Thursday, April 17, 2008

Estimates of State and Metropolitan Price Levels for Consumption Goods and Services in the United States, 2005

Bettina H. Aten*

Abstract

Price deflators are commonly used in time-to-time economic series to adjust for changes in price levels across years. This paper estimates spatial price deflators that may be used for adjusting price level differences across geographic areas. The work is based on micro-level price data from the Consumer Price Index of the Bureau of Labor Statistics and the American Community Survey of the Census Bureau. It uses a Bayesian two-stage spatial smoothing approach to estimate Spatial Price Indexes (SPIs) for 363 metropolitan areas and 51 states in the United States. An example of the relevance of SPIs is given by adjusting the Personal Income and Gross Domestic Product estimates by state and metropolitan area produced by the Bureau of Economic Analysis for the year 2005, and comparing the results to the nominal (non-adjusted) values.

Introduction

This paper develops exploratory estimates of the spatial price differences for consumption goods and services at the U.S. state and metropolitan area level for 2005. Spatial (place-to-place) price differences are important to regional and other sub-national accounting frameworks as they make possible comparisons of economic data that are adjusted for geographic differences in price levels. In international comparisons, these adjustments are termed *purchasing power parities (PPP)*; when divided by exchange rates they are called national price levels. In areas with a common currency like the Euro, the exchange rates are the same and the PPP becomes the price level.

Just as there are differences in price levels between European Union member countries, there are significant differences in the purchasing power of a currency across diverse areas of the United States, for example between metropolitan New York compared to rural South Dakota. I use the term Spatial Price Indexes (SPIs) to label these sub-national estimates of *PPPs*. The SPIs can be used to adjust consumption-related statistics, such as per capita incomes, expenditures and output, providing users with a more accurate picture of regional economic differences at one point in time.

The SPIs are built up in this paper from two main data sets. The first is the principal source of consumer price information in the United States, the Bureau of Labor Statistics

* Bettina H. Aten is an economist in the Regional Economics Directorate, Bureau of Economic Analysis. The results presented here are the responsibility of the author and not of the Bureau of Economic Analysis. Email: Bettina.Aten@bea.gov

Consumer Price Index (CPI) for 38 metropolitan and urban areas, which is of course a time-to-time index. Aten (2006) presented spatial price index estimates for 2003 and 2004 for these 38 areas, which cover 87% of the population but only about 15% of U.S. counties. In addition, some states are not covered at all by the CPI.

The second source of information is the county level monthly median housing costs for owners and rents from the 2005 American Community Survey (ACS) of the U.S. Census Bureau. Henceforth, the word *rents* denote the average of these costs – that is, the geometric mean[1] of the median selected monthly owner costs (with and without mortgages) and median gross rents[2]. The sub-national price level estimates presented here are generated using Bayesian inference and a multi-stage approach that bridges the results in the areas sampled by the CPI price surveys to the remaining non-sampled areas covered by the Census.

General description

The background to this paper is the work detailed in Aten (2005, 2006) on estimating place-to-place indexes for 38 metropolitan and urban areas. The paper estimates hedonic regressions for over two hundred consumption goods and services in the CPI, together with a multilateral price aggregation method, following Rao (2005). The resulting place-to-place indexes are termed spatial price indexes (SPI) to distinguish them from the Consumer Price Index (CPI) that tracks changes over time in one place. The CPI survey is designed as a probability sample to estimate price inflation for the items consumed by the population in these areas[3]. More disaggregated calculations or more extensive geographical coverage would require a redesign of the CPI survey, something that is not feasible in the short run.

Given that there are significant differences in price levels for the metropolitan and urban areas covered by the CPI, there is much interest in a) adjusting economic data to reflect these price differences, such as when making comparisons of income levels and expenditure levels (Bernstein et al [2000], Johnson et al [2001], Jolllife [2006]) and b) assessing the feasibility of estimating SPIs for different geographies, such as states and

---

[1] The ACS tables (Tables B25088 and B25064) provide the number of owner-occupied versus rental housing units, so *rents* are calculated as the weighted geometric mean of the ownership costs and gross *rents*, where the weights equal the proportion of owned and rented housing units in each county.

[2] *"Selected* ***monthly owner costs*** *are the sum of payments for mortgages, deeds of trust, contracts to purchase, or similar debts on the property; real estate taxes: fire, hazard, and flood insurance on the property; utilities (electric, gas, water, and sewer); and fuels (oil, coal, kerosene, wood, and so on). It also includes, where appropriate, the monthly condominium fee for condominiums and mobile home costs",*

" ***Gross rent*** *is the contract rent plus the estimated average monthly cost of utilities and fuels if these are paid by the renter",* page 64:
http://www.census.gov/acs/www/SBasics/congress_toolkit/Housing%20Fact%20Sheets.pdf

[3] The individual price quotes of the CPI are identified by location (zip code in most cases), but full coverage of all items exist only when aggregated to the 38 metro and urban areas. This is because the probability quote weights for the samples as well as the detailed expenditure weights by item are only available for the 38 areas.

regions (see for example Fuchs et al [1979], Ball and Fenwick [2004], Roos [2006]). Any such use involves making inferences for areas not sampled by the CPI.

One problem in making these inferences is the change of scale that arises in aggregations that are different from the observed levels, for example, from metro area to counties or from metro areas to states. A related problem is that some of the CPI areas cross state lines, while others refer to single counties[4]. For example, the District of Columbia is only one of 26 counties in the Greater Washington metropolitan area as defined in the CPI, but it is also a *quasi* state, or at least, for many purposes, a separate entity from the states of Virginia or Maryland. Los Angeles is one county and one CPI area by itself, but only one of 58 counties in the state of California. The CPI area termed South B (medium and small urban areas in the South Region), is made up of 84 smaller units, scattered across states such as Georgia, Tennessee, and South Carolina.

Combining and using these disparate spatial units is problematic for a number of reasons. The approach applied here is to break down these areas into somewhat less heterogeneous units, namely counties, then build up the county data back into state level estimates.

The second main issue is the lack of data for a great number of areas. We know from the survey design of the CPI that these non-sampled areas are systematically excluded because of their smaller, less dense populations and lower volumes of expenditures. This means that direct inferences from the sampled areas of the CPI to the non-sampled areas would be misleading because the distribution of expenditures and prices are also likely to be systematically different. The second stage of this paper aims to bridge the gap between the sampled and non-sampled CPI areas indirectly, using data on *rent* levels from the 2005 American Community Survey of the United States Census Bureau.

The consequences of scale, classification inconsistencies and sampling coverage that characterize these data have been discussed in the spatial statistical literature (Goodchild, Anselin and Deichmann [1993], Gotway and Young [2002], Baneerje and Gelfand [2004], Anselin and Gallo [2006]). In the social sciences, issues in spatial aggregation are known as the ecological fallacy problem and the modifiable areal unit problem. Anselin (2002), among others, extensively reviews the conceptual and practical consequences for applied spatial models in the econometric literature.

The methods adopted here attempt to mitigate, not resolve, some of the major estimating problems associated with changes of scale and spatial aggregation, but are by necessity data-driven. They are summarized below and then discussed more extensively in subsequent sections.

The estimation of the spatial price indexes (SPIs) at the state level is divided into three stages. The first takes the 38 CPI areas and decomposes them into smaller and more

---

[4] Some areas refer to townships within counties. The term county in this paper refers to counties and county equivalents, plus the 78 municipalities of Puerto Rico. More details on the geographical boundaries can be found in the next section.

consistent geographical areas, generally counties. The relationship between the average price levels for these areas and the observed county *rents* are modeled, and price levels are predicted for the individual counties within the 38 CPI areas.

The second stage involves bridging these predictions to the remaining counties in the U.S. that are not in the CPI sample, counties which tend to be in primarily non-metropolitan and rural areas. It is subdivided into two steps, the first one assigns initial values to all counties, while the second one again relies heavily on the modeled relationship between price levels and *rents*, which are observed for all U.S. counties covered by the Census, including those not in the CPI sample.

Both first and second stage models use Bayesian inferences to obtain spatially smoothed estimators. The final stage aggregates the county price levels to 51 states and 363 metropolitan areas and shows the values of Personal Income and Gross Domestic Product estimates that are deflated by their respective Spatial Price Indexes and thus adjusted for geographic differences in relative prices.

Background on the Data

Interarea Price Levels and Census rents

The detailed methodology for estimating SPIs for the 38 metropolitan and urban areas of the CPI is described in Aten (2005, 2006) but referred to 2003 and 2004 prices. The same methodology has been applied to 2005 prices for this paper. It includes estimating a weighted hedonic regression for each expenditure item that makes up consumer goods and services in the U.S., a total of about 400 items. These range from *rents* and new automobiles to shoes and haircuts. The hedonic regressions take into account item characteristics, such as unit size and packaging, as well as the location and type of outlet where it is sold, and uses probability sampling quotes as weights[5].

The resulting item price levels are then aggregated into major categories, such as Food and Beverages, Transportation, and Housing, and up to an overall SPI for consumption. Aggregation follows the Rao-system of multilateral price comparisons (Rao 2005) and uses expenditure weights at the 38 area level (see *Appendix Table A1* for a list of all counties comprising these areas).

The data on *rents* are taken from the Census Bureau. A previous version of this paper (Aten, 2007) used Census 2000 data, moving back the estimated price levels from 2003 to 2000 by the urban and non-urban CPI changes[6]. This paper instead uses 2005 prices

---

[5] Since the author anticipates estimating the 38 interarea price levels annually, the results for 2005 onward will be available as tables rather than published papers. Effort is underway to make them available for downloading at the BLS website as well as from BEA.

[6] Aten (2006) compares an extrapolation of 2003 to 2004 versus a direct estimate for the year 2004 and finds that there are minor differences when an aggregate CPI rate is used as the deflator, but negligible differences with a detailed item-level CPI deflator. Another way to reconcile the disparate data sets would

and the corresponding overall SPI for consumption estimated from the BLS, as well as the more recent 2005 American Community Survey (ACS). The ACS includes all counties with a population of 65,000 or more, a total of about 780 counties covering 82 percent of the nation's population. The ACS includes the proportion of owners and renters in each county, as well as median gross *rents* and the monthly estimated owner costs[7].

The 2005 *rents* for counties not in the ACS were computed in the following way. Their 2000 Census *rents* were moved to 2005 using the population weighted geometric mean of the ACS counties for each state. In other words, the change in median *rents* for these smaller (less than 65,000 population) counties was assumed to reflect the average change across the larger counties within each state, weighted by their populations. The 38 CPI areas correspond to 147 metropolitan areas, counties and places, and at the lowest geographical level, to 425 counties[8].

Table 1 shows the 2005 SPIs and also the corresponding average *rent* in dollars for each area. The *rent* level is equal to the *rent* in dollars divided by the average dollar *rent* for the 38 areas.

Table 1. Observed Price Levels (SPIs) and rents by Area for 2005

Region	Area	Freq	Area Name	SPI		Rent ($)	Rent Level
North East	A102	14	Philadelphia	1.04		1061	0.99
	A103	12	Boston	1.15		1309	1.22
	A104	6	Pittsburgh	0.81		715	0.67
	A109	5	NY city	1.35		1083	1.01
	A110	10	NY suburbs	1.39	max	1580	1.47
	A111	15	NJ suburbs	1.18		1425	1.33
Mid West	A207	13	Chicago	1.03		1191	1.11
	A208	10	Detroit	0.92		994	0.93
	A209	13	St. Louis	0.84		845	0.79
	A210	8	Cleveland	0.86		888	0.83
	A211	13	Minneapolis	1.01		1183	1.10
	A212	5	Milwaukee	0.86		982	0.91
	A213	13	Cincinnati	0.88		901	0.84

be to move the Census *rents* to 2003, but that would mean that all population estimates for the counties would also need to be adjusted to 2003, as well as any other right-hand variable that is tested.

[7] 2005 ACS FactFinder, subject tables B25088 and B25064 and an earlier footnote (Footnote 2) .

[8] A few counties span more than one CPI area, primarily when the county is comprised of townships. In these cases, the FIPS code of the county was assigned to one area only, based on the size of the sample and/or the population that it covered. They are the following:

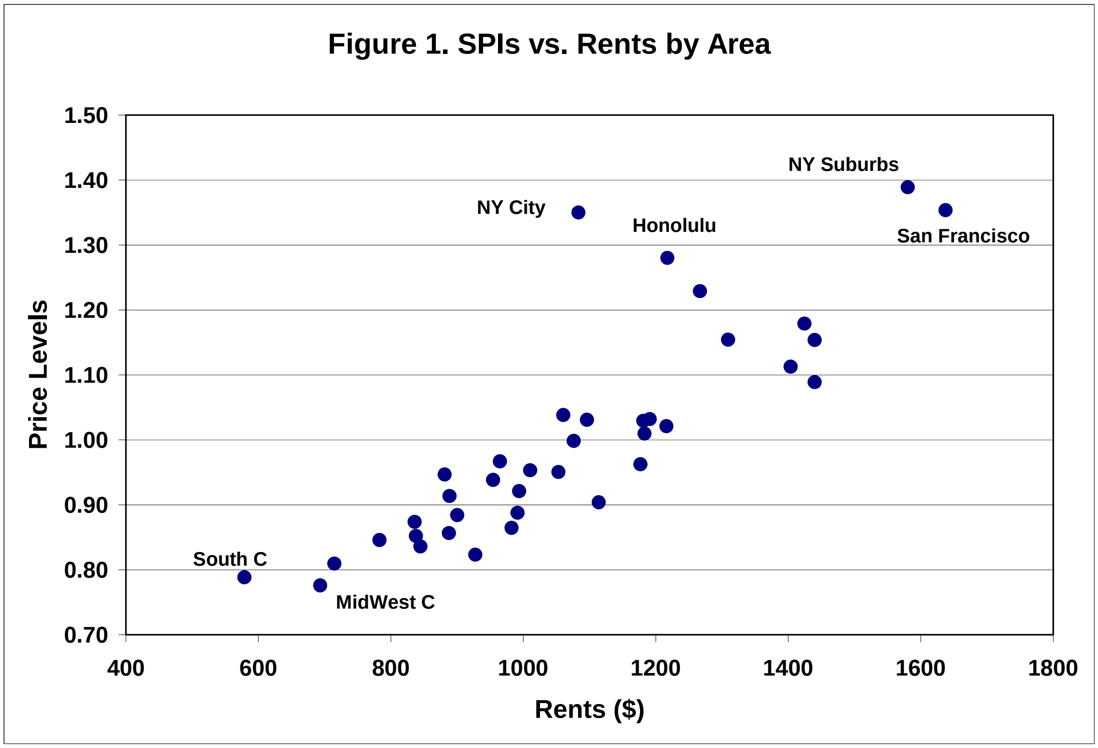
Litchfield, CT to area A110 (New York Suburbs)
Middlesex, CT to area X100 (Northeast B region)
Windham, CT to area X100 (Northeast B region)
Hampden, MA to area X100 (Northeast B region)

Eight towns within Litchfield are in the A110 area and five are in the X100 region but the ones in the A110 area account for two thirds of the population. Seven out of eight towns in Middlesex are in the X100 area, with 79% of the population. In Windham, only Thompson town with 11% of the population is in the A103 Boston with the rest in the X100 area, and similarly in Hampden, only Holland town with less than one percent of the population is in A103, with the remainder in the X100 Northeast B area.

Region	Area	Freq	Area Name	SPI		Rent ($)	Rent Level	
	A214	11	Kansas City	0.82		928	0.86	
South	A312	26	DC	1.09		1440	1.34	
	A313	7	Baltimore	1.00	mean	1076	1.00	mean
	A316	12	Dallas	0.95		1011	0.94	
	A318	8	Houston	0.94		955	0.89	
	A319	20	Atlanta	0.90		1114	1.04	
	A320	2	Miami	1.03		1096	1.02	
	A321	4	Tampa	0.87		836	0.78	
West	A419	1	Los Angeles	1.23		1267	1.18	
	A420	4	Greater LA	1.11		1404	1.31	
	A422	10	San Francisco	1.35		1638	1.52	max
	A423	6	Seattle	1.03		1181	1.10	
	A424	1	San Diego	1.15		1440	1.34	
	A425	8	Portland	0.95		1053	0.98	
	A426	1	Honolulu	1.28		1218	1.13	
	A427	1	Anchorage	1.02		1216	1.13	
	A429	2	Phoenix	0.97		965	0.90	
	A433	7	Denver	0.96		1177	1.10	
Non-metro	D200	7	MW Cs	0.78	min	694	0.65	
	D300	9	South Cs	0.79		579	0.54	min
	D400	2	West Cs	0.95		881	0.82	
	X100	21	NE Bs	0.91		889	0.83	
	X200	25	MW Bs	0.85		838	0.78	
	X300	84	South Bs	0.85		783	0.73	
	X499	9	West Bs	0.89		991	0.92	
	Sum	425	**Mean**	1.00		1074	1.00	
			Max	1.39		1638	1.52	
			Min	0.78		579	0.54	
			Range	0.61		1059	0.98	

The column labeled *Freq* denotes the number of counties that make up each area (four areas are made up of only one county: Los Angeles, San Diego, Honolulu and Anchorage). The mean of the price levels and the *rent* levels across the 38 areas is 1.00 by construction, while that of the unweighted *rents* is US$ 1,074. The range of the *rents* far exceeds that of the SPIs: 0.98 versus 0.61.

Figure 1 plots the relationships between the SPIs and the *rents* for 2005.



The San Francisco area had the highest *rents*, with an average of US$ 1,638 and a *rent* level of 1.52, while the South C areas, comprised of the urban parts of Arcadia FL, Morristown TN, Picayune MS and Statesboro GA were the lowest, with *rents* averaging US$ 579 and a *rent* level of 0.54. It is clear from the graph in *Figure 1* that New York City is an outlier, with low *rents* but relatively high price levels.

Methodology

First Stage

The first stage consists of obtaining a relationship between the price levels and the *rents* at the county level for all CPI areas. The 38 areas are mapped to their corresponding counties[9], a total of 425 observations corresponding to the *Freq* column listed in *Table 1*.

A simple log-linear relationship between price levels and *rents* was posited as the starting point, shown in *Equation (i)*. Alternatives specifications were tested, such as a log-log version, non-linear functions, fixed-effects for size and region, and models that included

[9] Observations in the Census data follow several designations: county is the lowest aggregation for many states, but for others there are Places and MCDs within a county FIPS code. For example, there are five townships in Maine that are part of York County, which in turn is one of the ten counties in the A103 Boston metropolitan area. Connecticut, Massachusetts, Vermont and New Hampshire also have several towns or cities within a county code. Unless otherwise noted, the subdivisions are aggregated to the county level. In the case of *rents*, this is the weighted geometric mean of the Places or MCDs within each county.

other sources of data, such as incomes (from the Internal Revenue Service), and Census demographic variables.

Introducing incomes and demographic variables raises endogeneity issues, namely whether incomes determine prices or vice-versa. The effect of including Census variables, such as race, education and other neighborhood-specific indicators was analyzed in some detail in Aten (2005). Although not insignificant, it was unclear whether one wants to use differences in racial and ethnic make-up to control for geographic price differences[10]. Since the objective is not to explain price levels, but rather to obtain estimates based on their correlation to price indicators that have a more extensive geographical coverage, it was felt that these variables should not be included, and only *rents* and population densities were retained as independent variables.

The dependent variable, the natural logarithm of price level for the area, is repeated across counties belonging to the same area, whereas the independent variables (observed *rents* and population density) are specific to individual counties within the areas[11]. Half of the 38 areas have less than ten counties, and three of them consist of only one county. The unequal sampling within these areas induces a non-constant variance to the error term. The error terms are also likely to be autocorrelated, as both *rents* and prices tend to be similar in nearby locations.

Some effort was made to reduce heteroskedasticity in the covariance structure of the error term by specifying a spatial stochastic process (see below for a discussion on the spatial weight matrix *W*) and to adjust for the unequal sampling by individually weighting the observations. Also, by using a Bayesian estimation framework, the results are likely to be more robust to outliers such New York City, shown in *Figure 1*.

An alternative to this specification is to use only the average of the independent variables for each area, reducing the number of observations to their original 38 areas. Although such a framework is appealing, it exacerbates the change of scale and ecological fallacy problem, as one would then have to apply the coefficients estimated for 38 areas to all counties within those areas.

Some adjustments can be made to deal with the differences between the aggregation levels (see for example, Holt, Trammer, Stell and Wrigley [1996], Huang and Cressie [1997]), but these seem to induce more, and arguably less transparent, assumptions about the relationship among the geographical levels, especially when trying to take into account spatial autocorrelation among the units of observation.

---

[10] A principal component analysis (Aten [2005]) revealed that about a third of the standard variance among Census 2000 variables in the *rent* regressions was because of the first component that contrasts race (percent white, percent white occupancy) with income (percent under poverty, percent renters, percent ownership of two plus cars).

[11] $\text{Ln } P_i = \text{Ln } P_g$ where *g* is the SPI for area *g* with more than one county *i*. Each observation is multiplied by the square root of its population ($\sqrt{\text{Pop}_{ig}}$).

Equation (i): First Stage Model

$$\ln P_i = \sum_j \beta_j X_{ij} + \varepsilon_i$$

$$\text{(a)} \quad \varepsilon_i \approx \mathrm{N}(0,\sigma^2)$$

$$\text{(b)} \quad \varepsilon_i \approx \mathrm{N}(0,\sigma^2\mathrm{V}),\ \mathrm{V{=}diag}(v_i,...,v_n)$$

$$\text{(c)} \quad \varepsilon_i = \lambda W \varepsilon_i + \mu_i,\ \ \mu_i \approx \mathrm{N}(0,\sigma^2)$$

$$\text{(d)} \quad \varepsilon_i = \lambda W \varepsilon_i + \mu_i,\ \mu_i \approx \mathrm{N}(0,\sigma^2\mathrm{V}),\ \mathrm{V{=}diag}(v_i,...,v_n)$$

Equation (i) has four versions. A simple linear model (a), a heteroskedastic version (b), a version with an explicit spatial component known as a spatial error model, where the spatial autocorrelation is captured in the error term (c), and its heteroskedastic version (d). In the (b) and (d) cases, the variance terms are unknown parameters to be estimated using a Bayesian methodology.

The parameters are found using ordinary least squares for the linear version, maximum likelihood estimators for the spatial error homoskedastic case ($V = I_n$), and a Gibbs sampling approach for the non-constant variance versions[12]. The prior distribution for the v_i terms is an independent chi-square distribution $\chi^2(r)$. Large r values imply that variances approach unity, so smaller values ranging from two to ten were used, and 1000 samples were taken from 1100 draws, following Smith and LeSage [2004].

The estimates of this first stage model are discussed in the Results section. The predicted individual county price levels are normalized so that their weighted average equals the observed price level for the area.

For a review of spatial econometric models, including their specification and testing, see for example, Anselin (1988, 2004), Getis et al (2004), LeSage et al (2004). Variants of the model, such as a spatial lag and spatial Durbin model, as well as numerous definitions of the W matrix were tested, and the sensitivity of the final results to alternative specifications is described in Aten (2007).

W is an n by n spatial weights matrix that specifies the relationship between the n observations. A non-zero element W_{ik} defines k as being a geographical neighbor to i. The term neighbor in this context may range from nearest neighbors, to contiguity, to inverse distance matrix definitions of neighbors. For example, a first-order nearest neighbor matrix will have ones in the row and columns corresponding to observations that are closest to each other geographically, and zero otherwise[13]. Inverse distance matrices will have entries in all the elements (except the main diagonal) indicating the inverse of the distance between the observations. The contiguity matrix is defined using

[12] All estimation was done in Matlab using the Spatial Econometrics package written by James LeSage (http://www.spatial-econometrics.com/)

[13] Other metrics, such as trade or commuting flows may be used in the W matrix, but distance is an easy to compute variable that is clearly exogenous, and has been shown to be correlated to price levels in other studies (Aten [1996, 1997]).

a Delaunay triangulation[14], with observations having from three to twelve neighbors. This is the matrix reported in this paper.

One interpretation of W is that of a spatial multiplier, $(I-\lambda W)^{-1}$, allowing for endogeneity in both dependent and independent variables, respectively[15]. The use of spatial weight matrices may be loosely interpreted as a 'de-trending' mechanism, intended to reduce the bias in the coefficients in the presence of spatial auto-correlation, similar to the use of spatial lags in time-series analysis. For a comprehensive discussion on interpreting spatial models, see Anselin (2002).

Second Stage

With the first stage price levels for 425 counties, the next stage is to predict the price levels for the remaining U.S. counties, including those not sampled by the CPI[16]. Various approaches are possible, the most relevant ones being those that deal with spatially dependent missing observations (Cressie [1993], Keleijan and Prucha {2004], LeSage and Pace [2004]). The simplest approach would be to take the parameters from the first stage model for the metro/urban areas and apply them to the observations in the non-urban areas. The major drawbacks to this approach are that the predictions would not take into account i) the very different sample populations – urban versus rural areas, and ii) the spatial relationship between the original and predicted observations.

A sophisticated approach advocated by Pace and LeSage [2008] would be to impute the conditional expectation of the missing dependent variables and obtain the model parameters simultaneously, termed an endogenous spatial smoothing approach. The method used here is an exogenous spatial smoothing approach, where a price level - labeled a bridged price level in what follows - is imputed instead of the conditional expectation of the missing dependent variables.

It has the advantage of using all the information on the independent variables for all counties, as well as their spatial relationship, but does not use the variance-covariance information between the sampled and non-sampled observations to inform the original imputation as suggested by Pace and LeSage. However, by allowing the variance of the errors to be non-constant and estimating them via a Bayesian approach, some of the information across sampled and bridge price levels is incorporated into the parameters. A detailed comparison of the endogenous versus exogenous spatial smoothing results will be left for a future paper.

---

[14] Delaunay triangles (the dual of a Voronoi diagram, also know as Thiessen polygons) returns a set of triangles such that no data points are contained in any triangle's circumcircle. The contiguity matrix is the adjacency matrix derived from this triangulation.

[15] This is analogous to a spatial lag that is applied to both dependent and independent variables – translating into the error term after some algebraic manipulation: $(I-\lambda W)\ln P = (I-\lambda W) \sum\beta X + \mu$, which implies $\ln P = \sum\beta X + (I-\lambda W)^{-1} \mu$, with $\varepsilon = \lambda W \varepsilon + \mu$. Another interpretation is that of $(I-\lambda W)$ as a spatial filter, as in a first differencing approach for time series.

[16] The unweighted average rent for the 425 counties is \$1,003 while for all other counties it is \$594. The two-sample equality of means t-test statistic is 25.99 ($p<0.0001$).

For simplicity, the 425 counties that constitute the 38 areas sampled by the CPI are denoted 'overlap' counties because they are in both the BLS CPI sample data and the Census data. The areas not sampled in the CPI are denoted 'census only' counties. Together, the overlap and census-only counties cover over 3200 counties in the U.S.

The imputed or bridged price levels are estimated as follows. First, the ratio of the weighted geometric mean of *rents* in census-only to overlap areas is calculated. This ratio is then multiplied by the weighted geometric average of the price levels in the counties predicted in Stage One. In *Equation (ii)*, '*census*' refers to census-only counties while 'overlap' includes Census and BLS CPI counties. The weights refer to population weights.

For example, in Missouri, the ratio is 0.87, with fifteen overlapping counties averaging \$540 and 172 census-only counties averaging \$468 in *rents*. This ratio is then multiplied by the weighted geometric average of the price levels in the fifteen counties predicted in the first stage (0.86). For Missouri, this includes eight counties in St. Louis (A209) and seven in Kansas City (A214). The result, 0.75, is an average estimated price level for the remaining 172 census-only counties in Missouri. This is termed the bridged price level.

Equation (ii): Bridge Ratios (R = rents, PL = Price Levels)

$$Ratio = \left(\overline{R}_{census} \big/ \overline{R}_{overlap}\right)$$

$$\text{where } \overline{R}_{census} = \exp\left(\frac{\sum_{i \in census} w_i \ln \mathrm{R}_i}{\sum_{i \in census} w_i}\right)$$

$$\overline{R}_{overlap} = \exp\left(\frac{\sum_{i \in overlap} w_i \ln R_i}{\sum_{i \in overlap} w_i}\right)$$

$$\overline{PL}_{census} = \overline{PL}_{overlap} * Ratio$$

$$\text{where } \overline{PL}_{overlap} = \exp\left(\frac{\sum_{i \in overlap} w_i \ln PL_i}{\sum_{i \in overlap} w_i}\right)$$

The process is repeated for all states, with the exception of states that have no overlap at all. These are Iowa, Montana, New Mexico, North Dakota, Rhode Island, Wyoming and Puerto Rico[17], where a higher geographical aggregation, the division, is used instead of

[17] Puerto Rico is included in this stage even though it is a territory and not a state as it is part of the Census American Community Survey. It will be excluded in the final steps as the BEA does not produce or publish data for Puerto Rico.

the state. There are nine divisions, their average *rents* and ratios are listed in *Table 3* in the Results section.

The bridged price level estimates for the census-only counties from *Equation (ii)*, together with the observed price levels for the overlap counties, become the dependent variables in the second stage regression model. The second stage mirrors the first stage in that the log of the estimated price levels for each county enter as dependent variables and the *rents* as well as observed population densities for each county are the independent variables. The observations are weighted by their population.

Both linear and heteroskedastic versions of the ordinary least squares formulation and the spatial error model are estimated, analogous to those in *Equation (i)* depicted earlier, (with a similar prior for the non-constant variances v_i, and taking 1000 samples from 1100 draws to obtain the posterior distributions of the parameters). As in the first stage, a spatial weight matrix W is used with n increasing from 425 to 3217, corresponding to all uniquely identified FIPS county codes in the Census *rent* data.

An important clarification should be made between the two W matrices – the smaller one that was used in the first stage ($n=425$) and the larger one that comprises all counties, including the counties in the first stage ($n=3217$). The smaller matrix is defined as a subset of the larger one, that is, contiguity and distance measures must hold in both matrices or the smaller matrix will be endogenous to the model[18].

For example, Honolulu and San Diego are considered neighbors if we only take into account a matrix of the 425 counties, but if one considers all the counties in the U.S., Honolulu will only be a neighbor to other Hawaiian counties. Similarly, Wilmington in Delaware is part of the greater Philadelphia area, and Queen Anne's county in Maryland is part of the Baltimore metropolitan area. These two counties are 'neighbors' if our population consists only of the 425 counties that make up the 38 BLS metropolitan and urban areas. However, they are not neighbors if all counties – urban and non-urban - in the United States are included – Kent county in Delaware, for one, would be between them. A spatial weight matrix that defines neighbors in the smaller sample but not in the larger population would be endogenous and not appropriate for this multi-stage estimation process[19].

Final Stage

The final stage consists of aggregating the predicted county price level estimates from the estimates in the second stage regression to an overall SPI. The aggregations correspond to two geographical definitions used by the BEA, the 51 states and 363 metropolitan

[18] This endogeneity was helpfully pointed out by Oleg Smirnov (see Smirnov [2007]).
[19] A comparison of the results using an 'endogenous' W showed some differences but none seemed large enough to affect the final SPIs significantly. The results were not formalized into tests and are not included in this paper.

areas[20]. Ideally, an aggregate consumption SPI would use consumption expenditure weights at the county level, but these are not available below the metro-area level.

However, if the purpose of the SPI is to compare economic data other than consumption, such as incomes or output, then these latter weights will provide a better proxy for spatially deflated incomes and output levels[21]. Here we use two types of sub-national data estimated by the BEA – Personal Income and Gross Domestic Product (see Lenze [2007] and Panek, Baumgardner & McCormick [2007])[22].

The income and product dollar figures for each county are divided by the estimated county price levels, resulting in a spatially 'deflated' or adjusted value, then summed to the state and metropolitan levels. The sums are normalized so that the unadjusted and the adjusted dollar totals are equal, that is, the overall United States SPI is equal to one. The results are described in more detail below.

Results

First Stage Results

The first stage estimation results are shown in *Table 2*. The independent variables are the county *rents* as defined in the previous section and the population density of each county within a BLS area. The column labeled OLS is the ordinary least squares estimate, the HET column stands for the heteroskedastic version, SER is the spatial error model (with the spatial W matrix defined using contiguity weights), and SER-HET is the heteroskedastic version of the spatial error model (see *Equation (i) (a)-(d)*).

Table 2. First Stage Regression Results (n=425)

Dependent: *Ln P*	**OLS**	**HET**	**SER**	**SER-HET**
	(a)	**(b)**	**(c)**	**(d)**
Intercept	-0.43	-0.41	-0.25	-0.30
Rents ($x10^{-3}$)	0.38	0.34	0.23	0.24
Density($x10^{-4}$)	0.08	0.12	0.04	0.06
Lambda (λ)	-	-	*0.87*	*0.70*
Rbar^2	0.65	0.58	0.74	0.71
MSE*	3512	1203	2576	1562

[20] See Metropolitan area definitions and BEA Economic Area definitions under http://www.bea.gov/regional/index.htm. The micropolitan areas and the metro/non-metro portions of each state may also be made available upon request.
[21] Dividing GDP by the price level provides a comparison of real volumes across areas, following common practice in international comparisons of real income and product. See for example, the OECD – Eurostat Methodological Manual of Purchasing Power Parities Box 1.1, Chapter 1 in www.oecd.org/std/ppp/manual
[22] Personal Incomes are published at the county level, but GDP only at the metropolitan area level. The latter are estimated, but not published at the county level, but were kindly provided by Matthew McCormick at the Regional Economic Analysis Division of BEA.

Dependent: *Ln P*	**OLS**	**HET**	**SER**	**SER-HET**
LLikelihood	-	-	-2148	-

All coefficients significant at the 1% level
** MSE=Mean of the MSEs for the 1000 draws in the HET regressions*

The *Rbar*^{2} is a 'pseudo' R^2 measure in the spatial models and equals the squared correlation between the predicted and observed price levels. The *Rbar*^{2} is lower in the heteroskedastic estimates as there is less weight given to the outliers. MSE is the mean squared error (σ^2), and is much smaller in both heteroskedastic models.

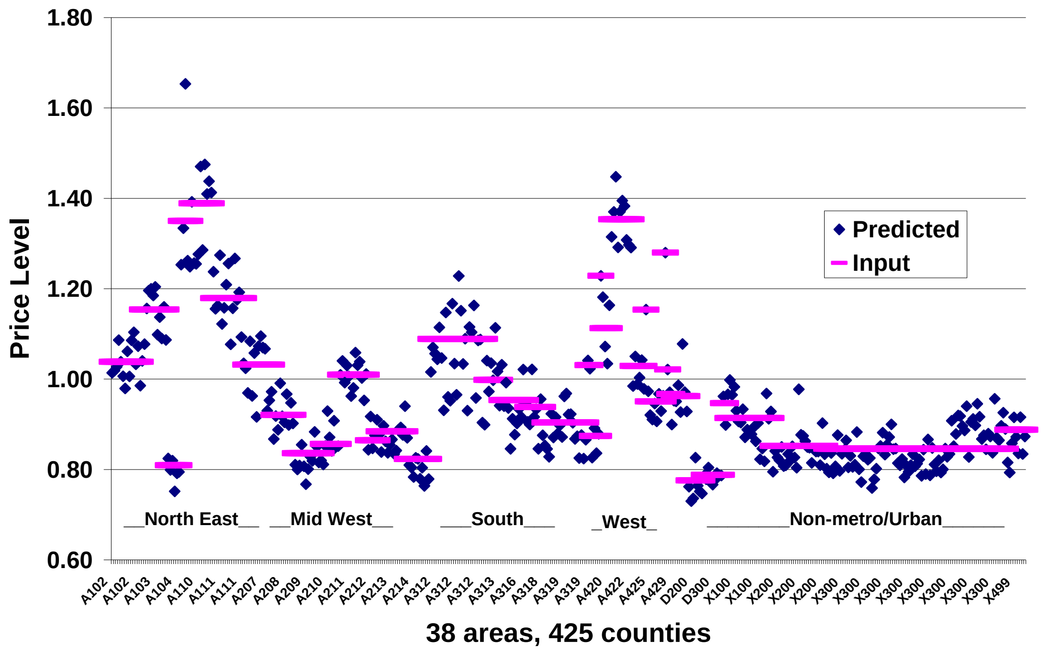
All coefficients are significant, including the lambda, which is the spatial weights matrix coefficient, suggesting that it should be included. Also, if we plot the distribution of the parameters for V (the v_i's), it is clear that there are outliers and the variance is not constant, so the heteroskedastic model is preferable.

Figure 2 illustrates the estimates, showing the observed input price levels and the predicted levels using the heteroskedastic spatial error model, (d) in *Table 2*. For example, the fourteen leftmost set of points on the horizontal axes of *Figure 2*, represent Philadelphia (A102) in the North East region while the rightmost nine points represent West B size areas (X499). The predicted values are normalized to their input values for each area.

Philadelphia has an observed input price level of 1.04 with an average weighted *rent* of $1,061 (*Table A1* in the *Appendix*). There are fourteen counties that make up the Philadelphia area. The lowest predicted price level is 0.979 for Cumberland county NJ, while the highest is 1.104 for Chester, PA, closely followed by Bucks County, PA. The corresponding *rent* variation is $920 for Cumberland versus $1,404 for Chester, but the lowest *rents* are for Philadelphia county PA, at $713. Philadelphia's predicted price level is 0.985 higher than Cumberland, partly due to its higher population density and the spillover effect of having neighbors with higher price levels.

The highest estimated price level is New York City, with 1.653, and an observed *rent* of $1189, while the lowest is Allen, Kansas, with a price level of 0.730 and *rents* averaging $467. The highest *rents* across all 425 counties were in Loudon, Virginia, part of the Washington, DC metro area, at $2014 and a price level of 1.228, while the lowest *rent* was for St. Landry, Louisiana, at $373, with an estimated price level of 0.759.

Figure 2. Predicted Price Levels First Stage



Although Loudon has a much higher *rent* level than New York City, the input price level for the Washington, DC area is much lower on average than for the greater New York area (1.089 versus 1.350), hence the predicted level will be proportionally lower, other things equal. Note also that the average of the input price levels is equal to one, so these predicted price levels are relative to the metropolitan areas, not the United States as a whole.

Second Stage Results: Rent Ratios

The predicted price levels from the previous stage are for the 425 counties within the 38 areas of the CPI. These 425 counties were denoted overlap counties because they are both in the CPI and in the Census, which includes all U.S. counties. Although these overlap counties account for roughly 87% of the population, the remaining counties are predominantly non-metropolitan and non-urban areas, and include entire states. This stage attempts to find a reasonable bridge between the overlap counties and the census-only counties.

The first step in bridging the two areas is to multiply the weighted geometric average of the price levels in the overlapping areas by the ratio of the *rents* (*Equation (iv)*). A summary of these results is shown in *Table 3*. *Rents* for overlap counties in each

Division and Region[23] are shown in column (2), while *rents* for census-only counties are in column (1). These are labeled 'overlap' and 'census' respectively. The ratio of the two is in column (3). The price level from the first stage for the overlap counties is in column (4), and the bridged price levels in column (5).

Overall, the ratio of *rents* in census-only counties to *rents* in overlap counties is 0.63 ($700 / $1105), shown on the first line of *Table 3*, indicating as expected, that the counties sampled by the BLS have significantly higher *rent* levels. This pattern is maintained across all regions and divisions.

Table 3. Rent Ratios and Bridged Price Levels

Region and Division	Rent* census ($) (1)	Rent* overlap ($) (2)	Ratio (1)/(2)= (3)	Price Level* overlap (4)	Bridged Level census (3)*(4)= (5)
Overall	**700**	**1105**	**0.63**	**1.03**	**0.65**
Northeast	791	1182	0.67	1.16	0.77
1. New England	909	1262	0.72	1.13	0.82
2. Middle Atlantic	755	1155	0.65	1.17	0.76
Midwest	699	1003	0.70	0.92	0.64
3. East North Central	730	1004	0.73	0.93	0.68
4. West North Central	654	1000	0.65	0.90	0.59
South	637	976	0.65	0.93	0.61
5. South Atlantic	656	1061	0.62	0.95	0.59
6. East South Central	625	732	0.85	0.83	0.71
7. West South Central	613	878	0.70	0.91	0.63
West	861	1266	0.68	1.11	0.76
8. Mountain	767	1026	0.75	0.94	0.70
9. Pacific	956	1340	0.71	1.17	0.83

**Population Weighted geometric means across counties. 'Overlap' denotes counties in the CPI and in the Census, 'Census' denotes census-only counties*.

The highest *rents* are in the Northeast and West, especially in the Pacific division that includes California, Hawaii, Alaska, Oregon and Washington. The lowest *rents* are in the East South Central division comprised of Alabama, Kentucky, Mississippi and Tennessee. The complete list of state *rents* and ratios is shown in *Table A2* in the *Appendix*.

If all the counties in a state are in the BLS sample, the column labeled *Rent* Census will be blank as there is no need for an estimated bridge price level. This is true for Connecticut, DC, and New Jersey. Conversely, Iowa, Montana, New Mexico, North Dakota, Rhode Island, Wyoming and Puerto Rico are states with no overlap counties, and therefore no *rent* ratios. In these cases, the division level ratio (*Table 2*) is used as a bridge instead of the state level ratio.

[23] Since the *rents* are taken from the Census Bureau, their Regions and Divisions are used rather than BLS or BEA Regions.

Only Arkansas, Mississippi, South Carolina, South Dakota and Tennessee have ratios above one, meaning that the census-only counties have *rents* that are on average higher than the *rents* in overlap counties. In all these states, the overlap counties belong to 'B' or 'C' size BLS areas, namely they are part of medium and small cities or urban but non-metropolitan areas. For example, in Arkansas, the overlap county is Jefferson whose largest town is Pine Bluff, rather than Pulaski, the larger county where Little Rock is located. Similarly, for Mississippi, the overlap county is Pearl River, where Picayune is the largest town, while Hinds county where Jackson is located, is not part of the BLS sample because it is not large enough to be in the 'A' size area[24]. The composition of counties within areas and states is in the *Appendix, Table A1*.

Second Stage Results: Regressions

The majority of the values for the dependent variable in this stage are derived from the *rent* ratios described above, as we have no direct information on their price levels. That is, for census-only counties, the bridge price levels are the same across a state or a division, because they are based on the ratio of *rents* between the census-only and the overlap counties in that state or region.

For the overlap counties, the price levels are the ones from the first stage. Both overlap and census-only bridge price levels are regressed against *rents* and densities, using the model structure introduced earlier: a simple linear model and a spatial error model, and their respective heteroskedastic versions. *Table 4* is a summary of the input data for the second stage regressions.

Table 4. Input Data Summary

(n=3219)	Mean*	CV (%)	Range	Minimum	Maximum
Price levels	0.718	20	1.12	0.53 (Dickenson, VA)	1.65 (New York, NY)
Rents ($)	648	38	1842	172 (Vieques, PR)[25]	2,014 (Loudon, VA)
Density (pop/sqmile)	270	612	66,617	0.047 (Yukon-Koyukuk, AK)	66,617 (New York, NY)
**Unweighted*					

Table 5 shows the results of the second stage regressions, using the contiguity spatial matrix for 3217 counties. As in the first stage, the independent variables are the county *rents* and the population densities and the observations are weighted by the square root of the population. The column labeled OLS is the ordinary least squares estimate, the HET

[24] A future research exercise would be to divide the estimation into separate 'A' size areas (31 of them) versus the four 'B' and three 'C' size areas.
[25] Puerto Rico is included in this stage as it is part of the Census. Excluding Puerto Rico, King county, TX has the lowest rent at $265.

column stands for the heteroskedastic version, SER is the spatial error model, and SER-HET is the heteroskedastic version of the spatial error model (see *Equation (i) (a)-(d)*).

Table 5. Second Stage Regressions (n=3217)

Dependent: *Ln P*	**OLS**	**HET**	**SER**	**SER-HET**
	(a)	**(b)**	**(c)**	**(d)**
Intercept	-0.69	-0.68	-0.61	-0.61
Rents ($x10^{-3}$)	0.56	0.54	0.49	0.47
Density($x10^{-4}$)	0.11	0.15	0.09	0.11
Lambda (λ)	-	-	*0.72*	*0.66*
Rbar^2	0.60	0.58	0.75	0.74
MSE*	1451	618	889	544
LLikelihood	-	-	-14560	-

All coefficients significant at the 1% level
** MSE=Mean of the MSEs for the 1000 draws in the HET regressions*

The differences across the models (a)-(d) follow the pattern of the first stage. The coefficient on the spatial weight matrix is lower than in the first stage, but still very significant, and the use of a heteroskedastic model again seems warranted as the distribution of the estimated variances from the Gibbs sampler is non-constant.

The predicted price levels are taken from the heteroskedastic spatial error model (SER-HET). If the county was one of the 425 in the original sample of metro and urban areas, its predicted price level is adjusted so that the predicted state average is equal to the average of the input price levels. For all other counties, the predicted price level is also adjusted by this factor[26]. This forces the predicted and input price levels for the counties in the sample to be consistent, and also makes the levels of the bridged counties consistent with the sample price levels.

Final Stage Results: Spatial Price Indexes (SPIs)

The SPIs are tabulated for various geographic aggregations using the predicted county price levels and both Personal Income data and Gross Domestic Product data[27] from the BEA, which does not include figures for Puerto Rico.

Table 6 shows the Personal Income[28] totals and per capita values as well as the adjusted totals and per capita values and the corresponding SPI[29]. The SPI is normalized so that

---

[26] Final predicted price level county *i* , state *s* = predicted level in county *i*, state *s* times the ratio of the state average input price levels to the state average predicted price levels for counties in the original 425 sample.
[27] http://www.bea.gov/regional/gsp/help/
[28] The definition of Personal Income and the geographical aggregations are from BEA: http://bea.gov/regional/reis/default.cfm?catable=CA1-3&section=2
[29] The SPI is multiplied by 100 for presentation purposes.

the total and adjusted personal incomes are equal and the SPI for the U.S. as a whole is one hundred.

Table 6. State SPIs for Personal Income: 2005

Obs	State	Personal Income (million $)	Adjusted Personal Income (million $)	SPI Personal Income	pcPI ($)	Adjusted pcPI ($)
1	AL	134,736	161,155	83.6	29,623	35,432
2	AK	23,588	23,641	99.8	35,564	35,644
3	AZ	178,706	182,586	97.9	30,019	30,671
4	AR	74,059	87,538	84.6	26,681	31,537
5	CA	1,335,386 max	1,105,526 max	120.8	36,936	30,578
6	CO	174,919	182,722	95.7	37,510	39,183
7	CT	165,890	140,214	118.3	47,388	40,053
8	DE	31,218	30,945	100.9	37,088	36,763
9	DC	30,739	29,075	105.7	52,811max	49,954 max
10	FL	604,131	629,067	96.0	34,001	35,404
11	GA	282,322	309,276	91.3	30,914	33,865
12	HI	43,913	33,672	130.4	34,489	26,445 min
13	ID	40,706	47,401	85.9	28,478	33,162
14	IL	462,928	457,617	101.2	36,264	35,848
15	IN	195,332	218,481	89.4	31,173	34,868
16	IA	93,919	116,190	80.8	31,670	39,180
17	KS	90,320	108,330	83.4	32,866	39,419
18	KY	117,967	138,891	84.9	28,272	33,286
19	LA	111,167	130,718	85.0	24,664 min	29,001
20	ME	40,612	39,926	101.7	30,808	30,288
21	MD	234,609	218,533	107.4	41,972	39,096
22	MA	279,860	237,481	117.8	43,501	36,914
23	MI	331,349	357,701	92.6	32,804	35,413
24	MN	191,175	199,173	96.0	37,290	38,850
25	MS	72,862	86,990	83.8	25,051	29,909
26	MO	181,066	218,155	83.0	31,231	37,628
27	MT	27,122	33,310	81.4	29,015	35,636
28	NE	57,885	67,191	86.1	32,923	38,217
29	NV	86,224	87,720	98.3	35,744	36,364
30	NH	49,356	43,443	113.6	37,768	33,244
31	NJ	381,466	311,695	122.4	43,831	35,814
32	NM	53,714	65,841	81.6	27,889	34,186
33	NY	771,990	576,971	133.8 max	39,967	29,871
34	NC	269,203	313,345	85.9	31,041	36,131
35	ND	19,899	25,869	76.9 min	31,357	40,763
36	OH	365,453	417,918	87.4	31,860	36,434
37	OK	106,119	126,847	83.7	29,948	35,798
38	OR	117,497	123,035	95.5	32,289	33,811
39	PA	433,400	451,476	96.0	34,937	36,394
40	RI	37,923	35,038	108.2	35,324	32,637
41	SC	120,123	137,523	87.3	28,285	32,382
42	SD	25,201	31,280	80.6	32,523	40,368
43	TN	184,443	208,124	88.6	30,969	34,945

Obs	State	Personal Income (million $)	Adjusted Personal Income (million $)	SPI Personal Income	pcPI ($)	Adjusted pcPI ($)
44	TX	744,270	793,943	93.7	32,460	34,627
45	UT	68,039	74,412	91.4	27,321	29,880
46	VT	20,362	21,554 min	94.5	32,717	34,632
47	VA	283,685	279,812	101.4	37,503	36,991
48	WA	223,232	214,494	104.1	35,479	34,090
49	WV	47,926	57,633	83.2	26,419	31,769
50	WI	183,948	208,869	88.1	33,278	37,786
51	WY	18,981 min	22,595	84.0	37,305	44,408
			Mean	**100.0**	**34,471**	**34,471**
	Total	**10,220,942**	**10,220,942**			
	Max	1,335,386	1,105,526	133.8	52,811	49,954
	Min	18,981	21,554	76.9	24,664	26,445
	Range	1,316,406	1,083,972	56.9	28,148	23,509

Table 7 is analogous to *Table 6*, with totals and per capital values for Gross Domestic Output[30] by state.

Table 7. State SPIs for Gross Domestic Product: 2005

Obs	State	GDP (million $)	Adjusted GDP (million $)	SPI GDP	pcGDP ($)	Adjusted pcGDP ($)
1	AL	151,342	181,975	83.2	33,274	40,009
2	AK	39,394	39,820	98.9	59,396	60,038
3	AZ	212,312	217,969	97.4	35,665	36,615
4	AR	87,004	103,432	84.1	31,345	37,263
5	CA	1,616,351 max	1,347,876 max	119.9	44,707	37,281
6	CO	214,337	228,522	93.8	45,962	49,004
7	CT	193,496	165,799	116.7	55,273	47,362
8	DE	56,731	56,249	100.9	67,397	66,824
9	DC	82,628	79,259	104.3	141,960 max	136,172 max
10	FL	666,639	698,170	95.5	37,519	39,293
11	GA	358,365	390,221	91.8	39,240	42,729
12	HI	54,773	42,628	128.5	43,017	33,479
13	ID	45,891	53,728	85.4	32,106	37,589
14	IL	555,599	550,236	101.0	43,524	43,104
15	IN	236,357	267,358	88.4	37,721	42,668
16	IA	117,635	145,788	80.7	39,668	49,161
17	KS	105,228	126,713	83.0	38,290	46,108
18	KY	138,616	163,776	84.6	33,221	39,250
19	LA	180,336	212,488	84.9	40,010	47,143
20	ME	44,906	44,268	101.4	34,066	33,582
21	MD	244,447	231,385	105.6	43,733	41,396

30 Source: BEA http://bea.gov/regional/index.htm

Obs	State	GDP (million $)	Adjusted GDP (million $)	SPI GDP	pcGDP ($)	Adjusted pcGDP ($)
22	MA	320,050	270,232	118.4	49,748	42,005
23	MI	372,148	403,887	92.1	36,843	39,986
24	MN	231,437	241,973	95.6	45,143	47,198
25	MS	79,786	96,009	83.1	27,432 min	33,010 min
26	MO	215,073	260,728	82.5	37,096	44,971
27	MT	29,915	37,099	80.6	32,004	39,690
28	NE	72,242	84,286	85.7	41,090	47,940
29	NV	110,158	113,560	97.0	45,665	47,076
30	NH	54,119	48,205	112.3	41,413	36,887
31	NJ	427,654	352,453	121.3	49,138	40,497
32	NM	69,692	86,422	80.6	36,185	44,872
33	NY	961,385	646,827	148.6 max	49,772	33,487
34	NC	350,700	405,955	86.4	40,438	46,810
35	ND	24,935	32,501	76.7 min	39,293	51,214
36	OH	442,243	510,369	86.7	38,554	44,493
37	OK	121,558	146,180	83.2	34,305	41,254
38	OR	141,831	148,879	95.3	38,977	40,914
39	PA	486,139	508,714	95.6	39,188	41,008
40	RI	43,623	41,101	106.1	40,633	38,284
41	SC	140,088	161,296	86.9	32,986	37,979
42	SD	30,541	37,847	80.7	39,414	48,842
43	TN	224,995	254,583	88.4	37,778	42,746
44	TX	989,333	1,061,235	93.2	43,149	46,285
45	UT	88,364	97,736	90.4	35,483	39,246
46	VT	23,056 min	24,501 min	94.1	37,044	39,366
47	VA	350,692	345,667	101.5	46,361	45,697
48	WA	271,381	260,466	104.2	43,132	41,397
49	WV	53,091	64,655	82.1	29,266	35,640
50	WI	216,985	248,913	87.2	39,255	45,031
51	WY	27,246	32,908	82.8	53,550	64,678
			Mean	**100.0**	**41,729**	**41,729**
	Total	**12,372,850**	**12,372,850**			
	Max	1,616,351	1,347,876	148.6	141,960	136,172
	Min	23,056	24,501	76.7	27,432	33,010
	Range	1,593,296	1,323,375	71.9	114,528	103,162

The range for the values adjusted by their SPIs is smaller as can be seen in both *Tables 6 and 7*. This is expected as the higher income (and GDP) states tend to have a high SPI, so that their adjusted values will be lower, and conversely, the lower income (and GDP) states will be adjusted upward as their price levels tend to be lower.

Note that the adjusted values for both Personal Income and GDP imply a very different ranking than one would obtain from the unadjusted estimates. For example, in *Table 6*, the lowest per capita personal income is for Louisiana at $24,664, but the lowest adjusted per capita personal income value is for Hawaii at $26,445 because of its relatively high SPI of 130.4.

The adjusted per capita income and per capita GDP estimates for all Metropolitan Statistical Areas are shown in *Table A3* in the *Appendix.*

Conclusions

The state SPIs are constructed from a set of 38 metropolitan and urban area price levels for consumption goods and services, plus detailed *rent*[31], data for all U.S. counties from the 2005 American Community Survey of the Census Bureau. These 38 SPIs are computed from individual price observations on hundreds of consumption items that make up the Consumer Price Index of the Bureau of Labor Statistics, covering the expenditures of approximately 87% of the U.S. population, but accounting for only 15% of the counties in the United States. The first stage of the work in this paper breaks down the original 38 areas into 425 counties and estimates price levels that are based on the relationship between *rents*, population densities and geographic proximity among the observations, using a spatial smoothing model and Bayesian framework.

The second stage involves bridging the estimates for these 425 counties to all other counties, 3219 in total (including the 78 municipalities in Puerto Rico). There is no direct price level information from the BLS for these other counties, as they are not included in the sampling framework of the CPI. However, the Census does have detailed *rent* data and complete coverage of all counties, and as *rents* on average, account for nearly thirty percent of overall consumer expenditures, they are used as the main auxiliary variable. As a first step, we take the *rent* ratios between sampled and non-sampled areas and apply that ratio to the existing price levels. The assumption is that as a first approximation, the ratio of price levels between the overlap counties (belonging to both BLS and Census samples) and the counties only sampled by the Census is the same as the ratio of their *rents*.

These initial price levels, called bridged price levels, are then regressed against the individual *rents* and population densities for all counties. The regressions mirror the first stage spatial smoothing and Bayesian framework, and include an explicit modeling of the geographic proximity of the counties, this time with fuller and continuous coverage. The resulting predicted price levels are then used to adjust a) Personal Income and b) Gross Domestic Product estimates measures by the BEA (which excludes Puerto Rico), and the results are summed to various geographic aggregations, including 51 States and 363 Metropolitan Areas.

The results demonstrate the feasibility of estimating state price levels from the best information available on prices and *rents* from the Bureau of Labor Statistics and the American Community Survey of the Census Bureau. Just as we deflate incomes and

[31] *Rents* in the BLS include both actual *rents* and owner-equivalent *rents* (for a more detailed description, see Aten [2006] and Footnote 2). The American Community Survey 2005 covers all counties with over 65,000 population, while the Census 2000 has all counties. The rent increase for non-ACS counties within each state was assumed to be equal to that of the ACS counties between 2000 and 2005, as there is no direct rent deflator available for these counties.

output over time to adjust for changes in prices across years using the CPI, the SPIs are spatial price deflators, adjusting incomes or output for differences in relative price levels across places.

An important extension of this work is to explore the development of SPIs that reflect more than consumption goods and services, although in international comparisons, the price level of consumption is often a good approximation of that for all of GDP from the expenditure side. This is because the relative prices of investment and government change systematically in opposite directions when measured across per capita incomes. It is not clear whether this pattern would be found across states or smaller geographies within one country, but it seems worth examination. One approach to this would be to see if there is a pattern across states in salaries and prices of inputs and outputs related to construction, producers' durable equipment and government compensation.

A second outgrowth of this work is to look at differences in price levels within expenditure categories, such as Food and Beverages, and within income groups, in order to make adjustments to federal and state aid programs that aim to target particular populations. Most of the non-urban counties in the United States had lower *rents* than their urban counterparts within a state, but the price levels of goods, such as fresh vegetables, and of medical and educational services were sometimes higher. Using both the time-to-time CPI index and the spatial price index (SPI) may broaden the analysis of patterns of consumption price levels while enabling a more focused approach to targeting areas of concern.

REFERENCES

Alegretto, Sylvia, (2005) 'Basic Family Budgets: Working families' budgets often fail to meet living expenses around the U.S.', Briefing Paper No.165, Economic Policy Institute, Washington, DC, September. (http://www.epi.org/content.cfm/bp165)

Anselin, Luc (1988), *'Spatial Econometrics: Methods and Models'*, Dordrecht, Kluwer.

Anselin, Luc and Julie Le Gallo (2006), 'Interpolation of Air Quality Measures in Hedonic Price Models: Spatial Aspects', Spatial Economic Analysis, Vol.1, No.1, June.

Anselin, Luc (2002), 'Under the Hood. Issues in the Specification and Interpretation of Spatial Regression Models',

Anselin, Luc, R.J. Florax & S.J. Rey (2004), 'Advances in Spatial Econometrics: Methodology, Tools and Applications', Springer, Berlin.

Aten, Bettina (2005), 'Report on Interarea Price Levels, 2003', working paper 2005–11, *Bureau of Economic Analysis*, May. (http://bea.gov/papers/working_papers.htm)

Aten, Bettina (2006), 'Interarea Price Levels: an experimental methodology', Monthly Labor Review, Vol. 129, No.9, Bureau of Labor Statistics, Washington, DC, September 2006.

Aten, Bettina (2007), 'Estimates of State Price Levels for Consumption Goods and Services: a first brush', *Bureau of Economic Analysis*, November. (http://www.bea.gov/papers/index.htm)

Ball, Adrian and David Fenwick (2004), 'Relative Regional Consumer Price Levels in 2003', Economic Trends, Vol.603, Office for National Statistics, UK.

Bernstein, Jared, Chauna Brocht, and Maggie Spade-Aguilar, (2000), '*How Much Is Enough? Basic Family Budgets for Working Families*', Economic Policy Institute, Washington, D.C..

Cressie, N. (1993), 'Statistics for Spatial Data', revised edition, John Wiley, New York.

Fuchs, Victor, Michael Roberts and Sharon Scott (1979), 'A State Price Index', *National Bureau of Economic Research*, Working Paper Series, February.

Getis, Art, J.Mure & H.G. Zollerl (2004), 'Spatial Econometrics and Spatial Statistics', London, Palgrave Macmillan.

Goodchild, Michael, Luc Anselin and U. Deichmann (1993), 'A Framework for the areal interpolation of socioeconomic data', Environment and Planning A, Vol.25, Issue 25.

Gotway, Carol and Linda Young (2002), 'Combining Incompatible Spatial Data', Journal of the American Statistical Association, June, Vol.97, No.458.

Holt D., Stell D., Trammer M, Wrighley N. (1996), 'Aggregation and ecological effects in geographically based data', in Geographical analysis, Vol. 28, n°. 3.

Huang, H.-C. and Cressie, N. (1997), ‘Multiscale Spatial Modeling’, in 1997 *Proceedings of the Section on Statistics and the Environment*, 49-54, American Statistical Association, Alexandria, VA.

Johnson, David S., John M. Rogers, and Lucilla Tan (2001), "A Century of Family Budgets in the United States", Monthly Labor Review, Vol. 124, No. 5, Bureau of Labor Statistics, Washington, DC.

Jolliffe, Dean (2006), ‘Poverty, Prices and Place: how sensitive is the spatial distribution of poverty to cost of living adjustments?’, Economic Inquiry, Vol. 44, No. 2, April.

Lenze, David (2007), ‘Local Area Personal Income for 2005’, Survey of Current Business, May.

LeSage, J.P. & Pace, R.K. (2004), ‘Advances in Econometrics: Spatial and Spatiotemporal Econometrics’, Elsevier Science, Oxford.

LeSage, J.P. & Pace, R.K. (2004), ‘Models for Spatially Dependent Missing Data’, Journal of Real Estate Finance and Economics, 29:2, Kluwer.

Pace, R.K. & LeSage, J.P. (2008), ‘Prediction in Spatial Econometric Models: Augmented and Corrected’, forthcoming, Encyclopedia of Geographical Information Science, Shashi Shekhar and Hui Xiong (eds.), Springer-Verlag.

Panek, Sharon, Frank Baumgardner and Matthew McCormick (2007), ‘Introducing New Measures of the Metropolitan Economy: Prototype GDP-by-Metropolitan-Area Estimates fro 2001-2005’, Survey of Current Business, November.

Rao, Prasada D. S (2005), ‘On the Equivalence of Weighted Country-Product-Dummy (CPD) Method and the Rao-System for Multilateral Price Comparisons’, Review of Income and Wealth, Series 51, Number 4, December.

Roos, Michael (2006), ‘Regional Price Levels in Germany’, Applied Economics, Vol.38, Issue 13, July.

Smirnov, Oleg (2007), ‘Spatial Sampling in the Presence of Spatial Dependence’, 54th Annual North American Meetings of the Regional Science Association International, Savannah, GA, November 7-11.

Smith, Tony E. and James P. LeSage (2004), ‘A Bayesian probit model with spatial dependencies’ in Advances in Econometrics: Volume 18: Spatial and Spatiotemporal Econometrics, (Oxford: Elsevier Ltd), James P. LeSage and R. Kelley Pace (eds.), pp. 127-160.

Appendix Table A1. Predicted Price Levels First Stage

Obs	Area Name	Area Code	County Name	State	County Fips	Input Plevel	Predicted Plevel	Actual Rent ($)	Wtd Mean Rent* ($)
1	PHILADELPHIA	A102	New Castle	DE	10003	1.038	1.014	1043	1061
2		A102	Cecil	MD	24015	1.038	1.019	1084	1061
3		A102	Atlantic	NJ	34001	1.038	1.027	1111	1061
4		A102	Burlington	NJ	34005	1.038	1.086	1340	1061
5		A102	Camden	NJ	34007	1.038	1.038	1115	1061
6		A102	Cape May	NJ	34009	1.038	1.007	1031	1061
7		A102	Cumberland	NJ	34011	1.038	0.979	920	1061
8		A102	Gloucester	NJ	34015	1.038	1.061	1238	1061
9		A102	Salem	NJ	34033	1.038	1.006	1033	1061
10		A102	Bucks	PA	42017	1.038	1.086	1328	1061
11		A102	Chester	PA	42029	1.038	1.104	1404	1061
12		A102	Delaware	PA	42045	1.038	1.033	1078	1061
13		A102	Montgomery	PA	42091	1.038	1.073	1265	1061
14		A102	Philadelphia	PA	42101	1.038	0.985	713	1061
15	BOSTON	A103	York	ME	23031	1.154	1.040	935	1309
16		A103	Bristol	MA	25005	1.154	1.077	1060	1309
17		A103	Essex	MA	25009	1.154	1.156	1340	1309
18		A103	Middlesex	MA	25017	1.154	1.196	1472	1309
19		A103	Norfolk	MA	25021	1.154	1.200	1487	1309
20		A103	Plymouth	MA	25023	1.154	1.185	1456	1309
21		A103	Suffolk	MA	25025	1.154	1.204	1295	1309
22		A103	Worcester	MA	25027	1.154	1.098	1150	1309
23		A103	Hillsborough	NH	33011	1.154	1.137	1294	1309
24		A103	Merrimack	NH	33013	1.154	1.090	1126	1309
25		A103	Rockingham	NH	33015	1.154	1.160	1375	1309
26		A103	Strafford	NH	33017	1.154	1.087	1111	1309
27	PITTSBURGH	A104	Allegheny	PA	42003	0.809	0.824	782	715
28		A104	Beaver	PA	42007	0.809	0.799	682	715
29		A104	Butler	PA	42019	0.809	0.820	792	715
30		A104	Fayette	PA	42051	0.809	0.752	437	715
31		A104	Washington	PA	42125	0.809	0.791	647	715
32		A104	Westmoreland	PA	42129	0.809	0.795	661	715
33	NY CITY	A109	Bronx	NY	36005	1.350	1.253	868	1083
34		A109	Kings	NY	36047	1.350	1.334	1044	1083
35		A109	New York	NY	36061	1.350	1.653	1189	1083
36		A109	Queens	NY	36081	1.350	1.262	1146	1083
37		A109	Richmond	NY	36085	1.350	1.248	1390	1083
38	NY SUBURBS	A110	Fairfield	CT	9001	1.389	1.392	1620	1580
39		A110	Litchfield	CT	9005	1.389	1.257	1228	1580
40		A110	New Haven	CT	9009	1.389	1.255	1196	1580
41		A110	Dutchess	NY	36027	1.389	1.276	1288	1580
42		A110	Nassau	NY	36059	1.389	1.470	1772	1580
43		A110	Orange	NY	36071	1.389	1.286	1316	1580
44		A110	Putnam	NY	36079	1.389	1.475	1880	1580
45		A110	Rockland	NY	36087	1.389	1.409	1666	1580
46		A110	Suffolk	NY	36103	1.389	1.438	1748	1580
47		A110	Westchester	NY	36119	1.389	1.413	1664	1580
48	NJ SUBURBS	A111	Bergen	NJ	34003	1.179	1.237	1633	1425
49		A111	Essex	NJ	34013	1.179	1.156	1300	1425
50		A111	Hudson	NJ	34017	1.179	1.163	1172	1425
51		A111	Hunterdon	NJ	34019	1.179	1.274	1834	1425
52		A111	Mercer	NJ	34021	1.179	1.122	1284	1425
53		A111	Middlesex	NJ	34023	1.179	1.158	1391	1425
54		A111	Monmouth	NJ	34025	1.179	1.209	1596	1425
55		A111	Morris	NJ	34027	1.179	1.256	1758	1425
56		A111	Ocean	NJ	34029	1.179	1.077	1131	1425

Table A1. Page 1 of 8

Appendix Table A1. Predicted Price Levels First Stage

Obs	Area Name	Area Code	County Name	State	County Fips	Input Plevel	Predicted Plevel	Actual Rent ($)	Wtd Mean Rent* ($)
57		A111	Passaic	NJ	34031	1.179	1.157	1384	1425
58		A111	Somerset	NJ	34035	1.179	1.267	1794	1425
59		A111	Sussex	NJ	34037	1.179	1.175	1503	1425
60		A111	Union	NJ	34039	1.179	1.192	1451	1425
61		A111	Warren	NJ	34041	1.179	1.093	1205	1425
62		A111	Pike	PA	42103	1.179	1.035	986	1425
63	CHICAGO	A207	Cook	IL	17031	1.032	1.024	1130	1191
64		A207	DeKalb	IL	17037	1.032	0.969	1028	1191
65		A207	DuPage	IL	17043	1.032	1.084	1426	1191
66		A207	Grundy	IL	17063	1.032	0.963	1002	1191
67		A207	Kane	IL	17089	1.032	1.058	1370	1191
68		A207	Kankakee	IL	17091	1.032	0.916	797	1191
69		A207	Kendall	IL	17093	1.032	1.073	1442	1191
70		A207	Lake	IL	17097	1.032	1.095	1498	1191
71		A207	McHenry	IL	17111	1.032	1.070	1426	1191
72		A207	Will	IL	17197	1.032	1.067	1408	1191
73		A207	Lake	IN	18089	1.032	0.930	839	1191
74		A207	Porter	IN	18127	1.032	0.953	953	1191
75		A207	Kenosha	WI	55059	1.032	0.972	1031	1191
76	DETROIT	A208	Genesee	MI	26049	0.921	0.867	786	994
77		A208	Lapeer	MI	26087	0.921	0.918	1031	994
78		A208	Lenawee	MI	26091	0.921	0.888	894	994
79		A208	Livingston	MI	26093	0.921	0.991	1341	994
80		A208	Macomb	MI	26099	0.921	0.918	994	994
81		A208	Monroe	MI	26115	0.921	0.904	966	994
82		A208	Oakland	MI	26125	0.921	0.967	1215	994
83		A208	St. Clair	MI	26147	0.921	0.899	941	994
84		A208	Washtenaw	MI	26161	0.921	0.947	1154	994
85		A208	Wayne	MI	26163	0.921	0.902	889	994
86	ST. LOUIS	A209	Clinton	IL	17027	0.836	0.811	763	845
87		A209	Jersey	IL	17083	0.836	0.800	709	845
88		A209	Madison	IL	17119	0.836	0.809	747	845
89		A209	Monroe	IL	17133	0.836	0.855	980	845
90		A209	St. Clair	IL	17163	0.836	0.807	739	845
91		A209	Crawford	MO	29055	0.836	0.767	539	845
92		A209	Franklin	MO	29071	0.836	0.801	713	845
93		A209	Jefferson	MO	29099	0.836	0.828	846	845
94		A209	Lincoln	MO	29113	0.836	0.819	807	845
95		A209	St. Charles	MO	29183	0.836	0.883	1105	845
96		A209	St. Louis	MO	29189	0.836	0.850	917	845
97		A209	Warren	MO	29219	0.836	0.816	789	845
98		A209	St. Louis City	MO	29510	0.836	0.820	688	845
99	CLEVELAND	A210	Ashtabula	OH	39007	0.856	0.811	708	888
100		A210	Cuyahoga	OH	39035	0.856	0.852	848	888
101		A210	Geauga	OH	39055	0.856	0.929	1264	888
102		A210	Lake	OH	39085	0.856	0.871	982	888
103		A210	Lorain	OH	39093	0.856	0.841	844	888
104		A210	Medina	OH	39103	0.856	0.908	1163	888
105		A210	Portage	OH	39133	0.856	0.851	900	888
106		A210	Summit	OH	39153	0.856	0.851	880	888
107	MINNEAPOLIS	A211	Anoka	MN	27003	1.010	1.009	1201	1183
108		A211	Carver	MN	27019	1.010	1.040	1337	1183
109		A211	Chisago	MN	27025	1.010	0.992	1145	1183
110		A211	Dakota	MN	27037	1.010	1.030	1286	1183
111		A211	Hennepin	MN	27053	1.010	1.006	1159	1183
112		A211	Isanti	MN	27059	1.010	0.962	1021	1183

Table A1. Page 2 of 8

Appendix Table A1. Predicted Price Levels First Stage

Obs	Area Name	Area Code	County Name	State	County Fips	Input Plevel	Predicted Plevel	Actual Rent ($)	Wtd Mean Rent* ($)
113		A211	Ramsey	MN	27123	1.010	0.981	1030	1183
114		A211	Scott	MN	27139	1.010	1.058	1406	1183
115		A211	Sherburne	MN	27141	1.010	1.031	1300	1183
116		A211	Washington	MN	27163	1.010	1.038	1323	1183
117		A211	Wright	MN	27171	1.010	1.003	1187	1183
118		A211	Pierce	WI	55093	1.010	0.953	981	1183
119		A211	St. Croix	WI	55109	1.010	1.011	1223	1183
120	MILWAUKEE	A212	Milwaukee	WI	55079	0.864	0.844	862	982
121		A212	Ozaukee	WI	55089	0.864	0.917	1283	982
122		A212	Racine	WI	55101	0.864	0.847	950	982
123		A212	Washington	WI	55131	0.864	0.876	1093	982
124		A212	Waukesha	WI	55133	0.864	0.910	1243	982
125	CINCINNATI	A213	Dearborn	IN	18029	0.884	0.877	895	901
126		A213	Ohio	IN	18115	0.884	0.839	713	901
127		A213	Boone	KY	21015	0.884	0.897	980	901
128		A213	Campbell	KY	21037	0.884	0.862	816	901
129		A213	Gallatin	KY	21077	0.884	0.837	705	901
130		A213	Grant	KY	21081	0.884	0.855	791	901
131		A213	Kenton	KY	21117	0.884	0.867	827	901
132		A213	Pendleton	KY	21191	0.884	0.834	692	901
133		A213	Brown	OH	39015	0.884	0.842	727	901
134		A213	Butler	OH	39017	0.884	0.888	933	901
135		A213	Clermont	OH	39025	0.884	0.893	963	901
136		A213	Hamilton	OH	39061	0.884	0.877	852	901
137		A213	Warren	OH	39165	0.884	0.940	1172	901
138	KANSAS CITY	A214	Johnson	KS	20091	0.823	0.870	1161	928
139		A214	Leavenworth	KS	20103	0.823	0.810	887	928
140		A214	Miami	KS	20121	0.823	0.804	862	928
141		A214	Wyandotte	KS	20209	0.823	0.783	731	928
142		A214	Cass	MO	29037	0.823	0.826	969	928
143		A214	Clay	MO	29047	0.823	0.824	950	928
144		A214	Clinton	MO	29049	0.823	0.780	734	928
145		A214	Jackson	MO	29095	0.823	0.804	837	928
146		A214	Lafayette	MO	29107	0.823	0.764	650	928
147		A214	Platte	MO	29165	0.823	0.841	1043	928
148		A214	Ray	MO	29177	0.823	0.779	730	928
149	DC	A312	District of Columbia	DC	11001	1.089	1.016	1053	1440
150		A312	Calvert	MD	24009	1.089	1.070	1451	1440
151		A312	Charles	MD	24017	1.089	1.056	1399	1440
152		A312	Frederick	MD	24021	1.089	1.044	1350	1440
153		A312	Montgomery	MD	24031	1.089	1.114	1583	1440
154		A312	Prince George's	MD	24033	1.089	1.046	1328	1440
155		A312	Washington	MD	24043	1.089	0.931	882	1440
156		A312	Arlington	VA	51013	1.089	1.147	1576	1440
157		A312	Clarke	VA	51043	1.089	0.960	1014	1440
158		A312	Culpeper	VA	51047	1.089	0.952	977	1440
159		A312	Fairfax	VA	51059	1.089	1.167	1758	1440
160		A312	Fauquier	VA	51061	1.089	1.034	1317	1440
161		A312	King George	VA	51099	1.089	0.965	1035	1440
162		A312	Loudoun	VA	51107	1.089	1.228	2014	1440
163		A312	Prince William	VA	51153	1.089	1.152	1737	1440
164		A312	Spotsylvania	VA	51177	1.089	1.034	1311	1440
165		A312	Stafford	VA	51179	1.089	1.089	1523	1440
166		A312	Warren	VA	51187	1.089	0.930	880	1440
167		A312	Alexandria City	VA	51510	1.089	1.115	1427	1440
168		A312	Fairfax City	VA	51600	1.089	1.104	1505	1440

Appendix Table A1. Predicted Price Levels First Stage

Obs	Area Name	Area Code	County Name	State	County Fips	Input Plevel	Predicted Plevel	Actual Rent ($)	Wtd Mean Rent* ($)
169		A312	Falls Church City	VA	51610	1.089	1.163	1674	1440
170		A312	Fredericksburg City	VA	51630	1.089	0.958	962	1440
171		A312	Manassas City	VA	51683	1.089	1.085	1431	1440
172		A312	Manassas Park City	VA	51685	1.089	1.087	1425	1440
173		A312	Berkeley	WV	54003	1.089	0.904	761	1440
174		A312	Jefferson	WV	54037	1.089	0.899	740	1440
175	BALTIMORE	A313	Anne Arundel	MD	24003	0.998	1.041	1309	1076
176		A313	Baltimore	MD	24005	0.998	0.972	1028	1076
177		A313	Carroll	MD	24013	0.998	1.035	1306	1076
178		A313	Harford	MD	24025	0.998	0.997	1150	1076
179		A313	Howard	MD	24027	0.998	1.113	1590	1076
180		A313	Queen Anne's	MD	24035	0.998	1.017	1240	1076
181		A313	Baltimore City	MD	24510	0.998	0.941	751	1076
182	DALLAS	A316	Collin	TX	48085	0.953	1.032	1369	1011
183		A316	Dallas	TX	48113	0.953	0.940	946	1011
184		A316	Denton	TX	48121	0.953	0.992	1212	1011
185		A316	Ellis	TX	48139	0.953	0.936	983	1011
186		A316	Henderson	TX	48213	0.953	0.846	568	1011
187		A316	Hood	TX	48221	0.953	0.912	879	1011
188		A316	Hunt	TX	48231	0.953	0.877	717	1011
189		A316	Johnson	TX	48251	0.953	0.902	830	1011
190		A316	Kaufman	TX	48257	0.953	0.934	974	1011
191		A316	Parker	TX	48367	0.953	0.916	897	1011
192		A316	Rockwall	TX	48397	0.953	1.021	1336	1011
193		A316	Tarrant	TX	48439	0.953	0.946	988	1011
194	HOUSTON	A318	Brazoria	TX	48039	0.938	0.906	851	955
195		A318	Chambers	TX	48071	0.938	0.899	825	955
196		A318	Fort Bend	TX	48157	0.938	1.022	1337	955
197		A318	Galveston	TX	48167	0.938	0.916	888	955
198		A318	Harris	TX	48201	0.938	0.933	930	955
199		A318	Liberty	TX	48291	0.938	0.846	573	955
200		A318	Montgomery	TX	48339	0.938	0.956	1067	955
201		A318	Waller	TX	48473	0.938	0.875	715	955
202	ATLANTA	A319	Barrow	GA	13013	0.904	0.853	911	1114
203		A319	Bartow	GA	13015	0.904	0.845	875	1114
204		A319	Carroll	GA	13045	0.904	0.828	791	1114
205		A319	Cherokee	GA	13057	0.904	0.923	1233	1114
206		A319	Clayton	GA	13063	0.904	0.871	960	1114
207		A319	Cobb	GA	13067	0.904	0.916	1164	1114
208		A319	Coweta	GA	13077	0.904	0.880	1038	1114
209		A319	DeKalb	GA	13089	0.904	0.898	1070	1114
210		A319	Douglas	GA	13097	0.904	0.871	992	1114
211		A319	Fayette	GA	13113	0.904	0.962	1398	1114
212		A319	Forsyth	GA	13117	0.904	0.968	1423	1114
213		A319	Fulton	GA	13121	0.904	0.922	1196	1114
214		A319	Gwinnett	GA	13135	0.904	0.923	1201	1114
215		A319	Henry	GA	13151	0.904	0.903	1140	1114
216		A319	Newton	GA	13217	0.904	0.868	980	1114
217		A319	Paulding	GA	13223	0.904	0.874	1008	1114
218		A319	Pickens	GA	13227	0.904	0.825	779	1114
219		A319	Rockdale	GA	13247	0.904	0.876	1014	1114
220		A319	Spalding	GA	13255	0.904	0.824	767	1114
221		A319	Walton	GA	13297	0.904	0.866	974	1114
222	MIAMI	A320	Broward	FL	12011	1.031	1.041	1134	1096
223		A320	Miami-Dade	FL	12086	1.031	1.023	1068	1096
224	TAMPA	A321	Hernando	FL	12053	0.874	0.826	644	836

Appendix Table A1. Predicted Price Levels First Stage

Obs	Area Name	Area Code	County Name	State	County Fips	Input Plevel	Predicted Plevel	Actual Rent ($)	Wtd Mean Rent* ($)
225		A321	Hillsborough	FL	12057	0.874	0.892	939	836
226		A321	Pasco	FL	12101	0.874	0.836	687	836
227		A321	Pinellas	FL	12103	0.874	0.879	831	836
228	LOS ANGELES	A419	Los Angeles	CA	6037	1.229	1.229	1267	1267
229	GREATER LA	A420	Orange	CA	6059	1.113	1.181	1616	1404
230		A420	Riverside	CA	6065	1.113	1.072	1296	1404
231		A420	San Bernardino	CA	6071	1.113	1.034	1153	1404
232		A420	Ventura	CA	6111	1.113	1.163	1629	1404
233	SAN FRANCISCO	A422	Alameda	CA	6001	1.353	1.314	1543	1638
234		A422	Contra Costa	CA	6013	1.353	1.370	1725	1638
235		A422	Marin	CA	6041	1.353	1.448	1973	1638
236		A422	Napa	CA	6055	1.353	1.292	1511	1638
237		A422	San Francisco	CA	6075	1.353	1.371	1404	1638
238		A422	San Mateo	CA	6081	1.353	1.395	1796	1638
239		A422	Santa Clara	CA	6085	1.353	1.383	1766	1638
240		A422	Santa Cruz	CA	6087	1.353	1.308	1555	1638
241		A422	Solano	CA	6095	1.353	1.297	1521	1638
242		A422	Sonoma	CA	6097	1.353	1.291	1506	1638
243	SEATTLE	A423	Island	WA	53029	1.029	0.984	1008	1181
244		A423	King	WA	53033	1.029	1.050	1263	1181
245		A423	Kitsap	WA	53035	1.029	0.989	1023	1181
246		A423	Pierce	WA	53053	1.029	1.003	1084	1181
247		A423	Snohomish	WA	53061	1.029	1.042	1243	1181
248		A423	Thurston	WA	53067	1.029	0.978	984	1181
249	SAN DIEGO	A424	San Diego	CA	6073	1.154	1.154	1440	1440
250	PORTLAND	A425	Clackamas	OR	41005	0.950	0.973	1165	1053
251		A425	Columbia	OR	41009	0.950	0.920	940	1053
252		A425	Marion	OR	41047	0.950	0.910	892	1053
253		A425	Multnomah	OR	41051	0.950	0.946	1019	1053
254		A425	Polk	OR	41053	0.950	0.907	878	1053
255		A425	Washington	OR	41067	0.950	0.967	1129	1053
256		A425	Yamhill	OR	41071	0.950	0.929	979	1053
257		A425	Clark	WA	53011	0.950	0.963	1114	1053
258	HONOLULU	A426	Honolulu	HI	15003	1.280	1.280	1218	1218
259	ANCHORAGE	A427	Anchorage Municipality	AK	2020	1.021	1.021	1216	1216
260	PHOENIX	A429	Maricopa	AZ	4013	0.967	0.971	985	965
261		A429	Pinal	AZ	4021	0.967	0.899	680	965
262	DENVER	A433	Adams	CO	8001	0.962	0.952	1162	1177
263		A433	Arapahoe	CO	8005	0.962	0.951	1148	1177
264		A433	Boulder	CO	8013	0.962	0.986	1306	1177
265		A433	Denver	CO	8031	0.962	0.927	978	1177
266		A433	Douglas	CO	8035	0.962	1.078	1673	1177
267		A433	Jefferson	CO	8059	0.962	0.971	1236	1177
268		A433	Weld	CO	8123	0.962	0.928	1065	1177
269	MW Cs	D200	Jefferson	IL	17081	0.776	0.762	643	694
270		D200	Allen	KS	20001	0.776	0.730	467	694
271		D200	Neosho	KS	20133	0.776	0.736	502	694
272		D200	Rice	MN	27131	0.776	0.826	973	694
273		D200	Brookings	SD	46011	0.776	0.764	655	694
274		D200	Lake	SD	46079	0.776	0.751	586	694
275		D200	Moody	SD	46101	0.776	0.747	561	694
276	SOUTH Cs	D300	DeSoto	FL	12027	0.788	0.787	573	579
277		D300	Hardee	FL	12049	0.788	0.778	529	579
278		D300	Bulloch	GA	13031	0.788	0.804	663	579
279		D300	Burke	GA	13033	0.788	0.781	542	579
280		D300	Jenkins	GA	13165	0.788	0.766	467	579

Appendix Table A1. Predicted Price Levels First Stage

Obs	Area Name	Area Code	County Name	State	County Fips	Input Plevel	Predicted Plevel	Actual Rent ($)	Wtd Mean Rent* ($)
281		D300	Screven	GA	13251	0.788	0.777	523	579
282		D300	Pearl River	MS	28109	0.788	0.792	599	579
283		D300	Hamblen	TN	47063	0.788	0.787	570	579
284		D300	Jefferson	TN	47089	0.788	0.786	570	579
285	WEST Cs	D400	Deschutes	OR	41017	0.947	0.962	955	881
286		D400	Whitman	WA	53075	0.947	0.898	676	881
287	NE Bs	X100	Hartford	CT	9003	0.914	0.966	1129	889
288		X100	Middlesex	CT	9007	0.914	0.998	1278	889
289		X100	New London	CT	9011	0.914	0.965	1140	889
290		X100	Tolland	CT	9013	0.914	0.983	1216	889
291		X100	Windham	CT	9015	0.914	0.930	994	889
292		X100	Franklin	MA	25011	0.914	0.906	888	889
293		X100	Hampden	MA	25013	0.914	0.904	863	889
294		X100	Hampshire	MA	25015	0.914	0.933	1006	889
295		X100	Cayuga	NY	36011	0.914	0.871	726	889
296		X100	Erie	NY	36029	0.914	0.888	789	889
297		X100	Madison	NY	36053	0.914	0.880	770	889
298		X100	Niagara	NY	36063	0.914	0.878	752	889
299		X100	Onondaga	NY	36067	0.914	0.893	819	889
300		X100	Oswego	NY	36075	0.914	0.862	684	889
301		X100	Berks	PA	42011	0.914	0.902	864	889
302		X100	Cambria	PA	42021	0.914	0.822	489	889
303		X100	Mercer	PA	42085	0.914	0.846	607	889
304		X100	Somerset	PA	42111	0.914	0.818	471	889
305		X100	Chittenden	VT	50007	0.914	0.968	1156	889
306		X100	Franklin	VT	50011	0.914	0.912	917	889
307		X100	Grand Isle	VT	50013	0.914	0.928	988	889
308	MW Bs	X200	Macon	IL	17115	0.852	0.795	582	838
309		X200	Elkhart	IN	18039	0.852	0.841	808	838
310		X200	Posey	IN	18129	0.852	0.827	745	838
311		X200	Vanderburgh	IN	18163	0.852	0.820	700	838
312		X200	Warrick	IN	18173	0.852	0.850	858	838
313		X200	Henderson	KY	21101	0.852	0.807	648	838
314		X200	Bay	MI	26017	0.852	0.809	654	838
315		X200	Midland	MI	26111	0.852	0.834	781	838
316		X200	Saginaw	MI	26145	0.852	0.819	705	838
317		X200	Lancaster	NE	31109	0.852	0.851	861	838
318		X200	Clark	OH	39023	0.852	0.827	740	838
319		X200	Columbiana	OH	39029	0.852	0.804	628	838
320		X200	Delaware	OH	39041	0.852	0.978	1428	838
321		X200	Fairfield	OH	39045	0.852	0.877	982	838
322		X200	Franklin	OH	39049	0.852	0.874	932	838
323		X200	Greene	OH	39057	0.852	0.863	916	838
324		X200	Licking	OH	39089	0.852	0.849	854	838
325		X200	Madison	OH	39097	0.852	0.848	850	838
326		X200	Mahoning	OH	39099	0.852	0.815	674	838
327		X200	Miami	OH	39109	0.852	0.845	830	838
328		X200	Montgomery	OH	39113	0.852	0.840	785	838
329		X200	Pickaway	OH	39129	0.852	0.839	808	838
330		X200	Trumbull	OH	39155	0.852	0.810	654	838
331		X200	Dane	WI	55025	0.852	0.903	1099	838
332		X200	Marathon	WI	55073	0.852	0.834	781	838
333	SOUTH Bs	X300	Blount	AL	1009	0.846	0.802	600	783
334		X300	Colbert	AL	1033	0.846	0.794	557	783
335		X300	Jefferson	AL	1073	0.846	0.837	763	783
336		X300	Lauderdale	AL	1077	0.846	0.791	544	783

Appendix Table A1. Predicted Price Levels First Stage

Obs	Area Name	Area Code	County Name	State	County Fips	Input Plevel	Predicted Plevel	Actual Rent ($)	Wtd Mean Rent* ($)
337		X300	St. Clair	AL	1115	0.846	0.807	626	783
338		X300	Shelby	AL	1117	0.846	0.876	960	783
339		X300	Jefferson	AR	5069	0.846	0.797	573	783
340		X300	Alachua	FL	12001	0.846	0.835	762	783
341		X300	Brevard	FL	12009	0.846	0.843	793	783
342		X300	Lee	FL	12071	0.846	0.865	896	783
343		X300	Marion	FL	12083	0.846	0.805	612	783
344		X300	Catoosa	GA	13047	0.846	0.830	736	783
345		X300	Dade	GA	13083	0.846	0.806	619	783
346		X300	Dougherty	GA	13095	0.846	0.811	640	783
347		X300	Lee	GA	13177	0.846	0.883	996	783
348		X300	Walker	GA	13295	0.846	0.800	590	783
349		X300	Acadia	LA	22001	0.846	0.772	446	783
350		X300	Ascension	LA	22005	0.846	0.829	732	783
351		X300	East Baton Rouge	LA	22033	0.846	0.835	746	783
352		X300	Lafayette	LA	22055	0.846	0.822	685	783
353		X300	Livingston	LA	22063	0.846	0.825	717	783
354		X300	St. Landry	LA	22097	0.846	0.759	373	783
355		X300	St. Martin	LA	22099	0.846	0.778	477	783
356		X300	West Baton Rouge	LA	22121	0.846	0.802	598	783
357		X300	Chatham	NC	37037	0.846	0.846	821	783
358		X300	Currituck	NC	37053	0.846	0.852	849	783
359		X300	Durham	NC	37063	0.846	0.882	972	783
360		X300	Franklin	NC	37069	0.846	0.833	755	783
361		X300	Johnston	NC	37101	0.846	0.855	860	783
362		X300	Orange	NC	37135	0.846	0.872	939	783
363		X300	Wake	NC	37183	0.846	0.900	1054	783
364		X300	Canadian	OK	40017	0.846	0.845	814	783
365		X300	Cleveland	OK	40027	0.846	0.846	815	783
366		X300	Logan	OK	40083	0.846	0.814	664	783
367		X300	McClain	OK	40087	0.846	0.809	639	783
368		X300	Oklahoma	OK	40109	0.846	0.823	687	783
369		X300	Pottawatomie	OK	40125	0.846	0.782	498	783
370		X300	Anderson	SC	45007	0.846	0.809	630	783
371		X300	Cherokee	SC	45021	0.846	0.795	564	783
372		X300	Florence	SC	45041	0.846	0.810	638	783
373		X300	Greenville	SC	45045	0.846	0.834	750	783
374		X300	Pickens	SC	45077	0.846	0.807	624	783
375		X300	Spartanburg	SC	45083	0.846	0.813	651	783
376		X300	Hamilton	TN	47065	0.846	0.822	691	783
377		X300	Marion	TN	47115	0.846	0.786	520	783
378		X300	Bexar	TX	48029	0.846	0.844	785	783
379		X300	Cameron	TX	48061	0.846	0.790	530	783
380		X300	Comal	TX	48091	0.846	0.867	916	783
381		X300	Ector	TX	48135	0.846	0.787	521	783
382		X300	Guadalupe	TX	48187	0.846	0.847	826	783
383		X300	Hardin	TX	48199	0.846	0.811	648	783
384		X300	Jefferson	TX	48245	0.846	0.796	567	783
385		X300	Midland	TX	48329	0.846	0.821	693	783
386		X300	Orange	TX	48361	0.846	0.793	552	783
387		X300	Potter	TX	48375	0.846	0.800	591	783
388		X300	Randall	TX	48381	0.846	0.846	819	783
389		X300	Wilson	TX	48493	0.846	0.828	732	783
390		X300	Charles City	VA	51036	0.846	0.834	764	783
391		X300	Chesterfield	VA	51041	0.846	0.908	1096	783
392		X300	Dinwiddie	VA	51053	0.846	0.851	847	783

Appendix Table A1. Predicted Price Levels First Stage

Obs	Area Name	Area Code	County Name	State	County Fips	Input Plevel	Predicted Plevel	Actual Rent ($)	Wtd Mean Rent* ($)
393		X300	Gloucester	VA	51073	0.846	0.878	972	783
394		X300	Goochland	VA	51075	0.846	0.920	1162	783
395		X300	Hanover	VA	51085	0.846	0.918	1153	783
396		X300	Henrico	VA	51087	0.846	0.896	1032	783
397		X300	Isle of Wight	VA	51093	0.846	0.887	1011	783
398		X300	James City	VA	51095	0.846	0.940	1246	783
399		X300	Mathews	VA	51115	0.846	0.827	728	783
400		X300	New Kent	VA	51127	0.846	0.905	1097	783
401		X300	Powhatan	VA	51145	0.846	0.912	1128	783
402		X300	Prince George	VA	51149	0.846	0.898	1061	783
403		X300	York	VA	51199	0.846	0.945	1264	783
404		X300	Chesapeake City	VA	51550	0.846	0.917	1137	783
405		X300	Colonial Heights City	VA	51570	0.846	0.867	868	783
406		X300	Hampton City	VA	51650	0.846	0.876	904	783
407		X300	Hopewell City	VA	51670	0.846	0.844	760	783
408		X300	Newport News City	VA	51700	0.846	0.879	919	783
409		X300	Norfolk City	VA	51710	0.846	0.873	862	783
410		X300	Petersburg City	VA	51730	0.846	0.837	741	783
411		X300	Poquoson City	VA	51735	0.846	0.956	1307	783
412		X300	Portsmouth City	VA	51740	0.846	0.870	872	783
413		X300	Richmond City	VA	51760	0.846	0.865	842	783
414		X300	Suffolk City	VA	51800	0.846	0.897	1057	783
415		X300	Virginia Beach City	VA	51810	0.846	0.926	1152	783
416		X300	Williamsburg City	VA	51830	0.846	0.889	993	783
417	WEST Bs	X499	Mohave	AZ	4015	0.888	0.816	667	991
418		X499	Yuma	AZ	4027	0.888	0.793	552	991
419		X499	Butte	CA	6007	0.888	0.858	871	991
420		X499	Stanislaus	CA	6099	0.888	0.915	1134	991
421		X499	Ada	ID	16001	0.888	0.872	936	991
422		X499	Canyon	ID	16027	0.888	0.835	759	991
423		X499	Clark	NV	32003	0.888	0.916	1137	991
424		X499	Nye	NV	32023	0.888	0.834	761	991
425		X499	Utah	UT	49049	0.888	0.873	941	991

* Population-weighted mean rent by Area

Table A2. Rent Ratios by State

	State	Rent* Census ($) (1)	Rent* Overlap ($) (2)	Ratio Rents (1)/(2)= (3)	Price Level* Overlap (4)	Bridged Level Census (5) = (3)*(4)
1	Alabama	568	739	0.77	0.83	0.64
2	Alaska	938	1216	0.77	1.02	0.79
3	Arizona	694	927	0.75	0.95	0.71
4	Arkansas	586	573	1.02	0.80	0.81
5	California	1060	1401	0.76	1.21	0.91
6	Colorado	915	1177	0.78	0.96	0.75
7	Connecticut		1270		1.15	
8	Delaware	758	1043	0.73	1.01	0.74
9	District of Columbia		1053		1.02	
10	Florida	855	940	0.91	0.94	0.86
11	Georgia	685	1071	0.64	0.90	0.57
12	Hawaii	1047	1218	0.86	1.28	1.10
13	Idaho	672	874	0.77	0.86	0.66
14	Illinois	677	1172	0.58	1.02	0.59
15	Indiana	756	826	0.92	0.89	0.82
16	Iowa	678				
17	Kansas	655	989	0.66	0.84	0.56
18	Kentucky	618	829	0.75	0.86	0.64
19	Louisiana	604	649	0.93	0.82	0.76
20	Maine	740	935	0.79	1.04	0.82
21	Maryland	795	1217	0.65	1.03	0.67
22	Massachusetts	1014	1275	0.80	1.13	0.90
23	Michigan	758	971	0.78	0.91	0.71
24	Minnesota	711	1180	0.60	1.01	0.61
25	Mississippi	600	599	1.00	0.79	0.79
26	Missouri	572	873	0.66	0.83	0.55
27	Montana	661				
28	Nebraska	735	861	0.85	0.85	0.73
29	Nevada	1042	1127	0.92	0.91	0.84
30	New Hampshire	885	1268	0.70	1.13	0.79
31	New Jersey		1367		1.15	
32	New Mexico	625				
33	New York	788	1196	0.66	1.30	0.86
34	North Carolina	717	982	0.73	0.88	0.65
35	North Dakota	578				
36	Ohio	681	877	0.78	0.86	0.67
37	Oklahoma	565	705	0.80	0.83	0.66
38	Oregon	749	1036	0.72	0.95	0.69
39	Pennsylvania	729	869	0.84	0.94	0.79
40	Rhode Island	1114				
41	South Carolina	690	672	1.03	0.82	0.84
42	South Dakota	612	624	0.98	0.76	0.74
43	Tennessee	683	648	1.05	0.81	0.86
44	Texas	640	916	0.70	0.92	0.64
45	Utah	906	941	0.96	0.87	0.84
46	Vermont	870	1090	0.80	0.95	0.76
47	Virginia	679	1280	0.53	1.01	0.53
48	Washington	765	1168	0.65	1.02	0.67
49	West Virginia	458	754	0.61	0.90	0.55
50	Wisconsin	774	1000	0.77	0.88	0.68
51	Wyoming	715				
52	Puerto Rico	294				

* Population Weighted geometric mean.
Overlap denotes counties in CPI and Census, Census denotes counties only in Census.

Table A3. Metropolitan Statistica Area SPIs: 2005

Obs	MSA	Metropolitan Statistica Area	State	Freq	Income		GDP	
					Adjusted		Adjusted	
					pc ($)	SPI	pc($)	SPI
		Non-metropolitan		1370	31,544	78.6	29,176	77.9
		Micropolitan		690	32,509	83.2	33,732	82.1
1	10180	Abilene	TX	3	33,803	82.1	35,257	81.3
2	10420	Akron	OH	2	37,280	89.6	41,466	88.3
3	10500	Albany	GA	5	31,257	79.8	36,350	77.5
4	10580	Albany-Schenectady-Troy	NY	5	36,562	97.3	42,289	96.1
5	10740	Albuquerque	NM	4	35,328	87.4	46,270	86.7
6	10780	Alexandria	LA	2	34,976	83.2	34,342	82.4
7	10900	Allentown-Bethlehem-Easton	PA-NJ	4	34,067	99.2	34,060	97.4
8	11020	Altoona	PA	1	33,862	81.4	36,264	80.3
9	11100	Amarillo	TX	4	32,849	85.8	40,858	82.0
10	11180	Ames	IA	1	37,870	84.5	47,026	83.3
11	11260	Anchorage	AK	2	36,851	104.3	61,008	104.1
12	11300	Anderson	IN	1	33,104	86.7	28,452	85.5
13	11340	Anderson	SC	1	32,141	83.9	29,452	82.7
14	11460	Ann Arbor	MI	1	38,806	102.3	50,135	100.9
15	11500	Anniston-Oxford	AL	1	35,251	79.9	37,154	78.8
16	11540	Appleton	WI	2	38,342	87.2	46,424	85.8
17	11700	Asheville	NC	4	36,090	81.5	37,444	80.7
18	12020	Athens-Clarke County	GA	4	30,016	85.3	35,832	83.0
19	12060	Atlanta-Sandy Springs-Marietta	GA	28	35,015	99.5	49,160	99.1
20	12100	Atlantic City	NJ	1	33,225	103.3	45,767	101.8
21	12220	Auburn-Opelika	AL	1	29,632	83.7	29,839	82.5
22	12260	Augusta-Richmond County	GA-SC	6	33,759	84.0	38,408	81.5
23	12420	Austin-Round Rock	TX	5	33,565	102.6	44,856	101.5
24	12540	Bakersfield	CA	1	27,003	92.6	33,024	91.3
25	12580	Baltimore-Towson	MD	7	40,400	102.3	44,678	99.6
26	12620	Bangor	ME	1	30,176	95.1	35,181	93.8
27	12700	Barnstable Town	MA	1	41,307	106.5	33,898	105.0
28	12940	Baton Rouge	LA	9	33,498	88.5	51,393	87.2
29	12980	Battle Creek	MI	1	34,262	82.6	40,379	81.4
30	13020	Bay City	MI	1	34,660	80.7	30,277	79.6
31	13140	Beaumont-Port Arthur	TX	3	35,246	81.0	39,795	79.7
32	13380	Bellingham	WA	1	30,561	96.7	37,579	95.4
33	13460	Bend	OR	1	33,570	95.6	42,525	94.3
34	13740	Billings	MT	2	39,544	83.4	46,933	82.4
35	13780	Binghamton	NY	2	32,910	87.3	31,121	85.7
36	13820	Birmingham-Hoover	AL	7	40,253	88.6	51,351	87.8
37	13900	Bismarck	ND	2	39,990	81.2	48,189	80.3
38	13980	Blacksburg-Christiansburg-Radford	VA	3	31,168	79.1	36,674	78.3
39	14020	Bloomington	IN	3	32,313	85.4	34,782	84.9
40	14060	Bloomington-Normal	IL	1	36,746	89.5	50,523	88.3
41	14260	Boise City-Nampa	ID	5	35,910	90.6	45,126	90.0
42	14460	Boston-Cambridge-Quincy	MA-NH	7	37,519	125.7	46,980	124.8
43	14500	Boulder	CO	1	43,961	104.3	53,731	102.8
44	14540	Bowling Green	KY	2	32,964	84.8	40,922	83.9
45	14740	Bremerton-Silverdale	WA	1	35,021	101.7	30,812	100.3
46	14860	Bridgeport-Stamford-Norwalk	CT	1	49,263	136.6	59,884	134.7
47	15180	Brownsville-Harlingen	TX	1	21,899	79.5	20,610	78.4
48	15260	Brunswick	GA	3	37,721	81.6	36,936	81.1
49	15380	Buffalo-Niagara Falls	NY	2	34,864	92.0	37,475	90.8
50	15500	Burlington	NC	1	32,941	83.6	35,010	82.5
51	15540	Burlington-South Burlington	VT	3	34,935	101.3	44,905	100.9
52	15940	Canton-Massillon	OH	2	34,352	84.0	36,766	82.9
53	15980	Cape Coral-Fort Myers	FL	1	38,747	94.4	40,238	93.1

Table A3. Metropolitan Statistica Area SPIs: 2005

Obs	MSA	Metropolitan Statistica Area	State	Freq	Income		GDP	
					Adjusted		Adjusted	
					pc ($)	SPI	pc($)	SPI
54	16180	Carson City	NV	1	40,175	94.3	52,024	93.0
55	16220	Casper	WY	1	52,209	79.4	99,409	78.3
56	16300	Cedar Rapids	IA	3	39,703	84.5	54,152	83.9
57	16580	Champaign-Urbana	IL	3	35,117	84.5	38,775	83.6
58	16620	Charleston	WV	5	36,348	84.5	48,947	83.3
59	16700	Charleston-North Charleston	SC	3	32,531	94.8	40,416	94.0
60	16740	Charlotte-Gastonia-Concord	NC-SC	6	39,384	93.3	66,901	93.1
61	16820	Charlottesville	VA	4	38,757	91.8	44,485	91.6
62	16860	Chattanooga	TN-GA	6	36,571	84.6	44,665	84.7
63	16940	Cheyenne	WY	1	42,018	87.4	48,086	86.2
64	16980	Chicago-Naperville-Joliet	IL-IN-WI	14	35,821	108.7	45,573	107.1
65	17020	Chico	CA	1	29,124	93.2	27,252	91.9
66	17140	Cincinnati-Middletown	OH-KY-IN	15	38,361	91.1	48,517	89.6
67	17300	Clarksville	TN-KY	4	35,466	86.0	39,297	83.6
68	17420	Cleveland	TN	2	33,285	83.5	37,536	82.9
69	17460	Cleveland-Elyria-Mentor	OH	5	38,766	91.4	52,202	89.4
70	17660	Coeur d'Alene	ID	1	30,449	88.6	30,831	87.3
71	17780	College Station-Bryan	TX	3	28,842	86.7	32,673	86.4
72	17820	Colorado Springs	CO	2	36,656	91.6	40,341	90.2
73	17860	Columbia	MO	2	38,147	81.6	43,172	80.8
74	17900	Columbia	SC	6	34,196	90.1	42,501	89.6
75	17980	Columbus	GA-AL	5	36,893	82.0	42,326	80.1
76	18020	Columbus	IN	1	38,667	87.8	53,926	86.6
77	18140	Columbus	OH	8	37,346	93.6	52,551	92.1
78	18580	Corpus Christi	TX	3	32,476	88.1	36,656	87.2
79	18700	Corvallis	OR	1	38,247	95.9	46,701	94.6
80	19060	Cumberland	MD-WV	2	33,565	75.5	29,361	74.2
81	19100	Dallas-Fort Worth-Arlington	TX	12	36,434	102.1	54,394	99.5
82	19140	Dalton	GA	2	34,587	79.2	54,080	78.1
83	19180	Danville	IL	1	33,496	74.8	33,834	73.8
84	19260	Danville	VA	1	33,852	76.7	34,611	75.6
85	19340	Davenport-Moline-Rock Island	IA-IL	4	39,399	82.5	48,121	81.5
86	19380	Dayton	OH	4	36,789	86.4	45,234	85.2
87	19460	Decatur	AL	2	36,018	81.7	39,649	80.7
88	19500	Decatur	IL	1	42,284	77.6	56,567	76.5
89	19660	Deltona-Daytona Beach-Ormond Beach	FL	1	31,904	88.9	25,966	87.6
90	19740	Denver-Aurora	CO	10	42,677	99.3	58,258	95.5
91	19780	Des Moines-West Des Moines	IA	5	42,418	89.0	67,696	88.0
92	19820	Detroit-Warren-Livonia	MI	6	37,906	99.0	45,296	97.8
93	20020	Dothan	AL	3	36,042	79.7	39,364	79.0
94	20100	Dover	DE	1	29,649	95.1	39,426	93.8
95	20220	Dubuque	IA	1	38,326	80.0	52,867	78.9
96	20260	Duluth	MN-WI	3	38,096	79.0	40,102	77.9
97	20500	Durham	NC	4	38,540	91.1	62,738	90.9
98	20740	Eau Claire	WI	2	35,793	80.7	42,854	79.7
99	20940	El Centro	CA	1	24,459	89.5	24,989	88.3
100	21060	Elizabethtown	KY	2	34,925	85.0	42,774	84.3
101	21140	Elkhart-Goshen	IN	1	35,281	89.9	54,194	88.7
102	21300	Elmira	NY	1	31,468	87.3	32,212	86.0
103	21340	El Paso	TX	1	28,160	82.6	37,424	81.4
104	21500	Erie	PA	1	32,005	86.5	34,552	85.3
105	21660	Eugene-Springfield	OR	1	33,017	90.4	34,952	89.1
106	21780	Evansville	IN-KY	6	37,961	85.8	49,841	84.3
107	21820	Fairbanks	AK	1	34,581	97.1	47,748	95.7
108	22020	Fargo	ND-MN	2	39,224	83.5	55,862	82.1

Table A3. Metropolitan Statistica Area SPIs: 2005

Obs	MSA	Metropolitan Statistica Area	State	Freq	Income		GDP	
					Adjusted		Adjusted	
					pc ($)	SPI	pc($)	SPI
109	22140	Farmington	NM	1	32,271	75.2	67,926	74.1
110	22180	Fayetteville	NC	2	36,895	85.7	44,349	84.6
111	22220	Fayetteville-Springdale-Rogers	AR-MO	4	31,479	88.9	42,980	88.0
112	22380	Flagstaff	AZ	1	30,142	93.0	32,859	91.7
113	22420	Flint	MI	1	31,923	86.3	31,538	85.1
114	22500	Florence	SC	2	33,337	82.6	39,244	81.6
115	22520	Florence-Muscle Shoals	AL	2	32,508	80.1	30,540	79.0
116	22540	Fond du Lac	WI	1	39,343	82.6	42,528	81.5
117	22660	Fort Collins-Loveland	CO	1	36,442	94.2	38,470	92.9
118	22900	Fort Smith	AR-OK	5	32,437	81.5	40,218	81.2
119	23020	Fort Walton Beach-Crestview-Destin	FL	1	39,349	89.6	56,247	88.4
120	23060	Fort Wayne	IN	3	36,118	86.4	44,990	85.2
121	23420	Fresno	CA	1	27,378	94.8	30,520	93.5
122	23460	Gadsden	AL	1	34,070	78.2	30,017	77.2
123	23540	Gainesville	FL	2	34,070	87.9	39,449	86.9
124	23580	Gainesville	GA	1	29,774	89.0	38,769	87.7
125	24020	Glens Falls	NY	2	30,441	92.2	28,678	91.2
126	24140	Goldsboro	NC	1	32,307	80.9	36,634	79.8
127	24220	Grand Forks	ND-MN	2	35,897	80.8	41,811	79.8
128	24300	Grand Junction	CO	1	35,259	81.8	36,166	80.7
129	24340	Grand Rapids-Wyoming	MI	4	35,811	88.9	46,414	88.0
130	24500	Great Falls	MT	1	37,658	81.4	37,784	80.2
131	24540	Greeley	CO	1	26,772	92.8	29,996	91.5
132	24580	Green Bay	WI	3	37,803	86.7	51,726	86.1
133	24660	Greensboro-High Point	NC	3	36,502	86.2	51,675	86.0
134	24780	Greenville	NC	2	33,328	82.8	36,915	81.9
135	24860	Greenville-Mauldin-Easley	SC	3	33,756	87.3	43,424	86.7
136	25060	Gulfport-Biloxi	MS	3	30,465	86.1	39,759	85.1
137	25180	Hagerstown-Martinsburg	MD-WV	3	32,535	90.6	31,584	89.4
138	25260	Hanford-Corcoran	CA	1	23,761	90.6	25,332	89.4
139	25420	Harrisburg-Carlisle	PA	3	37,467	93.9	51,021	92.8
140	25500	Harrisonburg	VA	1	32,783	80.6	51,988	79.5
141	25540	Hartford-West Hartford-East Hartford	CT	3	38,727	109.4	52,584	107.4
142	25620	Hattiesburg	MS	3	29,565	83.5	35,693	81.5
143	25860	Hickory-Lenoir-Morganton	NC	4	34,513	79.2	40,714	78.5
144	25980	Hinesville-Fort Stewart	GA	2	27,210	82.8	41,677	82.2
145	26100	Holland-Grand Haven	MI	1	32,860	93.6	39,311	92.3
146	26180	Honolulu	HI	1	27,645	133.2	34,577	131.4
147	26300	Hot Springs	AR	1	34,570	80.5	31,224	79.4
148	26380	Houma-Bayou Cane-Thibodaux	LA	2	32,365	80.4	42,194	79.4
149	26420	Houston-Sugar Land-Baytown	TX	10	39,815	98.5	61,101	96.7
150	26580	Huntington-Ashland	WV-KY-OH	5	32,008	80.3	34,410	79.9
151	26620	Huntsville	AL	2	38,207	87.4	50,351	86.5
152	26820	Idaho Falls	ID	2	34,192	82.0	37,854	80.9
153	26900	Indianapolis-Carmel	IN	10	37,878	96.1	57,138	93.5
154	26980	Iowa City	IA	2	39,422	86.1	50,336	85.5
155	27060	Ithaca	NY	1	30,203	94.2	35,135	92.9
156	27100	Jackson	MI	1	31,415	86.9	33,409	85.7
157	27140	Jackson	MS	5	33,617	90.1	43,240	88.9
158	27180	Jackson	TN	2	32,476	87.8	44,041	86.9
159	27260	Jacksonville	FL	5	35,920	95.5	45,277	93.1
160	27340	Jacksonville	NC	1	39,202	83.4	42,563	82.3
161	27500	Janesville	WI	1	34,014	84.7	34,722	83.5
162	27620	Jefferson City	MO	4	37,342	78.0	46,079	77.4
163	27740	Johnson City	TN	3	31,669	82.2	34,033	81.9

Table A3. Metropolitan Statistica Area SPIs: 2005

Obs	MSA	Metropolitan Statistica Area	State	Freq	Income		GDP	
					Adjusted		Adjusted	
					pc ($)	SPI	pc($)	SPI
164	27780	Johnstown	PA	1	33,641	78.8	30,180	77.7
165	27860	Jonesboro	AR	2	29,720	83.3	36,320	82.6
166	27900	Joplin	MO	2	34,250	75.0	40,261	73.9
167	28020	Kalamazoo-Portage	MI	2	35,152	86.5	38,987	85.7
168	28100	Kankakee-Bradley	IL	1	31,794	85.8	29,480	84.6
169	28140	Kansas City	MO-KS	15	39,705	90.1	52,641	88.9
170	28420	Kennewick-Richland-Pasco	WA	2	29,771	95.2	35,430	93.9
171	28660	Killeen-Temple-Fort Hood	TX	3	33,722	88.4	35,815	87.6
172	28700	Kingsport-Bristol-Bristol	TN-VA	4	34,343	78.8	36,043	78.1
173	28740	Kingston	NY	1	29,344	101.6	22,421	100.2
174	28940	Knoxville	TN	5	35,587	86.8	46,791	85.8
175	29020	Kokomo	IN	2	35,583	86.8	41,941	85.7
176	29100	La Crosse	WI-MN	2	37,094	83.2	45,446	82.1
177	29140	Lafayette	IN	3	32,184	88.5	43,055	87.7
178	29180	Lafayette	LA	2	35,540	86.1	59,325	85.7
179	29340	Lake Charles	LA	2	28,731	81.3	75,496	80.2
180	29420	Lake Havasu City-Kingman	AZ	1	25,096	87.9	20,218	86.7
181	29460	Lakeland	FL	1	33,617	86.0	31,467	84.8
182	29540	Lancaster	PA	1	34,331	95.1	38,041	93.7
183	29620	Lansing-East Lansing	MI	3	33,685	90.0	41,795	88.4
184	29700	Laredo	TX	1	21,951	85.7	26,971	84.5
185	29740	Las Cruces	NM	1	30,270	76.2	29,841	75.2
186	29820	Las Vegas-Paradise	NV	1	35,161	99.5	48,210	98.1
187	29940	Lawrence	KS	1	32,604	87.1	33,942	85.9
188	30020	Lawton	OK	1	33,830	83.6	36,995	82.4
189	30140	Lebanon	PA	1	35,996	87.6	28,865	86.4
190	30300	Lewiston	ID-WA	2	33,769	83.3	33,058	81.7
191	30340	Lewiston-Auburn	ME	1	29,882	98.9	31,048	97.5
192	30460	Lexington-Fayette	KY	6	37,718	89.4	52,683	88.4
193	30620	Lima	OH	1	34,766	78.8	48,492	77.7
194	30700	Lincoln	NE	2	37,726	88.3	49,636	87.2
195	30780	Little Rock-North Little Rock-Conway	AR	6	36,614	89.5	46,444	88.7
196	30860	Logan	UT-ID	2	26,995	83.8	27,551	82.7
197	30980	Longview	TX	3	36,931	81.0	46,287	80.1
198	31020	Longview	WA	1	28,905	90.9	30,342	89.6
199	31100	Los Angeles-Long Beach-Santa Ana	CA	2	30,486	120.5	41,113	119.1
200	31140	Louisville-Jefferson County	KY-IN	13	37,371	90.3	46,512	88.9
201	31180	Lubbock	TX	2	33,059	85.0	37,497	83.9
202	31340	Lynchburg	VA	4	37,190	77.6	41,240	76.4
203	31420	Macon	GA	5	36,248	81.7	39,790	80.5
204	31460	Madera	CA	1	23,491	94.5	23,176	93.2
205	31540	Madison	WI	3	41,270	94.5	57,971	93.6
206	31700	Manchester-Nashua	NH	1	33,149	120.3	39,205	118.6
207	31900	Mansfield	OH	1	34,375	78.3	38,972	77.2
208	32580	McAllen-Edinburg-Mission	TX	1	20,919	78.2	21,119	77.1
209	32780	Medford	OR	1	33,815	89.4	34,778	88.2
210	32820	Memphis	TN-MS-AR	8	35,418	94.7	48,105	93.7
211	32900	Merced	CA	1	23,432	97.6	22,556	96.2
212	33100	Miami-Fort Lauderdale-Pompano Beach	FL	3	36,125	103.8	41,703	102.4
213	33140	Michigan City-La Porte	IN	1	31,177	87.3	33,049	86.1
214	33260	Midland	TX	1	47,753	85.6	75,110	84.4
215	33340	Milwaukee-Waukesha-West Allis	WI	4	40,419	94.4	52,596	92.3
216	33460	Minneapolis-St. Paul-Bloomington	MN-WI	13	40,541	103.8	53,556	101.8
217	33540	Missoula	MT	1	36,031	84.9	47,258	83.8
218	33660	Mobile	AL	1	30,124	85.0	38,150	83.8

Table A3. Metropolitan Statistica Area SPIs: 2005

Obs	MSA	Metropolitan Statistica Area	State	Freq	Income		GDP	
					Adjusted		Adjusted	
					pc ($)	SPI	pc($)	SPI
219	33700	Modesto	CA	1	25,379	105.6	26,360	104.2
220	33740	Monroe	LA	2	32,455	83.2	40,148	82.3
221	33780	Monroe	MI	1	33,020	93.5	26,645	92.2
222	33860	Montgomery	AL	4	37,397	85.5	43,709	84.2
223	34060	Morgantown	WV	2	33,023	85.0	44,244	84.3
224	34100	Morristown	TN	3	30,029	81.5	32,399	80.7
225	34580	Mount Vernon-Anacortes	WA	1	31,793	99.9	41,258	98.5
226	34620	Muncie	IN	1	33,011	83.1	33,690	81.9
227	34740	Muskegon-Norton Shores	MI	1	30,346	84.7	30,981	83.5
228	34820	Myrtle Beach-Conway-North Myrtle Beach	SC	1	30,958	86.5	43,851	85.3
229	34900	Napa	CA	1	34,704	125.8	39,041	124.1
230	34940	Naples-Marco Island	FL	1	47,361	104.5	43,231	103.0
231	34980	Nashville-Davidson-Murfreesboro-Franklin	TN	13	38,305	95.7	51,245	94.2
232	35300	New Haven-Milford	CT	1	35,127	111.9	36,795	110.3
233	35380	New Orleans-Metairie-Kenner	LA	7	21,864	92.4	52,304	90.1
234	35620	New York-Northern New Jersey-Long Island	NY-NJ-PA	23	30,875	146.6	35,682	159.6
235	35660	Niles-Benton Harbor	MI	1	35,777	81.7	37,442	80.6
236	35980	Norwich-New London	CT	1	36,446	107.8	41,071	106.3
237	36100	Ocala	FL	1	32,722	82.2	27,167	81.0
238	36140	Ocean City	NJ	1	39,813	99.4	41,528	98.0
239	36220	Odessa	TX	1	32,420	78.9	42,534	77.8
240	36260	Ogden-Clearfield	UT	3	30,379	92.4	31,005	91.0
241	36420	Oklahoma City	OK	7	37,939	86.7	47,382	85.2
242	36500	Olympia	WA	1	33,890	99.6	31,564	98.2
243	36540	Omaha-Council Bluffs	NE-IA	8	41,025	91.3	53,912	90.3
244	36740	Orlando-Kissimmee	FL	4	32,098	98.3	47,259	97.9
245	36780	Oshkosh-Neenah	WI	1	38,993	84.6	50,683	83.4
246	36980	Owensboro	KY	3	34,065	81.7	40,949	80.8
247	37100	Oxnard-Thousand Oaks-Ventura	CA	1	30,260	133.4	30,685	131.5
248	37340	Palm Bay-Melbourne-Titusville	FL	1	35,406	89.8	34,078	88.6
249	37380	Palm Coast	FL	1	28,797	94.8	31,859	93.5
250	37460	Panama City-Lynn Haven	FL	1	35,110	86.3	41,060	85.1
251	37620	Parkersburg-Marietta-Vienna	WV-OH	4	32,730	81.9	37,328	81.1
252	37700	Pascagoula	MS	2	28,894	86.3	29,059	85.3
253	37860	Pensacola-Ferry Pass-Brent	FL	2	32,060	88.0	31,700	86.2
254	37900	Peoria	IL	5	40,161	83.9	47,354	82.6
255	37980	Philadelphia-Camden-Wilmington	PA-NJ-DE-MD	11	37,285	109.2	47,331	107.3
256	38060	Phoenix-Mesa-Scottsdale	AZ	2	31,844	101.8	41,171	100.7
257	38220	Pine Bluff	AR	3	28,572	82.0	32,188	81.3
258	38300	Pittsburgh	PA	7	41,056	89.0	48,319	88.6
259	38340	Pittsfield	MA	1	40,999	91.7	44,951	90.4
260	38540	Pocatello	ID	2	30,734	81.5	34,472	80.4
261	38860	Portland-South Portland-Biddeford	ME	3	31,484	111.1	39,193	110.3
262	38900	Portland-Vancouver-Beaverton	OR-WA	7	34,429	102.9	44,997	101.2
263	38940	Port St. Lucie	FL	2	37,474	92.7	29,479	91.4
264	39100	Poughkeepsie-Newburgh-Middletown	NY	2	28,781	116.9	24,860	115.3
265	39140	Prescott	AZ	1	26,992	90.8	22,057	89.6
266	39300	Providence-New Bedford-Fall River	RI-MA	6	32,790	106.8	34,845	105.2
267	39340	Provo-Orem	UT	2	22,873	90.6	27,255	89.4
268	39380	Pueblo	CO	1	32,152	79.7	28,579	78.6
269	39460	Punta Gorda	FL	1	34,221	87.3	24,570	86.1
270	39540	Racine	WI	1	37,599	89.6	37,148	88.3
271	39580	Raleigh-Cary	NC	3	37,282	95.6	48,012	94.9
272	39660	Rapid City	SD	2	40,007	82.7	43,783	81.6
273	39740	Reading	PA	1	33,580	94.3	35,128	93.0

Table A3. Metropolitan Statistica Area SPIs: 2005

Obs	MSA	Metropolitan Statistica Area	State	Freq	Income		GDP	
					Adjusted		Adjusted	
					pc ($)	SPI	pc($)	SPI
274	39820	Redding	CA	1	30,675	94.9	30,264	93.6
275	39900	Reno-Sparks	NV	2	42,008	98.3	48,066	96.9
276	40060	Richmond	VA	17	39,768	91.9	52,500	90.1
277	40140	Riverside-San Bernardino-Ontario	CA	2	24,192	110.0	23,978	108.3
278	40220	Roanoke	VA	5	39,609	82.3	48,405	80.6
279	40340	Rochester	MN	3	41,114	91.3	49,903	90.5
280	40380	Rochester	NY	5	34,841	97.2	42,042	96.1
281	40420	Rockford	IL	2	31,607	89.6	36,193	87.9
282	40580	Rocky Mount	NC	2	34,360	80.7	47,750	79.6
283	40660	Rome	GA	1	37,336	76.9	43,066	75.8
284	40900	Sacramento-Arden-Arcade-Roseville	CA	4	31,024	114.3	37,060	112.0
285	40980	Saginaw-Saginaw Township North	MI	1	32,966	82.7	38,117	81.5
286	41060	St. Cloud	MN	2	33,687	87.5	43,641	86.3
287	41100	St. George	UT	1	27,006	83.6	29,271	82.4
288	41140	St. Joseph	MO-KS	4	35,457	74.8	39,271	73.5
289	41180	St. Louis	MO-IL	16	40,584	87.7	48,318	86.4
290	41420	Salem	OR	2	30,884	92.9	32,319	91.6
291	41500	Salinas	CA	1	30,190	118.5	34,085	116.9
292	41540	Salisbury	MD	2	32,930	86.7	34,749	85.9
293	41620	Salt Lake City	UT	3	33,749	95.2	51,645	93.6
294	41660	San Angelo	TX	2	34,958	82.2	36,938	81.1
295	41700	San Antonio	TX	8	33,638	90.4	39,776	89.2
296	41740	San Diego-Carlsbad-San Marcos	CA	1	33,146	122.4	41,265	120.7
297	41780	Sandusky	OH	1	39,571	84.5	44,576	83.3
298	41860	San Francisco-Oakland-Fremont	CA	5	37,550	139.9	46,831	137.7
299	41940	San Jose-Sunnyvale-Santa Clara	CA	2	35,193	143.4	49,460	141.5
300	42020	San Luis Obispo-Paso Robles	CA	1	30,780	111.5	33,541	109.9
301	42060	Santa Barbara-Santa Maria-Goleta	CA	1	34,411	117.7	37,282	116.0
302	42100	Santa Cruz-Watsonville	CA	1	33,060	129.0	28,834	127.2
303	42140	Santa Fe	NM	1	42,041	90.2	47,461	89.0
304	42220	Santa Rosa-Petaluma	CA	1	32,180	125.7	31,931	124.0
305	42260	Sarasota-Bradenton-Venice	FL	2	44,315	93.8	37,199	92.4
306	42340	Savannah	GA	3	36,777	88.3	40,047	87.0
307	42540	Scranton-Wilkes-Barre	PA	3	35,603	85.8	36,604	84.6
308	42660	Seattle-Tacoma-Bellevue	WA	3	37,176	111.9	51,156	110.9
309	42680	Sebastian-Vero Beach	FL	1	51,089	90.5	34,433	89.2
310	43100	Sheboygan	WI	1	40,002	86.0	50,527	84.8
311	43300	Sherman-Denison	TX	1	30,997	84.5	29,299	83.4
312	43340	Shreveport-Bossier City	LA	3	36,041	83.3	57,278	81.9
313	43580	Sioux City	IA-NE-SD	4	36,775	79.9	45,657	79.0
314	43620	Sioux Falls	SD	4	41,826	87.4	67,729	86.5
315	43780	South Bend-Mishawaka	IN-MI	2	36,248	87.5	40,582	86.7
316	43900	Spartanburg	SC	1	31,435	84.8	40,323	83.6
317	44060	Spokane	WA	1	32,204	90.7	37,913	89.4
318	44100	Springfield	IL	2	40,461	83.3	45,949	82.0
319	44140	Springfield	MA	3	34,057	95.9	30,917	94.5
320	44180	Springfield	MO	5	35,607	78.0	42,217	76.8
321	44220	Springfield	OH	1	34,303	83.0	28,337	81.9
322	44300	State College	PA	1	32,960	88.9	39,273	87.6
323	44700	Stockton	CA	1	23,431	111.3	23,644	109.7
324	44940	Sumter	SC	1	30,431	82.3	32,214	81.1
325	45060	Syracuse	NY	3	33,861	92.1	40,096	91.2
326	45220	Tallahassee	FL	4	32,830	90.9	38,178	90.4
327	45300	Tampa-St. Petersburg-Clearwater	FL	4	35,570	93.5	40,780	93.5
328	45460	Terre Haute	IN	4	32,339	81.5	36,053	80.4

Table A3. Metropolitan Statistica Area SPIs: 2005

Obs	MSA	Metropolitan Statistica Area	State	Freq	Income		GDP	
					Adjusted		Adjusted	
					pc ($)	SPI	pc($)	SPI
329	45500	Texarkana	TX-AR	2	34,222	79.4	35,945	78.3
330	45780	Toledo	OH	4	35,721	86.5	44,582	85.3
331	45820	Topeka	KS	5	39,284	79.1	44,896	78.1
332	45940	Trenton-Ewing	NJ	1	40,525	113.3	52,568	111.7
333	46060	Tucson	AZ	1	30,871	93.5	31,724	92.2
334	46140	Tulsa	OK	7	39,667	87.4	49,896	86.9
335	46220	Tuscaloosa	AL	3	35,685	82.8	43,441	82.1
336	46340	Tyler	TX	1	36,361	86.1	44,993	84.9
337	46540	Utica-Rome	NY	2	31,379	86.9	30,506	85.8
338	46660	Valdosta	GA	4	31,496	78.9	34,731	78.2
339	46700	Vallejo-Fairfield	CA	1	26,403	126.9	22,697	125.1
340	47020	Victoria	TX	3	35,718	81.5	47,530	80.0
341	47220	Vineland-Millville-Bridgeton	NJ	1	29,870	94.2	31,780	92.9
342	47260	Virginia Beach-Norfolk-Newport News	VA-NC	14	35,038	94.6	44,122	92.1
343	47300	Visalia-Porterville	CA	1	26,340	89.3	26,712	88.0
344	47380	Waco	TX	1	31,640	84.9	36,521	83.7
345	47580	Warner Robins	GA	1	33,961	83.9	42,161	82.8
346	47900	Washington-Arlington-Alexandria	DC-VA-MD-WV	17	40,101	121.4	55,703	118.7
347	47940	Waterloo-Cedar Falls	IA	3	39,204	78.6	53,229	77.6
348	48140	Wausau	WI	1	39,100	82.3	49,252	81.1
349	48260	Weirton-Steubenville	WV-OH	3	34,162	76.9	34,759	76.0
350	48300	Wenatchee	WA	2	30,981	89.7	35,153	88.0
351	48540	Wheeling	WV-OH	3	35,501	77.6	38,446	77.4
352	48620	Wichita	KS	4	41,210	81.7	46,940	80.5
353	48660	Wichita Falls	TX	3	36,699	82.7	41,466	81.6
354	48700	Williamsport	PA	1	32,788	85.5	34,055	84.3
355	48900	Wilmington	NC	3	34,406	86.4	43,410	85.6
356	49020	Winchester	VA-WV	2	33,651	88.8	43,132	88.0
357	49180	Winston-Salem	NC	4	38,563	85.6	54,780	85.2
358	49340	Worcester	MA	1	34,128	108.0	30,682	106.5
359	49420	Yakima	WA	1	29,578	85.7	31,692	84.5
360	49620	York-Hanover	PA	1	34,312	94.4	35,405	93.1
361	49660	Youngstown-Warren-Boardman	OH-PA	3	34,222	80.9	35,423	79.7
362	49700	Yuba City	CA	2	27,178	94.2	26,187	92.8
363	49740	Yuma	AZ	1	25,219	83.3	27,536	82.1
			Total	3133				
			Mean		34,471	100	41,729	100