Assessing Impacts of OCS Activities on Public Infrastructure, Services, and Population in Coastal Communities Following Hurricanes Katrina and Rita

Matt Fannin, Mark Schafer,
Walter Keithly, Arun Adhikari, Ashley Barras
Louisiana State University

New Orleans, LA
7 January 2009

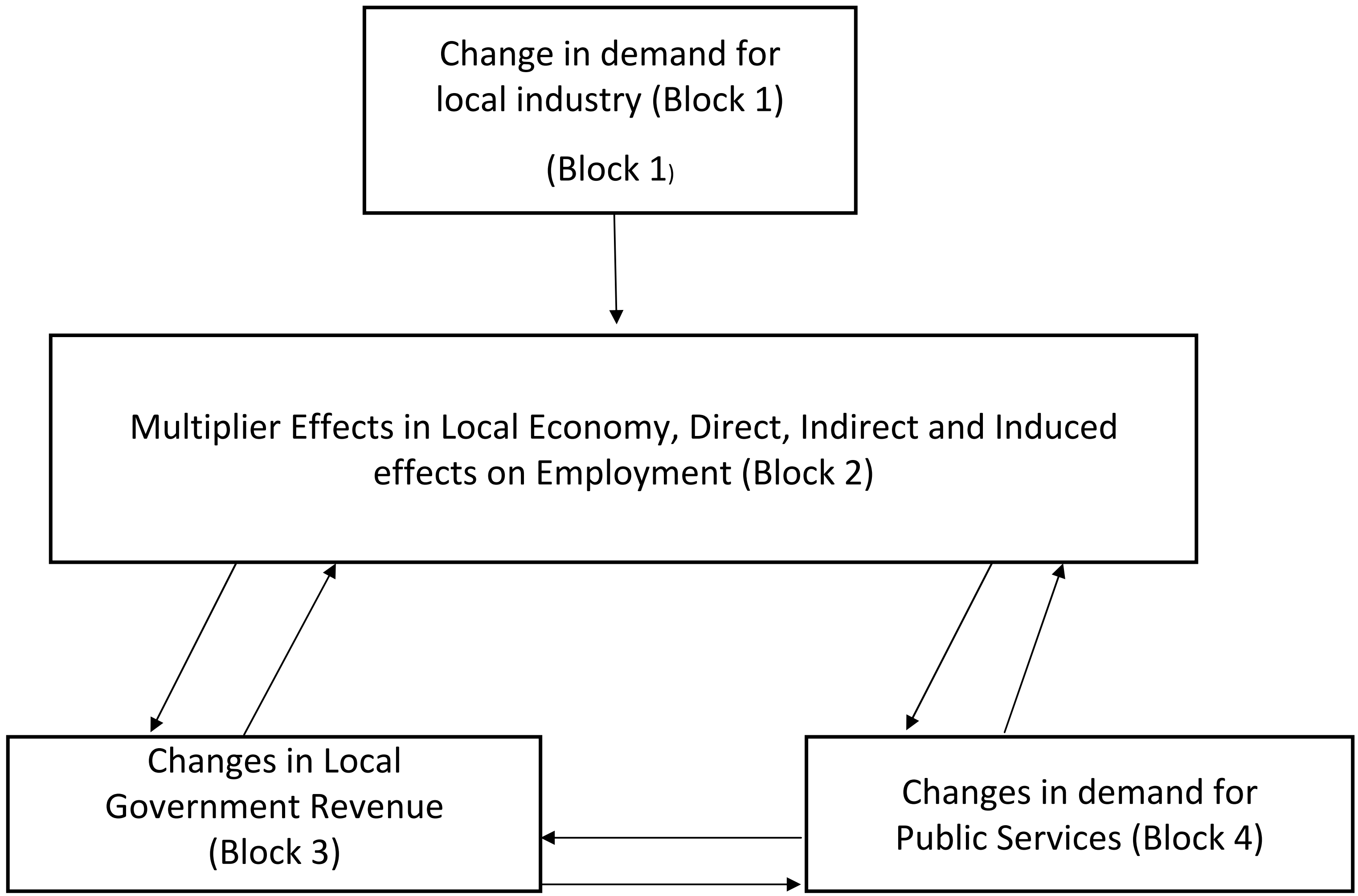
Objectives of the Study

1) Develop a socio-economic baseline and assessment of public sector infrastructure and services of coastal communities in Louisiana.

2) Develop a Coastal Community Impact Model (CCIM) for assessing public sector revenue and expenditure impacts from OCS-related activities.

3) Construct and apply OCS-related and/or post-storm development (or policy) scenarios to assess short-run economic impacts as well as long-run impacts on public service revenue and expenditure in coastal Louisiana communities following Hurricanes Katrina and Rita.

Overview of Coastal Community Impact Model (CCIM)



Conceptual Framework of Labor Force Module

- Conceptually, the labor force module intersects labor force demand and labor force supply or $X_D = X_S$,

  where X_D is labor force demand and X_S is labor force supply (Johnson 2006). The demand curve for the labor force is a function of the wage rate, or $X_D = f(w)$;

  where w is the wage rate. We can invert the labor demand equation to obtain $w = g(X_D)$

- We can also evaluate the supply as disaggregated into the following components

  $X_S = X_{LF} - X_U - X_O + X_I$

  where X_{LF} is the total labor force, X_U is the total unemployment, X_O is the total number of outcommuters, and X_I is the total number of incommuters. We can then evaluate each component of the total labor supply as a function of employment as well as a vector of supply shifters (Johnson 2006)

Conceptual Framework

$$X_{LF} = f_L\,(w, Z_{LF}\ ) = f_L\,(g\,(X_D\ ), Z_{LF}\ )$$
$$X_O\ = f_L\,(w, Z_O\ ) = f_L\,(g\,(X_D\ ), Z_O\ )$$
$$X_I\ = f_L\,(w, Z_I\ ) = f_L\,(g\,(X_D\ ), Z_I\ )$$

where *Z* is a vector of supply shifters for labor force, outcommuters, and incommuters.

Empirical Framework of Labor Force Module

- The theoretical model is typically represented by the following economic models (Johnson 2006):
  - Unemployed = Labor force +In-commuters – Employment – Outcommuters
  - Labor force = f(employment, housing conditions, cost of living, public services, taxes, industry mix, area)
  - Out-commuting = f(employment, external employment, external labor force, housing conditions, cost of living, public services, taxes, industry mix, area, distance to jobs)
  - In-commuting = f(employment, external employment, external labor force, housing conditions, cost of living, public services, taxes, industry mix, area, distance to residence)

Empirical Specification of Labor Force Module

- Literature guides us to estimate the following functional forms of our model:
  - *Population*= *f*{constant, place of work employment}
  - *In-commuter earnings*= *f*{constant, ln (labor force), ln (external labor force index)}
  - *Out-commuter earnings*= *f*{constant, ln (labor force), ln (external employment index)}

Empirical Specification for Expenditure

- *per capita public safety* $= f$ {constant, per capita assessed value, per capita income, % African American}

- *per capita public works* $= f$ {constant, (per capita assessed value, arable land density, per capita retail sales, per capita local road miles}

Methodology (Regression Analysis)

- First, OLS for labor force module and fiscal module (expenditure) are calculated
- Variables were selected according to the variables used by Fannin et al. 2008
- Quantile regression is then performed for both modules to determine forecast errors in specific quantiles and to compare the performance between OLS and different quantiles
- Quantiles are selected at 0.25, 0.5, 0.75 and 0.9

Methodology (Regression Analysis)

- Forecast errors are calculated by the formula $\Sigma\{(yhat - y)/y\}$ and the mean, median and standard deviation forecast errors are calculated for both modules but only the median forecast errors are reported

- Theil's coefficient (U1) is then calculated by the formula $\Sigma\sqrt{}(yhat-y)^2 \; / \; \Sigma \sqrt{}y^2 + \Sigma \sqrt{}(yhat)^2$

Alternative Approach: Quantile Regression

Quantile regression results in estimates approximating either the median or other quantiles of the response variable whereas method of least squares results in estimates that approximate the conditional *mean* of the response variable given certain values of the predictor variables.

Advantage of using quantile regression to estimate the median, rather than ordinary least squares regression to estimate the mean, is that quantile regression will be more robust in response to large outliers.

Standard errors and confidence limits for the quantile regression coefficient estimates can be obtained with asymptotic and bootstrapping methods. Both methods provide robust results (Koenecker and Hallock 2001), with the bootstrap method preferred as more practical (Hao and Naiman 2007).

Alternative Approach: Quantile Regression

- Quantile regression alleviates many statistical problems : errors-in-variables; omitted variables bias; sensitivity to outliers; and non-normal error distributions (Barnes and Hughes 2002).

- Data we are using are heteroskedastic; hence, we could divide the data into various quantiles depending upon the sample size and evaluate or correct problems in different quantiles (small units) rather than working with complete data set at once.

Labor Force Module Performance for the year 2000

Dependent Variable	**OLS**		**Quantiles**							
			0.25		0.50		0.75		0.90	
	Forecast Error	Theil's Coeff (U1)	Forecast Error	Theil's Coeff (U1)	Forecast Error	Theil's Coeff (U1)	Forecast Error	Theil's Coeff (U1)	Forecast Error	Theil's Coeff (U1)
In-commuter Earnings	-0.1303	0.26	-0.049	**0.13**	**0.029**	0.21	0.256	0.52	0.164	0.28
Out-commuter Earnings	-0.340	**0.24**	-0.536	0.32	**0.340**	**0.30**	1.179	0.49	1.067	0.31

Labor Force Module Performance for the year 2004 based on parameter estimates of the year 2000

Dependent Variable	OLS		Quantiles							
			0.25		0.50		0.75		0.90	
	Forecast Error	Theil's Coeff (U1)	Forecast Error	Theil's Coeff (U1)	Forecast Error	Theil's Coeff (U1)	Forecast Error	Theil's Coeff (U1)	Forecast Error	Theil's Coeff (U1)
In-commuter Earnings	-0.253	**0.28**	0.656	0.81	0.248	0.68	-0.108	**0.58**	0.620	0.64
Out-commuter Earnings	-0.351	**0.27**	-0.604	0.33	**0.268**	0.29	0.750	0.37	0.795	**0.28**

Fiscal Module (Expenditure on per capita basis) Performance for the year 2004

Dependent Variable	**OLS**		**Quantiles**							
			0.25		0.50		0.75		0.90	
	Forecast Error	Theil's Coeff (U1)	Forecast Error	Theil's Coeff (U1)	Forecast Error	Theil's Coeff (U1)	Forecast Error	Theil's Coeff (U1)	Forecast Error	Theil's Coeff (U1)
Public Safety	0.333	0.36	0.094	0.14	**0.068**	0.30	0.298	0.32	0.140	0.22
Public Works	0.002	0.19	0.505	0.21	**-2.9E-06**	0.12	0.004	0.21	-9.0E-07	**0.11**

Future work

Future work consists the of inclusion of Spatial autoregressive, Spatial error and Panel data models.

Spatial autoregressive model (SAR) is denoted as:

$y = \rho Wy + X\beta + \varepsilon$

$\varepsilon \sim N(0, \sigma^2 I_n)$

where

y is the dependent variable

W is a spatial weight matrix

ρ is a coefficient on the spatially lagged dependent variable Wy,

Spatial error model (SEM) is denoted as

$y = X\beta + \mu$

where, $\mu = \lambda W\mu + \varepsilon$, $\varepsilon \sim N(0, \sigma^2 I_n)$ and,

μ is a vector of spatially correlated errors

λ is a coefficient on the spatially correlated errors

Methodology (Shift Share)

Shift Share is variance decomposition method

Historically used to decompose employment change

e_i = total employment in i^{th} sector for a region.
E = total employment of the nation.
E_i = total employment for the nation for the i^{th} sector.

Methodology (Shift Share)

For any time t+1, the change in the employment can be calculated by

Change in employment = $G + (G_i - G) + (g_i - G_i)$

where,

G – national growth effect or share change effect

$(E_{t+1} - E_t)/E_t$

$G_i - G$ – industry mix effect or mix change effect

$((E_{it+1} - E_{it})/E_{it} - G)$

$(g_i - G_i)$ – competitive effect or shift change effect

$((e_{it+1} - e_{it})/e_{it} - G_i$

Methodology (Shift Share)

- Here, instead of employment growth, we calculate parish government expenditure and asset change from the year 2004 to 2006
- Sectors for expenditures include Public Safety, Public Works, General Government and Health and Welfare
- Sectors for assets include Cash, Receivables + Investments, and Capital Assets + Transfers + Other Assets

Methodology (Shift Share)

- Here,

  e_i = total expenditure or assets in i^{th} sector for OCS parishes in Louisiana.

  E = total expenditure or assets for OCS parishes of Louisiana.

  E_i = total expenditure or assets for OCS parishes of Louisiana for the i^{th} sector.

Shift Share Assets Change from 2004 to 2006 (On Dollar Basis)

Category	National Growth	Industry mix	Mean Local Effect	Mean Total Change
Cash	29.6%	10.8%	32.7%	73.24%
Receivable + Investments	29.6%	27.3%	-8.1%	48.95%
Capital Assets + Transfers + Other Assets	29.6%	12.3%	20.6%	38.03%

Local Change Effect (Dollar Basis)

Parish	Local Change (%)			Parish	Local Change (%)		
	Cash	Receivables + Investments	Capital Assets, Transfer and Other Assets		Cash	Receivables + Investments	Capital Assets, Transfer and Other Assets
Acadia	593.2	-112.3	14.3	Evangeline	-33.1	-47.1	-19.1
Allen	19.5	-57.2	-17.2	Iberia	-65.1	88.1	-21.6
Ascension	13.1	-21.9	8.7	Iberville	-11.1	-36.4	13.2
Assumption	-32.1	-14.1	-9.7	Jefferson	-73.1	-27.9	-10.1
Beauregard	-38.7	-56.9	11.1	Jefferson Davis	35.4	-4.9	-18.1
Calcasieu	96.9	-41.9	-22.4	Lafayette	-12.8	-38.8	-14.2
Cameron	114.5	36.5	4.4	Lafourche	-64.1	-15.8	92.7
East Baton Rouge	9.3	41.3	-7.2	Livingston	-40.8	224.8	606.3

Local Change Effect (Dollar Basis)

Parish	Shift Change (%)			Parish	Shift Change (%)		
	Cash	Receivables + Investments	Capital Assets, Transfer and Other Assets		Cash	Receivables + Investments	Capital Assets, Transfer and Other Assets
Plaquemines	-84.9	86.9	-5.9	St. Tammany	202.3	128.5	-10.0
St. Bernard	-35.7	21.4	-114.4	Tangipahoa	176.2	-23.6	5.7
St. Charles	320.6	-17.9	-11.6	Terrebonne	10.5	2.7	33.3
St. James	9.0	-3.0	-23.2	Vermillion	-6.4	2.1	-19.1
St. John the Baptist	36.7	-97.2	132.3	Vernon	-13.7	-81.6	54.8
St. Landry	-32.5	-56.3	-5.5	Washington	-2.4	-25.1	-14.9
St. Martin	-4.2	-36.4	13.1	West Baton Rouge	31.7	-41.2	3.1
St. Mary	-102.3	-25.6	-0.6				

Public Expenditure Change from 2004 to 2006 (On Dollar Basis)

Category	National Growth	Mean Industry mix	Mean Local Effect	Mean Total Change
Public Safety	19.4%	31.5%	158.2%	209.1%
Public Works	19.4%	-14.3%	128.6%	133.7%
General Government	19.4%	-10.0%	8.58%	17.9%
Health and Welfare	19.4%	-10.1%	-2.46%	6.81%

Future work

- We will be looking at spatial spillover and location effects in shift share analysis by creating spatial weight matrix and then incorporating in the traditional shift share formula

- The general formula for new model replaces G_i with $\breve{g}_i$, which is a spatial lag variable that denotes the growth rate of sector i in the neighborhood regions.
  $(\text{growth})_i = G + (\breve{g}_i - G) + (g_i - \breve{g}_i)$

- The spatial lag variable $\breve{g}_i$, is essentially a weighted average of neighboring regions, and is acquired by multiplying a square spatial weight matrix (R X R), W, times the conformable column vector of neighboring values. W is, therefore, a spatial weight matrix whose elements w_{jk} describe the level of interdependence between spatial units j and k.

- R is the number of regions (parishes) in the system

Fuzzy-Set Parish Profiles

Mark Schafer
Ashley M. Barras

Fuzzy-Sets

- Bridge between qualitative and quantitative methods
- Definition: A fine-grained, continuous measure that has been carefully calibrated using substantive and theoretical knowledge relevant to set membership (Ragin 2000).
- Based on Set Theory — Degree of membership in a set

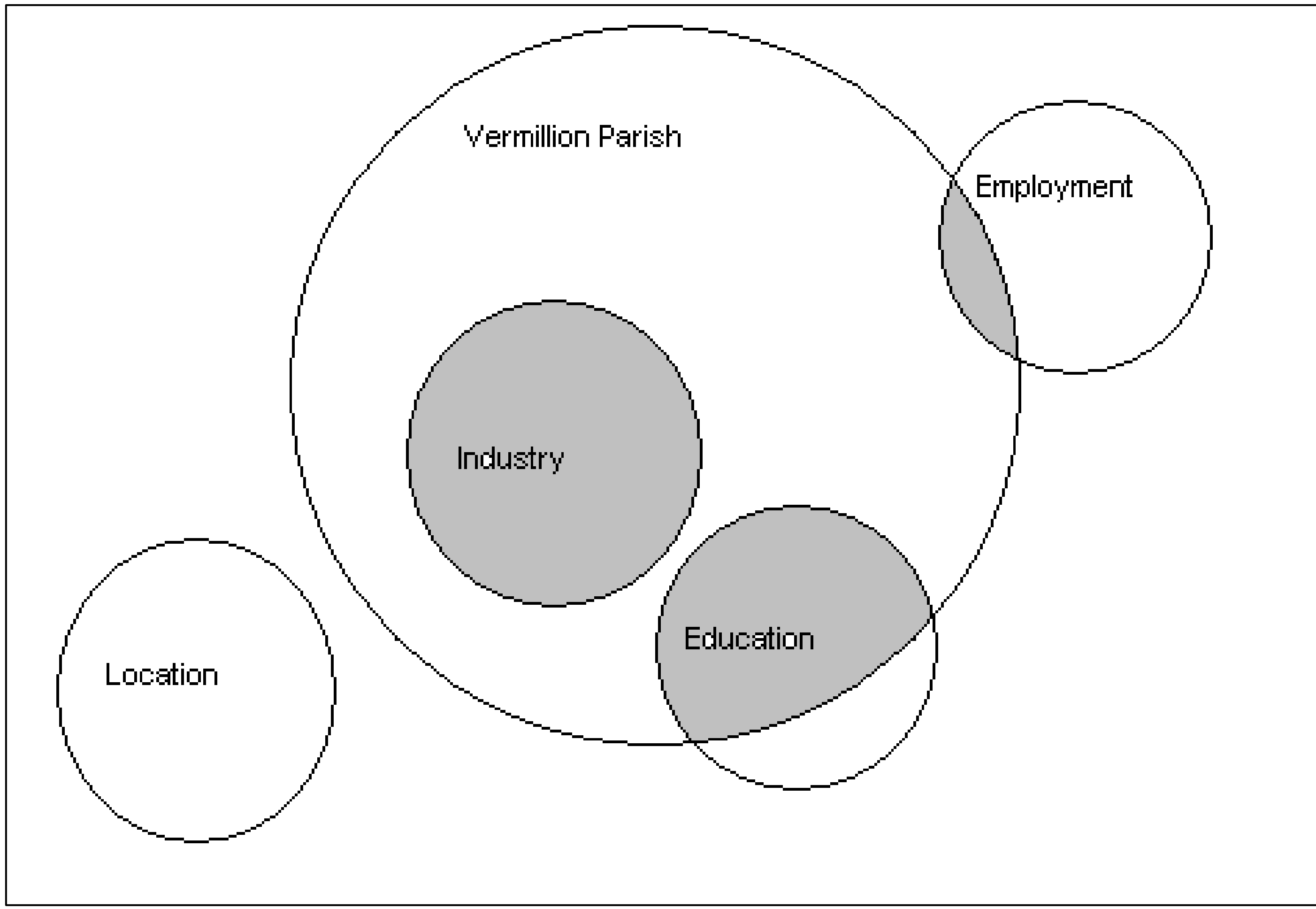
Why use Fuzzy-Set Profiles

1. Improve match between concepts with measures
2. Enable richer dialogue between ideas and evidence
3. Focus on relevant diversity
4. Enable analysis of conjunctural causation:
   - Quantitative analyses attempt to isolate individual effects
   - Fuzzy-Set analysis focuses on effects of combinations or configurations of factors

Objectives of Fuzzy-Set Profiles

- Allow comparisons across parishes, regions, or cities
  - Amenable to both large and small-N comparisons
- Analyze patterns and relationships:
  - General relationships
  - Effects of oil & gas industry
    - In combination with other parish-level characteristics
- Make use of annually available secondary data
  - To assess trends

Each Parish described in terms of configuration of set memberships:
Example:



Conceptualization

- Profile elements defined in terms of set membership
  - Full Membership $X=1$
  - Non Membership $X=0$
  - Partial Membership $0<X<1$
    - $0<X<0.5$ (more “out” than “in”)
    - $0.5<X<1$ (more “in” than “out”)
- Compare parishes (or regions or cities) across sets of profile elements
- Each parish defined by complete set of profile elements

Profile Elements (current organization)

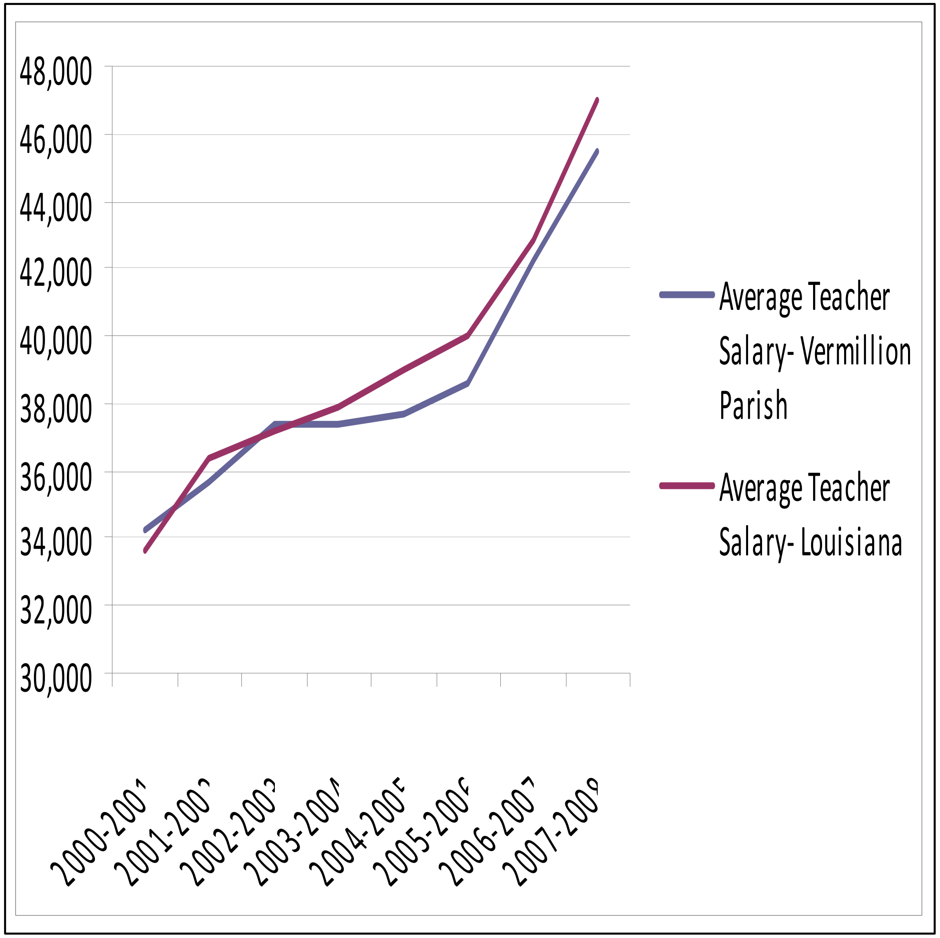
- Socioeconomic Sets
  - Industry sets
  - Employment sets
  - Labor Force sets
  - Social Capital sets
- Human Capital Sets
  - Education sets
  - Health sets
- Infrastructure and Service Provision Sets
  - School Board sets
  - Police Jury sets

Example 1: Employment Profile

- Set Name: Parish Dependency on Oil & Gas Industry for Employment
  - = 1.0 if fully dependent
  - = 0.8 if highly dependent
  - = 0.2 if minimally dependent
  - = 0.0 if not dependent at all
- Strategy:
  - Quantify and index important oil & gas sectors
  - Establish thresholds for set membership categories
    - Similar to ERS definition of mining dependency

Example 2: Education Profile

- School districts (e.g. parish units in LA) must provide quality public education
- This includes hiring and retaining highly qualified teachers
- Increases costs, average teacher salaries increase (see next slide
- We might ask how oil & gas industry shifts affect local school district capacity and increase teacher salaries



Education Profile, Continued

- Two potential sets:

1. Comparative: offered competitive teacher salary (2000–2005)
   - 1 = far above state average
   - .8 = above state average
   - .5 = near state average
   - .2 = below state average
   - 0 = far below state average

Education Profile, Continued

2. Second Potential Set—Trend

Set Name: met demand for increased teacher salaries (increases)

- 1 = rate of increase much higher than state average
- .8 = rate of increase higher than state average
- .5 = rate of increase at state average
- .2 = rate of increase below state average
- 0 = rate of increase far below state average

Benefits of These Profiles

1. Focus on concepts not data:
   - Secondary data used to match concepts of interest
     - Linguistic markers focus on conceptualization of what "impact" of offshore activity means
     - Data used to represent meaningful concepts
2. Relevant diversity
   - Grouping "like" parishes
   - Cross-group comparisons over time
3. Analysis
   - Qualitative and quantitative analytical strategies enabled
   - Qualitative strategies can be used with any N (number of parishes)
   - Quantitative strategies can be used with larger Ns

References

Barnes, M.L. and Hughes, A.W. 2002. A quantile regression analysis of the cross section of stock market returns. Federal Reserve Bank of Boston Working Paper No. 02-2.

Fannin, J.M., D.W. Hughes, W. Keithly, W. Olatubi, and J. Guo. 2008. Deepwater energy industry impacts on economic growth and public service provision in Lafourche Parish, Louisiana. Socio Economic Planning Sciences 42:190–205.

Hao L. and Naiman D.Q. 2007. Quantile Regression. Thousand Oaks, CA: Sage Publications. 136 pp.

References (continued)

Johnson, T.G., D. M. Otto and S.C. Deller. 2006. Introduction to community policy analysis modeling. In: Johnson, T.G., D.M. Otto and S.C. Deller, eds. Community Policy Analysis Modeling, First Edition. Ames, IA: Blackwell Publishing. Pp. 3-16.

Koenker, R. and K. Hallock. 2001. Quantile regression: An introduction. Journal of Economic Perspectives 15:143-156.

Ragin, C.C. 2000. Fuzzy Set Social Science. Chicago: University of Chicago Press. 370 pp.