those communities with changing status.

Many of the estimated coefficients for the variables in the second stage are insignificant or have ambiguous results. The estimated coefficient for *AREA* is

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states with LOSTs are inherently more decentralized by running a logit model which includes historical revenue and expenditure values. Their results greatly reduce LOST rate endogeneity concerns, as the historical values are statistically insignificant in their model.

[27] Worded otherwise, these communities imposed LOST simply because they had something to tax.

[28] See Figure 4 for a map of the location of discount retailers in relation to Interstate Highways and metro areas.

significant in only the estimation for communities with changing status, where there is a positive association. *COLLEGE* is positive and significant only for communities without a discount retailer. Several of the county typology codes (*MANF*, *FSGOV*, *HOUSE*, and *POPLOSS*) are negative and significant, as expected, in several estimations.

UINF has a negative and statistically significant estimated coefficient, as expected, in several of the estimations. Since lower numbers are assigned to more urban areas, this indicates that higher sales tax collections are associated with more urban influence.

VI. Estimation Extensions

The empirical specification can be extended in numerous ways. They include exploring the implications of rurality, the effect of LOST on property tax collections, the effect of decomposing the proximity variables into 5 and 10 mile or minute increments, utilizing an alternative estimation technique to test for robustness, a preliminary investigation into tax rate elasticities, and defining a "region" with the Bureau of Economic Analysis's Economic Areas. All extensions and their results are presented below.

Estimations for Rural Communities

The estimation is extended to further investigate the implications of rurality and having less urban influence. Rural communities are often overlooked in analyses and many of these communities could greatly benefit from new revenue sources to fund public goods. Rogers (2004) finds that communities on the urban fringe appear to have different abilities to use LOST policy to generate additional revenues compared to their metro and rural counterparts. Additionally, she finds that places with little urban influence (i.e. rural areas) may have a greater ability to use LOST rates to increase additional revenues.

Because LOST, discount retailers, and the combination of the two may have a highly different impact in rural communities, these estimations look only at communities where most of the community is classified as highly rural and then, further narrowing the scope, only those without a discount retailer. The results are reported in Tables 10 and 11.

In Stage One for all rural communities, the variable of interest *BIG3* has an unexpected negative estimated coefficient, which is inconsistent with previous results. A possible explanation for this is that of the 62 communities included in the rural sample, only one community had a discount retailer throughout the entirety of the sample period. Only three others had discount retailers open during the sample period. This small number may cause bias in the estimated coefficient.

An alternative explanation is that, and this is unknown since the number of retail establishments data has only been calculated at the county level, a discount retailer in a rural community may be so detrimental to the pre-existing small stores (by pricing their products much lower than these small stores are able) that there is a general decrease in sales tax revenues.

The county tax rate, *CORATE*, and recreational expenditures, *REC*, coefficient estimates are again positively significant in the sales tax collections estimation. The municipal tax rate, *MRATE*, is positive and significant in the estimation for all rural communities.[29] This is important since, as explained previously, many rural communities could benefit greatly from alternative sources of revenue and at this time not many rural communities have implemented a local option sales tax.

The number of highway miles in the community, per capita income, and recreational expenditures are found to be positively related to both sales tax collections and pull factors, as in previous estimations. Population again has a positive estimated coefficient in the estimation for only communities without a discount retailer, but an unexpected negative estimated coefficient in the estimation for all rural communities.

The coefficient estimates for *20MILES* is statistically insignificant. This is consistent with Eathington and Swenson (2002) who found that in Iowa, the geographical distance from a Wal-Mart was statistically insignificant in terms of regional retail sales share for a rural, non-metro community. However, *20MINS* has positive estimated coefficients for sales tax collections in both estimations and is significant in terms of pull factors only in the estimation for all rural communities.[30] The same explanation as that proposed previously would apply here. It is possible that due to the remoteness of these areas, consumers being able to drive to a discount retailer would increase the attractiveness of living there.

In the second stage, the estimated coefficient for the number of airports is both positive and significant for the estimations for both subsamples, implying that rural

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[29] MTR is excluded from the estimation for rural communities without a discount retailer since no communities in this subsample imposed local option sales taxes.

[30] There is a distinct difference between the coefficient magnitude and significance for drive time and drive distance in these estimations, inconsistent with previous estimations. A possible explanation is that based on the geographic remoteness of these communities (mountainous, highly forested {see Figure 4}) only 11% of the discount retailers within 20 miles are within 20 minutes. This is compared to 28% for all communities without a discount retailer and 20% for communities with a discount retailer. This would have more impact on gross sales tax receipts than pull factors, as most areas within the defined region would be similar geographically.

communities served by regional airports have higher sales tax bases.[31] *COLLEGE* is statistically insignificant for sales tax collections in the estimation for all rural communities and unexpectedly is associated with a negative impact on pull factors over time.

In the same estimation, *AREA* is negatively associated with both sales tax collections and pull factors. Although it seems natural to assume that a larger community would have higher sales tax receipts, for rural communities, since population is already accounted for, an increase in area would just mean that residents are even more spread out geographically making it less likely that large shopping areas will open.

Property Tax Estimation

Lewis (2001) states that due to the unpopularity of the property tax, municipalities have been diversifying their revenue base towards other taxes and fees, including local option sales taxes. Whether this is the case for communities imposing LOST in New York is explored here.

Following Jung (2001) it is assumed that a prior year's LOST collections are used to determine a current year's property tax millage rate. Specific LOST collection is not available, therefore, the municipal tax rate is introduced into the estimation as a lagged value. If the imposition of a LOST is being utilized as a viable alternative to raising property taxes, a negative sign on the estimated coefficient would be indicated. Table 12 reports the results.

[31] Urban influence and county typology codes were not included in this estimation due to the homogeneity of communities in the sample.

Population, total local government expenditures, median home values, highway miles, the presence of a college, and urban influence codes are included as explanatory variables in this estimation and are all expected to have a positive relationship to property tax collections. The percent of the population classified as rural would be expected to negatively affect property taxes due to less retail and residential development.[32]

As expected, population, total municipal expenditures, median home values, highway miles, and urban influence are positively associated with property tax collections. The presence of a college has a negative coefficient estimate, as most colleges are not subject to property taxes. The county tax rate and rural population coefficients are statistically insignificant.

The estimated coefficient for the lagged municipal tax rate variable is negative and significant at the 10% level, suggesting that the imposition of a 1% LOST is associated with decreases in property tax collections of $63,171 (2.5% of the mean, approximately $5.70 per capita) in the State of New York. This is consistent with Jung's (2001) finding that per capita property tax collections in Georgia counties imposing LOST were $12 lower than in non-LOST counties.

Estimations Decomposing the Proximity Variables

Another way to extend the model is to again consider the number of discount retailers within 20 miles and within 20 minutes, but with the drive distances and drive times in incremental values. Estimations, using the same explanatory variables and technique as in the previous estimations, were performed for communities with and without a discount retailer. Tables 13 and 14 report the results for these incremental

[32] The estimation was performed using ordinary least squares (OLS) and, after positively testing for heteroscedasticity, White's standard errors.

value variables. Other variables are omitted from the tables in an effort to conserve space, as there were no noteworthy changes.

The results, in terms of which variables' estimated coefficients were statistically significant and whether these variables were positively or negatively associated with the dependent variables, were identical for both outcome measures. The results suggest that discount retailers outside the community[33] but within very close proximities have no significant relationship to sales tax collections or sales tax pull factors. Only the rural community estimation produced a statistically significant estimate for the *0-5MILE* variable. It suggests that a discount retailer outside of a rural community but within 5 miles will decrease that community's pull on regional sales tax collections by 6%.

As the distance increases, there is a positive relationship, possibly due to urbanization effects. This was the case for all subsamples and there was no significant distinction or trend between the 6-10 mile and 11-20 mile increments. The only inconsistency with these results and the previous is for communities with a discount retailer. In the prior estimations, another discount retailer within 20 miles from a community with a discount retailer of its own was associated with a negative impact on sales tax collections, as would be expected. However, that negative effect does not show up here when the proximity values are decomposed.

Estimation Utilizing an Alternative Estimation Technique

Heckman (1979) discusses a general model to deal with problems involving a treatment and an outcome. In this study, the treatment is the presence of a discount retailer and the outcome is sales tax collections (or sales tax collection pull factors).

[33] Except when aggregated across all communities

Applying the general model developed by Heckman and discussed in Johnston and DiNardo (1997), the simplest way to model the effect of discount retailers in the communities in which they are located would be to fit the following model on the sample of communities with a discount retailer:

$$y_i = X_i \beta + \varepsilon_{1i} \qquad \textbf{(5)}$$

where *y* is sales tax collections and *X* is a vector of explanatory variables such as population and tax rates. Since the sample in the above estimation is the group of communities with a discount retailer, it is not a random sample of New York communities, which may bias coefficients. To correct for this, Heckman proposed a two-step estimator utilizing a participation equation.

The participation equation, whether or not a discount retailer chooses to locate within the community, can be written as

$$T_i = if\,(Z_i \gamma + \varepsilon_{0i} > 0), \quad 0 \text{ otherwise} \qquad \textbf{(6)}$$

where *Z* is a vector of explanatory variables for discount retailer location choices. A discount retailer will locate within a community if $Z_i\gamma > \varepsilon_{0i}$.

Heckman proposed to first run a probit model of the treatment on the vector Z to obtain estimates of γ/σ_0, where σ_0 is the standard error of ε_{0i}. Then, use these estimates to construct an omitted variable, sometimes called the Mills ratio,

$$\frac{\varphi(Z_i \gamma / \sigma_0)}{\Phi(Z_i \lambda / \sigma_0)} \qquad \textbf{(7)}$$

where φ is the standard normal density and Φ is its cumulative distribution function.

Lastly, run an ordinary least squares estimation on *X* using the estimated Mills ratio as an additional regressor, transforming **(5)** into

$$y_i = X_i B + \frac{\phi(Z_i \gamma / \sigma_0)}{\Phi(Z_i \gamma / \sigma_0)} \hat{\sigma} \qquad \textbf{(8)}$$

Given the endogeneity test performed earlier in this analysis, where a discount retailer's decision to locate was tested on sales tax collection and income growth rates and no association was found, those variables are excluded from *Z*. Included in *Z* are the municipal tax rate, the county tax rate, population, recreational expenditures, the unemployment rate, highway miles, and the number of discount retailers outside the community but within a 20 mile radius. Following Hicks and Wilburn's suggestion (2001) that a discount retailer's location choice depends largely on the location of their competitors, a dummy variable indicating a competitor already located within the community is also included in *Z*.

As explained above, the results from this estimation are used to obtain estimates of γ/σ_0, which were then used to construct the Mills ratio. The Mills ratio is then used as an additional regressor in the estimation of sales tax collections, using the same explanatory variables that were used throughout the study.

For the purpose of comparison, the results from the two-stage, fixed effects estimation (reported in Table 7) are also reported in Table 15. The results are largely robust across the two estimation techniques. The fixed effects model still seems most appropriate, however, due to the prominent county and community specific variables in this dataset.

Preliminary Investigation of Cross-Tax Elasticities

An interesting extension of this analysis would be a thorough investigation of the cross tax elasticity between county sales tax rates and municipal tax rates for communities both with and without discount retailers. Although a thorough investigation is beyond the scope of the current analysis, an initial estimation is included here.

Table 16 reports results from an estimation using the same explanatory variables and technique as the previous estimations, but extending the definition of sales tax rates. A two-stage fixed effects model is employed, with sales tax collections and pull factors regressed, separately, on the time-changing variables and fixed effects. In stage two, the estimated coefficients from the fixed effects are regressed on the time-invariant variables.

In addition to *CORATE* and *MRATE* used in the previous estimations, an interaction term between the two *(INTRATE)* is also included. The value of including *INTRATE*, where $INTRATE = CORATE * MRATE$, is to determine how the two tax rates interacting with each other affect sales tax revenues. If the estimated coefficient for *INTRATE* is positive, as would be expected, the interpretation is that if both *CORATE* and *MRATE* are increased there will be an increase in total sales tax collections or the pull factor. Furthermore, a larger increase in *CORATE* will amplify the effect of an increase in *MRATE* on sales tax collections.[34]

Consistent with the previous results, the estimated coefficient for *CORATE* is positive and statistically significant in all sales tax collection estimations except when aggregated across all communities. It is also positive in the pull factors estimations, except for those communities without a discount retailer in which higher county sales tax

[34] Other variables are excluded from the table as there were no noteworthy changes.

rates are associated with lower pull on regional sales taxes over time. The pull factor results are also consistent with the previous results.

The estimated coefficient for *MRATE* was largely statistically insignificant in the previous estimations and this, again, is the case. *MRATE* was, however, positive and statistically significant previously for communities with changing status and is here, as well.

Two discrepancies exist for *MRATE* estimated coefficients when *INTRATE* is added to the model. In the sales tax collections estimation for communities with a discount retailer, the *MRATE* coefficient was previously insignificant and is now positive and significant. The estimated coefficient is positive and represents almost 4% of the median sales tax collections in these communities. This suggests that despite higher sales tax rates, consumers still choose to shop where they can take advantage of large discount retailers and the other retailers that usually open as a result. This makes municipal sales tax rates a viable option for raising revenues in these communities, allowing them to increase sales tax revenues due to the discount retailer itself, the other retailers it attracts through its role as an anchor store, and from this additional revenue option.

Additionally, for rural communities[35], *MRATE* previously had a positive and significant estimated coefficient. Here it is still significant but has a negative association with sales tax collections. This subsample estimation is also the only one where *INTRATE* is statistically significant. For rural communities, county tax rates have a positive association with sales tax collections, while sales taxes imposed at the municipal level have a negative association. The cross elasticity between the two is positive,

[35] Rural communities without discount retailers are omitted from this extension since no LOST are imposed within this subsample.

implying that decreasing municipal sales tax rates will lead to an increase in overall sales tax collections in these communities. However, several counties in New York do not impose county sales taxes, so LOST would be more viable in these areas.

Since *INTRATE* was statistically insignificant in most of the estimations, another set of estimations were run to attempt to get further insight into the effect of a change in the sales tax rates in these communities. Rather than using the variables *CORATE*, *MRATE*, and *INTRATE*, a rate representing the total sales tax rate, *TRATE*, is used, where $TRATE = CORATE + MRATE$.

TRATE is positive and statistically significant in all of the sales tax collections estimations, again, except when aggregated across all communities. This implies that increasing the overall tax rate, whether it be in the form of an increase in *CORATE* or *MRATE* as it makes no difference to consumers, will result in an increase in sales tax collections. This is important because, as expressed earlier, it suggests that consumers are still on the upward-sloping side of a sales tax Laffer Curve and raising sales tax rates is still an option, although not necessarily the best, for raising sales tax revenues.

An important distinction is that what has been identified here is best described as a short-run Laffer curve, as outlined by Buchanan and Lee (1982). There are two assumptions in their model: that government always seeks to obtain additional sales tax revenues and that political decision makers have lives shorter than the time it takes for the private sector to adjust to a change in taxes. They identify both a short and long-run Laffer Curve, where in the short-run an increase in the sales tax rate leads to an increase in sales tax revenues. They also identify a political equilibrium which is the peak of the short-run curve, as well as where it intersects the long-run curve.[36]

The intersection is still on the upward-sloping side of the long-run curve. Therefore, Buchanan and Lee point out that anyone arguing that government would never (or should never) operate on the downward-sloping side of a Laffer curve has adopted a short-run attitude. Anyone arguing that a decrease in the sales tax rate will lead to supply-side responses and increasing sales tax collections has adopted a long-run perspective.

What has been identified in the analysis in this chapter is a short-run Laffer curve, where increasing sales tax rates will lead to increases in sales tax collections. In the long-run, however, discount retailers and consumers alike will adjust to the tax increase. Discount retailers may choose to locate in "edge cities," those just outside communities with higher sales tax rates, if they feel higher sales tax rates are detrimental to their business. Therefore, in the long-run communities may not be able to capture the increase in sales tax revenues from discount retailers found in earlier estimations if sales tax rates are increasingly high.

Defining Regions Using Economic Areas

In the previous estimations a region is defined for the pull factor analysis as contiguous counties. For the county level analysis, $county_i$'s region is defined as those that share a border with it. For the community level analysis, $community_i$'s region is defined all those communities within the same county and within counties sharing a border. Using the Bureau of Economic Analysis's Economic Areas to define a region is

[36] Agglomeration benefits will also play a role.

an alternative definition. A map of these statistical areas for New York is given in Figure 5.

The Economic Areas consist of a "node", a metro area that serves as a center of economic activity, and the surrounding counties that are economically related to the node. Since the labor force of an economic area should work and reside within that area, commuting patterns are the main factor used in determining which surrounding counties are included in the area of a given node.

There are both advantages and drawbacks associated with using these areas as a definition for the pull factor ratio. The advantage is clear. The BEA states that data for these areas are used by government agencies for planning public-sector projects and programs, by businesses in determining plant locations and sales territories, and by university and other research groups for doing regional economic studies.

However, with this definition, contiguous counties are often separated and proximity is obviously very important in determining consumer shopping patterns. The results for the pull factor estimations using BEA Economic Areas are presented in Tables 17-21. Differences between these results and those estimated with the previous pull factor definition are discussed below.

For the county level analysis, there are few differences. *HWMILES* and *EST* coefficients were positively and negatively significant, respectively, with the previous pull factor definition. Neither is significant here. The biggest difference occurs with the *INCOME* variable coefficient, which was positive and significant previously but negatively significant here. For the estimation testing all communities, the only difference is that in the Economic Area estimation the number of discount retailers within 20 minutes coefficient is now negative and significant.

For communities with a discount retailer, several coefficient estimates that are statistically significant when analyzing contiguous counties are not when the analysis uses Economic Area levels. This is the case for *REC*, *INCOME*, *20MILES*, *20MINS*, and *HOUSE* coefficients.

For communities without a discount retailer, there are more discrepancies. Again, several variables which were statistically significant with the previous pull factor definition (*INCOME*, *20MINS*, *COLLEGES*, and *AIRPORTS*) are not significant in this estimation. Several coefficients that were not significant with the prior definition are significant now that the analysis is expanded geographically. Three county typology code coefficients are now, as expected, negative and significant (*MANF*, *SERV*, and *HOUSE*). *REC* and, unexpectedly, *POPLOSS*, are now both positive and significant.

The most significant changes are those for the sales tax rates variables. The county tax rate coefficient was negative and significant when the pull factor definition only included contiguous counties. Now, when expanded to include the entire Economic Area, it is positive and significant. The municipal tax rate coefficient, which was previously insignificant, is now positively significant.

For the “all rural” estimation the only differences that exist are the estimated coefficients for *REC* and *INCOME*. Both were positive and significant previously and are now both are insignificant. Also, *20MILES*, which had an insignificant coefficient previously, is now positively significant. Looking at only the rural communities without discount retailers, there are only two differences. The *CORATE* coefficient, which was previously insignificant, is now negative and significant. The *HWMILES* coefficient is significant with both definitions of pull factor, but the sign of the estimated coefficient changes. When considering only contiguous counties, highway miles are estimated to have a positive association with pull factors. When considering the entire Economic Area, the number of highway miles in a rural area without a discount retailer has a negative association.

Lastly, for those communities where the number of discount retailers has changed there are, again, few differences. *BIG3* and *CORATE* coefficients, which were both previously positive and significant, are not insignificant. The *COLLEGES* coefficient, which was previously insignificant, is now positively significant.

In summary, the only clear trend that exists with the switch between the two definitions is for *INCOME* and *REC*. Both of these variables were positively associated with sales taxes in most cases when considering only contiguous counties and on a more expanded level have no significant impact on pull factors. *REC*, specifically, would be expected to "wash out" when considering a larger area, as a tourist attraction is highly localized.

VI. Conclusions and Additional Research

Discount retailers and their impact on tax revenues, wages, and locally-owned businesses within communities have been the topic of much recent debate. Other studies focusing on the role of discount retailers, for example, have analyzed the effect on employment and the overall number of retail establishments. This paper uses a thirteen-year cross-section time-series analysis to investigate the impact of discount retailers on regional economies, specifically in the context of sales tax collections. To consider the competitive environment, the combined effect from the Big 3 discount retailers is analyzed. Potential endogeneity of the location decision is tested. A two-stage, fixed-effect estimation technique is used, with the Heckman Correction Method as a check for robustness.

The results are particularly relevant for local policymakers wishing to increase their sales tax collections to better fund public goods within the community. The results suggest that having a discount retailer located within a community has a strong positive association with sales tax collections and sales tax collection pull factors. Sales tax collections in communities with discount retailers are diminished if there are other discount retailers nearby. This is consistent with previous research. In contrast to previous research, however, my results are ambiguous regarding the impact on communities without a discount retailer but close to a community with one.

Also relevant to local policymaking decisions are the sales tax rate results. In all estimations an increase in sales tax rates is associated with an increase in sales tax revenues, identifying that the communities included in this study are on the upward-sloping side of a short-run Laffer curve. LOSTs appear to be a viable option for raising sales tax revenues, but only for those communities with a discount retailer or, specifically, for rural communities without high county tax rates. This builds on Rogers's (2004) discussion of urban fringe tax elasticities.

LOSTs show a negative association with property tax revenues, suggesting they can and are being utilized as a substitute for raising property taxes. Specifically relevant for rural communities are the results suggesting that when these communities are serviced by a regional airport there is a positive association with sales tax collections.

This research can be extended in many ways. A straightforward extension includes calculating a spatial weighted average to compare the effect of each community's tax rate in relationship to the tax rates of surrounding communities. An analysis of local land fiscalization would also be interesting given adequate data. As Lewis (2001) pointed out, fiscal motivations are often assumed to shape local government's land use decisions. Further study, for instance, could analyze the role of discount retailers in community zoning decisions.

Additionally, cities often offer incentives to attract discount retailers, such as tax breaks and new traffic patterns to accommodate customers. Further analysis could test whether these incentives pay for themselves with higher tax revenues.

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Chapter Two

Safer Hurricanes and the Role of Mitigation: Analyzing Population Growth and Damage in Coastal Counties

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Safer Hurricanes and the Role of Mitigation: Analyzing Population Growth and Damage in Coastal Counties

Abstract

The rising cost of hurricanes and other natural hazards has long been a concern to policy makers and insurance industry executives. A heretofore over-looked explanation of rising hurricane damages is offered here – improved hurricane forecasts and more extensive evacuations have made hurricanes less lethal and reduced the full cost of living on hurricane prone coasts, paradoxically increasing damages. A time varying measure of hurricane lethality is estimated for land falling hurricanes in the mainland U.S. between 1940 and 1999, showing the decrease in fatalities over time. Results from this estimation are used to confirm that the reduction in fatalities in coastal counties has played a role in increasing both population and hurricane damages in these areas. The significant role that mitigation can play in reducing damages is also analyzed.

I. Introduction

The United States has seen the costs of natural hazards and disasters rise dramatically over the past several decades. The costliest natural hazards in U.S. history, the Northridge Earthquake and Hurricane Andrew, have occurred within the last dozen years, and seven of the ten worst have occurred since 1989. Average annual losses from all natural hazards have increased from $20 million per million residents in 1975 to $1 billion per million residents in 1994 (in constant 1994 dollars; Mileti 1999).

The nation has invested millions of dollars specifically to understand and forecast hurricanes. Research efforts led by the National Hurricane Center (Simpson 1998) have succeeded in making land falling hurricanes less deadly. In the 1990s the modernization of the National Weather Service, featuring the installation of the Advanced Weather Interactive Processing System to process data from radar, satellites and surface observations at high speeds and a nationwide network of Doppler weather radars, contributed to improved forecasts of weather hazards (Friday 1994). Annual hurricane fatalities have fallen from .5 per million residents nationally during the 1950s to .05 per million residents during the 1980s and 1990s. Kunkel et al. (1999) attribute the decline to improved hurricane forecasts.[37]

Although hurricanes have become less deadly over time, like hazards in general, the resulting damages have increased - particularly in recent years. By 1995 hurricane damage in the 1990s had already exceeded total damage in the 1970s and 1980s

[37] The National Hurricane Center maintains a continuous watch for tropical cyclones throughout hurricane season, May 15 through November 30. The Center issues watches and warnings for hurricanes threatening landfall, and orders evacuations based on the warnings. Throughout the remainder of the year the Center provides training for emergency managers from the U.S. and other countries affected by tropical storms and conducts research on hurricanes and forecasts.

combined. This escalation has lead to interest among policy makers and researchers about the causes of increasing hurricane damages. This chapter considers an explanation which has not been widely discussed, namely the very reduction in hurricane lethality.

This analysis is timely given that between August 13th and September 26th, 2004 four hurricanes hit Florida and Alabama. Effects of these storms were felt along both the Gulf and Atlantic Coasts of the United States and well into the Eastern and Northeastern States. Collective damages from these hurricanes are expected to exceed those from Hurricane Andrew, the costliest disaster in United States history.

Researchers have spent years attempting to devise plans to reduce damages from these storms before they have a chance to occur. This analysis also looks at mitigation efforts and the role they play in reducing damages, outlining several mitigation tools deemed most effective over the past several decades. It highlights the important role that communities, counties, states, and insurance companies have in encouraging, sometimes reluctant or unable, homeowners to actively mitigate and reduce the role of insurance.

Presumably, the most effective way to encourage mitigation is by quantifying its benefits. The problem that lies therein is that although mitigation is widely considered to reduce damages, there is no data on mitigation measures undertaken, making it impossible to quantify their benefits. Cutter (1993) and others point out that awareness of prevention strategies often makes little difference to homeowners since hurricane, as well as other disaster, preparedness is not viewed as a "here-and-now" issue. Adoption of prevention measures depends mainly on past experience with the hazard in question.

Therefore, one can assume that if a county has experienced a prior hurricane, mitigation measures have been taken. Based on this, this analysis uses a past hurricane as a proxy for mitigation measures to quantify their effect on damages, helping to alleviate the issue of missing data.

This study is obviously most relevant to those communities located in hurricane prone areas, but also has important implications at the national level. The rising cost of natural disasters and the demonstrated potential for catastrophes with costs in excess of $20 billion pose a threat to the insurance industry. Catastrophe losses are not independent and thus threaten the financial viability of insurance companies, which turn to reinsurance and U.S government reinsurance subsidization.

Section two looks at proposed causes of increased hurricane damages, followed by a section presenting a model where the decrease in hurricane lethality increases the utility of living on the coast. Section four discusses the role of mitigation. Section five models fatalities from hurricanes and the remaining three sections build upon that model to estimate population growth in coastal counties, damages from hurricanes, and the role mitigation can play in reducing damages.

II. Proposed causes of increased hurricane damages

Increasing hurricane damages has lead to interest among policy makers and researchers to identify the causing factors. Some observers attribute rising damages to an increase in the number and severity of hurricanes. For instance, a 1995 Congressional report asserts that hurricanes "have become increasingly frequent and severe over the last four decades as climatic conditions have changed in the tropics" (cited in Pielke and Landsea 1998, p.623). This explanation, however, is simply false. Katz (2002) for instance finds no statistically significant increase in the number of land falling hurricanes over time.[38] And the period from 1991 to 1994 had the fewest tropical storms of any four year period in the last fifty years.

Increasing societal vulnerability, namely more people and wealth along hurricane prone coasts, seems to explain increasing hurricane damages. Figure 6 illustrates the increase in coastal county populations. The figure graphs population growth rates by decade for 130 U.S. counties on the Atlantic and Gulf coasts along with the overall U.S. population growth rate in each decade. As illustrated, the coastal counties grew faster than the nation in each decade of the 20th Century. A wealthier population will also have more property vulnerable to destruction by a hurricane. Pielke and Landsea (1998), Changnon et al. (2000), and Katz (2002) find no time trend for hurricane damages after normalizing for changes in population and wealth in addition to inflation.

An understanding of increasing hurricane losses requires an explanation for the increase in coastal county populations, and several have been advanced. One is the rising standard of living in the U.S.: wealthier people will spend more on luxuries, like living near the ocean.

Another possibility involves low probability event bias. Considerable evidence suggests that people do not behave according to expected utility theory with respect to low probability, high consequence events like hurricanes. Instead of considering the expected cost of these events, which is considerable, people act as if such events "couldn't happen to me" and treat the low probability as a zero probability (Kunreuther 1978, Camerer and Kunreuther 1989).

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[38] See also Table 22 reporting land falling hurricanes in the U. S. by decade.

Finally, a number of government policies, including subsidized insurance, disaster assistance, and structural mitigation measures (e.g. rebuilding roads and restoring beaches after storms) contribute to over building on hurricane prone coasts (Platt 1999).[39]

As stated, this chapter considers an alternative explanation which has not been widely discussed, namely the very reduction in hurricane lethality. By reducing the probability of fatalities from hurricanes, improved hurricane warnings, better evacuation, and engineering advances reduce the expected cost of living along hurricane exposed coasts. At least a part of the increase in coastal populations is then a consequence of the law of demand.

Evidence is provided of the impact of reduced hurricane fatalities on damages using a database of land falling hurricanes in the U.S. between 1940 and 1999. It is not argued that reduced lethality is the exclusive cause of increasing hurricane damages, only that is a contributing and over-looked factor. This explanation is a familiar one to economists, an example of offsetting behavior in response to an exogenous change in the riskiness of an activity, as first proposed by Peltzman (1975) for automobile safety.

III. Hurricane Forecasts and Locational Choice

The Theory

Do people consider natural hazards and other natural amenities in making location decisions? Considerable prior research says they do. Labor market studies find that wages across different cities include premiums for workers living in bad weather cities (those with more snow and colder January temperatures). A study of the real estate

[39] Garrett and Sobel (2003) document political influence on presidential disaster declarations and the dollar value of disaster assistance provided under the Stafford Act.

market in Los Angeles found that people would have to pay a premium for a house in an area of the city with higher air quality (Brookshire et al. 1982). Brookshire et al. (1985) found that houses in California in state designated special seismic zones near earthquake fault lines sold at a discount compared to homes at a safer distance from fault lines. Beron et al. (1997) found that the discount for homes in the seismic zones declined after the 1989 Loma Prieta earthquake, which did not cause as much death and destruction as an earthquake of that magnitude had been expected to.

Improvements in safety lower the expected cost of dangerous or reckless activity. An increase in the recklessness is expected to follow as a consequence of the law of demand. Such offsetting behavior was first identified by Peltzman (1975) in the behavior of drivers in response to automobile safety regulations in the 1960s. It is also related to the problem of moral hazard in insurance, because coverage against a loss reduces the return to effort to avoid the loss.

A hazard can be made less deadly in three distinct ways which yield different predictions regarding damages. A hazard could be made less dangerous by reducing the probability of the hazard occurring. For example, weather modification efforts offer the promise of reducing the frequency of damaging hailstorms. Alternatively, a hazard can be made less dangerous by reducing its severity, such as the removal of underbrush reducing the severity of wild fires. Lastly, structures in the hazard area could be strengthened to withstand the hazard, as with earthquake resistant buildings and elevating homes located on a flood plain. The example offered here assumes that the probability of fatality or injury conditional on the hazard occurring is reduced but the probability of the hazard and its destructive effect on property is not affected.

All three methods of reducing the lethality of hazards will increase the at-risk population, but only in the third case will damage definitely be expected to increase. In the first two cases the effect on total damages is indeterminate because the reduction in expected damages per household in the hazard area offsets the increase in the exposed population. Asserted here is the expectation that the reductions in hurricane lethality fit the third category - due to more timely and accurate warnings and evacuations, while damage to structures in the hurricane's path is not reduced.

The Model

In this section a simple model of household location choice is examined to derive testable predictions concerning hurricane lethality and damages. Consider a representative household's choice to live on a hurricane exposed coast. Let π be the probability of a hurricane and let σ be the probability that the household suffers a casualty given that a hurricane strikes the household's residence on the coast. Let *I* be the household's income, which is assumed to be independent of location decision, and let *L* be the dollar value of property losses which occur if the household lives on the coast and their residence is struck by a hurricane. The household can purchase insurance against property damage. Let *x* be the dollar value of coverage purchased and let *p* be the price per dollar of coverage. The household's total premium is $p*x$ and they receive a payment of *x* if a hurricane loss occurs. Let *y* denote the disposable income spent on consumption goods.

Utility is a function of disposable income *y*, the location decision, and the household's health state. Let θ denote the household's state of health, with θ^h indicating full health and θ^i indicating that the household has suffered a hurricane casualty.[40] It is assumed that utility is lower (and the marginal utility of income higher) when the household suffers a hurricane casualty. Let a superscript on the utility function designate the household's location choice, with *c* representing the hurricane vulnerable coast and *o* the location away from the coast. Let $U^c(y,\theta)$ be the household's expected utility if they choose to live on the coast, which can be written

$$U^c(y,\theta) = (1-\pi)*U^c(I-px,\theta^h) + \pi*(1-\sigma)*U^c(I-L-px+x,\theta^h) + \pi*\sigma*U^c(I-L-px+x,\theta^i) \qquad \textbf{(1)}$$

It is assumed that *x* is the household's expected utility maximizing insurance purchase. Utility if the household chooses to live inland is $U^o(y,\theta^h)$, which is the household's reservation utility level. The household will live on the coast if $U^c(y,\theta) \geq U^o(y,\theta^h)$.

Next the comparative statics of the household's location decision are examined. Consider first the effect of a change in the probability of a casualty, σ. Forecasts allow residents to evacuate in advance of an approaching hurricane, so improved warnings will reduce σ, but not the probability of a hurricane, π. A change in σ does not affect the reservation level of utility, $U^o(y,\theta^h)$. Thus the effect on $U^c(y,\theta)$ is

$$\partial U^c / \partial\sigma = \pi*[U^c(I-L-px+x,\theta^i) - U^c(I-L-px+x,\theta^h), \qquad \textbf{(2)}$$

which is negative given that the marginal utility of income is higher when the household suffers an injury, $U^c(y,\theta^i) > U^c(y,\theta^h)$, a typical assumption. A reduction in the probability of injury from a hurricane raises expected utility from living on the coast and

[40] In this simple formulation all casualties are considered equivalent. Gradations of casualties could be introduced but would not affect the testable hypotheses derived here.

will, ceteris paribus, increase the population on the vulnerable coast. If all households, including the new residents, suffer similar losses, *L*, the increase in population will increase the property damage from a hurricane. From **(2)** it is seen that the effect on utility of a reduction in σ depends on the probability of a hurricane. Thus a reduction in hurricane fatalities will have a greater impact on coastal population and hurricane damages in coastal areas facing a greater risk of hurricane landfall.[41] This is the main testable prediction of the analysis.

An increase in income also affects the household's location choice. An increase in income increases the household's reservation level of utility, $\partial U^o / \partial I > 0$. The effect of an increase in income on the utility of living on the coast (ignoring the effect of the change in *I* on losses from a hurricane or insurance purchase) can be written

$$\begin{aligned} \partial U^c / \partial I &= (1-\pi)\partial U^c(I - px, \theta^h)/\partial y + \\ &\pi(1-\sigma)\partial U^c(I - L - px + x, \theta^h)/\partial y + \pi\sigma\partial U^c(I - L - px + x, \theta^i)/\partial y \end{aligned} \qquad \textbf{(3).}$$

An increase in income raises the utility of living on the coast. With the standard assumptions of diminishing marginal utility of income and higher marginal utility of income given a lower state of health, then it follows that $*U^c / * I > *U^o / * I$ and an increase in income will increase coastal populations and hurricane property damage.

Finally, the effect of a change in the price of insurance, ignoring the effect on the quantity of insurance purchased, is

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[41] Frontsin and Holtman (1994) argue that an ability to evacuate from an approaching hurricane encourages residents to substitute lower quality construction, which would provide an additional method by which improved forecasts can increase damages. Note that the effect of a decrease in the probability of hurricane casualties for a household on the overall number of casualties is theoretically ambiguous due to the Peltzman (1975) offsetting behavior effect.

$$\begin{aligned}&\partial U^c / \partial p = \\ &-(1-\pi)\partial U^c(I-px,\theta^h)/\partial y - \pi(1-\sigma)\partial U^c(I-L-px+x,\theta^h)/\partial y - \\ &\pi\sigma\partial U^c(I-L-px+x,\theta^i)/\partial y\end{aligned} \quad \textbf{(4).}$$

An increase in the price of insurance lowers the utility of living on the coast, and the impact of the price change on the quantity of insurance purchased does not alter this result. Thus, a tax payer subsidy or cross-subsidization in regulated insurance rates also increases coastal populations and hurricane damages. No direct measure of coastal county insurance subsidies over time exists. States regulate insurance companies, which suggests the value of including state fixed effects in the analysis of hurricane damage.

The reduction in hurricane lethality apparent in the raw time series data of hurricane fatalities was noted earlier. Presumably, improved forecasts and better evacuations are responsible for declining fatalities. However, an improvement in construction techniques, which allow buildings to better withstand hurricanes, could also produce lower fatalities. Improved construction techniques would reduce both σ and L; more households would locate on hurricane exposed coasts but lower losses per household imply that damages may not increase. Fronstin and Holtman (1994), however, found that newer subdivisions suffered greater damage in Hurricane Andrew which indicates that building techniques, at least as employed, have not improved significantly.

IV. Hurricane Mitigation

Overview of Mitigation Tools

Although hurricanes do not occur as often as some natural hazards, they are among the most damaging and lethal. Substantial literature has focused on what can be done to reduce damages from hurricanes. Cutter (2001) suggests that that the first step toward creating disaster-resistant communities is to establish the current level of vulnerability. From there, a crucial step is a shift in public policy from a mindset focused on post-disaster assistance, to a more proactive mindset fostering mitigation efforts and pre-disaster planning.

Mileti (1999) outlines five mitigation techniques that have proven to be the most effective over the course of the last two decades: land use planning, building codes, insurance, engineering, and warnings. He states that land use planning, creating higher-density communities with flexible long-term plans, is the newest approach and currently shows the most promise. However, there is no overall federal policy to coordinate this effort in hazardous areas.

By establishing minimum requirements for materials used, based on climate and geology, building codes are collections of laws and ordinances that help structures withstand disasters. Advancements in engineering, often using sophisticated technology, make the strengthening of building codes possible. Burby (1998) points out building codes have been the principal mitigation effort used, however they only apply to new construction and can do little to help existing buildings.

Insurance companies providing coverage in hazardous areas can help facilitate the mitigation effort. Insurance companies can help educate and provide information to the public, participate in the strengthening of building codes, offer financial incentives to policyholders performing their own mitigation efforts[42], and limit the amount of insurance available in hazardous areas. Because it subsidizes people and firms in hazardous areas, Burby (1998) states that readily available insurance can produce

[42] However, they are quite limited by regulation.

complacency.[43] He points out that in recent years insurance companies began reaching out to builders in hazard-prone areas, asking them to acknowledge that the structures they build are at risk and to mitigate accordingly.

Community audio warning systems are suggested as another mitigation tool. However, the vast improvements in hurricane forecasting makes it possible for forecasters to predict with 50% accuracy exactly where a hurricane will hit within 24 hours. A prediction with 80% confidence can be made 12 hours before a hurricane strike (Mileti 1999). Because the greatest focus has been on supporting evacuation planning rather than mitigation (Burby 1998), forecasting improvements have made communities reluctant to purchase audio warning systems for cost-benefit reasons.

Public Mitigation Sentiment

Individuals do not always process hazard information in rational ways. Because natural hazards, such as hurricanes, are low probability high consequence events, people often do a poor job of using the available information to evaluate their surroundings and the consequences of their actions. Individuals often choose easy and inexpensive mitigation measures over those that might be more effective (Mileti 1999).

Godschalk, Brody, and Burby (2003) found lack of public interest in hazard mitigation in a case study of 5 hazard-prone areas. Citizens in community groups felt they lacked the necessary knowledge to provide input on technical issues such as engineering and building codes. They were also found to be most interested in "here-and-now" issues like traffic congestion, rather than with hazard mitigation efforts.

[43] This point is contended by Burby, as well as others. However, it should be made clear that insurance in and of itself does not involve subsidization. Some states set price controls, causing policies to be underwritten with rates that involve subsidization.

Simmons, Kruse, and Smith (2002) point out that there has been a general consensus among disaster experts that homeowners will not voluntarily adopt mitigation measures.

Storm shutters for windows and glass doors are a popular mitigation measure to protect homes from flying debris and “envelope” a home to prevent roof damage. Peacock (2003) found in a random survey of Florida homeowners that while 27% of the respondents stated they either have storm shutters or some type of coverage for 100% of all glass on the home, only 11% have something that would fall within building codes. Just over half of those without any coverage said they felt they just didn’t need it.

Why do some people simply fail to mitigate? Risk perception has already been outlined above. Income is another issue. A positive relationship usually exists between household income and preparedness measures (Mileti 1999). Anbarci, Escaleras, and Register (2005) use income in their model of earthquake fatalities, assuming that the relatively wealthy self-insure while the relatively poor are left to the mercy of the earthquake.

Peacock (1998) found that new home buyers are sensitive to hurricane issues but that after the financial stress of purchasing a home are unable to afford shutters. Additionally, many times homeowners bear the entire cost of mitigation. Insurance companies are sometimes unable to grant discounts in premiums for mitigation, which could subsidize measures.

Another possibility is that mitigation may not be efficient. There is not a lot of evidence that mitigation passes a cost-benefit test.

Despite their relative disinterest in mitigation and the financial issues associated with many of the more effective measures, there is substantial evidence that people living in hazardous areas do mitigate. This is especially the case when they have experienced a hurricane or live in an area with a hurricane history. Simmons, Kruse, and Smith (2002) found that homeowners in a community with a long history of hurricanes place a positive value on self-insurance. In Godschalk, Brody, and Burby's (2003) survey, only counties that had recently experienced losses had a strong interest in mitigation.

Peacock (2003) finds that both experience and knowledge seem to lead individuals to take mitigation actions of some sort. Cutter (1993) states that awareness of prevention strategies tends to make little difference and that it is past experience that determines the actual adoption of prevention measures. As previously discussed, warning systems are often decided against based on cost-benefit issues. When they are adopted, it is usually based on humanitarian sentiments following another disaster (Mileti 1999).

Not having a past hurricane experience can lead to extensive damages from even a relatively minor hurricane. For twenty years before Hurricane Hugo hit South Carolina in 1989, engineers had been recommending that buildings be designed to withstand hurricane force winds. One of the counties hit, Georgetown, had not been hit by a hurricane during modern recording.[44] Thus, the suggestions of the engineers were not accepted. Even though Hugo was not severe, Georgetown County suffered extensive damage.

[44] Recording of hurricanes and resulting fatalities is comprehensive from 1900 to the present. Comprehensive recording of damages experienced commenced near 1940.

Community Involvement

Lack of adequate preparation and coordination of services are endemic (Burby 1998). In many communities within the United States, simple mitigation measures are suggested over longer-term and, in some planners' opinions, more effective measures.[45] Mileti (1999) attributes this to the fact that they are less expensive and easier to sell politically. Evidence exists that community involvement in mitigation efforts enhances individual effort. Beyond that, community plans proposed under state mandates are of higher quality (Berke, Roenigk 1996).

Burby (1998) defines a mitigation plan as a county or community's statement of intent. It should give specific courses of action and commit the community to that course. The power of local governments to foster mitigation varies according to their goals and the methods available. These include their regulatory power to design and enforce building codes, fiscal power to first acquire tax revenue and then fund proposed projects, and, in some cases, their power of acquisition to use eminent domain to gain control over particularly hazardous areas.

The community effort can be aided by state government involvement. For example, a 1998 Florida law encouraged each county to develop a separate local mitigation strategy that would be updated on a yearly basis. Community plan quality has been found to vary with the wealth of the community, just as individual mitigation varies with income. However, Berke and Roenigk (1996) found that if there is a state mandate in place, community wealth is not a factor in community plan quality.

As more state and local initiatives and requirements are put in place, mitigation becomes contagious. Peacock (2003) found that communities with local regulations have

[45] There is no credible evidence to support the contention that longer-term measures are indeed more effective.

more homeowners that mitigate. Furthermore, households in areas where most of the neighbors mitigate have higher quality mitigation measures.

The Effect of Mitigation on Damages

It is a well-known that mitigation efforts reduce damages. However, the evidence is mainly anecdotal. For example, the Lighthouse Resort in Ft. Meyers, Florida experienced seven hurricanes over the last two decades resulting in $100,000 of repair costs per storm. Following a 2002 joint State, Federal, local, and owner mitigation project, despite feeling the direct effects of Hurricane Charley in 2004, the Lighthouse Resort remained undamaged and experienced no flooding (FEMA 2004).

In order to quantify the effect mitigation has on damages and further encourage individuals and government planners to mitigate, the amount of mitigation needs to be known. And unfortunately it is not. Mileti (1999) points out that there is no database on mitigation efforts – what they are, where they occur, or how much they cost – to determine their effect on damages and then provide a baseline for local cost-benefit analysis.

To quantify the effect of mitigation on damages, while mitigation itself is unknown, this analysis uses a proxy for mitigation measures undertaken. The experience of a prior hurricane, the previously discussed factor that appears to be the most influential in determining mitigation, is used as the proxy.

V. Data and Stage One Econometric Specification and Results

Improved forecasts, better preparation and evacuation, and improved engineering might all reduce the expected number of deaths from a given hurricane, but the prediction would be expected to hold only ceteris paribus, that is, holding the strength and location of the hurricane constant. Consequently, the number of persons killed in the last hurricane or the last ten hurricanes can not be used as a measure of lethality. Instead, a regression model of hurricane fatalities is first estimated in order to produce a time varying estimate of lethality. Fatalities directly caused by a hurricane are first estimated as a function of storm strength and other control variables. The model also includes decade dummy variables to allow the lethality of hurricanes to vary over time.

Results from this estimation are then used to model population growth, damages, and the role of mitigation. There is first an estimation to test how fatality reductions have affected coastal county populations. Then the determinants of hurricane damages are estimated to see if a change in hurricane lethality affects damages. Additionally, this same estimation is performed to test for the effect of mitigation measures by including a variable representing mitigation measured undertaken.

The data set is taken from the National Hurricane Center's archive of land falling hurricanes in the United States.[46] Hurricanes during 1940-1999 are included in the fatalities regression. Table 22 reports the breakdown of land falling hurricanes by category on the Saffir-Simpson scale and by decade. The Saffir-Simpson scale measures the intensity of the hurricane and its destructive potential. Ratings on the scale are integer values from 1 to 5, with a category 5 hurricane the most intense, and are based on wind speed, storm surge and potential damage. [47, 48] A total of 94 hurricanes made

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[35] The hurricane archive was accessed at http://www.nhc.noaa.gov/pastall.shtml.

[47] A category 1 storm is a minimal hurricane and has sustained wind speeds of 74-95 miles per hour and a 4-5 foot storm surge, while a category 5 hurricane has sustained winds in excess of 155 miles per hour and a storm surge in excess of 18 feet. Note that the damages corresponding to the five categories do not

landfall between 1940 and 1999, with 73 striking between 1950 and 1999. Category 1 hurricanes (at landfall) were most common (32 of 94), while only 7 storms reached Category 4 and two were rated Category 5. Mean fatalities were 24 with a median of 3 and a range of 0 to 394. Mean damages were, in constant dollars, \$1.54 billion with a median of \$242 million and a range of \$1.14 million to \$28.8 billion (Hurricane Andrew in 1992).

The fatalities regression estimates the determinants of the number of persons killed by a hurricane. The number of persons killed by hurricane *i* is modeled as follows:

$$Fatalities_i = f(Category_i, Density_i, D40_i, D50_i, D60_i, D70_i, D80_i) \qquad \textbf{(5)}$$

Fatalities is the number of persons directly killed by hurricane *i* and does not include deaths from inland flooding. *Category* is the rating of the hurricane on the Saffir-Simpson Hurricane scale at the time of landfall. *Density* is the average population density in persons per square mile of the counties struck by the hurricane, as listed in the National Hurricane Center's hurricane archive. The population for a county in a given year was estimated using linear interpolation from the decennial censuses. A higher population density of the storm path should increase the number of fatalities.

D40, *D50*, *D60*, *D70* and *D80* are dummy variables which equal one if the hurricane occurred in the decades 1940s, 1950s, 1960s, 1970s or 1980s respectively, or zero otherwise, with the 1990s the omitted decade. Thus, the lethality of hurricanes is allowed to vary over the decades, with the decade dummies capturing the effect of improved hurricane warnings and public dissemination of these warnings. It is expected

increase in linear fashion; a category 4 hurricane would be expected to cause 100 times the damage of a category 1 hurricane

[48] For details on the Saffir-Simpson scale see www.nhc.noaa.gov/aboutsshs.shtml.

that hurricanes have become less lethal over time; with the 1990s as the omitted decade, positive estimated coefficients are expected on the decade dummy variables, with the magnitude of the coefficients becoming smaller over time.

The number of fatalities produced by a hurricane is a count variable, taking on integer values with a high proportion of zeros. Of the 94 hurricanes in the sample, 23 produced no direct fatalities, and the median number of fatalities is 3 compared with a mean of 24.3. Thus the fatalities function is estimated using a Poisson regression (Greene 2000, pp.880-886). The Poisson model assumes that the number of persons killed by hurricane i, Y_i, is distributed as a Poisson random variable. The probability of a given number of fatalities is

$$\text{Prob}(Y_i = y_i) = e^{\lambda i} * \lambda_i^{y_i} / y_i!, \qquad y_i = 0,1,2,\ldots \qquad \textbf{(6)}$$

The parameter λ_i depends on the vector of independent variables x_i described above.

Fatalities Results

Table 23 presents the Poisson estimates of hurricane fatalities. Not surprisingly, the estimated coefficient for *Category* is a positive and highly significant determinant of fatalities; a one category increase in the strength of a hurricane almost triples expected casualties. *Density* also has a positive estimated coefficient, which is significant at better than the 1% level. As expected, hurricanes which strike more highly populated coastal areas are more deadly.

The decade dummy variables are all statistically significant at better than the 1% level, except *D70* which is significant at only the 10% level. All of the decade dummies are positive except *D80*, which is negative and significant. Roughly speaking, a downward trend in hurricane lethality is evident, as the coefficients on *D40* and *D50* are the largest, while the 1980s and 1990s are the least lethal decades. The differences between the decade dummy variables are significant at the 5% level as well, so from the 1950s through 1980s there are consistent and statistically significant reductions in lethality each decade.

Alternative Fatalities Specification

Using a linear time trend rather than decade dummies is an alternative way to specify the *Fatalities* equation.

$$Fatalities_i = f(Category_i, Density_i, TimeTrend_i) \quad \textbf{(7)}$$

The last column of Table 23 presents the results for this specification. The signs of the estimated coefficients for *Category* and *Density* are the same as when decade dummy variables were used, as is their approximate magnitude. The negative sign on the estimated coefficient for *TimeTrend* suggests that hurricanes have, as suggested, become less lethal over time.

VI. Modeling the Determinants of Coastal County Growth

A model of population growth in coastal counties is estimated to test whether a decline in the hurricane fatality rate causes an increase in coastal county population. The data set for this estimation is a panel of decennial population changes in 146 counties in 15 states along the Atlantic and Gulf of Mexico coasts between 1950 and 2000, accounting for a total of 730 observations. Two dependent variables are employed: the change in the number of persons living in the county during the decade, *ΔPop*, and the percentage change in the county population during the decade, *%ΔPop*. The first measure indicates society's total vulnerability while the second indicates the proportional change in vulnerability.

County population changes are estimated using the following models:

$$\begin{aligned}\Delta Pop = \beta_0 + \beta_1 * RFR + \beta_2 * InititalPop + \beta_3 * Area + \\ \beta_4 * Hit + \beta_5 * PHurricane + \beta_6 * USPop + \beta_7 * State\end{aligned} \quad \textbf{(8)}$$

$$\begin{aligned}\%\Delta Pop = \beta_0 + \beta_1 * RFR + \beta_2 * Density + \beta_3 * Hit + \\ \beta_4 * PHurricane + \beta_5 * USPop + \beta_6 State\end{aligned} \quad \textbf{(9)}$$

The independent variable of interest is the recent fatality rate, the *RFR*, which is constructed based on the time varying measure of hurricane fatalities estimated in the previous section. A reduction in hurricane lethality is expected to increase coastal populations, but only with a lag as it will take time for people to recognize the reduction in lethality and then move their residence. Consequently the dummy variable for the previous decade is used as the hurricane lethality variable for the current decade, so for population growth between 1960 and 1970, *RFR* is the coefficient of *D50* from Table 23.

The other control variables are as follows. *InititalPop* is the population of the country at the start of the decade. *Area* is the land area of the county in square miles; a larger county has more land to accommodate new residents, holding constant the initial population. Thus a positive estimated coefficient is expected for *Area*. *Density* is the population density of the county in thousands of persons per square mile at the start of the decade. This captures whether the county is already highly populated at the start of the period and is included in place of *InitialPop* and *Area* in the percentage growth regression.

Hit is a dummy variable which equals one if the county was struck by a hurricane during the decade of the observation. A hurricane during the decade will damage existing homes, businesses and infrastructure. The diversion of resources to reconstruction is expected to reduce county growth. A current hurricane could also affect residents' (or potential residents') perception of hurricane risk, so a negative estimated coefficient is expected for *Hit*.

PHurricane is the annual probability of a major hurricane striking the county, as reported in Sheets and Williams (2001). A major hurricane is defined as a hurricane of Category 3 or higher on the Saffir-Simpson scale. A higher probability of a hurricane increases expected hurricane damages, provided that residents pay the full cost of damage through higher insurance premiums or out-of-pocket after a loss. A higher probability of a landfalling hurricane should reduce county growth. But this measure, which does not change for a county over time, might also capture other characteristics which increase the desirability of living in the county.

USPop is the U.S. population in millions at the start of the decade. If the country as a whole grows faster in a decade, all counties should grow faster, as well, coastal counties included. The model is estimated with state dummy variables; *Florida*, for instance, equals one if the county is located in Florida and zero otherwise. The state dummy variables capture differences in the desirability of different states' coast lines as well as any state policies like insurance subsidies or land use regulations which inhibit or encourage coastal development. Virginia is the omitted state (last alphabetically of the 15 coastal states) so the estimated coefficients on the state variables indicate the effect relative to Virginia.

Population Estimation Results

Table 24 presents the regression results for county population. The estimates employ White's heteroskedasticity-consistent standard errors. For each model *RFR* has a negative and significant estimated coefficient, indicating that reductions in hurricane fatalities are positively associated with population growth. Note that in the *ΔPop* model *RFR* is significant at only the ten percent level, but is significant at the one percent level in the *%ΔPop* model. Overall, the model performs much better for *ΔPop* than *%ΔPop* as indicated by the adjusted R^2. [49]

Of the other control variables, note that *Hit* has a negative estimated coefficient in both specifications but is not significant, so counties did not grow significantly slower in a decade in which they were struck by a hurricane. *InitialPop* and *Area* have positive estimated coefficients and are significant determinants of *ΔPop* but *Density* is insignificant in the specification for *%ΔPop*. The state fixed effects are reported in Table 25, although no consistent pattern of significance emerged for any state across the two specifications, indicating that certain coastal states are not growing inherently faster than others.

VII. Modeling Hurricane Damages

The determinants of property damage caused by a hurricane are estimated in another estimation. Damage estimates are missing for a number of hurricanes prior to 1950, so those during 1950-1999 are included in this regression. Damages are modeled as follows:

[49] .4427 compared with .0704

$$Damage_i = \beta_0 + \beta_1 * Category_i + \beta_2 * Density_i + \beta_3 * Income_i + \beta_4 * Year + \beta_{5*} RFR_i + \beta_6 * PH_i + \beta_7 * RFR_i * PH_i + \varepsilon_i \quad \textbf{(10)}$$

Damage is the value of property damage caused by the hurricane in millions of dollars, adjusted for inflation using the GDP deflator. *Category* is the rating of the hurricane on the Saffir-Simpson scale; it is expected that stronger hurricanes will produce more damage, $\beta_1 > 0$.

Density is the population density of the counties affected by the hurricane and is expected to increase damages, $\beta_2 > 0$. *Income* is the per capita income of the counties struck by the hurricane. Since the value of real and personal property on a high income coastal area is higher, the dollar value of damage should be higher, $\beta_3 > 0$. But higher income individuals will also spend more to protect themselves and their property against hazards, which would reduce damage. Thus either a positive or negative sign for coefficient could be observed. *Year* is a time trend included to capture any effects of improved construction techniques or changes in building codes over time which might affect property damage.

RFR is the time varying measure of the deadliness of hurricanes, based on the coefficient point estimate of the decade dummy variable from the *Fatalities* estimation. A decline in hurricane fatalities reduces the cost of living on a hurricane prone coast, so it is expected that this will increase coastal population and damages. Again, a lag is required for people to recognize that hurricanes have become less deadly and move into hurricane exposed coasts. Consequently the coefficient from the previous decade's dummy variable is used as the *RFR* for a hurricane in year *t*. Thus the coefficient on *D70* in the fatalities regression is the value of *RFR* for any hurricane occurring during the decade of the 1980s.

The strength of the hurricane must be controlled for and a limit must be set for recent hurricanes due to the randomness in the occurrence of land falling hurricanes. *PH* is an estimate of the annual probability of a major hurricane at different points along the coast line. This variable was taken from estimates for various cities along the Atlantic and Gulf coasts contained in Sheets and Williams (2001).

In the expected utility model, an increase in π, ceteris paribus, reduces the utility of living on the coast, but different π's are observed at different locations so the utility of living on these different stretches of coast may differ, rendering a prediction for *PH* difficult. The expected present value of hurricane loss reduction mechanisms, for instance, will depend on the annual probability of a hurricane. If more hurricane-prone areas employ better building techniques or other loss reduction mechanisms, *PH* will have a negative sign. Alternatively, if hurricane prone states subsidize or cross-subsidize hurricane insurance, *PH* could have a positive sign.

*RFR*PH* is an interaction term capturing the combined effect of the recent fatality rate and probability of a hurricane. A decrease in hurricane lethality will have its greatest impact on damages in the most hurricane prone coastal areas. A negative sign on this interaction term, $\beta_7 < 0$, provides the sharpest test of the damage augmenting effect of hurricane forecasts and warnings.

Results of Modeling Hurricane Damages

Table 26 presents the least squares estimation of hurricane damages.[50] The first column displays estimates using the point estimates of the dummy variables from Table 23 as the *RFR* variable. All of the control variables are significant at the 10% level or better. The *Category* and *Density* coefficients, as expected, have positive signs, so a stronger hurricane striking a more densely populated coast will cause greater damage, as expected. A one category increase in the strength of a land falling hurricane increases expected damages by about $1.4 billion dollars, which is just less than the mean damage of all hurricanes in the sample of $1.54 billion.

Income is negatively associated with damages. Although the value of real and personal property is higher in higher income areas, wealthier residents seem to take more precautions to mitigate hurricane losses. Since wind-borne debris is a major contributor to structural damage, destruction of poorly constructed homes can damage other structures in the neighborhood. The negative sign on the *Income* coefficient is actually consistent with Fronstin and Holtman's (1994) result that subdivisions with higher average home prices suffered less damage in Hurricane Andrew.

Year has a positive coefficient, so, ceteris paribus, more recent hurricanes have been causing greater damage, which is also consistent with Fronstin and Holtman's (1994) finding that newer subdivisions suffered greater damage in Hurricane Andrew. *Year* may be capturing the effect of increasing wealth over time, with the *Income* variable capturing the cross-sectional impact of wealth on losses.

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[50] A Breusch-Pagan heteroscedasticity test failed to reject the null hypothesis of homoscedasticity at even the 10% significance level. The test statistic was 44.44, with p-value of .1085.

The coefficient on *PH*, the probability of a major hurricane, is positive and significant. After controlling for *Category*, population *Density*, and *Income*, regions with a higher probability of a hurricane still suffer greater damages.[51] This is a surprising result since durable loss reduction measures like strengthened building techniques and hurricane shutters have higher expected benefits in more hurricane prone regions and thus should be more likely to be installed (or their installation mandated). This result is consistent with possible insurance cross subsidization or weak enforcement of building codes in hurricane prone regions.

Of most significance to the hypothesis investigated here, the recent hurricane fatality rate, *RFR*, has a positive direct effect on damages, but a negative effect when interacted with the probability of a major hurricane. The *RFR* variable is significant at only the 5% level but the interaction term significant at the 1% level. The interaction coefficient provides the strongest test of the role of reducing the lethality of hurricanes or hurricane damages, and a reduction in the lethality of hurricanes does increase damages over the next decade in more hurricane prone regions.

The marginal effect of a decrease in *RFR* becomes positive when the annual probability of a major hurricane exceeds about 3.9%, a threshold exceeded in most counties of south Florida and along the Texas gulf coast. The magnitude of the impact of the declining fatality rate on damages is quantitatively quite significant. The increase in expected damages due to the observed decline in the fatality rate is $5.1 billion when the

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[51] Note that due to the interaction term the partial effect of hurricane probability on damages becomes negative if RFR is greater than 1.21, which it is with the 1950s value. The damages model was also estimated using an estimate of the probability of any hurricane also reported in Sheets and Williams (2001), since it is not know a priori what measure of hurricane risk people might use in estimating π. The signs of the estimated coefficients were the same as reported in Table 26, but the model overall did not perform as well with an adjusted R^2 of only .199. Consequently it is concluded that the probability of a major hurricane seems to approximate the public's subjective measure of hurricane risk.

probability of a major hurricane is 7% and $10.9 billion when the probability of a major hurricane is at its maximum of 10.5%.[52,53]

The damage model was also estimated using the lower bounds and upper bounds of the 95% confidence intervals for the estimates of the coefficients of the decade dummy variables to determine if the results were robust to plausible changes in the estimated lethality of hurricanes. The second and third columns of Table 26 present the results. The results are not affected in any substantial way. The estimated impact of the observed decrease in hurricane lethality with a 7% probability of a major hurricane is $4.8 billion with the lower bounds estimate and $5.5 billion with the upper bounds.

Estimating Damages with State Fixed Effects

The potential for state policies, particularly regulation of the insurance industry, to create subsidies for living on hurricane exposed coasts was noted earlier. To explore this possibility, state fixed effect variables were created. Because some hurricanes struck more than one state, the state variables were defined to equal the fraction of the population of the area struck by the hurricane living in that state, based on the counties listed for each storm. The fourth column of Table 26 presents this estimation, which uses

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[52] The observed reduction in the hurricane fatality rate is assumed to equal the difference between mean of the point estimates of D40 and D50 and the point estimate of D80 and the omitted decade, the 1990s, so $\Delta RFR = -1.38$.

[53] The use of an estimated parameter from the first stage as the RFR variable creates the potential for a generated regressor bias as noted by Pagan (1984), which could bias the estimate of the standard errors downward. Unfortunately there is no widely accepted correction for this type of bias in this type of model. To examine the robustness of the results, the models were estimated using Newey-West and White's standard errors. The interaction term remained significant in both cases, at the 10% level using Newey-West standard errors and at the 10% level in a one-tailed test with White's standard errors.

the point estimates of the decade dummy variables for the RFR variable, with the state variables reported in Table 27 separately.

Inclusion of state effects does not affect the estimates very much at all, and the state variables are both individually and jointly insignificant.[54] The state fixed effects model does produce a slightly higher estimate of the impact of the observed reduction in hurricane lethality on damages of $5.6 billion (with a 7% probability of a hurricane), compared to $5.1 in the model in column 1.

Damages Estimated Using Alternative Recent Fatality Rate

The *Damages* equation can also be estimated building on the alternative specification of the *Fatalities* estimation given in equation **(7).** This utilized a linear time trend rather than decade dummy variables to measure the decreasing lethality of hurricanes over time. As the decade dummy variables were used to create the *RFR* variable for the *Damages* estimation, using this alternative specification necessitates the creation of a different lethality measure. This alternative specification offers another advantage, beyond serving as a check for robustness.

Recall that *RFR* in the *Damages* regression is the estimated coefficient of the previous decade's dummy variable from the *Fatalities* regression, while the new measure of lethality, *NewRFR*, will be the year effect from ten years prior. A potential cause for concern with the decade dummy variables specification is that *RFR* for a hurricane occurring in 1978, for example, will be the same as *RFR* for a hurricane occurring in

[54] Both Wald and F-tests failed to reject the null hypothesis of joint insignificance of the state variables at even the 10% level. The test statistic for the Wald test was 14.82 with 13 degrees of freedom and a p-value of .3185, while the test statistic for the F-test was 1.140 with a p-value of .3488.

1971. Both *RFR*'s will be the decade dummy variable for the 1960's from the *Fatalities* estimation. Here, a hurricane occurring in 1979 will have a *NewRFR* of "68," while the 1971 hurricane will have a *NewRFR* of "61."

Since a linear time trend is now part of the lethality measure, the time trend is now removed from the Damages equation so that

$$\begin{aligned} Damage_i &= \beta_0 + \beta_1 * Category_i + \beta_2 * Density_i + \beta_3 * Income_i + \\ &\beta_4 * NewRFR_i + \beta_5 * PH_i + \beta_6 * RFR_i * PH_i + \varepsilon_i \end{aligned} \qquad \textbf{(11).}$$

The last column of Table 26 reports the results. The results are similar with this new specification, but, most importantly, the interaction term in negative and significant at the 1% level.

VIII. Mitigation Revisited

Defining a "Previous" Hurricane

The *Damages* analysis is now extended to look at past hurricanes. A past hurricane is used as a proxy for mitigation measures, since there is no available data. This is appropriate if communities really do mitigate after the fact. As there is no obvious way how to define what should be considered a "prior hurricane," several definitions will be tested. The estimation results will help decide how best to define this variable. Each definition has both advantages and drawbacks.

The first issue when defining a past hurricane is whether all hurricanes should be considered or only major hurricanes. Both will be tested. A "past hurricane" could be defined as the total number of prior hurricanes that have hit the affected counties, or, similarly, using a dummy variable to indicate whether any of the affected counties had been hit by a prior hurricane, where the value would be one if the counties had and zero otherwise.

The definition of a "past hurricane" may also need to account for how many of the counties directly affected by the current storm have been hit by a previous hurricane. For example, in 2004 Hurricane Frances made landfall first in Florida with a very large eye, crossed the entire state, and later made landfall again in Alabama. Many counties were directly affected; some had been hit by a previous hurricane, some not. Although this recent storm is not included in the data set for this analysis, similar situations have occurred in the past where some, but not all, of the counties involved were hit by a previous hurricane. Based on this, yet another possibility for defining a prior hurricane could be the percent of all counties directly hit that had experienced prior hurricanes.

Similarly, a dummy variable could be used to indicate whether a majority (75%) of the counties directly affected by the storm were hit with any hurricanes at least ten years prior. Different percentage cutoff points (50%) and (90%) for the indication of a positive binary value will also be tested, as well as varying time intervals (5+ years and 15+ years).

Lastly, there is the possibility that the effect of being hit by a hurricane begins to "wear off" after a certain amount of time. Perhaps within the first five or ten years after a hurricane hit residents are wary and continue to mitigate even without subsequent storms. If no other storms are experienced, as new residents move in and long-time residents become less wary, mitigation may significantly taper off. To test for this, the last definition of a "past hurricane" will account for whether any of the counties hit by a current storm were previously hit with 5 years, within 10 years, or within 15 years.

Using the same specification that was used to model damages, but including the variable for a past hurricane, *PastH*, the effect of mitigation measures will be modeled as

$$\begin{aligned} Damage_i = \beta_0 + \beta_1 * PastH_i + \beta_2 * Category_i + \beta_3 * Density_i + \beta_4 * Year_i + \\ \beta_5 * Income + \beta_6 * PH_i + \beta_7 * RFR_i + \beta_8 * RFR_i * PH_i + \varepsilon_i \end{aligned} \qquad \textbf{(12)}$$

Listed below are the 63 ways *PastH* was defined.

	5 or more years ago	10 or more years ago	15 or more years ago	w/i 5 years	w/i 10 years	w/i 15 years
Total previous hits	All and Major Only	All and Major Only	All and Major Only	All and Major Only	All and Major Only	All and Major Only
% of counties previously hit	All and Major Only	All and Major Only	All and Major Only	All and Major Only	All and Major Only	All and Major Only
Dummy variable if previously hit	All and Major Only	All and Major Only	All and Major Only	All and Major Only	All and Major Only	All and Major Only
Dummy variable if 50% previously hit	All and Major Only	All and Major Only	All and Major Only	All	All	All
Dummy variable if 75% previously hit	All and Major Only	All and Major Only	All and Major Only	All	All	All
Dummy variable if 90% previously hit	All and Major Only	All and Major Only	All and Major Only	All	All	All

Mitigation Results

Tables 28 through 39 report the results from the ordinary least squares estimation testing the effect of mitigation measures, proxied through a variable representing a prior hurricane, and its effect on damages sustained from hurricanes. All other explanatory variables are significant in each estimation, at least at the 10% level. These are excluded from the results tables as there are no noteworthy changes from the model for damages in terms of the estimated coefficients' signs, statistical significance, or magnitude.

PastH, the variable of interest, is significant in only four of the 63 estimations. However, two of those are also the same two estimations with the highest R-squared values, indicating that they are likely the most effective definitions of a past hurricane.

These two definitions use dummy variables to indicate whether 75% of the counties were hit ten or more years ago and whether 90% of the counties were hit 15 or more years ago. In both estimations *PastH* has a negative estimated coefficient, indicating that a previous hurricane far enough into the past for effective mitigation measures to be put in place effectively decreases damages. The estimated coefficient for *PastH* indicates that a prior hurricane 10 years or more in the past reduces damages by $1.38 billion dollars. Interestingly, the estimated coefficient for *Category* indicates that a one-category increase in storm strength leads to an increase in damages of $1.49 billion dollars. This suggests that effective mitigation measures after a past hurricane can reduce damages from a subsequent hurricane by one Saffir-Simpson scale category. For example, a category 3 hurricane hitting a county that had been previously hit results in the same damage that would be caused by a category 2 storm in a similar county that had not experienced any prior storms.

Why was *PastH* insignificant in the other estimations? The definition which included the total number of past hurricanes could pose endogeneity issues. Correlation could exist between this variable and the probability of a major hurricane, also included in the estimation. Clearly, how many hurricanes have hit an area in the past would be highly related to the probability of a hurricane making landfall in that area.

Defining a "past hurricane" by utilizing a dummy variable to indicate whether the affected counties had been hit by a prior hurricane poses some considerations. First, there is a minimum amount of time necessary for mitigation measures to be taken. Cutter (2001) asserts that creating disaster-resistant communities takes time. Using the entire sample period does not account for this. For example, Santa Rosa County in Florida was hit by two hurricanes in 1995, Erin in early August followed by Opal in October. Using a dummy variable to indicate a previous hurricane and using the entire sample set would mean indicating Santa Rosa County had been hit by a previous hurricane for the Hurricane Opal observation. However, 1995 was the first year in the twentieth century that Santa Rosa County had experienced a hurricane.

Again, the purpose of indicating a prior storm is to proxy mitigation measures. If a county had not been hit by a hurricane in over a century, there would not be any real, effective mitigation measures put in place over the course of a few months. Following the same method utilized earlier in this analysis, using a previous decade’s measure of hurricane lethality when modeling the lag time for citizens to recognize hurricanes have become less lethal and the subsequent affect on damages, it makes more sense to look at whether the counties were hit with a hurricane ten or more years ago. This would allow ample time for effective mitigation measures, if any, to be put in place

A third aspect of the definition is the percent of all counties in the storm path that had experienced prior hurricanes. In many cases, counties may have to work together to put effective mitigation measures in place. For example, Peacock (2003) found that households in communities that were included in the South Florida Building Code (Miami-Dade, Broward, and Monroe) had sufficiently higher quality mitigation measures than other counties. Godschalk, Brody, and Burby (2002) found that although Florida’s planning mandate is largely beneficial, many individual communities or even counties were unable to alone implement the broad-based incentives specified at the state level.

Using a percent measure would imply that there should be more mitigation effort if, for example, 33% of the counties were previously hit than if only 25% were hit. This is, most likely, not the case since it appears broader cooperation among counties is necessary for anything substantial to be put in place. Additionally, high exposure would be necessary for the insurance companies offering plans within the area to become involved in the mitigation effort.

For the 63 possible definitions of *PastH*, the overall results were split in terms of the sign for the estimated coefficients. However, the three cases in which *PastH* was negative and positively significant had very similar points estimates (-1349.25, -1388.21, and -1718.81), supporting the idea that mitigation can play a significant role.

IX. Conclusions

Previous research has established that rising costs of natural hazards are, for many hazards, due to increased societal vulnerability; that is, the costs for many hazards have not been increasing when normalized for changes in population and wealth as well as inflation. Explanations for rising damages for these natural hazards then must address why more people and property are located in hazard prone areas. A seemingly paradoxical cause for increasing vulnerability has been presented here – the investments by society to reduce the lethality of hazards.

The probability of being killed or injured is part of the price people must pay to live in a hazard prone area and so as a hazard becomes less deadly more people should live in the hazard area. This proposition was tested for hurricanes. A reduction in the lethality of hurricanes, as estimated in a regression analysis of fatalities from landfalling hurricanes in the continental U.S., increases population growth in Atlantic and Gulf coast counties, everything else equal. As Mileti (1999) argues, natural hazards interact with the built environment in a complicated manner. The analysis here illustrates one dimensions of the complexity.

Economists since Peltzman (1975) have identified a number of offsetting behaviors, that as technology or regulation reduce the full cost of risky behavior, people will engage in more of the risky behavior. Considered here is an application of offsetting behavior to natural hazards, specifically hurricanes. Advances in meteorology, engineering and emergency management have combined to make hurricanes less deadly over time. Yet if hurricanes are less likely to produce fatalities and injuries, living along an exposed coast becomes more inviting and coastal populations should increase. Hurricanes will kill fewer people but produce more property damage. Evidence is offered here for this proposition through an analysis of land falling hurricanes in the U.S. between 1940 and 1999. The results suggest that the reduction in hurricane lethality has a statistically significant and quantitatively large effect on damages on the portions of the coast most prone to hurricanes. Only the case of hurricanes has been examined here, but future research could examine the lethality/damage tradeoff for other hazards. Future research can also incorporate other explanatory variables (such as the age distribution of the affected areas) and analyze the effect of a "late-strengthening" hurricane.

A reduction in the lethality of hurricanes may increase expected hurricane damages but still raise social welfare. If the risk to life and limb deterred some prospective residents from living along a hurricane exposed coast, this is also a social cost of hurricanes in addition to property damage. But the risk to life and limb is one borne by residents, while other costs of hurricanes can be externalized. If the regulation of insurance or disaster relief subsidizes coastal living, however, making hurricanes less deadly can lower social welfare. As hurricanes become less deadly, the cost to society of socializing property losses increases.

Increasing populations along exposed coasts provide a potential new hurricane hazard. As Dow and Cutter (2002) stress, the growth of coastal populations threaten to exceed the capacity of the highway infrastructure to allow timely evacuation. Indeed, the prospect of massive traffic jams affected residents' evacuation decision in advance of Hurricane Floyd in 1999. Traffic congestion is a negative externality which households are unlikely to take into account the impact of their decision to live along the coast on others' ability to evacuate. Thus even if residents bear the full expected cost of hurricane damage, an evacuation externality might result in greater than optimal coastal populations, and be exacerbated as hurricanes become less deadly.

Mitigation efforts are thought, since evidence is mainly anecdotal, to reduce damages, especially when encouraged by state and local governments and insurance companies. Despite this as well as their knowledge of living in a hazardous area, many individuals and homeowners, based on the relative low probability of hurricane damage, are reluctant to mitigate.

The results suggest that as the percent of counties hit by the current storm increases, the category of the storm has less of an effect on damages, indicating that a prior hurricane does affect resident behavior. Specifically, if three quarters of the counties hit were hit previously, it effectively reduces damages to a point where the damages experienced are those that would be experienced in similar counties for a storm of one category less strength.

There is no significant effect from mitigation measures if the past hurricane hit within ten years of the current hurricane. Most likely this is due to the cost of retrofitting the existing housing stock. It could be efficient to incorporate new technology and building codes into future construction but not to tear down older structures.

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Tables

Table 1: Seven important studies dealing with discount retailers

	Stone (1995)	Franklin (2001)	Ozment And Martin (1990)	Gruidl and Andrianacos (1994)	Chervin, Edmiston, Murray (2000)	Hicks and Wilburn (2001)	Basker (2004)
Dependent Variable	Retail Sales Pull factor for Wal-Mart and non Wal-Mart towns (categorized by retailer types)	Wal-Mart Supercenter market share	Retail Sales, Employment, Establishments (categorized by retailer types)	Retail Sales Pull factor	Per capita Sales (pcs)	Employment, Number of Retail Establishments	Retail Employment
Independent Variables		Household income, Population, year		Income, Population, U rate, Retail, # of discount retailers	Income, U Rate, Tax Diff., Retail, 65 +, Commuters, Distance, Pop. density, Poverty, Family size, State pcs	Wal-Marts, Distance, U rate, Labor force	Urban, Year, County, Wal-Marts
Empirical Analysis	Comparison of means	OLS	Comparison of means	OLS	Cross-section, time-series – AR(1)	Cross-section, time-series – spatial weights	OLS
Level of Analysis	Community	Metro	County	County	County	County	County
Geography	Iowa	National	AR, MO, OK	Illinois	Tennessee	West Virginia	National
# of Years	5	1	5	5	36 months	11	23
Observations	170	54	820	380	756	555	40,227

Table 2: Descriptive Statistics

	County	Communities				Rural Communities	
		All	With Discount Retailer	Without Discount Retailer	Changing Status	All	Without Discount Retailer
Discount Retailers	2.21 (2.00)	0.14 (0.00)	1.55 (1.00)		0.71 (1.00)	.06 (0.00)	0.00 (0.00)
Population	190,724 (82,313)	11,102 (3,480)	44,459 (26,301)	8,036 (3,039)	21,024 (15,337)	4,732 (2,295)	3,639 (2,182)
Sales Tax Collections	48,795,459 *PC: 191.38*	1,191,651 *PC: 93.50*	7,098,324 *PC: 146.51*	665,208 *PC: 88.20*	2,636,230 *PC: 117.39*	382,700 *PC: 90.42*	236,314 *PC: 76.96*
Debt	118,420,165 *PC: 324.83*	6,486,112 *PC: 347.49*	31,266,705 *PC: 685.57*	3,844,493 *PC: 315.12*	12,433,246 *PC: 523.48*	1,346,698 *PC: 402.37*	767,292 *PC: 378.00*
Property Tax Collections	53,470,021 *PC: 240.29*	2,510,763 *PC: 179.59*	10,288,201 *PC: 276.17*	1,681,686 *PC: 170.63*	4,697,982 *PC: 212.73*	611,285 *PC: 151.91*	472,440 *PC: 149.83*
Total Expenditures	245,809,666 *PC: 1136.64*	8,195,374 *PC: 570.48*	37,725,111 *PC: 942.26*	5,047,495 *PC: 532.85*	17,913,641 *PC: 862.36*	2,946,583 *PC: 590.75*	1,657,017 PC: 599.12
Area	823 (693)	32 (35)	29 (29)	32 (34)	29 (35)	44 (44)	44 (42)
Recreation Expenditures	4,758,724 *PC: 13.21*	557,205 *PC: 29.49*	2,407,945 *PC: 54.16*	215,603 *PC: 26.83*	987,310 *PC: 44.53*	134,040 PC: 25.21	71,983 *PC: 19.78*
County Tax Rate	3.26 (3.00)					3.18 (3.00)	3.24 (3.00)
Municipal Tax Rate		0.07 (0.00)	0.30 (0.00)	0.03 (0.00)	0.44 (0.00)	0.05 (0.00)	0.00 (0.00)
Per Capita Income	17,150 (16,406)	16,827 (15,901)	17,925 (17,000)	16,659 (15,748)	18,429 (17,560)	15,772 (15,067)	15,802 (15,026)

*** Mean (Median)** ***Mean Per Capita (PC) Values in Italics***

Table 3: Endogeneity Test Results – Effect of Income and Sales Tax Collection Growth on Discount Retailer Location Choice

	Lagged growth rate	***2-year lagged growth rate***
INCOME	0.0129	0.0120
(GINC)	(0.3915)	(0.3175)
SALES TAX COLLECTIONS	-0.0029	-0.0018
(GSTC)	(-1.4096)	(-1.0073)

Probit Models used

$$Locate_{it} = \beta_0 + \beta_1 * ginc_{it-1} + \beta_2 * gstc_{it-1}$$

$$Locate_{it} = \beta_0 + \beta_1 * ginc_{it-2} + \beta_2 * gstc_{it-2}$$

Table 4: Test for Endogeneity of Sales Tax Rates to Sales Tax Revenues

	Municipal Tax Rate (MRATE)	***County Tax Rate (CORATE)***	***Total Tax Rate (TRATE)***
Sales Tax Collections Growth ($GSTC_{it}$)	-6.92 E-05 (-1.1197)	-5.78 E-05 (-0.6019)	-0.0001 (-1.4627)
Sales Tax Collections Growth,Lag ($GSTC_{it-1}$)	-7.13 E-05 (-1.1532)	-2.59 E-05 (-0.2698)	-9.72 E-05 (-1.1211)
Sales Tax Collections Growth, 2-year Lag ($GSTC_{it-2}$)	-6.07 E-05 (-0.9830)	-6.38 E-05 (-0.6596)	-0.0001 (-1.4219)

Models Used

$$MRATE_{it} = \beta_0 + \beta_1 * GSTC_{it} + \beta_2 * GSTC_{it-1} + \beta_3 * GSTC_{it-2}$$

$$CORATE_{it} = \beta_0 + \beta_1 * GSTC_{it} + \beta_2 * GSTC_{it-1} + \beta_3 * GSTC_{it-2}$$

$$TRATE_{it} = \beta_0 + \beta_1 * GSTC_{it} + \beta_2 * GSTC_{it-1} + \beta_3 * GSTC_{it-2}$$

Table 5: County Level Analysis

Stage One Results	***Sales Tax Collections***	***Sales Tax Pull Factors***
CONSTANT	-4.8 E+07***	-0.2555***
	(-4.4055)	(-4.7908)
BIG3	10093260***	0.0167***
	(12.8674)	(4.2806)
POP	1661.52***	
	(16.1842)	
CORATE	3889791*	0.1067***
	(1.7424)	(9.4974)
REC	1.1129***	2.91 E-09***
	(5.5216)	(2.8976)
HWMILES	7472.32***	9.20 E-06**
	(8.5512)	(2.1218)
URATE	-1280555	0.0014
	(-0.5667)	(0.1233)
INCOME	-113.022	4.42 E-05***
	(-0.3071)	(23.9802)
EST	-1317.17***	-4.41 E-06***
	(-4.4117)	(-2.9343)
Stage Two Results		**Stage 1: N = 741**
AREA	-37358	1601.83
	(-0.3676)	(1.0093)
COL	-1.2 E+08***	-347785
	(-3.5056)	(-0.642)
AIR	348123	484351
	(0.0107)	(0.9544)
UINF	-2.5 E+08**	1199937
	(-2.3221)	(0.7080)
MANF	-8.2 E+07	2338991
	(-0.7019)	(1.2863)
SERV	6805706	2610583
	(0.0548)	(1.3474)
FSGOV	36908954	2300681
	(0.2929)	(1.1691)
HOUSE	-5.1 E+08***	23184
	(-3.5996)	(0.0106)
POPLOSS	18969269	25622
	(0.1715)	(0.0148)

Stage 2: N = 57

Fixed effects also estimated in Stage One but not reported in table.

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat.

Stage One: Sales Tax Collections regressed on time-variant variables, fixed effects
Stage Two: Fixed effects coefficients regressed on time-invariant variables

Table 6: All Communities

	Sales Tax Collections	***Sales Tax Collections***	***Sales Tax Pull Factors***	***Sales Tax Pull Factors***
Stage One Results				
CONSTANT	-583287***	-470961**	0.0298	0.0239
	(-2.5159)	(-2.0431)	(1.0030)	(0.8064)
BIG3	1172165***	1161592***	0.0174***	0.0179***
	(22.7584)	(22.6115)	(2.6662)	(2.7414)
POP	-49.5481***	-41.1314***		
	(-5.7346)	(-4.7272)		
MRATE	19235	21619	0.0048	0.0050
	(0.7461)	(0.8409)	(1.4650)	(1.4514)
CORATE	-8093.38	-6847.42	3.44E-05	7.96E-05
	(-0.4959)	(-0.4209)	(0.0164)	(0.0381)
REC	0.2104***	0.2040***	-2.80E-09	-2.75E-09
	(14.8304)	(14.3867)	(-1.5929)	(-1.5670)
HWMILES	9421.06**	7536.77*	-0.0025***	-0.0024***
	(2.0609)	(1.6578)	(-4.3831)	(-4.2462)
INCOME	36.1061***	35.0874***	2.58E-05***	2.61E-05***
	(8.1483)	(9.5498)	(45.5877)	(55.6663)
20MILES	23228***		0.0007	
	(3.1725)		(0.7808)	
20MINS		129039***		-0.0013
		(7.4873)		(-0.6093)
Stage Two Results				**Stage One: N = 8450**
AREA	-5455.13	-5102.26	0.0001	0.0001
	(-0.8410)	(-0.8139)	(0.2337)	(0.2420)
COL	289025	270230	-0.0213	-0.0214
	(0.6376)	(0.6168)	(-0.6042)	(-0.6144)
AIR	-346585	-303226	-0.0328	-0.0326
	(-0.6595)	(-0.5970)	(-0.8033)	(-0.8098)
UINF	115160	99076	0.0092	0.0101
	(0.2552)	(0.2271)	(0.2613)	(0.2907)
MANF	333035	353766	-0.0038	-0.0050
	(0.6523)	(0.7169)	(-0.0957)	(-0.1288)
SERV	521464	546867	-0.0112	-0.0123
	(1.0242)	(1.1114)	(-0.2846)	(-0.3126)
FSGOV	541650	548519	0.0654	0.0650
	(0.9464)	(0.9917)	(1.4732)	(1.4822)
HOUSE	-396205	-363642	-0.0482	-0.0476
	(-0.6961)	(-0.6610)	(-1.0902)	(-1.0885)
POPLOSS	-79685	-94797	0.0126	0.0128
	(-0.2015)	(-0.2480)	(0.4090)	(0.4230)

Stage 2: N = 650

Fixed effects also estimated in Stage One but not reported in table.

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat.

Stage One: Sales Tax Collections regressed on time-variant variables, fixed effects
Stage Two: Fixed effects coefficients regressed on time-invariant variables

Table 7: Communities With a Discount Retailer

Stage One Results

	Sales Tax Collections	***Sales Tax Collections***	***Sales Tax Pull Factors***	***Sales Tax Pull Factors***
CONSTANT	-2.5 E+07***	-2.3 E+07***	-0.8956***	-0.7929***
	(-8.2253)	(-7.4465)	(-4.5710)	(-3.9300)
POP	253.5468***	251.2008***		
	(23.0243)	(21.9358)		
MRATE	118545	25144.75	-0.0121	-0.0185
	(0.1356)	(0.0281)	(-0.2102)	(-0.3127)
CORATE	1630576***	1248658**	0.0779**	0.0563
	(2.9030)	(2.1633)	(2.1134)	(1.4807)
REC	-0.3815***	-0.3468***	2.12 E-08***	2.21 E-08***
	(-5.0200)	(-4.4365)	(4.7123)	(4.6693)
HWMILES	-21864***	-22765***	-0.0002	-0.0003**
	(-5.7198)	(-5.7386)	(-1.6092)	(-2.4447)
INCOME	760.3441***	641.1286***	4.62 E-05***	3.89 E-05***
	(13.6241)	(12.0084)	(13.4965)	(11.6670)
20MILES	-484974***		-0.0291***	
	(-9.0199)		(-8.6957)	
20MINS		-726060***		-0.0390***
		(-7.2173)		(-6.4188)
Stage Two Results			**Stage 1: N = 572**	
AREA	8658.714	4583.583	-0.0002	-0.0004
	(0.8393)	(0.4403)	(-0.2093)	(-0.5238)
COL	296213.4	340530	-0.0131	-0.0104
	(1.4463)	(1.6479)	(-0.8935)	(0.6791)
AIR	-164359	-267583	0.00098	0.0042
	(-0.4837)	(-0.7804)	(0.4034)	(0.1629)
UINF	-980826*	-1144824*	0.0705*	0.0615
	(-1.7112)	(-1.9795)	(1.7144)	(1.4300)
MANF	-2215175***	-2506658***	-0.0523	-0.0719
	(-3.2705)	(-3.6679)	(-1.0748)	(-1.4150)
SERV	-948193	-1173291*	0.0289	0.1247
	(-1.4385)	(-1.7642)	(0.6112)	(0.2522)
FSGOV	-3290631***	-3737576**	-0.1152	-0.1420*
	(-3.1076)	(-3.4982)	(-1.5160)	(-1.7882)
HOUSE	-252120	-423949	-0.1117**	-0.1228**
	(-0.3894)	(-0.6489)	(-2.4022)	(-2.5297)
POPLOSS	-1005305*	-1173564**	-0.0491	-0.0574
	(-2.0144)	(-2.3306)	(-1.3691)	(-1.5324)
			Stage 2: N = 44	

Fixed effects also estimated in Stage One but not reported in table.

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat.

Stage One: Sales Tax Collections regressed on time-variant variables, fixed effects
Stage Two: Fixed effects coefficients regressed on time-invariant variables

Table 8: Communities without a discount retailer

Stage One Results

	Sales Tax Collections	***Sales Tax Collections***	***Sales Tax Pull Factors***	***Sales Tax Pull Factors***
CONSTANT	-1410342**	-1489005**	0.1757**	0.1748**
	(-2.0804)	(-2.2278)	(2.1508)	(2.1410)
POP	50.8284***	49.2547***		
	(23.6799)	(23.3595)		
MRATE	157283	213136	-0.1226	-0.1203
	(0.2429)	(0.3339)	(-1.5708)	(-1.5429)
CORATE	273618***	299824***	-0.0256**	-0.0247**
	(2.9694)	(3.3004)	(-2.3021)	(2.2236)
REC	-0.1443***	-0.1325***	-8.29 E-10	-7.50 E-10
	(-6.4580)	(-6.0145)	(-0.4901)	(-0.4439)
HWMILES	3600.381***	3837.723***	-0.0001*	-0.0001*
	(5.7319)	(6.2279)	(-1.7500)	(-1.8251)
INCOME	2.6954	-4.0061	7.95 E-06***	7.99 E-06***
	(0.4899)	(-0.7614)	(12.0055)	(12.4320)
20MILES	53661***		0.0024**	
	(6.2937)		(2.4176)	
20MINS		299541***		0.0080***
		(15.4615)		(3.3838)
Stage Two Results				**Stage 1: N = 7488**
AREA	633.9571	440.9179	-4.20 E-05	-4.81 E-05
	(0.6435)	(0.4451)	(-0.3903)	(-0.4456)
COL	221739*	229285*	0.0286**	0.0286**
	(1.4129)	(1.4742)	(2.0320)	(2.0283)
AIR	2765.784	12678	-0.0192*	-0.0190*
	(0.0452)	(0.2141)	(-1.6909)	(-1.6722)
UINF	-208912***	-200477***	0.0013	0.0015
	(-3.2771)	(-3.0882)	(0.1617)	(0.1905)
MANF	78056.94	93205	0.0026	0.0030
	(1.3489)	(1.6210)	(0.2947)	(0.3364)
SERV	-93778	-102530	0.1287	0.0126
	(-1.3113)	(-1.4352)	(1.4737)	(1.4351)
FSGOV	78333	90390	-0.0146	-0.0141
	(0.9565)	(1.0783)	(-1.5383)	(-1.4820)
HOUSE	291191**	281167**	0.0013	0.0009
	(2.3834)	(2.2566)	(0.1320)	(0.0962)
POPLOSS	-188884***	-204096***	-0.0003	-0.0007
	(-3.5573)	(-3.8081)	(-0.0388)	(-0.1047)
				Stage 2: N = 576

Fixed effects also estimated in Stage One but not reported in table.
Stage Two, columns 1 and 2, are estimated with White's standard errors after rejecting homoscedasticity.
Test stats: 2.8147, 2.9189

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat.

Stage One: Sales Tax Collections regressed on time-variant variables, fixed effects
Stage Two: Fixed effects coefficients regressed on time-invariant variables

Table 9: Changing Communities
Stage One Results

	Sales Tax Collections	***Sales Tax Collections***	***Pull Factors***	***Pull Factors***
CONSTANT	3191660***	3116180***	0.9750***	0.9041***
	(2.7608)	(2.6321)	(8.4486)	(7.8228)
BIG3	352324***	307621***	0.0365***	0.0364***
	(3.6342)	(3.0596)	(3.5548)	(3.4480)
POP	90.0722*	47.8403		
	(1.8792)	(0.9049)		
MTR	771683***	756989***	0.0772***	0.0789***
	(4.0732)	(3.9470)	(3.7689)	(3.7894)
CORATE	399029***	337003***	0.0465***	0.0439***
	(3.3286)	(2.7468)	(3.6033)	(3.3268)
REC	0.3395***	0.4094***	1.17E-08	1.72E-08
	(3.2270)	(3.8748)	(1.0481)	(1.5378)
HWMILES	-38077***	40830***	-0.0071***	-0.0071***
	(-0.6055)	(-4.5400)	(-7.6345)	(-7.1963)
INCOME	2.7167	20.6867	1.00E-05***	1.20E-05***
	(0.1781)	(1.4306)	(6.0639)	(7.5887)
20MILES	158717***		0.0145***	
	(-4.3784)		(4.1772)	
20MINS		519069***		0.0295**
		(4.0456)		(2.3745)
Stage Two Results			**Stage 1: N = 330**	
AREA	126994***	145098***	0.0202***	0.0198***
	(3.6258)	(3.3201)	(3.6269)	(3.5647)
COL	1994374	2508689*	0.3195	0.2970
	(1.5282)	(1.4492)	(1.6158)	(1.5094)
AIR	-1839971	-2091839	-0.1292	-0.1204
	(-1.0244)	(-0.9809)	(-0.5640)	(-0.5286)
UINF	-2102615	-1724490	-0.3463	-0.2646
	(-1.4794)	(-1.0178)	(-1.3335)	(-1.0241)
MANF	-2211936	-2486847	-0.3229	-0.3174
	(-1.5860)	(-1.3765)	(-1.0141)	(-1.0018)
SERV	-2124664	-2050160	-0.2591	-0.2212
	(-1.4249)	(-0.9798)	(-0.7660)	(-0.6572)
FSGOV	292099	444251	-0.1538	-0.1814
	(0.0875)	(0.1114)	(-0.4284)	(-0.5079)
HOUSE	-3027999	-2420391	-0.3489	-0.2934
	(-1.4669)	(-0.9698)	(-0.7101)	(-0.6001)
POPLOSS	34852	43368	0.0666	0.0761
	(0.0289)	(0.0300)	(0.3006)	(0.3452)
			Stage 2: N = 30	

Fixed effects also estimated in Stage One but not reported in table.
Stage Two, columns 1 and 2, are estimated with White's standard errors after rejecting homoscedasticity.
Test stats: 3.5719, 3.5812

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat.

Stage One: Sales Tax Collections regressed on time-variant variables, fixed effects
Stage Two: Fixed effects coefficients regressed on time-invariant variables

Table 10: All Rural Communities

Stage One Results	***Sales Tax Collections***	***Sales Tax Collections***	***Pull Factors***	***Pull Factors***
CONSTANT	-407468***	-359682***	-0.3177***	-0.2969
	(-4.5807)	(-4.2035)	(-5.7521)	(-5.5717)
BIG3	-112148***	-114088***	-0.0047	-0.0044
	(-3.6160)	(-3.7456)	(-0.2395)	(-0.2254)
POP	-110.8719***	-114.2170***		
	(-11.4692)	(-11.9874)		
MTR	225670***	230029***	-0.0063	-0.0065
	(7.1878)	(7.4500)	(-0.3400)	(-0.3534)
CORATE	41711***	47170***	0.0344***	0.0369***
	(3.5263)	(4.0516)	(4.4347)	(4.7969)
REC	0.4025***	0.3962***	5.18E-08**	4.91E-08**
	(10.5234)	(10.5327)	(2.0483)	(1.9590)
HWMILES	16367***	16826***	0.0069***	0.0072***
	(3.8822)	(4.0630)	(2.5013)	(2.6378)
INCOME	10.2587***	9.3404***	1.47E-05***	1.43E-05***
	(6.4073)	(6.3388)	(13.8832)	(14.6509)
20MILES	10629		0.0062	
	(1.5248)		(1.3378)	
20MINS		95404***		0.0474***
		(5.2529)		(3.9008)
Stage Two Results			**Stage 1: N = 806**	
AREA	-17447***	-17858***	-0.004	-0.0058*
	(-3.4181)	(-3.3875)	(-0.2864)	(-1.8347)
COL	747034	774234	0.2156	-0.3327***
	(1.5540)	(1.5904)	(1.4756)	(3.2570)
AIR	1386850***	1413145***	-0.0505	-0.2198**
	(2.9665)	(2.9701)	(-0.3461)	(-2.2894)
UINF	-325900***	-318417***	0.0156	-0.1037***
	(-3.7097)	(3.5531)	(0.2855)	(-2.6209)
			Stage 2: N = 62	

Fixed effects also estimated in Stage One but not reported in table
Stage Two, columns 1, 2, and 4, are estimated with White's standard errors after rejecting homoscedasticity.
Test stats: 118.4688, 128.2673, 53.1907

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat.

Stage One: Sales Tax Collections regressed on time-variant variables, fixed effects
Stage Two: Fixed effects coefficients regressed on time-invariant variables

Table 11: Rural Communities without discount retailers

Stage One Results	***Sales Tax Collections***	***Sales Tax Collections***	***Sales Tax Pull Factors***	***Sales Tax Pull Factors***
CONSTANT	-346155***	-334044***	-0.0489	-0.0474
	(-6.5972)	(-6.1541)	(-0.7378)	(-0.7149)
POP	6.6867***	11.5827***		
	(2.7498)	(4.8038)		
CORATE	43057.3***	26420.2*	-0.0128	-0.0042
	(3.1712)	(1.8690)	(-0.7421)	(-0.2402)
REC	0.6868***	0.6108***	-8.13 E-08	-8.53 E-08
	(11.1145)	(9.7013)	(5.32 E-08)	(-1.6059)
HWMILES	1708.145***	1408.362***	0.0007***	0.0007***
	(11.0517)	(8.8208)	(4.6603)	(4.0369)
INCOME	5.4728***	7.6743***	1.14 E-05***	1.11 E-05***
	(3.7592)	(5.2050)	(6.2080)	(6.1595)
20MILES	-140.082		-0.0075	
	(-0.0331)		(-1.4327)	
20MINS		77332.38***		-0.0172
		(7.0047)		(-1.2758)
Stage Two Results				**Stage 1: N = 754**
AREA	-295.368	-373.717	0.0013	0.0013
	(-0.8586)	(-1.0957)	(0.8463)	(0.8479)
COL	-54702.1*	-38670.7	0.1270	0.1337
	(-1.7285)	(-1.2325)	(0.8686)	(0.9186)
AIR	81602.74**	94635.23**	-0.1984	-0.2029
	(2.0776)	(2.4301)	(-1.0937)	(-1.2285)
UINF	13890.66	13595.46	-0.1901*	-0.1916*
	(0.5904)	(0.5828)	(-1.7491)	(-1.7702)
				Stage 2: N = 58

Fixed effects also estimated in Stage One but not reported in table.

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat.

Stage One: Sales Tax Collections regressed on time-variant variables, fixed effects
Stage Two: Fixed effects coefficients regressed on time-invariant variables

Table 12: Property tax collections

	Property Tax Collections
CONSTANT	-1260766***
	(-3.6079)
POP	220.9684***
	(17.9874)
CORATE	-2170.73
	(-0.1003)
MRATE LAG	-63171.3*
	(-1.8519)
TOTAL EXP	0.1588***
	(52.9137)
RURAL	28.6235
	(1.5418)
MHOME	6.9458***
	(4.9262)
HW MILES	38705.19***
	(5.7669)
COL	-1 E+07***
	(-18.6958)
UINF	212306.8*
	(1.7762)
	N = 650, T = 13

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat

Table 13: Sales Tax Collections Increments

	0-5MILES	6-10MILES	11-20MILES	0-10MINS	11-20MINS
1A. ALL COMMUNITIES	86235** (2.1708)	91009*** (5.0610)	-3861.76 (-0.4197)		
1B. ALL COMMUNITIES				63898 (1.0199)	134799*** (7.3144)
2A. WITHOUT BIG3	92389 (0.7418)	88278 (1.5401)	64800*** (2.6002)		
2B. WITHOUT BIG3				305738 (1.6271)	104091* (1.8360)
3A. WITH BIG3	1072722 (1.4849)	-202023 (-0.7063)	716314*** (3.9425)		
3B. WITH BIG3				6873.15 (0.0042)	565654** (2.1834)
4A. CHANGING STATUS	N/A	1060975*** (9.9280)	20646 (0.6110)		
4B. CHANGING STATUS				N/A	519069 (0.0001)
5A. RURAL COMMUNITIES	-40793 (-0.7785)	121192*** (5.4199)	6773.48 (0.8317)		
5B. RURAL COMMUNITIES				N/A	95404*** (5.2529)
6A. RURAL W/O BIG3	68807 (0.9810)	-38311 (-1.2843)	684.30 (0.0660)		
6B. RURAL W/O BIG3				N/A	77332*** (7.0047)

1A and B: N = 741; 2A and B: N = 8450; 3A and B: N = 7488; 4A and B: N = 330; 5A and B: N = 806; 6A and B: N = 754

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat

Table 14: Pull Factor Increments

	0-5MILES	6-10MILES	11-20MILES	0-10MINS	11-20MINS
1A. ALL COMMUNITIES	-0.0028 (-0.5528)	0.0015 (0.6409)	0.0008 (0.6828)		
1B. ALL COMMUNITIES				0.0028 (0.3448)	-0.0020 (-0.8445)
2A. WITHOUT BIG3	-0.0027 (-0.1822)	0.0057 (0.8238)	-0.0027 (-0.8846)		
2B. WITHOUT BIG3				0.0281 (0.9211)	-0.0050 (-0.7282)
3A. WITH BIG3	0.0186 (0.3885)	-0.0017 (-0.0921)	0.0285** (2.3768)		
3B. WITH BIG3				0.1221 (1.1383)	0.0183 (1.0805)
4A. CHANGING STATUS	N/A	0.0587*** (5.4694)	0.0057 (1.4513)		
4B. CHANGING STATUS				N/A	0.0295** (0.0181)
5A. RURAL COMMUNITIES	-0.0680* (-1.9420)	0.0586*** (3.9423)	0.0084 (1.5443)		
5B. RURAL COMMUNITIES				N/A	0.0472*** (3.9008)
6A. RURAL W/O BIG3	-0.0504 (-0.5870)	0.0435 (1.2056)	0.0073 (0.5711)		
6B. RURAL W/O BIG3				N/A	-0.0172 (-1.2758)

1A and B: N = 8450; 2A and B: N = 7488; 3A and B: N = 572; 4A and B: N = 330; 5A and B: N = 806; 6A and B: N = 754

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat

Table 15: Communities with a Discount Retailer , Alternative Estimation Technique

	Heckman Correction Estimation	***Two-Stage, Fixed Effects Estimation***
CONSTANT	-17883256***	-2.5 E+07***
	(-8.4746)	(-8.2253)
POP	260.3143***	253.5468***
	(25.0798)	(23.0243)
MRATE	537087	118545
	(1.3331)	(0.1356)
CORATE	956980***	1630576***
	(2.5614)	(2.9030)
REC	-0.3826***	-0.3815***
	(-5.1128)	(-5.0200)
HWMILES	-23964***	-21864***
	(-6.5158)	(-5.7198)
INCOME	760.3437***	760.3441***
	(13.9573)	(13.6241)
20MILES	-513947***	-484974***
	(-9.9100)	(-9.0199)
AREA	-7415.735	8658.714
	(-0.7970)	(0.8393)
COL	69234	296213
	(0.3654)	(1.4463)
AIR	-190548	-164359
	(-0.6362)	(-0.4837)
UINF	-1458412***	-980826*
	(-2.7347)	(-1.7112)
MANF	-1615923***	-2215175***
	(-2.5669)	(-3.2705)
SERV	-1101769**	-948193
	(-1.9692)	(-1.4385)
FSGOV	-2829921***	-3290631***
	(-2.6556)	(-3.1076)
HOUSE	-67444	-252120
	(-0.1164)	(-0.3894)
POPLOSS	-1138301***	-1005305*
	(-2.5566)	(-2.0144)
	N = 572	**Stage 1: N = 572; Stage 2: N = 44**

***significant at the 1% level; **significant at the 5% level; *significant at the 10% level
Number in parentheses is t-stat

Table 16: Cross Tax Elasticities

	Sales Tax Collections					Pull Factors				
	All	**W/ BIG3**	**W/O BIG3**	**Changing**	**Rural**	**All**	**W/ BIG3**	**W/O BIG3**	**Changing**	**Rural**
CORATE	-9596.12 (-0.5742)	2886657*** (3.5625)	275869*** (2.9764)	488189*** (2.6435)	19928* (1.6663)	-0.0001 (0.3546)	0.1328*** (2.4919)	-0.0246** (-2.2060)	0.0426** (2.1312)	0.0329*** (4.0374)
MRATE	-2992.96 (-0.0506)	2770504* (1.8312)	410569 (0.3183)	940811*** (2.8779)	-247673*** (-3.1862)	0.0027 (-0.0520)	0.1036 (1.0422)	-0.0183 (-0.1176)	0.0698** (1.9768)	-0.0342 (-0.6525)
INTRATE	11599 (0.4180)	-115075 (-0.2270)	-115075 (-0.2270)	-50059 (-0.6351)	190686*** (6.6210)	0.0011 (0.3161)	-0.0370 (-1.4244)	-0.0474 (-0.7757)	0.0022 (0.2586)	0.0105 (0.5689)

1: N = 8450; 2: N = 7488; 3: N = 572; 4: N = 330; 5: N = 806

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat

	All	**W/ BIG3**	**W/O BIG3**	**Changing**	**Rural**	**All**	**W/ BIG3**	**W/O BIG3**	**Changing**	**Rural**
TRATE	-4481.90 (-0.2796)	1157509** (2.1891)	304720*** (3.1828)	419320*** (3.4832)	56785*** (4.8165)	0.0007 (0.3259)	0.0513 (1.4589)	-0.0260** (-2.3454)	0.0320* (1.7455)	0.0294*** (3.9753)

1: N = 8450; 2: N = 7488; 3: N = 572; 4: N = 330; 5: N = 806

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat

Table 17: County Level Analysis, BEA areas

Stage One Results

	Sales Tax Pull Factors
CONSTANT	1.1826***
	(16.1545)
BIG3	0.0151***
	(2.8326)
CORATE	0.1570***
	(10.1833)
REC	2.87 E-09**
	(2.0773)
HWMILES	-6.64 E-06
	(-1.1161)
URATE	-0.0151
	(-0.9726)
INCOME	-2.14 E-05***
	(-8.4321)
EST	2.79 E-07
	(0.1353)
Stage Two Results	**N = 741**
AREA	1601.83
	(1.0093)
COL	-347785
	(-0.642)
AIR	484351
	(0.9544)
UINF	1199937
	(0.7080)
MANF	2338991
	(1.2863)
SERV	2610583
	(1.3474)
FSGOV	2300681
	(1.1691)
HOUSE	23184
	(0.0106)
POPLOSS	25622
	(0.0148)
	N = 57

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat

Stage One: Sales Tax Collections regressed on time-variant variables, fixed effects
Stage Two: Fixed effects coefficients regressed on time-invariant variables

Table 18: All Communities, BEA Areas

Stage One Results

	Sales Tax Pull Factors	***Sales Tax Pull Factors***
CONSTANT	1.0505***	1.0361***
	(20.4943)	(20.2765)
BIG3	-0.0296***	-0.0277***
	(-2.6311)	(-2.4597)
MRATE	0.0012	0.0010
	(0.2141)	(0.1789)
CORATE	0.0052	0.0052
	(1.4511)	(1.4381)
REC	-3.28E-09	-3.02E-09
	(-1.0822)	(-0.9980)
HWMILES	-0.0059***	-0.0057***
	(-5.8348)	(-5.6751)
INCOME	1.58E-05***	1.62E-05***
	(16.2402)	(20.0379)
20MILES	-0.0012	
	(-0.7135)	
20MINS		-0.0111***
		(-2.9363)

Stage Two Results

AREA	-0.0001	-0.0001
	(-0.0987)	(-0.1167)
COL	-0.0434	-0.0434
	(-0.5424)	(-0.5489)
AIR	-0.0542	-0.0563
	(-0.5839)	(-0.6147)
UINF	0.0522	0.0549
	(0.6536)	(0.6960)
MANF	0.0367	0.0319
	(0.4066)	(0.3578)
SERV	0.0089	0.0040
	(0.0981)	(0.0454)
FSGOV	0.0909	0.0891
	(0.8989)	(0.8928)
HOUSE	-0.1133	-0.1143
	(-1.1244)	(-1.1487)
POPLOSS	0.0124	0.0131
	(0.1778)	(0.1904)
	N = 8450	**N = 650**

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat

Stage One: Sales Tax Collections regressed on time-variant variables, fixed effects
Stage Two: Fixed effects coefficients regressed on time-invariant variables

Table 19: Communities With/Without Discount Retailers, BEA Areas

Stage One Results

	Communities With Retailers			Communities Without Retailers	
CONSTANT	0.4859***	0.4881***	**CONSTANT**	1.2060***	1.2058***
	(5.0065)	(5.0295)		(23.0855)	(23.0820)
MRATE	0.1212	0.01197	**MRATE**	1.1523***	1.1517***
	(0.4266)	(0.4210)		(23.0927)	(23.0797)
CORATE	0.0693***	0.0689***	**CORATE**	0.0844***	0.0842***
	(3.7920)	(3.7629)		(11.8855)	(11.8530)
REC	2.75 E-09	2.74 E-09	**REC**	2.20 E-09**	2.15 E-09**
	(1.2309)	(1.2023)		(2.0358)	(1.9932)
HWMILES	-5.08 E-05	-5.39 E-05	**HWMILES**	-0.0001***	-0.0001***
	(-0.7924)	(-0.8516)		(-2.7699)	(-2.7223)
INCOME	1.68 E-06	1.51 E-06	**INCOME**	3.34 E-07	2.58 E-07
	(0.9931)	(0.9424)		(0.7880)	(0.6265)
20MILES	-0.0006		**20MILES**	-0.0008	
	(-0.3846)			(-1.2315)	
20MINS		-0.0007	**20MINS**		0.0015
		(-0.2408)			(-1.0132)
Stage Two Results	**N = 572**				**N = 7488**
AREA	-0.0101	-0.0101	**AREA**	0.0009	0.0009
	(-1.2491)	(-1.2500)		(1.1592)	(1.1613)
COL	-0.0051	-0.0051	**COL**	-0.0340	-0.0340
	(-0.0319)	(-0.0316)		(-0.3512)	(-0.3508)
AIR	0.1368	0.1367	**AIR**	-0.0465	-0.0465
	(0.5135)	(0.5132)		(-0.5952)	(-0.5953)
UINF	0.1722	0.1721	**UINF**	-0.0339	-0.0339
	(0.3831)	(0.3829)		(-0.6333)	(-0.6340)
MANF	0.0544	0.0539	**MANF**	-0.1201**	-0.1202**
	(0.1025)	(0.1015)		(-2.0083)	(-2.0096)
SERV	0.6313	0.6308	**SERV**	-0.1125*	-0.1125*
	(1.2213)	(1.2206)		(-1.8687)	(-1.8676)
FSGOV	-0.4402	-0.4408	**FSGOV**	-0.0955	-0.0957
	(-0.5301)	(-0.5309)		(-1.4552)	(-1.4579)
HOUSE	-0.3834	-0.3837	**HOUSE**	-0.1729***	-0.1728***
	(-0.7551)	(-0.7558)		(-2.5614)	(-2.5605)
POPLOSS	-0.2897	-0.2898	**POPLOSS**	0.1097**	0.1098**
	(-0.7402)	(-0.7407)		(2.3439)	(2.3464)
	N = 44				**N = 576**

***significant at the 1% level; **significant at the 5% level; *significant at the 10% level
Number in parentheses is t-stat

Stage One: Sales Tax Collections regressed on time-variant variables, fixed effects
Stage Two: Fixed effects coefficients regressed on time-invariant variables

Table 20: Rural Communities, BEA Areas

Stage One Results

	All Rural Communities			***Rural, Without Discount Retailers***	
CONSTANT	-0.1950*	-0.1294*	**CONSTANT**	0.4552***	0.4566***
	(-1.6646)	(-1.1501)		(7.578)	(7.6039)
BIG3	-0.0763*	-0.0761	**BIG3**		
	(-1.8227)	(-1.8472)			
MRATE	0.0132	0.0130	**MRATE**		
	(0.3357)	(0.3336)			
CORATE	0.0636***	0.0707***	**CORATE**	-0.0343**	-0.0260*
	(3.8708)	(4.3641)		(-2.1774)	(-1.6676)
REC	2.67E-08	1.90E-08	**REC**	1.56 E-08	1.13 E-08
	(0.4985)	(0.3594)		(0.3235)	(0.2332)
HWMILES	0.0160***	0.0167***	**HWMILES**	-0.0005***	-0.0005***
	(2.7236)	(2.8902)		(-3.5052)	(-4.0562)
INCOME	6.21E-08	-5.63E-07	**INCOME**	5.75 E-06***	5.43 E-06***
	(0.0277)	(-0.2728)		(3.5058)	(3.2620)
20MILES	0.0201**		**20MILES**	0.0066	
	(2.0494)			(1.3925)	
20MINS		0.1294***	**20MINS**		0.0185
		(5.0633)			(1.5147)
Stage Two Results		**N = 754**			**N = 806**
AREA	0.0013	0.0013	**AREA**	-0.0134***	-0.0141***
	(0.8463)	(0.8479)		(-5.3359)	(-5.3409)
COL	0.1270	0.1337	**COL**	-0.7067***	-0.7067***
	(0.8686)	(0.9186)		(-3.1419)	(-2.983501
AIR	-0.1984	-0.2029	**AIR**	-0.4472**	-0.4692**
	(-1.0937)	(-1.1229)		(-1.9904)	(-1.9831)
UINF	-0.1901*	-0.1916*	**UINF**	0.4651***	0.4383**
	(-1.7491)	(-1.7702)		(2.7852)	(2.4930)
		N = 58			**N = 62**

***significant at the 1% level; **significant at the 5% level; *significant at the 10% level
Number in parentheses is t-stat

Stage One: Sales Tax Collections regressed on time-variant variables, fixed effects
Stage Two: Fixed effects coefficients regressed on time-invariant variables

Table 21: Communities With Changing Status, BEA Areas

Stage One Results

	Sales Tax Pull Factors	***Sales Tax Pull Factors***
CONSTANT	2.7149***	2.7045
	(16.6419)	(16.922)
BIG3	0.0042	-0.0004
	(0.2918)	(-0.0248)
MRATE	0.0836***	0.0813***
	(2.8863)	(2.8215)
CORATE	0.0241	0.0178
	(1.3176)	(0.9738)
REC	-6.82E-09	-3.71E-09
	(-0.4333)	(-0.2395)
HWMILES	-0.0164***	-0.0172***
	(-12.4284)	(-12.6556)
INCOME	4.23E-06*	5.37E-06***
	(1.8094)	(2.4620)
20MILES	0.0144***	
	(2.9409)	
20MINS		0.0615***
		(3.5803)
Stage Two Results		**N = 330**
AREA	0.0450***	0.0466***
	(3.5532)	(3.5972)
COL	0.7765*	0.7927*
	(1.7260)	(1.7220)
AIR	-0.3549	-0.3426
	(-0.6810)	(-0.6426)
UINF	-0.7718	-0.7201
	(-1.3061)	(-1.1910)
MANF	-0.7001	-0.7234
	(-0.9662)	(-0.9756)
SERV	-0.6818	-0.6714
	(-0.8858)	(-0.8525)
FSGOV	-0.3988	-0.4402
	(-0.4882)	(-0.5266)
HOUSE	-0.3654	-0.3317
	(-0.3269)	(-0.2900)
POPLOSS	0.0399	0.0562
	(0.0791)	(0.1089)
		N = 30

***significant at the 1% level;
**significant at the 5% level;
*significant at the 10% level
Number in parentheses is t-stat

Stage One: Sales Tax Collections regressed on time-variant variables, fixed effects
Stage Two: Fixed effects coefficients regressed on time-invariant variables

Table 22: Landfalling U.S. Hurricanes by Saffir-Simpson Category by Decade

	Category					
Decade	**1**	**2**	**3**	**4**	**5**	**Total**
1940's	5	8	7	1	0	21
1950's	4	1	8	2	0	15
1960's	4	5	3	2	1	15
1970's	6	2	4	0	0	12
1980's	8	2	4	1	0	15
1990's	5	6	4	1	0	16
Total	32	24	30	7	1	94

Table 23: Poisson Regression of Hurricane Fatalities

	Coefficient	Standard Error	Lower 95% Confidence Interval	Upper 95% Confidence Interval	Coefficient (Alternative Specification)
Constant	-.6580*** (-5.8247)	.1130	-0.8794	-0.4366	0.6819*** (8.3089)
Category	1.0813*** (42.3404)	.0255	1.0313	1.1314	1.0989*** (48.5480)
Density	.0007*** (20.1708)	.0000	0.0006	0.0008	0.0007*** (20.5434)
D40	.9937*** (10.8945)	.0912	0.8149	1.1725	
D50	1.3543*** (15.3218)	.0844	1.1811	1.5276	
D60	.4865*** (5.0412)	.0965	0.2974	0.6757	
D70	.2145* (1.6890)	.1270	-0.0344	0.4634	
D80	-.4082*** (-3.1749)	.1286	-0.6602	-0.1562	
Time Trend					-0.0281*** (-19.2398)
Pseudo R2	0.4614				0.4298

N = 93

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is z-stat

Table 24: Determinants of Coastal County Population Growth

	ΔPop	%ΔPop
Constant	60973**	1.9941**
	(2.0003)	(2.8412)
Lethality	-12449*	-0.2882**
	(1.8632)	(2.9542)
InitialPop	.1158***	
	(5.4344)	
Area	31.623***	
	(4.4825)	
Density		-0.1770
		(1.1408)
U.S. Pop	-0.0004***	-0.0074*
	(2.6737)	(3.0401)
PHurricane	11209***	0.0218
	(4.5676)	(1.4825)
Hit	-1880	-0.0433
	(0.3996)	(1.5153)
R2	.4580	.0947
Adjusted R2	.4427	.0704

N = 73

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat
Both models include state fixed effects reported in Table 25.

Table 25: State Fixed Effects for Models in Table 24

	ΔPop	%ΔPop
AL	-59927***	-0.2153
	(-4.7450)	(-1.1558)
FL	-20036**	0.0679
	(-2.4304)	(0.3713)
GA	-10136***	-0.0889
	(-2.7196)	(-0.4665)
LA	-29469***	-0.1766
	(-3.7544)	(-0.9405)
MAS	-15571**	-0.1317
	(-2.3012)	(-0.6942)
MD	-5217	-0.2763
	(-1.2923)	(-1.4267)
ME	-14413**	-0.2367
	(-2.1664)	(-1.2392)
MS	-30966***	-0.1442
	(-4.0416)	(-0.7783)
NC	-38249***	-0.2796
	(-4.2819)	(-1.5302)
NJ	-1999	-0.1150
	(-0.1772)	(-0.5236)
NY	10150	-0.0758
	(0.1550)	(-0.3315)
RI	-18835***	-0.2474
	(-3.0679)	(-1.2794)
SC	-28764***	-0.1822
	(-4.1308)	(-0.9906)
TX	-34860***	-0.2467
	(-4.5191)	(-1.3594)

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat

Table 26: Analysis of Hurricane Damages

	Coefficients Using RFR estimates	Coefficients Using Lower RFR Bound	Coefficients Using Upper RFR Bound	Coefficients for Estimation With State FE	Coefficients for Estimation Using *NewRFR* as Lethality Measure
Constant	-6037** (2.2990)	-5189** (-2.1957)	-6855** (-2.3406)	-1234 (0.0631)	600.0612 (0.2722)
Category of Hurricane	1427*** (3.9802)	1427*** (3.9871)	1427*** (3.9742)	1386*** (3.6390)	1545*** (4.3307)
Population Density	1.3219** (2.0879)	1.3101** (2.0744)	1.3316** (2.0969)	6.6393** (2.8884)	1.3020** (2.0491)
Income	-3.1770** (-2.1534)	-0.3194** (-2.1676)	-0.3145** (-2.1300)	-0.3737* (2.0499)	-0.3298** (-2.2447)
Year	141.397* (1.9515)	147.736** (2.0000)	133.559* (1.8866)	160.231 (1.6567)	
Fatality Rate (RFR)	4675** (2.2793)	4601** (2.3128)	4697** (2.2310)	5609* (2.1533)	766.526 (0.3972)
Prob. Hurricane (PH)	1454*** (3.8960)	1462*** (3.9188)	1440*** (3.8636)	1767** (4.1517)	-319.606 (-0.9748)
RFR*PH	-1199*** (3.3941)	-1206*** (-3.4208)	-1186*** (-3.3564)	-1385** (3.6231)	-1541*** (-3.1317)
R2	.3808	.3821	0.3788	.5157	.3645
Adjusted R2	.3141	.3156	0.3120	.3421	.3068

N = 73

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat
The first column presents estimates using the point estimates of the Recent Fatality Rate variable from Table 2, while the second and third columns use the upper and lower bounds of the 95% confidence interval of the estimates from Table 2.

Table 27: State Fixed Effects for Damages Estimation

	State FE Coefficients
AL	-3967
	(-0.1997)
CT	-19350
	(-0.1622)
FL	-6815
	(-0.3547)
GA	-9292
	(-0.3137)
LA	-4304
	(-0.2241)
MAS	-7072
	(-0.3599)
ME	-5686
	(-0.2950)
MS	-7792
	(-0.4051)
NC	-6540
	(-0.3361)
NY	-30357
	(-1.3619)
SC	-4929
	(-0.2549)
TX	-7299
	(-0.3799)

N = 73

Number in parentheses is t-stat

Table 28: "Prior" defined: total number of past hurricanes

	5+	10+	15+	M5+	M10+	M15+
C	-4762.29*	-4663.21	-4762.32	-5105.67*	-4832.10*	-4375.28
	(-1.6569)	(-1.5828)	(-1.5742)	(-1.7499)	(-1.6333)	(-1.4502)
CAT	1372.30***	1374.28***	1381.38***	1397.77***	1386.42***	1366.45***
	(3.7972)	(3.7979)	(3.8052)	(3.8642)	(3.8320)	(3.7768)
YV	133.19*	131.802*	132.686*	135.989*	133.272*	130.746*
	(1.8307)	(1.8049)	(1.8097)	(1.8611)	(1.8221)	(1.7922)
PD	1.4086**	1.4031**	1.3748**	1.3754**	1.3778**	1.3752**
	(2.2103)	(2.1999)	(2.1566)	(2.1511)	(2.1621)	(2.1698)
RFR	4206.16**	4185.30**	4218.59**	4446.59**	4367.72**	4212.56**
	(2.0093)	(1.9884)	(1.9866)	(2.1369)	(2.0967)	(2.0165)
AI	-0.3810**	-0.3824**	-0.3765**	-0.3694**	-0.3778**	-0.3981**
	(-2.4041)	(-2.3846)	(-2.3087)	(-2.2586)	(-2.3254)	(-2.4269)
PRMH	1278.33***	1287.18***	1312.35***	1355.05***	1332.84***	1295.04***
	(3.1469)	(3.1649)	(3.2095)	(3.4112)	(3.3518)	(3.2472)
INT1	-1138.92***	-1142.75***	-1149.32***	-1196.07***	-1193.58***	-1175.52***
	(-3.1875)	(-3.1962)	(-3.2019)	(-3.3726)	(-3.3715)	(-3.3263)
PastH	124.896	124.467	116.928	143.006	172.019	231.392
	(1.0842)	(1.0270)	(0.8543)	(0.7437)	(0.8899)	(1.1126)
R2	0.3919	0.3908	0.3878	0.3861	0.3883	0.3925
Adj. R2	0.3159	0.3147	0.3112	0.3093	0.3119	0.3166

N = 73

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat

Table 29: "Prior" defined: dummy variable if counties were previously hit

	D5+	D10+	D15+	MD5+	MD10+	MD15+
C	-5885.68**	-6063.55**	-5949.67	-5926.45**	-6035.10**	-6035.10**
	(-2.1277)	(-2.2286)	(-2.2498)	(-2.2310)	(-2.2770)	(-2.2770)
CAT	1443.00***	1424.26***	1468.87***	1446.66***	1427.47***	1427.47***
	(3.8834)	(3.8987)	(3.9908)	(3.9747)	(3.8973)	(3.8973)
YV	143.136*	140.844*	153.859*	148.078**	141.562*	141.562*
	(1.9452)	(1.8975)	(2.0211)	(1.9828)	(1.9182)	(1.9182)
PD	1.2617*	1.3342*	1.1699*	1.2333*	1.3192**	1.3192**
	(1.7671)	(1.8967)	(1.6921)	(1.8350)	(1.9915)	(1.9915)
RFR	4644.44**	4678.06**	4692.12**	4605.57**	4672.34***	4672.34**
	(2.2407)	(2.2617)	(2.2754)	(2.2239)	(2.2533)	(2.2533)
AI	-0.3139**	-0.3184**	-0.3069**	-0.3112**	-0.3173***	-0.3173**
	(-2.0918)	(-2.1267)	(-2.0526)	(-2.0845)	(-2.1055)	(-2.1055)
PRMH	1446.73***	1454.89***	1440.78***	1446.00***	1453.28***	1453.28***
	(3.8297)	(3.8583)	(3.8338)	(3.8458)	(3.8535)	(3.8535)
INT1	-1186.28***	-1202.21***	-1154.54***	-1162.94***	-1198.12***	-1198.12***
	(-3.2692)	(-3.3176)	(-3.1709)	(-3.1740)	(-3.2707)	(-3.2707)
PastH	-286.669	59.474	-783.083	-498.128	-16.5088	-16.509
	(-0.1878)	(0.0415)	(-0.5631)	(-0.4144)	(-0.0154)	(-0.0154)
R2	0.3811	0.3808	0.3838	0.3824	0.3808	0.3808
Adj. R2	0.3038	0.3034	0.3068	0.3052	0.3034	0.3034

N = 73

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat

Table 30: "Prior" defined: percent of counties previously hit

	P5+	P10+	P15+	MP5+	MP10+	MP15+
C	-6000.31**	-6346.21**	-6500.02**	-6066.93**	-5867.66**	-5479.60**
	(-2.2700)	(-2.3999)	(-2.4153)	(-2.2945)	(-2.1857)	(-2.0017)
CAT	1452.47***	1482.16***	1497.42***	1436.99***	1396.53***	1343.95***
	(3.9783)	(4.0861)	(4.0542)	(3.9733)	(3.7730)	(3.5740)
YV	147.255**	159.120**	153.098**	145.847**	135.219*	127.939*
	(1.9891)	(2.1333)	(2.0690)	(1.9775)	(1.8054)	(1.7087)
PD	1.2876**	1.2659**	1.3117**	1.2900**	1.3412**	1.3376**
	(2.0072)	(1.9916)	(2.0664)	(2.0090)	(2.0969)	(2.1044)
RFR	4756.92**	4775.16**	4919.17**	4732.77**	4632.89**	4440.42**
	(2.2963)	(2.3253)	(2.3683)	(2.2871)	(2.2402)	(2.1333)
AI	-0.3212**	-0.3123**	-0.3058**	-0.3144**	-0.3210**	-0.3309**
	(-2.1611)	(-2.1149)	(-2.0583)	(-2.1139)	(-2.1574)	(-2.2199)
PRMH	1457.66***	1413.47***	1431.05***	1467.93***	1451.18***	1458.61***
	(3.8817)	(3.7660)	(3.8157)	(3.8917)	(3.8625)	(3.8954)
INT1	-1203.32***	-1141.83***	-1192.02***	-1204.39***	-1210.48***	-1195.09***
	(-3.3832)	(-3.1886)	(-3.3638)	(-3.3841)	(-3.3900)	(-3.3700)
PastH	-4.0837	-9.1844	-8.3205	-3.9251	3.5935	8.0517
	(-0.4547)	(-0.9973)	(-0.8275)	(-0.4043)	(0.3636)	(0.7514)
R2	0.3828	0.3903	0.3873	0.3824	0.3821	0.3862
Adj. R2	0.3056	0.3140	0.3107	0.3051	0.3048	0.3095

N = 73

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat

Table 31: "Prior" defined: dummy variable if 75% of counties were previously hit

	D5+ (75%)	D10+ (75%)	D15+ (75%)	MD5+ (75%)	MD10+ (75%)	MD15+ (75%)
C	-6007.01**	-6329.16**	-6442.31**	-6006.24**	-5737.83**	-5275.28**
	(-2.2702)	(-2.4398)	(-2.4709)	(-2.2689)	(-2.1591)	(-1.9705)
CAT	1432.73***	1495.52***	1468.99***	1418.13***	1363.32***	1318.91***
	(3.9640)	(4.2056)	(4.1361)	(3.9148)	(3.7109)	(3.6035)
YV	143.707**	161.123**	158.061**	139.508*	130.605*	121.126*
	(1.9599)	(2.2269)	(2.1846)	(1.9034)	(1.7696)	(1.6426)
PD	1.3067**	1.1957*	1.2543**	1.3274**	1.3334**	1.3268**
	(2.0439)	(1.9025)	(2.0002)	(2.0806)	(2.1003)	(2.1067)
RFR	4730.16**	4726.94**	4980.16**	4641.42**	4605.07**	4336.06**
	(2.2822)	(2.3378)	(2.4464)	(2.2430)	(2.2378)	(2.1081)
AI	-0.3204**	-0.3054**	-0.3087**	-0.3181**	-0.3175**	-0.3261**
	(-2.1531)	(-2.0971)	(-2.1158)	(-2.1409)	(-2.1467)	(-2.2200)
PRMH	1464.54***	1380.48***	1423.90***	1446.16***	1453.49***	1469.22***
	(3.8819)	(3.7280)	(3.8569)	(3.8381)	(3.8858)	(3.9564)
INT1	-1209.55***	-1127.61***	-1203.10***	-1196.39***	-1222.54***	-1203.78***
	(-3.3854)	(-3.2136)	(-3.4451)	(-3.3597)	(-3.4402)	(-3.4242)
PastH	-237.293	-1388.21*	-1510.82	214.162	712.100	1249.61
	(-0.3180)	(-1.7024)	(-1.6014)	(0.2772)	(0.8245)	(1.2998)
R2	0.3818	0.4076	0.4046	0.3815	0.3873	0.3967
Adj.R2	0.3045	0.3336	0.3302	0.3042	0.3107	0.3213

N = 73

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat

Table 32: "Prior" defined: dummy variable if 50% of counties were previously hit

	D5+ (50%)	D10+ (50%)	D15+ (50%)	MD5+ (50%)	MD10+ (50%)	MD15+ (50%)
C	-5937.79**	-6716.22***	-6912.78***	-6089.73**	-5963.23**	-5521.22**
	(-2.2457)	(-2.5610)	(-2.5893)	(-2.3014)	(-2.1964)	(-2.0217)
CAT	1447.58***	1515.84***	1531.73***	1427.27***	1419.94***	1354.63***
	(4.0005)	(4.2387)	(4.2274)	(3.9567)	(3.8885)	(3.6291)
YV	145.083**	168.158**	158.381**	143.755**	139.571*	130.556*
	(1.9856)	(2.2954)	(2.1776)	(1.9652)	(1.8727)	(1.7581)
PD	1.2914**	1.2778**	1.3366**	1.2997**	1.3253**	1.3052**
	(2.0233)	(2.0438)	(2.1297)	(2.0323)	(2.0753)	(2.0525)
RFR	4714.66**	4811.93**	5100.88**	4729.10**	4653.12**	4467.42**
	(2.2863)	(2.3761)	(2.4842)	(2.2862)	(2.2431)	(2.1493)
AI	-0.3187**	-0.3020**	-0.2901**	-0.3112**	-0.3195**	-0.3285**
	(-2.1498)	(-2.0703)	(-1.9675)	(-2.0842)	(-2.1387)	(-2.2072)
PRMH	1460.10***	1395.60***	1419.12***	1474.09***	1449.61***	1458.87***
	(3.8924)	(3.7743)	(3.8296)	(3.8913)	(3.8400)	(3.8947)
INT1	-1203.02***	-1099.77***	-1193.38***	-1208.20***	-1200.95***	-1199.45***
	(-3.3871)	(-3.1091)	(-3.4069)	(-3.3908)	(-3.3704)	(-3.3816)
PastH	-452.52	-1349.25*	-1311.89	-325.032	102.403	648.384
	(-0.6048)	(-1.6683)	(-1.4729)	(-0.4100)	(0.1220)	(0.7218)
R2	0.3843	0.4066	0.4011	0.3824	0.3809	0.3858
Adj.R2	0.3073	0.3324	0.3262	0.3052	0.3035	0.3090

N = 73

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat

Table 33: "Prior" defined: dummy variable if 90% of counties were previously hit

	D5+ (90%)	D10+ (90%)	D15+ (90%)	MD5+ (90%)	MD10+ (90%)	MD15+ (90%)
C	-5992.05**	-6270.09**	-6712.84***	-6037.55**	-5964.90**	-5669.25**
	(-2.2644)	(-2.4045)	(-2.5633)	(-2.2814)	(-2.2365)	(-2.0984)
CAT	1430.95***	1435.27***	1458.09***	1427.34***	1413.60***	1384.53***
	(3.9640)	(4.0397)	(4.1214)	(3.9444)	(3.8614)	(3.7812)
YV	143.423**	163.497**	172.374**	141.544*	137.595*	127.844*
	(1.9611)	(2.2284)	(2.3386)	(1.9355)	(1.8315)	(1.6847)
PD	1.2996**	1.2042*	1.2313**	1.3205**	1.3313**	1.3456**
	(2.0303)	(1.9034)	(1.9657)	(2.0654)	(2.0823)	(2.1119)
RFR	4713.81**	4897.94**	5423.08***	4676.89**	4627.85**	4403.22**
	(2.2802)	(2.4027)	(2.6210)	(2.2619)	(2.2272)	(2.0919)
AI	-0.3188**	-0.3234**	-0.3343**	-0.3176**	-0.3142**	-0.3105**
	(-2.1460)	(-2.2109)	(-2.2936)	(-2.1352)	(-2.1018)	(-2.0891)
PRMH	1461.16***	1420.08***	1465.42***	1454.56***	1447.47***	1440.84***
	(3.8847)	(3.8325)	(3.9835)	(3.8610)	(3.8391)	(3.8380)
INT1	-1208.82***	-1159.50***	-1244.03***	-1199.90***	-1199.33***	-1180.24***
	(-3.3897)	(-3.3004)	(-3.5611)	(-3.3670)	(-3.3688)	(-3.3122)
PastH	-287.899	-1263.21	-1718.81*	-28.539	192.300	650.419
	(-0.3781)	(-1.4710)	(-1.7012)	(-0.0366)	(0.2139)	(0.6320)
R2	0.3822	0.4010	0.4076	0.3808	0.3812	0.3846
Adj.R2	0.3049	0.3262	0.3335	0.3034	0.3039	0.3077

N = 73

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat

Table 34: "Prior Hurricane" defined: total number of hurricanes to hit within a certain time period

	w/i 5	w/i 10	w/i 15	Mw/i 5	Mw/i 10	Mw/i 15
C	-6037.50**	-6156.97**	-6230.53**	-6066.57**	-5977.89**	-5889.30**
	(-2.2781)	(2.3036)	(-2.3546)	(-2.2920)	(-2.2415)	(-2.2105)
CAT	1426.53***	1425.13***	1417.50***	1425.45***	1424.00***	1416.76***
	(3.9495)	(3.9482)	(3.9406)	(3.9487)	(3.9404)	(3.9207)
YV	141.402*	143.598**	144.932**	140.917*	140.728*	140.314*
	(1.9330)	(1.9587)	(1.9901)	(1.9305)	(1.9252)	(1.9233)
PD	1.3219**	1.3294**	1.3741**	1.3434**	1.3077**	1.2768**
	(2.0714)	(2.0836)	(2.1513)	(2.0918)	(2.0339)	(1.9782)
RFR	4675.22**	4761.22**	4827.13**	4710.52**	4641.00**	4570.03**
	(2.2396)	(2.2843)	(2.3355)	(2.2761)	(2.2363)	(2.1994)
AI	-0.3177**	-0.3211**	-0.3273**	-0.3191**	-0.3160**	-0.3140**
	(-2.1163)	(-2.1555)	(-2.2040)	(-2.1461)	(-2.1209)	(-2.1112)
PRMH	1453.73***	1448.71***	1419.80***	1456.38***	1451.32***	1452.15***
	(3.8650)	(3.8519)	(3.7673)	(3.8742)	(3.8580)	(3.8673)
INT1	-1199.51***	-1212.28***	-1217.83***	-1214.78***	-1191.53***	-1171.34***
	(-3.3068)	(-3.3833)	(-3.4276)	(-3.3737)	(-3.3206)	(-3.2411)
PastH	0.5178	104.638	191.758	208.804	-94.124	-183.214
	(0.0011)	(0.3084)	(0.7713)	(0.2815)	(-0.1775)	(-0.4361)
R2	0.3808	0.3817	0.3865	0.3815	0.3811	0.3826
Adj.R2	0.3034	0.3044	0.3098	0.3042	0.3037	0.3054

N = 73

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat

Table 35: "Prior" defined: dummy variable if counties were hit within a certain time period

	Dw/i 5	Dw/i 10	Dw/i 15	DMw/i 5	DMw/i 10	DMw/i 15
C	-6032.66**	-6511.40**	-6772.61**	-6070.86**	-5963.57**	-5865.44**
	(-2.2771)	(-2.4131)	(-2.4301)	(-2.2954)	(-2.2279)	(-2.1415)
CAT	1426.05***	1432.55***	1443.40***	1426.38***	1422.07***	1417.74***
	(3.9458)	(3.9852)	(4.0096)	(3.9536)	(3.9290)	(3.9072)
YV	141.531*	148.890**	150.431**	140.707*	140.088*	139.387*
	(1.9361)	(2.0327)	(2.0463)	(1.9286)	(1.9097)	(1.8975)
PD	1.3226**	1.3056**	1.3367**	1.3532**	1.3063**	1.2942**
	(2.0721)	(2.0554)	(2.1047)	(2.1061)	(2.0296)	(1.9976)
RFR	4673.58**	4790.95**	4996.08**	4735.48**	4627.90**	4567.66**
	(2.2608)	(2.3238)	(2.3849)	(2.2870)	(2.2222)	(2.1617)
AI	-0.3174**	-0.3244**	-0.3266**	-0.3206**	-0.3144**	-0.3150**
	(-2.1310)	(-2.1891)	(-2.2016)	(-2.1559)	(-2.0988)	(-2.1134)
PRMH	1452.93***	1438.15	1463.38***	1457.43***	1451.51***	1449.34***
	(3.8582)	(3.8387)	(3.9093)	(3.8790)	(3.8591)	(3.8516)
INT1	-1197.58***	-1196.87***	-1236.02***	-1223.04***	-1192.04***	-1182.02***
	(-3.3324)	(-3.3774)	(-3.4598)	(-3.3879)	(-3.3263)	(-3.2547)
PastH	-29.082	602.169***	656.168	334.042	-139.062	-188.337
	(-0.0384)	(0.8041)	(0.8052)	(0.3841)	(-0.1816)	(-0.2420)
R2	0.3808	0.3870	0.3870	0.3822	0.3811	0.3813
Adj.R2	0.3034	0.3103	0.3104	0.3050	0.3037	0.3040

N = 73

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat

Table 36: "Prior" defined: percent of counties hit within a certain time period

	Pw/i 5	Pw/i 10	Pw/i 15	PMw/i 5	PMw/i 10	PMw/i 15
C	-5933.82**	-6223.46**	-6082.85**	-6468.06**	-5971.31**	-5651.10**
	(-2.2165)	(-2.2711)	(-2.1658)	(-2.4125)	(-2.1657)	(-2.0047)
CAT	1418.38***	1433.15***	1428.87***	1444.97***	1420.50***	1391.64***
	(3.9130)	(3.9601)	(3.9211)	(4.0152)	(3.8597)	(3.7465)
YV	139.400*	144.285*	141.731*	147.770**	140.421**	137.075*
	(1.8988)	(1.9545)	(1.9325)	(2.0239)	(1.9000)	(1.8586)
PD	1.3379**	1.3128**	1.3222**	1.4000**	1.3135**	1.2705*
	(2.0875)	(2.0554)	(2.0722)	(2.1831)	(2.0345)	(1.9531)
RFR	4588.41**	4731.73**	4693.79**	5077.45**	4645.45**	4474.51**
	(2.1907)	(2.2777)	(2.2314)	(2.4059)	(2.2169)	(2.1046)
AI	-0.3134**	-0.3183**	-0.3175**	-0.3289**	-0.3169**	-0.3166**
	(-2.0956)	(-2.1416)	(-2.1340)	(-2.2153)	(-2.1270)	(-2.1314)
PRMH	1449.91***	1445.35***	1452.80***	1498.02***	1452.55***	1453.21***
	(3.8545)	(3.8317)	(3.8587)	(3.9668)	(3.8605)	(3.8693)
INT1	-1185.76***	-1195.73***	-1201.01***	-1281.93***	-1196.38***	-1171.97***
	(-3.2927)	(-3.3565)	(-3.3583)	(-3.4885)	(-3.3427)	(-3.2334)
PastH	-2.4693	2.1996	0.4269	10.1465	-0.8039	-3.7074
	(-0.2509)	(0.2599)	(0.0484)	(0.8426)	(-0.0853)	(-0.3944)
R2	0.3814	0.3814	0.3808	0.3876	0.3808	0.3823
Adj.R2	0.3041	0.3041	0.3034	0.3110	0.3035	0.3051

N = 73

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat

Table 37: "Prior" defined: dummy variable if 50% of counties were hit within a certain time period

	Dw/i 5 (50%)	Dw/i 10 (50%)	Dw/i 15 (50%)
C	-5905.85**	-6382.13**	-6255.13**
	(-2.1981)	(-2.3564)	(-2.2882)
CAT	1414.45***	1431.94***	1430.50***
	(3.8903)	(3.9731)	(3.9611)
YV	138.670*	147.247**	143.156**
	(1.8833)	(2.0018)	(1.9563)
PD	1.3402**	1.3003**	1.3202**
	(2.0906)	(2.0393)	(2.0706)
RFR	4564.08**	4778.04**	4780.96**
	(2.1694)	(2.3085)	(2.2845)
AI	-0.3133**	-0.3189**	-0.3167**
	(-2.0971)	(-2.1500)	(-2.1316)
PRMH	1450.93***	1434.43***	1447.11***
	(3.8595)	(3.8088)	(3.8453)
INT1	-1185.96***	-1185.05***	-1208.89***
	(-3.3016)	(-3.3274)	(-3.3850)
PastH	-248.77	428.377	240.233
	(-0.2781)	(0.5691)	(0.3145)
R2	0.3815	0.3839	0.3817
Adj.R2	0.3042	0.3069	0.3044
			N = 73

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat

Table 38: "Prior" defined: dummy variable if 75% of counties were hit within a certain time period

	Dw/i 5 (75%)	Dw/i 10 (75%)	Dw/i 15 (75%)
C	-5973.26**	-5319.02**	-4987.53*
	(-2.2183)	(-1.9605)	(-1.8010)
CAT	1422.30***	1374.75***	1315.31***
	(3.9220)	(3.8020)	(3.5555)
YV	139.36*	128.367*	134.125*
	(1.8651)	(1.7470)	(1.8493)
PD	1.3336**	1.3575**	1.3194**
	(2.0694)	(2.1425)	(2.0896)
RFR	4613.91**	4310.05**	4200.63**
	(2.1759)	(2.0729)	(2.0142)
AI	-0.3147**	-0.3083**	-0.3236**
	(-2.0916)	(-2.0873)	(-2.1984)
PRMH	1452.33***	1460.47***	1469.35***
	(3.8611)	(3.9162)	(3.9462)
INT1	-1192.87***	-1184.18***	-1163.78***
	(-3.3160)	(-3.3503)	(-3.2899)
PastH	-127.45	-835.830	-926.700
	(-0.1285)	(-1.0431)	(-1.1656)
R2	0.3809	0.3911	0.3936
Adj.R2	0.3036	0.3150	0.3179
			N = 73

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat

Table 39: "Prior" defined: dummy variable if 90% of counties were hit within a certain time period

	Dw/i 5 (90%)	Dw/i 10 (90%)	Dw/i 15 (90%)
C	-5947.14**	-5319.02**	-4987.53*
	(-2.2257)	(-1.9605)	(-1.8010)
CAT	1422.48***	1374.75***	1315.31***
	(3.9357)	(3.8020)	(3.5555)
YV	137.938*	128.367*	134.125*
	(1.8539)	(1.7470)	(1.8493)
PD	1.3469**	1.3575**	1.3194**
	(2.0841)	(2.1425)	(2.0896)
RFR	4567.55**	4310.05**	4200.63**
	(2.1604)	(2.0729)	(2.0142)
AI	-0.3120**	-0.3083**	-0.3236**
	(-2.0725)	(-2.0873)	(-2.1984)
PRMH	1451.99***	1460.47***	1469.35***
	(3.8624)	(3.9162)	(3.9462)
INT1	-1186.98***	-1184.18***	-1163.78***
	(-3.2993)	(-3.3503)	(-3.2899)
PastH	-244.422	-835.830	-926.699
	(-0.2392)	(-1.0431)	(-1.1656)
R2	0.3813	0.3911	0.3936
Adj.R2	0.3040	0.3150	0.3179
			N = 73

***significant at the 1% level
**significant at the 5% level
*significant at the 10% level
Number in parentheses is t-stat

Figures

Figure 1: Current Analysis in Relation to Existing Literature

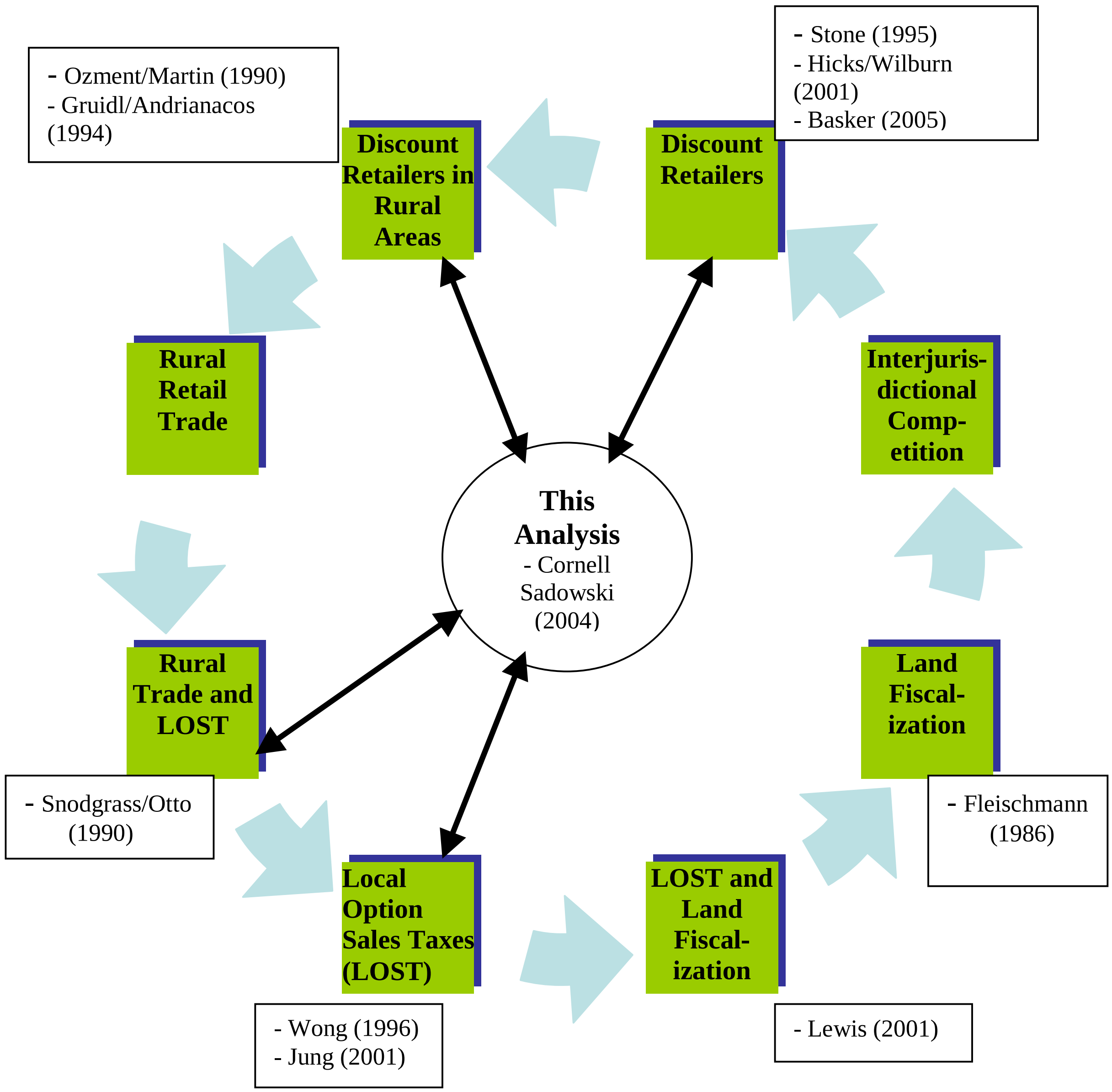
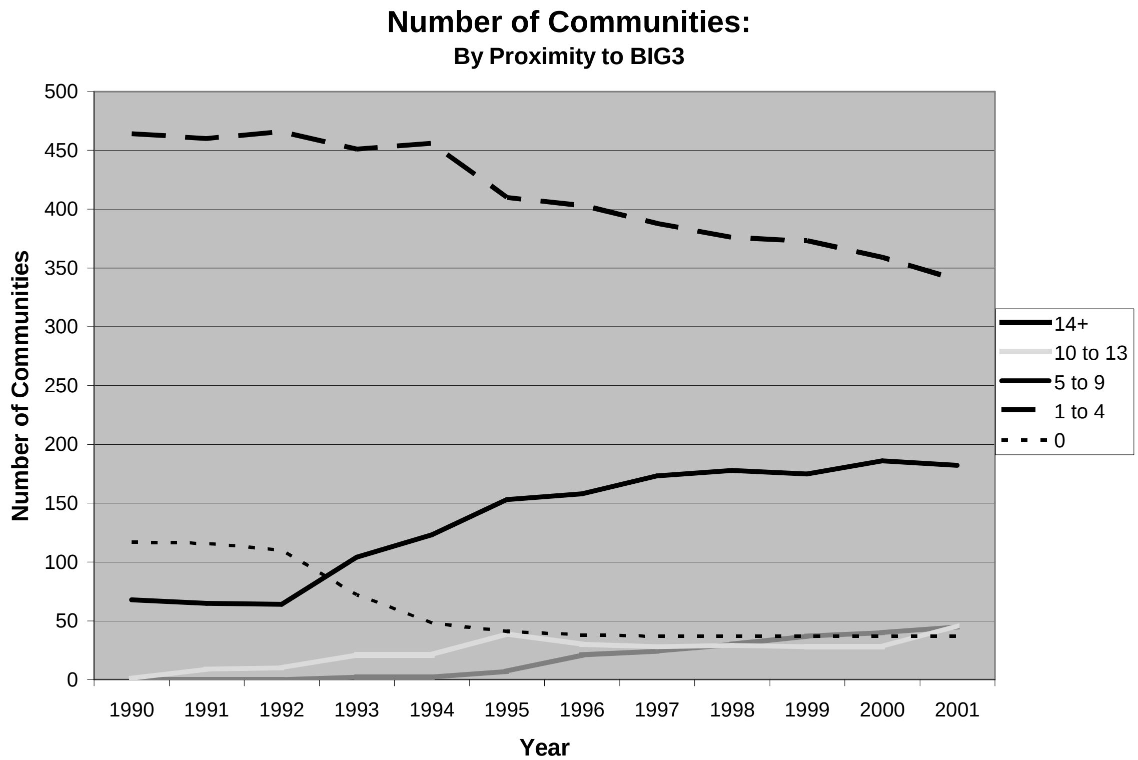


Figure 2:



Number of Communities:
By Proximity to BIG3
Number of Communities
500
450
400
350
300
250
200
150
100
50
0
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
Year
14+
10 to 13
5 to 9
1 to 4
0

Figure 3: Discount Retailer Locations in New York State

Figure 4: Rural Communities Without a Discount Retailer, Terrain Map

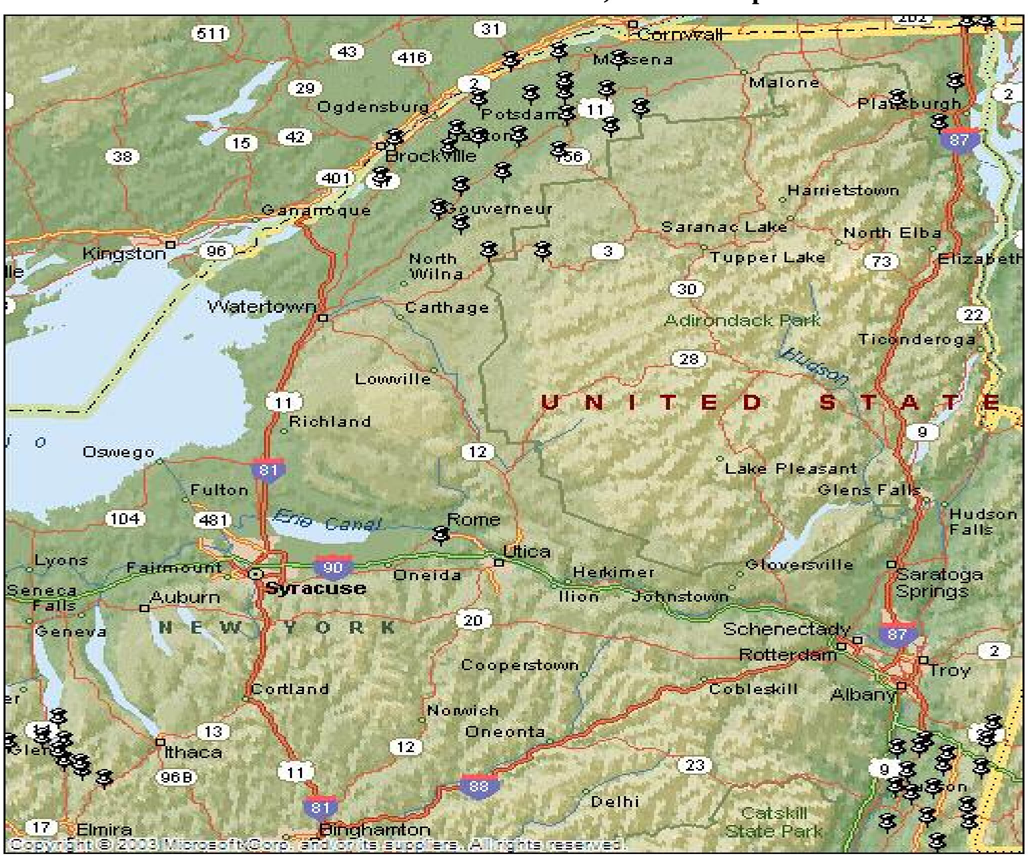


Figure 5: BEA Economic Areas – New York State

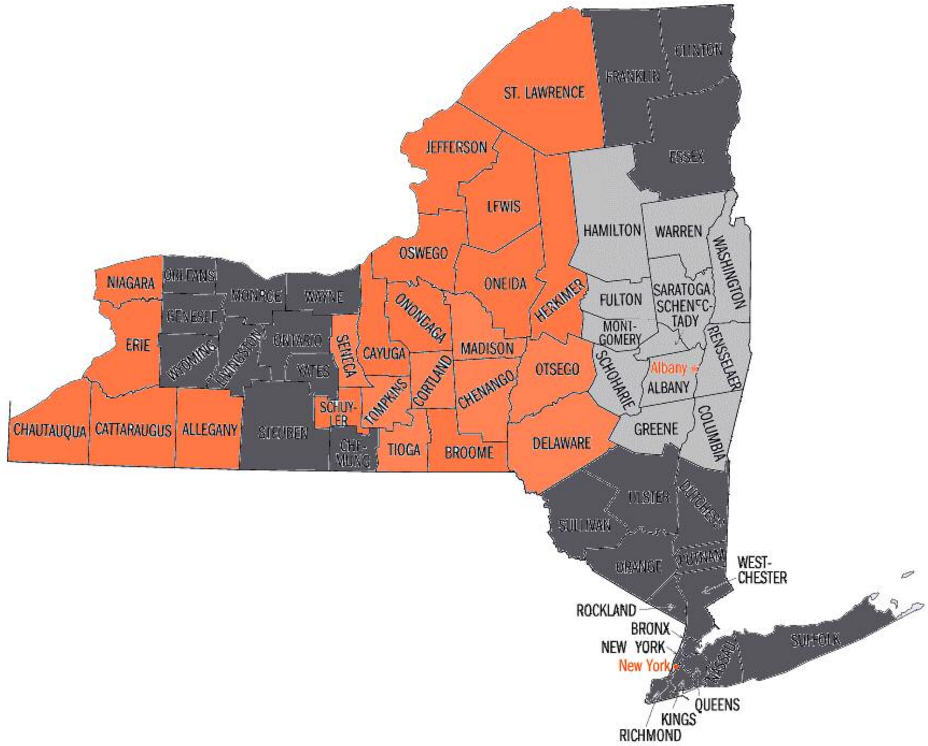


Figure 6:

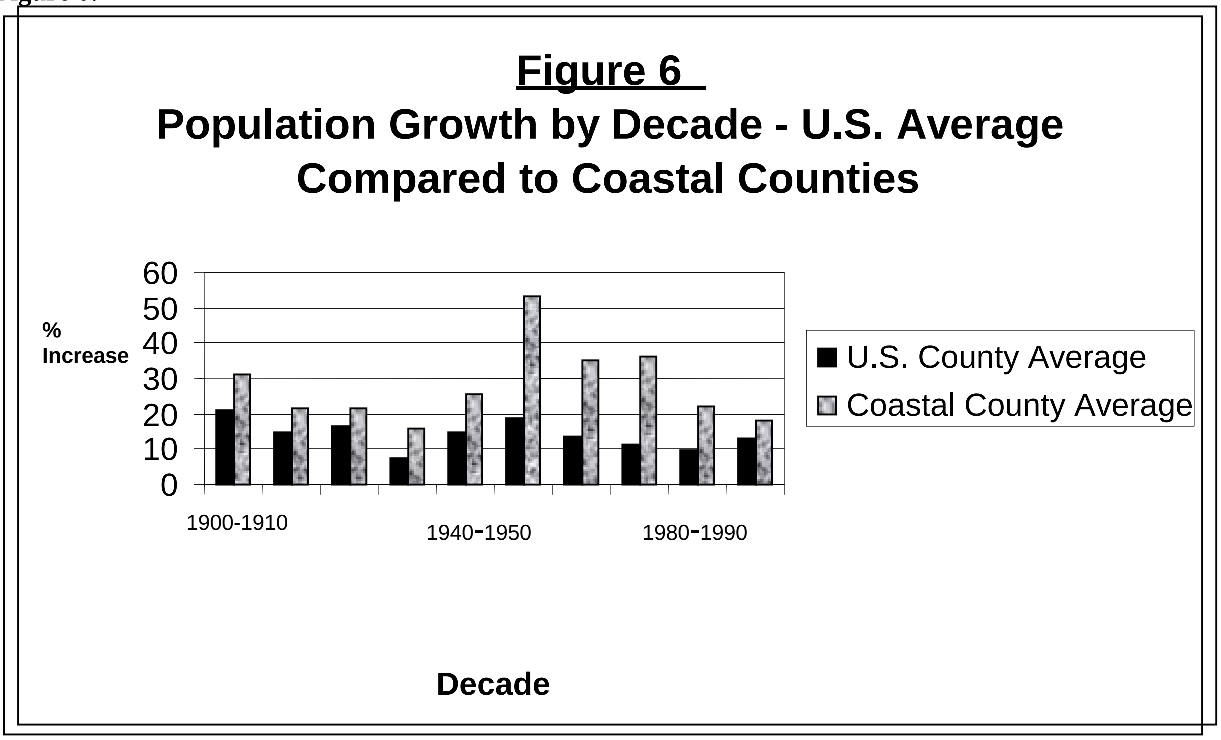


Figure 6
Population Growth by Decade - U.S. Average
Compared to Coastal Counties
%
Increase
60
50
40
30
20
10
0
1900-1910
1940-1950
1980-1990
U.S. County Average
Coastal County Average
Decade

Appendix

The Economic Research Service/U.S. Department of Agriculture Urban Influence Codes distinguish metropolitan counties by size and non-metropolitan counties by the size of the largest city or town or by proximity to metro areas. Since an area's geography has a significant impact on its economic development, ERS developed this set of county-level categories to capture differences among economic opportunities.

Table A.1: Urban Influence Codes

Code	Description
Metropolitan counties:	
1	In large metro area of 1+ million residents
2	In small metro area of less than 1 million residents
Nonmetropolitan counties:	
3	Micropolitan* adjacent to large metro
4	Noncore** adjacent to large metro
5	Micropolitan adjacent to small metro
6	Noncore adjacent to small metro with own town
7	Noncore adjacent to small metro no own town
8	Micropolitan not adjacent to a metro area
9	Noncore adjacent to micro with own town
10	Noncore adjacent to micro with no own town
11	Noncore not adjacent to metro or micro with own town
12	Noncore not adjacent to metro or micro with no own town

(Source: www.ers.usda.gov/Briefing/Rurality/urbaninf)

*micropolitan is defined as an area outside of a metro with an urban cluster of 10,000 or more people

**noncore areas are outside of a metro area without an urban cluster of 10,000 or more people

(ERS/USDA 2003)

The Economic Research Service/U.S. Department of Agriculture county Typology codes were developed to reflect the importance of an area's economic and social characteristics on its development and need for public programs. County typology codes use binary values to classify counties as follows

Table A.2: Typology Codes

Variable	Description
farm	Farm-dependent county indicator. 0=no 1=yes
mine	Mining-dependent county indicator. 0=no 1=yes
manf	Manufacturing-dependent county indicator. 0=no 1=yes
fsgov	Federal/State government-dependent county indicator. 0=no 1=yes
serv	Services-dependent county indicator. 0=no 1=yes
nonsp	Nonspecialized-dependent county indicator. 0=no 1=yes
house	Housing stress county indicator. 0=no 1=yes
loweduc	Low-education county indicator. 0=no 1=yes
lowemp	Low-employment county indicator. 0=no 1=yes
perpov	Persistent poverty county indicator. 0=no 1=yes
poploss	Population loss county indicator. 0=no 1=yes
rec	Nonmetro recreation county indicator. 0=no 1=yes
retire	Retirement destination county indicator. 0=no 1=yes

(ERS/USDA 2004)