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Estimates of State Price Levels for Consumption Goods and Services: a first brush[*]

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Introduction

This paper develops exploratory estimates of the spatial price differences for consumption goods and services at the U.S. state level. 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 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 rent surveys from the U.S. Census Bureau. The estimates presented here are generated using a multi-stage approach that bridges the results in the areas sampled by the CPI price surveys to the remaining non-sampled areas using the Census rent information.

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 in 2003 and 2004. These 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 to cover a fixed set of geographical areas, so that SPIs can only be directly estimated at

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this 38 metropolitan and urban area level. 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]) and b) assessing the feasibility of estimating SPIs for different geographies, such as states and 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[1]. 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 rental price levels from the 2000 Census.

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.

[1] 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.

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 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. The final stage builds up the aggregate state price levels based on these estimated county price levels, and tests the sensitivity of these results to alternative specifications.

Background on the Data

Interarea Price Levels and Census Rents

The methodology for estimating SPIs for the 38 metropolitan and urban areas of the CPI has been detailed in Aten (2005, 2006) using 2003 and 2004 prices. It includes estimating a weighted hedonic regression for each expenditure item that make 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. 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, using item expenditure weights at the 38 area level (see *Appendix Table A1* for a list of all counties comprising these areas).

The 2000 Census rents consist of monthly rental estimates at seven levels of geographic aggregation, three definitions of units, and five bedroom size categories. The non-cash rental units were excluded in this study. The recent movers are included, defined as having moved within the last two years. These rental observations are averaged geometrically across five bedroom size categories: from zero to four bedrooms, weighted by the number of units in each category. The Census data include state, county, metropolitan area, place and county subdivision code, thus permitting a good geographical matching to the BLS Consumer Price Index (CPI) data. The 38 CPI areas correspond to 147 metropolitan areas, counties and places, and at the lowest geographical level, to 425 counties[2].

The SPIs refer to 2003 prices, but the Census rents are for the year 2000. In principle, one would need to redo the SPIs using 2000 prices, but for experimental purposes, the 2003 results from Aten (2006) have been moved back to 2000 using the CPI-Urban price change for each area[3]. *Table 1* shows these SPIs and also the corresponding average rent for each area from the Census data.

Table 1. Observed Price Levels and Rents by Area

Region	Area	Freq	Area Name	SPI	Rent ($)	Rent Level
North East	A102	14	Philadelphia	1.01	658	0.99
	A103	12	Boston	1.12	755	1.14
	A104	6	Pittsburgh	0.84	492	0.74
	A109	5	NY city	1.28	750	1.13
	A110	10	NY suburbs	1.29	893	1.35
	A111	15	NJ suburbs	1.14	779	1.18
Mid West	A207	13	Chicago	1.05	669	1.01
	A208	10	Detroit	0.94	596	0.90
	A209	13	St. Louis	0.87	528	0.80
	A210	8	Cleveland	0.89	552	0.83
	A211	13	Minneapolis	0.99	655	0.99
	A212	5	Milwaukee	0.91	578	0.87
	A213	13	Cincinnati	0.87	521	0.79
	A214	11	Kansas City	0.86	576	0.87
South	A312	26	DC	1.06	806	1.22
	A313	7	Baltimore	0.97	629	0.95
	A316	12	Dallas	0.97	659	0.99
	A318	8	Houston	0.95	600	0.91
	A319	20	Atlanta	0.94	749	1.13
	A320	2	Miami	1.02	701	1.06

[2] 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.

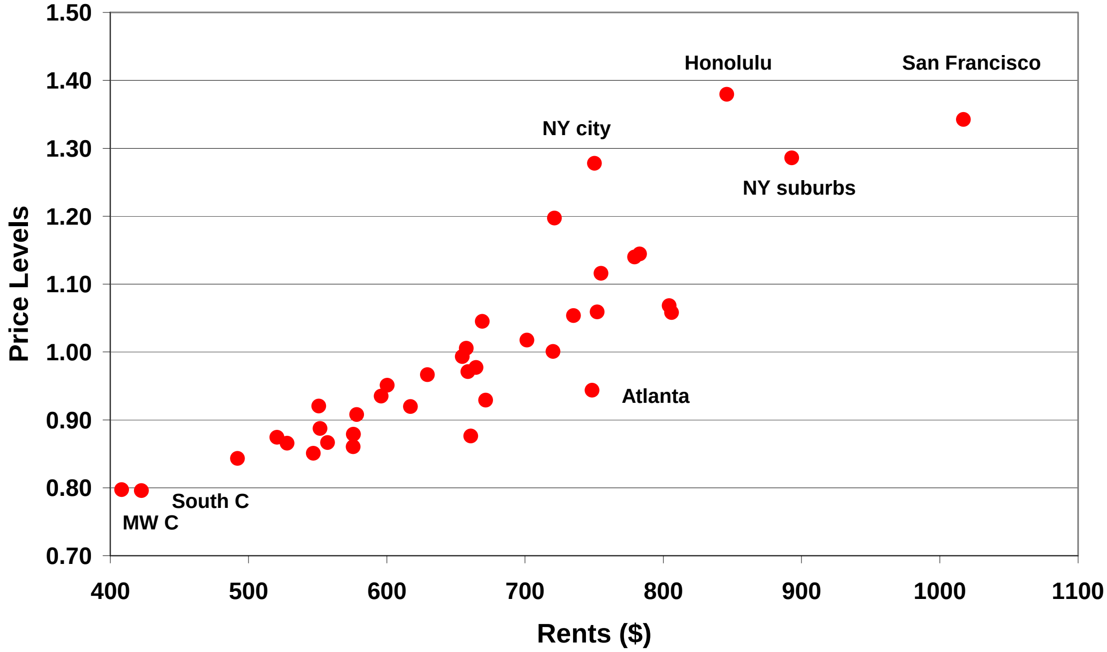
[3] Aten (2006) compares an extrapolation of 2003 to 2004 versus a direct estimate for the year 2004 and finds that there are minor differences when an aggregate CPI rate is used as the deflator, but negligible differences with a detailed item-level CPI deflator. Another way to reconcile the disparate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

Region	Area	Freq	Area Name	SPI		Rent ($)	Rent Level	
	A321	4	Tampa	0.92		617	0.93	
West	A419	1	Los Angeles	1.20		721	1.09	
	A420	4	Greater LA	1.07		804	1.21	
	A422	10	San Francisco	1.34		1017	1.53	max
	A423	6	Seattle	1.05		735	1.11	
	A424	1	San Diego	1.14		783	1.18	
	A425	8	Portland	0.98		665	1.00	mean
	A426	1	Honolulu	1.38	max	846	1.28	
	A427	1	Anchorage	1.06		752	1.13	
	A429	2	Phoenix	0.93		672	1.01	
	A433	7	Denver	1.00	mean	720	1.09	
Non-metro	D200	7	MW Cs	0.80		408	0.62	min
	D300	9	South Cs	0.80	min	423	0.64	
	D400	2	West Cs	0.88		576	0.87	
	X100	21	NE Bs	0.92		551	0.83	
	X200	25	MW Bs	0.85		547	0.82	
	X300	84	South Bs	0.87		557	0.84	
	X499	9	West Bs	0.88		661	1.00	
	Sum	425	Mean	1.00		663	1.00	
			Max	1.38		1017	1.53	
			Min	0.80		408	0.62	
			Range	0.58		609	0.92	

The column labeled *Freq* denotes the number of counties that make up the BLS area (four areas are made up of only one county: Los Angeles, San Diego, Honolulu and Anchorage). The mean of the price levels across the 38 areas is 1.00 by construction, while that of the unweighted rents is US$ 663. The range of the rents far exceeds that of the SPIs: 0.92 versus 0.58. The San Francisco area had the highest rent, with an average of $1,017 and a rent level of 1.53, while the Midwest C urban areas, comprised of Rice MN, Allen and Neosho KS, Brookings, Lake, Moody SD and Jefferson IL were the lowest, with rents averaging $408 and a rent level of 0.62.

Figure 1 plots the relationship between these two variables.

Figure 1.SPIs vs. Rents by Area



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[4], a total of 425 observations listed as *Freq* in *Table 1*. For these 425 counties, the observed rents are averaged geometrically across five bedroom-size categories, weighted by the number of housing units that were sampled in each category.

A simple log-linear relationship was posited, shown in *Equations (i) to (iii)*. Alternatives specifications were tested, such as a log-log version, a non-linear function of rents, and one that included 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. It was also unclear whether one wants to use differences in racial and ethnic

[4] 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.

make-up to control for geographic price differences[5]. 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.

Equations (i)-(iii): First Stage Base Models

$$(i)\ \ln P_i = \sum_j \beta_j X_j + \varepsilon_i; \quad \text{(NonS)}$$

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

$$(ii)\ \ln P_i = \rho W\ \ln P_i + \sum_j \beta_j X_j + \varepsilon_i; \quad \text{(SLag)}$$

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

$$(iii)\ \ln P_i = \sum_j \beta_j X_j + \varepsilon_i \quad \text{(SErr)}$$

$$\varepsilon_i = \lambda W \varepsilon_i + \mu_i;$$

$$\mu_i \approx \mathrm{N}(0,\sigma^2)$$

The dependent variable, the price level for the area, is repeated across the counties belonging to the same area, whereas the independent variables (observed rents and population density) are specific to individual counties within the areas. This 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 and by using individually weighted observations.

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 reduces heteroskedasticity, 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.

[5] Aten (2005) looks at the sensitivity of housing rent price levels to variables in the Census.

Equation (i) is a simple non-spatial model (NonS) with the log of the prices as the dependent variable and rents and population density as independent variables. Equations (ii) and (iii) have an explicit spatial component. The SLag model is a spatial auto-regressive model because of the addition of a spatial 'lag' in the form of $W^*(lnP_i)$ on the right-hand side while the SErr model is a spatial error model, with residual spatial autocorrelation in both dependent and independent variables captured in the error term. 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).

W is an n x 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 ranges in this context 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[6]. 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 a Delaunay triangulation[7], with observations having from three to twelve neighbors.

One interpretation of W is that of a spatial multiplier, $(I-\rho W)^{-1}$ in the SLag model and $(I-\lambda W)^{-1}$ in the SErr model, allowing for endogeneity in the dependent variable or in both dependent and independent variables, respectively[8]. The use of spatial weight matrices may be loosely interpreted as a 'de-trending' mechanism, intended to reduce the bias in the rent 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).

The parameters are found using weighted least squares (NonS model) and maximum likelihood estimators (in SLag and SErr models), with weights proportional to the population[9]. The weights are intended to reduce the variance of the residuals and increase the efficiency of the estimates. In addition to the rent and density variables, regional and size dummies were tested to help determine the stability of the rent and density parameters in each model.

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[6] 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]).

[7] 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.

[8] In the SLag model, $(I-\rho W)\ln P=\sum\beta X + \varepsilon$; in the SErr model, the 'lag' applies 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 $(I-\rho W)$ and $(I-\lambda W)$ are spatial filters, as in a first differencing approach for time series.

[9] These weights are assumed to be inversely proportional to the variances, as larger areas will generally sample more prices (and rents).

The results of the 'best' model in each of the three specifications are presented in the Results section, but numerous variations were tested, and a summary of the sensitivity of the estimates to different combinations of spatial weights matrices *W* is shown at the end of the paper. The predicted individual county price levels are normalized so that their weighted average equals the average price level for the area. That is, the weighted averages of the within-area county price levels equal the original observed input price levels.

Second Stage

The second stage involves bridging the predicted price levels in the 425 counties from the previous stage to all U.S. counties that are covered by the Census, including areas not sampled by the CPI. This is done in several steps. For ease of exposition, 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 rental data. The areas not sampled in the CPI are denoted 'census only' counties. Together, the overlap and census-only counties cover the 3219 counties.

First, the ratio of the weighted geometric mean of rents in census-only areas 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 *Equations (iv)*, 'over' refers to overlap counties, while 'census' refers to counties only in the Census rent sample. The weights refer to population weights.

For example, in Missouri, the rent ratio is 0.87, with fifteen counties that overlap averaging $540 in rents and 172 counties only in the census averaging $468. 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 non-sampled 172 counties in Missouri.

Equations (iv): Bridge Ratios

$$Ratio = \left(\overline{Rent}_{census} \Big/ \overline{Rent}_{overlap}\right)$$

$$\text{where } \overline{Rent}_{census} = \exp\left(\sum_{j \in census} w_j \ln Rent_j \Big/ \sum_{j \in census} w_j\right)$$

$$\overline{Rent}_{overlap} = \exp\left(\sum_{i \in overlap} w_i \ln Rent_i \Big/ \sum_{i \in overlap} w_i\right),$$

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

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

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[10], where a higher geographical aggregation, the division, is used instead of 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 from *Equation (iv)* become the dependent variables in the second stage regression model. It mirrors the first stage regressions in that the estimated price levels for each county enter as dependent variables, and are repeated across areas bridged by the same ratio. The actual individual rents as well as observed population densities for each county are the independent variables. The observations are weighted in proportion to the population. A weighted least squares formulation is tested (NonS) as well as two spatial models– the spatial lag (SLag) and the spatial error (SErr) models, identical in form to *Equations (i) to (iii)* depicted earlier. As in the first stage, different spatial weight matrices are used but instead of 425 observations, *n* increases to 3219, corresponding to all uniquely identified FIPS county codes in the Census rent data.

Final Stage

The final stage estimates the State Price Indexes or SPIs using the weighted geometric average of the predicted county values from the previous step. Ideally one would use expenditure weights but these are not available below the 38 area level, so population weights are used. The results are described in more detail below, followed by a discussion of their sensitivity to various specifications.

Results

First Stage Results

The first stage estimation results consist of the three basic equations: a non-spatial (NonS) formulation and two spatial (SLag and SErr) models. The independent variables are the rents and the population density. The base models shown in *Table 2* have separate regional intercept dummies. Alternative constraints and combinations were tested, including twelve different weight matrices (Ws) for each formulation. These are discussed in more detail in the Sensitivity section.

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[10] Puerto Rico is included in this study even though it is a territory and not a state as it has a full set of sampled rents for its 78 municipalities.

Table 2. First Stage Regressions Base Models

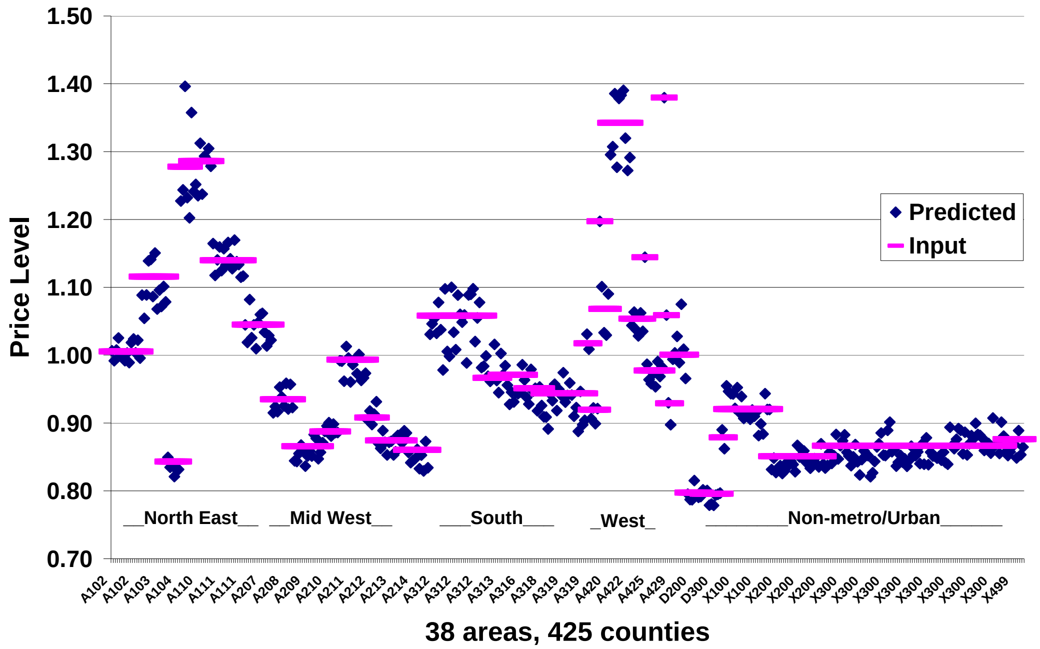
Dependent: ***Ln P***	**NonS**	**SLag**	**SErr**
West	-0.26**	-0.16**	-0.05*
Northeast	0.01	-0.01	-0.03
Midwest	-0.09**	-0.07**	-0.15**
South	-0.11**	-0.08**	-0.15**
	-	-	-
Rents ($x10^{-3}$)	0.47**	0.29**	0.22**
Density($x10^{-4}$)	0.10**	0.08**	0.07**
Rho (ρ)	-	*0.47***	-
Lambda (λ)	-	-	*0.69***
Spatial Matrix W	-	*C*	*C*
$Rbar^2$	0.69	0.72	0.76
MSE	410	309	304
LLikelihood	-	-1684	-1695
Nobs, Nvar	425,6	425,6	425,6

*** significant at 1% level, * significant at 5% level*

The base models shown are the ones with a combination of low unexplained variance (Mean Square Error [MSE]), high log likelihood ratio (LLikelihood), and significant coefficients. 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. These bases models are not significantly different vis-à-vis the unconstrained model[11]. Also, residuals were visually inspected for patterns, including heteroskedasticity and autocorrelation. Differences between SLag and SErr models were greater than differences between spatial weight matrices (except in the case of inverse distances), with SErr residuals behaving more 'normally' as might be expected. This is because the SLag models are correcting for the autocorrelation of the dependent variable, but not adjusting for the autocorrelation in the rents or in the densities as well, which the SErr model does.

[11] The F-test with (3, 425) degrees of freedom for the semi-constrained versus the unconstrained model in all cases averaged 2.0.

Figure 2. Predicted Price Levels First Stage Regression



The inverse distance spatial weight matrix resulted in some implausibly high (or low) predicted values for some observations. This occurs when the distance between two spatial units are very small, causing the inverse of the distance to be extremely large. For example in Virginia, Fairfax city and Fairfax county are separate observations in the Census, but they are technically within a few hundred feet of each other. The predicted price level for each observation is subtracted by its lagged value, the lag equaling ρW. If the relevant elements of W are disproportionately high as in this example, then the result can be a disproportionately low predicted value. A full listing of the 425 predicted price levels from this stage can be found in *Table A1* the *Appendix*.

Figure 2 highlights the results, showing the observed input price levels and the predicted levels using only the SErr base model in *Table 2.* The leftmost set of points on the horizontal axes of *Figure 2*, represent Philadelphia (A102) in the North East region. Philadelphia has an observed input price level of 1.005 with an average weighted rent of $658 (*Table A1* in the *Appendix*). There are fourteen counties that make up the Philadelphia area. The lowest predicted price level is 0.992 for both Cumberland county NJ, and Cecil county MD, while the highest is 1.025 for Burlington county NJ, closely followed by Chester county, PA. The corresponding rent variation is $622 for Cumberland and $778 for Burlington, but the lowest rents are for Philadelphia county PA, at $576. Philadelphia's predicted price level is 0.996, higher than Cumberland or Cecil counties' level, partly due to its higher population density and the spillover effect of having neighbors with higher price levels.

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[12] 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 0.86, shown on the last line of *Table 3*, while the bridged price level for census-only counties is 0.89 compared to the price level of 1.04 for overlap counties.

Table 3. Rent Ratios and Bridged Price Levels

Region	Division	Rent* census ($) (1)	Rent* overlap ($) (2)	Ratio census/overlap (3)=(1)/(2)	Price Level* overlap (4)	Bridged Level census (5)=(3)*(4)
1. Northeast		638	718	0.89	1.14	1.01
	1. New England	639	738	0.87	1.09	0.94
	2. Middle Atlantic	637	713	0.89	1.15	1.03
2. Midwest		521	595	0.88	0.93	0.82
	3. East North Central	539	597	0.90	0.94	0.85
	4. West North Central	487	587	0.83	0.91	0.75
3. South		544	641	0.85	0.94	0.80
	5. South Atlantic	578	686	0.84	0.96	0.81
	6. East South	482	506	0.95	0.86	0.81

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

Region	Division	Rent* census ($) (1)	Rent* overlap ($) (2)	Ratio census/overlap (3)=(1)/(2)	Price Level* overlap (4)	Bridged Level census (5)=(3)*(4)
	Central					
	7. West South Central	532	592	0.90	0.93	0.84
4. West		686	771	0.89	1.12	0.99
	8. Mountain	599	688	0.87	0.94	0.81
	9. Pacific	726	790	0.92	1.16	1.07
Metro		619	687	0.90	1.04	0.94
Non-Metro		449	460	0.98	0.82	0.80
Overall		**587**	**686**	**0.86**	**1.04**	**0.89**

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

Rents in overlap areas are generally higher than in census-only areas. 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*.

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. The composition of counties within areas and states is in the *Appendix, Table A1*.

Maine and Georgia have the lowest ratios: 0.74 and 0.76 respectively. Maine's overlap county is York, home of Kennebunkport, and part of the Boston metropolitan area (A103), with high rents compared to the rest of Maine. Although some of Georgia's counties are in 'B' and 'C' size areas, the bulk of the overlap counties are part of the Atlanta metropolitan area (A319), also with relatively high observed rents. 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.

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 structures introduced earlier: a non-spatial, a spatial lag and a spatial error model.

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
Input Price levels	0.849	12%	0.71	0.69 (non-urban areas, KS)	1.40 (New York, NY)
Rent ($)	$442	30%	$1,119	$100 (Kalawao[13], HI)	$1,219 (Santa Clara, CA)
Density*	51	909%	19,720	0.002 (Yukon-Koyukuk, AK)	19,720 (New York, NY)

** in square nautical miles (1 nautical mile is equal to 1.151 miles)*

Table 5 shows the results of the three regressions, using the contiguity spatial matrix for 3219 counties. As in the first stage, both the spatial lag (SLag) and spatial error (SErr) models have a much lower mean square error (MSE) than the non-spatial model. Unlike the first stage the table does not include regional dummies. They are discussed in more detail in the Sensitivity section.

Table 5. Second Stage Regressions

Dependent: *Ln P*	NonS	SLag	SErr
Intercept	-0.48**	-0.32**	-0.38*
Rents ($x10^{-3}$)	0.68**	0.45**	0.51**
Density($x10^{-4}$)	0.16**	0.12**	0.13**
Rho (ρ)	-	*0.46***	-
Lambda (λ)	-	-	*0.66***
Matrix W	-	*C*	*C*
$Rbar^2$	0.55	0.57	0.68
MSE	135	100	95

[13] The county is on a small peninsula called Kalaupapa on the north coast of the island of Moloka'i. It is isolated from the rest of Moloka'i by sea cliffs over a quarter-mile high — the only land access is a mule trail. The state once exiled people with Hansen's disease in Kalaupapa, and it is the second smallest county in the U.S, behind Loving County, TX. (Wikipedia).

Dependent: ***Ln P***	**NonS**	**SLag**	**SErr**
LLikelihood	-	-10927	-10939
Nobs, Nvar	3219,3	3219,3	3219,3

Table 6 shows a summary of the predicted price levels from the coefficients in the three second stage regressions. The non-spatial (NonS) and the spatial error (SErr) models result in more similar predicted price levels than the spatial lag (SLag) model. This is partly because the spatial error adjusts for autocorrelation in the independent variables (rents and densities), as well as in the dependent variable. The SLag model does not take into account neighboring rents and densities, and as a result, the size of the errors in observations that are extreme will be exaggerated, especially when their weights are also very small.

Table 6. Summary of Predicted Price Levels

(n=3219)	Mean	CV	Range	Lowest values	Highest values
NonS	0.84	9.9%	0.87	0.66 (Kalawao, HI)	1.53 (New York, NY)
				0.69 (King, TX)	1.43 (Santa Clara, CA)
SLag	0.79	14.7%	1.74	0.04 (Kenedy, TX)	1.78 (Falls Church city, VA)
				0.06 (Loving, TX)	1.66 (Manassas Park city, VA)
SErr	0.86	7.3%	0.67	0.72 (Kalawao, HI)	1.39 (New York, NY)
				0.74 (King, TX)	1.28 (Santa Clara, CA)

Two observations have implausibly low predicted price levels (0.04 and 0.06) using the SLag model: Kenedy and Loving, TX respectively. They have extremely small populations (400 and 67 people), and very low population densities. Even the most extreme low density area, Yukon-Koyokuk in Alaska, has over 6000 people, one hundred times the reported population of Loving.

Similarly, Falls Church city has an extremely high density because of its small area (with a relatively low population count as well as high rents), and its predicted price level is overstated. The disparities between the detailed predictions for the SLag model could be smoothed over if the observations were grouped or adjusted individually – by combining independent cities for example, in the case of the Virginia observations[14], but this was not done here.

[14] BEA does combine cities and counties in VA but these observations follow the BLS and Census definitions.

Final Stage Results: Spatial Price Indexes (SPIs) for States

The SPIs for each state are the population weighted geometric averages of county price levels calculated in the following way. If the county was in the original sample of metro and urban areas, then the original input price level is used. If not, that is, if the county is a bridged county, then the predicted price level from the SErr (contiguity) model is used.

Table 7 shows the estimated state price levels by SPI rank, normalized so that the average of the states equals one. The last two columns show the actual rents observed from the Census, and the corresponding rent levels when these are also normalized across the states to equal one. They are depicted in *Figure 4* with rents on the horizontal axis and SPIs on the vertical axis. These mimic *Table 1* and *Figure 1* at the beginning of the paper with the input SPIs and rent levels for the 38 areas. Hawaii has the highest rent level (1.44) and the highest SPI (1.36). New York has the second highest predicted SPI (1.26) but only the 7^{th} highest rent level (1.24), a result that would be consistent with rent controls in effect.

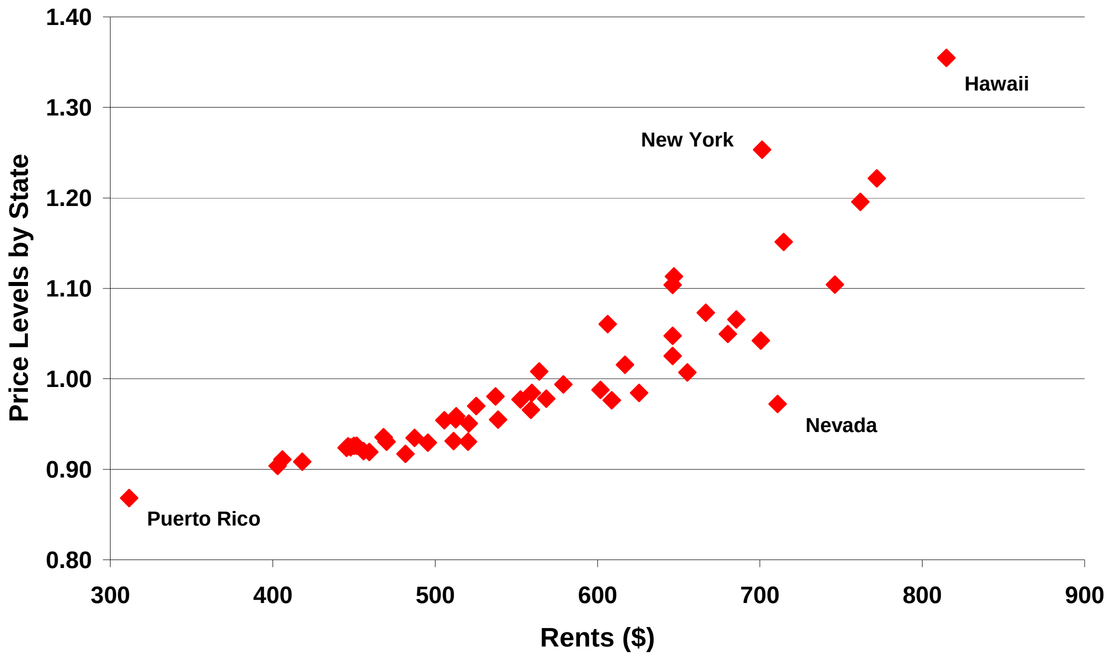
Table 7. Predicted Price Levels (Population Weighted) and Observed Rents by State

Rank	By SPI (predicted)	SPI	Rank	By Rent (actual)	Rent ($)	Rent Level
1	Hawaii	1.355	1	Hawaii	815	1.440
2	New York	1.253	2	California	772	1.364
3	California	1.222	3	New Jersey	762	1.347
4	New Jersey	1.196	4	Alaska	746	1.319
5	Massachusetts	1.151	5	Massachusetts	715	1.263
6	New Hampshire	1.113	6	Nevada	711	1.257
7	Alaska	1.104	7	New York	701	1.240
8	District of Columbia	1.104	8	Connecticut	701	1.238
9	Washington	1.073	9	Maryland	686	1.212
10	Maryland	1.066	10	Colorado	680	1.202
11	Illinois	1.061	11	Washington	667	1.178
12	Colorado	1.050	12	Virginia	655	1.158
13	Delaware	1.048	13	New Hampshire	647	1.144
14	Connecticut	1.042	14	District of Columbia	646	1.142
15	Florida	1.025	15	Florida	646	1.142
16	Oregon	1.016	16	Delaware	646	1.142
17	Minnesota	1.008	17	Arizona	626	1.106
18	Virginia	1.007	18	Oregon	617	1.090
19	Texas	0.994	19	Georgia	609	1.076
20	Utah	0.988	20	Illinois	606	1.072
21	Arizona	0.984	21	Utah	602	1.064
22	Rhode Island	0.984	22	Texas	579	1.023
23	Pennsylvania	0.980	23	Vermont	568	1.005
24	Vermont	0.978	24	Minnesota	564	0.997
25	Michigan	0.977	25	Rhode Island	560	0.989

Rank	By SPI (predicted)	SPI	Rank	By Rent (actual)	Rent ($)	Rent Level
26	Georgia	0.976	26	North Carolina	559	0.988
27	Nevada	0.972	27	Michigan	553	0.977
28	Indiana	0.970	28	Wisconsin	539	0.952
29	North Carolina	0.966	29	Pennsylvania	537	0.949
30	New Mexico	0.959	30	Indiana	525	0.928
31	Tennessee	0.955	31	South Carolina	521	0.920
32	Wisconsin	0.955	32	Ohio	520	0.919
33	Maine	0.954	33	New Mexico	513	0.907
34	South Carolina	0.951	34	Tennessee	513	0.906
35	Iowa	0.935	35	Idaho	511	0.904
36	Nebraska	0.935	36	Maine	506	0.894
37	Idaho	0.931	37	Kansas	496	0.876
38	Ohio	0.931	38	Nebraska	487	0.861
39	Louisiana	0.930	39	Missouri	482	0.851
40	Kansas	0.929	40	Louisiana	470	0.831
41	Arkansas	0.926	41	Iowa	468	0.828
42	Montana	0.926	42	Oklahoma	459	0.812
43	Mississippi	0.925	43	Alabama	456	0.806
44	Kentucky	0.924	44	Arkansas	452	0.798
45	Wyoming	0.924	45	Montana	450	0.795
46	Alabama	0.920	46	Kentucky	448	0.792
47	Oklahoma	0.919	47	Mississippi	446	0.789
48	Missouri	0.917	48	Wyoming	446	0.787
49	West Virginia	0.911	49	South Dakota	418	0.739
50	South Dakota	0.908	50	West Virginia	406	0.718
51	North Dakota	0.904	51	North Dakota	403	0.712
52	Puerto Rico	0.868	52	Puerto Rico	312	0.551
	Average	1.00			*566*	1.00
	Maximum	1.35			815	1.44
	Minimum	0.87			312	0.55
	Range	0.49			503	0.89
	CV	10%				20%

The predicted state SPIs have a much smaller range than the rents (0.49 vs 0.89), and it is interesting to note the change in rank order among the states. In addition to Hawaii, California, New Jersey, Alaska and Massachusetts, Nevada is reported to have one of the highest rents, with an observed average of $711, higher than New York state. The main counties responsible for this relatively high rent are Clark and Douglas counties, which include Las Vegas and Tahoe, respectively. Also noteworthy is the relatively high SPI for New Hampshire. Four out of ten counties in New Hampshire are considered part of the Boston metro area, with high input price levels.

Figure 4. SPIs vs. Rents by State



Sensitivity of SPIs

Since there are various stages where key assumptions are made in the estimation process, the sensitivity of the results to alternative formulations and models were analyzed at each stage. The following differences are highlighted:

a. sensitivity to geographic outliers in the first stage (Alaska and Hawaii)
b. sensitivity to the choice of weight matrix in the first stage
c. sensitivity to the choice of model and weight matrix in the second stage

a. Sensitivity to Outliers: Alaska and Hawaii

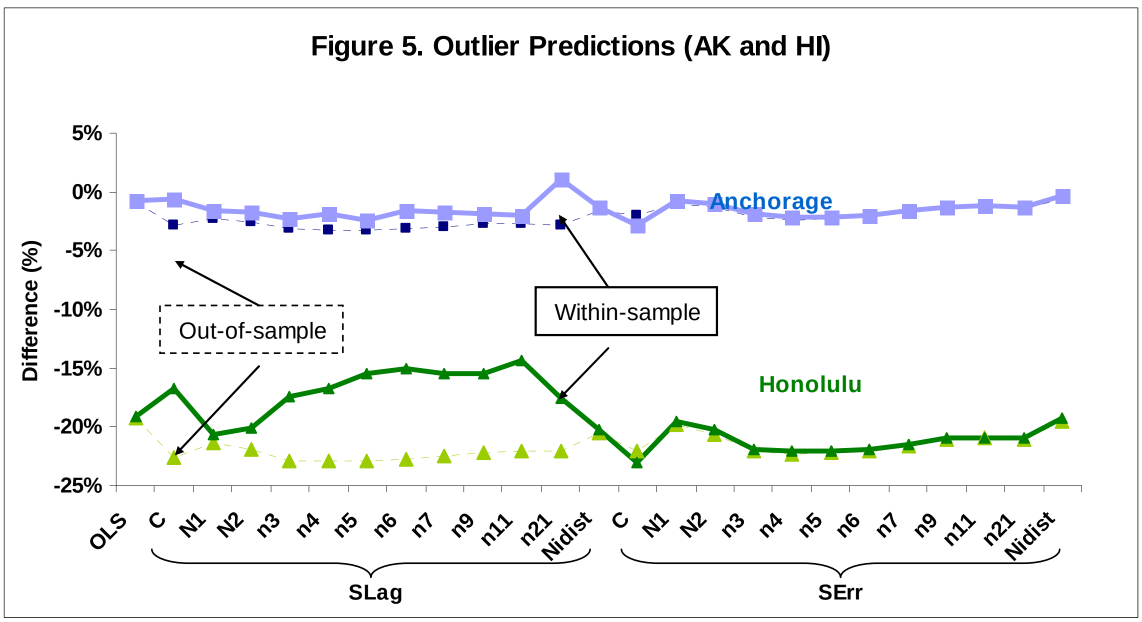
In the first stage, four out of the 38 areas consist of a single county: Los Angeles, (not including Greater LA, which is a separate area), San Diego, Honolulu and Anchorage. Since Hawaii and Alaska are geographic outliers, and two of the base models (the SLag and SErr models) explicitly use the geographic relationship among the areas, Honolulu and Anchorage were excluded as a test of out-of-sample sensitivity. The predicted price levels for the two areas were compared to the predictions from the full (within-sample) model[15].

[15] The predicted out-of-sample price levels assume that the weight matrix entries for Honolulu and Anchorage are zero, that is, they are geographically isolated from other areas.

Within-sample and out-of-sample predictions were very close to each other when the SErr model was used, but all models under-predicted the price level for these two areas. The differences were minor for Anchorage (averaging -2.2% across all models and weight matrices for the out-of-sample prediction and -1.6% for the in-sample predictions). For Honolulu, the differences were significant (averaging -21.6% and -19% respectively), but the magnitude of the differences was similar regardless of model and/or weight matrix.

Figure 5 show the differences between predicted and observed price levels for Hawaii and Anchorage respectively.

The horizontal axis describes each model: OLS, SLag and SErr, with different weight matrices. These include the contiguity matrix plus eleven other weight matrices (ranging from one nearest-neighbor to twenty-one nearest neighbors, plus the inverse distance matrix) for each of the SLag and SErr models. The vertical axis is the difference between the predicted price level and the input price level, in percentage terms. The input price level for Anchorage was 1.06 and for Honolulu, 1.38 (*Table 1*).



One reason for the large difference between predicted and input price levels for Honolulu is that the only independent price information that is being used in this study are rents. Although rents are high in Honolulu (1.28 in *Table 1*), they were only 84% of the rent levels in San Francisco, according to the Census data, while the SPI for Honolulu was 3% higher than for San Francisco (*Table 1*). It could be argued that other consumption characteristics of Hawaii that are likely to raise price levels are not being captured. For example, the higher cost of shipping is important in raising gas prices, and it was shown in Aten (2005) that price levels for most other consumption goods in Honolulu were also relatively high compared to the rest of the U.S.

Note that although the model severely under-predicts the price level for Honolulu, the observed price level is the one used for subsequent stages, as there is only one county in Honolulu. This is true for Anchorage and the other two single county areas (Los Angeles and San Diego) as well. For areas with more than one county, the mean of the predicted price level is normalized to the observed price level, so that in effect, we are using only the variation about the mean for the prediction of the within-area counties, not the actual levels.

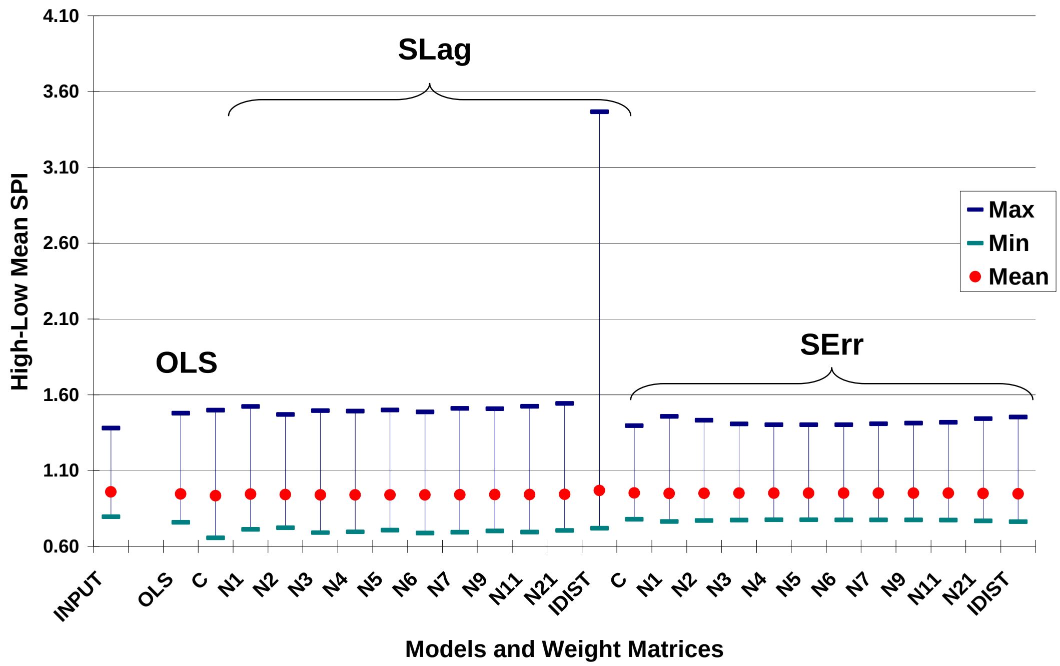
b. Sensitivity to the choice of weight matrix in the first stage

The first stage regression results shown in *Table 2* used the Contiguity matrix as the spatial weight. Eleven other matrices were created to test the sensitivity of the model to the choice of weights in the SLag and SErr models. These consist of nearest neighbor matrices ranging from first-order nearest neighbor to twenty-first order (one to seven, nine, eleven and twenty-one neighbors), and an inverse distance matrix. The latter resulted in some disproportionately high and low values in the SLag model, partly due to some spatial units that are very close together, as discussed earlier in the text.

In the first-order nearest neighbor matrix W, each row has only one entry (equal to 1), corresponding to the nearest observation. For example, $W_{19} = 1$ (the 9^{th} observation is the nearest neighbor to the first observation). However, W is not necessarily symmetric, as the nearest neighbor to the 9^{th} observation is observation 8, so $W_{91}=0$ and $W_{98}=1$. The second-order nearest neighbor matrix will have two entries per row, each equal to 0.5, while the twenty-first order matrix has 21 entries, each equal to 0.0476.

In *Figure 6* the different methods are listed on the horizontal axis while the range of the resulting SPIs are on the vertical axis. The range is the maximum predicted county price level minus the minimum predicted county price level for the 425 counties comprising the 38 input areas.

Figure 6. Sensitivity of Predicted SPIs (n=425) in First Stage



The SErr models have the least spread overall, and differences across matrices are slight compared to differences between the methods. The mean SErr range is 0.65 (from a minimum of 0.62 for the contiguity matrix to a maximum of 0.69 for the first nearest neighbor and the inverse distance matrix). The mean SLag range is higher at 0.97 (minimum is 0.75 for the second-order nearest neighbor to 2.75 for inverse distance), while the OLS model predicts a SPI range of 0.72.

Looking at actual levels, the lowest input price level was 0.80 for the South C areas (*Table 1*) and the highest one for Honolulu at 1.38. The SErr C model predicts the within-area low-high price levels to be 0.779 and 1.396, for Screven GA, and New York NY, respectively (*Table A1 Appendix*). The input price level for the New York area was 1.28 (*Table 1*), but the predicted levels for its counties ranged from a low of 1.202 for Richmond, to 1.396 for NY city. Honolulu, HI is only fifth-highest, being a single county and normalized to its input level of 1.38 (*Table A1 Appendix*). The SErr model with a contiguity matrix is the most conservative, as it results in the lowest spread across the 425 counties within the 38 areas.

c. Sensitivity to the choice of model and weight matrix in the second stage

This section looks at the differences in state SPIs when different weight matrices and model specifications are used in the second stage regression. The three base models (non-spatial, spatial lag and spatial error with a contiguity matrix) were described earlier.

The spatial lag model gives rise to implausible predicted levels when the values of the independent variables are extreme, combined with very low weights. These differences can be mitigated by joining observations to form different spatial units, but this exercise was not done here. Instead, various weight matrices were created for the full set of 3219 observations, and the resulting state SPIs were compared.

Table A3 in the *Appendix* lists the states in alphabetical order. The *Freq* column indicates the number of counties within each state. The other columns are the price levels of observed rents (column 1), the input price levels for the first stage regression (column 2), the input price levels for the second stage regression (column 3) and then the various estimated final state SPIs using different methods and matrices. These are the preferred method with the SErr model and contiguity matrix (column 4), the SLag with contiguity (column 5), the NonS model (column 6), followed by columns 7-12 containing the SErr model with a first-order nearest neighbor matrix (n1), a third-order matrix (n3), fifth-order (n5), seventh-order (n7), ninth-order (n9), and eleventh-order (n11) nearest neighbor matrix. Lastly, two more SErr models are shown, one with only regional dummies (column 13), and one with both regional dummies and separate slopes for rents and densities (column 14). Both use the contiguity spatial weight matrix. All levels are normalized to the average of the states for comparison purposes.

Hawaii is consistently the highest priced state, followed by New York, California and New Jersey. Puerto Rico is always the lowest, with West Virginia or North Dakota vying for second lowest place. The results are fairly consistent across methods, with the largest differences to be found between the SErr models, regardless of matrix, and the SLag and NonS models (columns 5 & 6). The latter two predict state SPIs that are more similar to those of the SErr models with dummy variables (columns 13 &14).

The greatest range was in the SLag model and the NonS model (0.57), while the smallest range (0.49) was in the SErr models, for the contiguity matrix (column 4) and the fifth to eleventh nearest neighbor matrices (columns 9-12).

One disadvantage of the unconstrained SErr model with separate slopes and intercepts by region (column 14), is that there are outliers within each region, resulting in predicted SPI for these outliers that are arguably under or over-predictions. For example, states in the Northeast region versus the South. The Northeast region has a higher average and thus Maine's predicted SPI is 1.01 in column 14, but only 0.95 in all other columns. Conversely, Alabama and Arkansas drop from about 0.92 in the SErr models to 0.89 with a regional dummy for the South, as in column 14. In the first stage, the use of regional dummies was justified because it was a subset of counties that represented only metropolitan and urban areas, and these were scattered across the country. In this second stage, all counties are included and the geographic coverage is over a more continuous surface.

Conclusions

The state SPIs are constructed from a starting set of 38 metropolitan and urban area price levels for consumption goods and services, plus detailed rent data for all U.S. counties from the 2000 Census. Although the 38 areas in the CPI cover approximately 87% of the U.S. population, geographically they account for only 15% of the counties. The first stage of this exercise 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, and then normalizes them to the original observed BLS means in each area.

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 BLS sampling framework of the CPI. However, the Census does have detailed rent data and complete coverage of all counties, and as rents[16], on average, account for nearly thirty percent of overall consumer expenditures, they are used as the main auxiliary data in this stage. As 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 3219 counties. The regression model mirrors the first stage model, and includes a spatial matrix that makes explicit the geographic proximity of the counties, this time with fuller and continuous coverage. The resulting predicted price levels for each non-sampled county are then aggregated to the state level, resulting in a second-round approximation of the state-level spatial price indexes or SPIs.

Hawaii had the highest SPI: 35.5% higher than the average of the states, followed by New York and California. Other states that were at least ten percent higher than the average were New Jersey, Massachusetts, New Hampshire, Alaska, and the District of Columbia. States with the lowest price level index were Puerto Rico[17] at 86.8% of the average, North and South Dakota and West Virginia, all around the 91% level. Nevada is a state with relatively high rent levels (1.26) but a low SPI (0.97). while New York is the opposite: lower rent level (1.24) but a higher relative SPI (1.25). The range of the SPIs is about 50%, from 15% below average to 35% above average, a much lower range than the rents that vary from a minimum of $312 to a maximum of $815, equivalent to a range of 90%.

[16] Rents in the BLS include both Rents and Owner Equivalent Rents (for a more detailed description, see Aten [2006])
[17] As noted earlier, Puerto Rico is not a state but has a full set of sampled rents in the Census, so was included in this study.

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 Census Bureau[18]. Future applications of the results should feed back into checks on the robustness of the methods developed in this paper.

For example, one simple application is to adjust nominal personal income at the state and metropolitan level to reflect differences in consumption prices. This is illustrated in *Table A4* in the Appendix. The first column is the 2000 total personal income estimates, labeled *nominal*[19]. The second column lists the incomes adjusted by the county level SPIs. These adjusted county personal incomes are then summed to derive an average personal income for each state[20]. The differences in rank order between the first two columns are given in the last column. Negative values imply that the adjusted rank is lower than the nominal rank, meaning that price levels in that state are higher than average and the adjusted income total is relatively smaller. For example, New York drops from second to third place behind Texas when total personal incomes are adjusted by the price level. Conversely, North Carolina, Missouri, West Virginia and North Dakota, all with relatively low price levels, have a higher adjusted income that their nominal incomes and jump two places up in rank.

Another important extension of this work is to explore the use of state SPIs in developing GDP (Gross Domestic Product) by State estimates adjusted for price differences. 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 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 third 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.

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[18] Since the Census is decennial, other auxiliary sources of price data should be considered, such as the more timely American Community Survey.

[19] http://www.bea.gov/regional/spi/

[20] That is, the SPIs are weighted by the total personal incomes of each county, and will differ from the SPIs weighted by population shown in *Table 7*.

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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	1.005	1.006	686	658
2		A102	Cecil	MD	24015	1.005	0.992	623	658
3		A102	Atlantic	NJ	34001	1.005	1.007	695	658
4		A102	Burlington	NJ	34005	1.005	1.025	778	658
5		A102	Camden	NJ	34007	1.005	1.000	651	658
6		A102	Cape May	NJ	34009	1.005	0.997	649	658
7		A102	Cumberland	NJ	34011	1.005	0.992	622	658
8		A102	Gloucester	NJ	34015	1.005	1.003	674	658
9		A102	Salem	NJ	34033	1.005	0.989	610	658
10		A102	Bucks	PA	42017	1.005	1.019	745	658
11		A102	Chester	PA	42029	1.005	1.024	770	658
12		A102	Delaware	PA	42045	1.005	1.003	666	658
13		A102	Montgomery	PA	42091	1.005	1.022	758	658
14		A102	Philadelphia	PA	42101	1.005	0.996	576	658
15	Boston	A103	York	ME	23031	1.116	1.088	677	755
16		A103	Bristol	MA	25005	1.116	1.054	525	755
17		A103	Essex	MA	25009	1.116	1.089	672	755
18		A103	Middlesex	MA	25017	1.116	1.139	880	755
19		A103	Norfolk	MA	25021	1.116	1.141	890	755
20		A103	Plymouth	MA	25023	1.116	1.086	666	755
21		A103	Suffolk	MA	25025	1.116	1.151	832	755
22		A103	Worcester	MA	25027	1.116	1.068	587	755
23		A103	Hillsborough	NH	33011	1.116	1.096	706	755
24		A103	Merrimack	NH	33013	1.116	1.072	606	755
25		A103	Rockingham	NH	33015	1.116	1.101	731	755
26		A103	Strafford	NH	33017	1.116	1.079	633	755
27	Pittsburth	A104	Allegheny	PA	42003	0.843	0.849	525	492
28		A104	Beaver	PA	42007	0.843	0.835	453	492
29		A104	Butler	PA	42019	0.843	0.842	491	492
30		A104	Fayette	PA	42051	0.843	0.821	376	492
31		A104	Washington	PA	42125	0.843	0.831	431	492
32		A104	Westmoreland	PA	42129	0.843	0.831	435	492
33	NY City	A109	Bronx	NY	36005	1.278	1.227	636	750
34		A109	Kings	NY	36047	1.278	1.244	691	750
35		A109	New York	NY	36061	1.278	1.396	868	750
36		A109	Queens	NY	36081	1.278	1.232	794	750
37		A109	Richmond	NY	36085	1.278	1.202	773	750
38	NY suburbs	A110	Fairfield	CT	9001	1.286	1.357	1157	893
39		A110	Litchfield	CT	9005	1.286	1.241	742	893
40		A110	New Haven	CT	9009	1.286	1.252	779	893
41		A110	Dutchess	NY	36027	1.286	1.235	717	893
42		A110	Nassau	NY	36059	1.286	1.312	991	893
43		A110	Orange	NY	36071	1.286	1.237	725	893
44		A110	Putnam	NY	36079	1.286	1.293	932	893
45		A110	Rockland	NY	36087	1.286	1.289	912	893
46		A110	Suffolk	NY	36103	1.286	1.305	971	893
47		A110	Westchester	NY	36119	1.286	1.278	869	893
48	NJ suburbs	A111	Bergen	NJ	34003	1.140	1.165	901	779
49		A111	Essex	NJ	34013	1.140	1.118	681	779
50		A111	Hudson	NJ	34017	1.140	1.141	712	779
51		A111	Hunterdon	NJ	34019	1.140	1.160	897	779
52		A111	Mercer	NJ	34021	1.140	1.125	748	779
53		A111	Middlesex	NJ	34023	1.140	1.157	875	779
54		A111	Monmouth	NJ	34025	1.140	1.133	784	779
55		A111	Morris	NJ	34027	1.140	1.166	920	779
56		A111	Ocean	NJ	34029	1.140	1.142	824	779

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	1.140	1.127	752	779
58		A111	Somerset	NJ	34035	1.140	1.169	934	779
59		A111	Sussex	NJ	34037	1.140	1.138	809	779
60		A111	Union	NJ	34039	1.140	1.134	766	779
61		A111	Warren	NJ	34041	1.140	1.115	714	779
62		A111	Pike	PA	42103	1.140	1.117	722	779
63	Chicago	A207	Cook	IL	17031	1.045	1.045	662	669
64		A207	DeKalb	IL	17037	1.045	1.019	578	669
65		A207	DuPage	IL	17043	1.045	1.082	850	669
66		A207	Grundy	IL	17063	1.045	1.026	609	669
67		A207	Kane	IL	17089	1.045	1.045	693	669
68		A207	Kankakee	IL	17091	1.045	1.010	536	669
69		A207	Kendall	IL	17093	1.045	1.048	711	669
70		A207	Lake	IL	17097	1.045	1.060	759	669
71		A207	McHenry	IL	17111	1.045	1.062	770	669
72		A207	Will	IL	17197	1.045	1.034	646	669
73		A207	Lake	IN	18089	1.045	1.014	551	669
74		A207	Porter	IN	18127	1.045	1.029	623	669
75		A207	Kenosha	WI	55059	1.045	1.022	591	669
76	Detroit	A208	Genesee	MI	26049	0.935	0.915	507	596
77		A208	Lapeer	MI	26087	0.935	0.924	556	596
78		A208	Lenawee	MI	26091	0.935	0.916	517	596
79		A208	Livingston	MI	26093	0.935	0.953	698	596
80		A208	Macomb	MI	26099	0.935	0.939	623	596
81		A208	Monroe	MI	26115	0.935	0.925	561	596
82		A208	Oakland	MI	26125	0.935	0.959	721	596
83		A208	St. Clair	MI	26147	0.935	0.921	538	596
84		A208	Washtenaw	MI	26161	0.935	0.957	715	596
85		A208	Wayne	MI	26163	0.935	0.923	534	596
86	St. Louis	A209	Clinton	IL	17027	0.866	0.844	433	528
87		A209	Jersey	IL	17083	0.866	0.843	428	528
88		A209	Madison	IL	17119	0.866	0.855	490	528
89		A209	Monroe	IL	17133	0.866	0.867	559	528
90		A209	St. Clair	IL	17163	0.866	0.860	516	528
91		A209	Crawford	MO	29055	0.866	0.836	389	528
92		A209	Franklin	MO	29071	0.866	0.851	472	528
93		A209	Jefferson	MO	29099	0.866	0.858	510	528
94		A209	Lincoln	MO	29113	0.866	0.851	471	528
95		A209	St. Charles	MO	29183	0.866	0.883	639	528
96		A209	St. Louis	MO	29189	0.866	0.877	603	528
97		A209	Warren	MO	29219	0.866	0.847	448	528
98		A209	St. Louis City	MO	29510	0.866	0.857	451	528
99	Cleveland	A210	Ashtabula	OH	39007	0.887	0.871	477	552
100		A210	Cuyahoga	OH	39035	0.887	0.888	548	552
101		A210	Geauga	OH	39055	0.887	0.896	608	552
102		A210	Lake	OH	39085	0.887	0.900	629	552
103		A210	Lorain	OH	39093	0.887	0.881	528	552
104		A210	Medina	OH	39103	0.887	0.898	622	552
105		A210	Portage	OH	39133	0.887	0.886	555	552
106		A210	Summit	OH	39153	0.887	0.886	550	552
107	Minneapolis	A211	Anoka	MN	27003	0.993	0.992	657	655
108		A211	Carver	MN	27019	0.993	0.991	656	655
109		A211	Chisago	MN	27025	0.993	0.962	515	655
110		A211	Dakota	MN	27037	0.993	1.013	754	655
111		A211	Hennepin	MN	27053	0.993	0.996	668	655
112		A211	Isanti	MN	27059	0.993	0.960	509	655

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	0.993	0.986	615	655
114		A211	Scott	MN	27139	0.993	0.994	667	655
115		A211	Sherburne	MN	27141	0.993	0.973	568	655
116		A211	Washington	MN	27163	0.993	1.001	701	655
117		A211	Wright	MN	27171	0.993	0.963	521	655
118		A211	Pierce	WI	55093	0.993	0.966	538	655
119		A211	St. Croix	WI	55109	0.993	0.973	571	655
120	Milwaukee	A212	Milwaukee	WI	55079	0.908	0.904	555	578
121		A212	Ozaukee	WI	55089	0.908	0.918	651	578
122		A212	Racine	WI	55101	0.908	0.898	548	578
123		A212	Washington	WI	55131	0.908	0.913	627	578
124		A212	Waukesha	WI	55133	0.908	0.931	718	578
125	Cincinnati	A213	Dearborn	IN	18029	0.874	0.870	509	521
126		A213	Ohio	IN	18115	0.874	0.863	469	521
127		A213	Boone	KY	21015	0.874	0.889	607	521
128		A213	Campbell	KY	21037	0.874	0.872	515	521
129		A213	Gallatin	KY	21077	0.874	0.853	416	521
130		A213	Grant	KY	21081	0.874	0.871	516	521
131		A213	Kenton	KY	21117	0.874	0.873	520	521
132		A213	Pendleton	KY	21191	0.874	0.853	416	521
133		A213	Brown	OH	39015	0.874	0.858	442	521
134		A213	Butler	OH	39017	0.874	0.882	567	521
135		A213	Clermont	OH	39025	0.874	0.880	558	521
136		A213	Hamilton	OH	39061	0.874	0.871	498	521
137		A213	Warren	OH	39165	0.874	0.888	605	521
138	Kansas City	A214	Johnson	KS	20091	0.860	0.885	716	576
139		A214	Leavenworth	KS	20103	0.860	0.857	567	576
140		A214	Miami	KS	20121	0.860	0.842	484	576
141		A214	Wyandotte	KS	20209	0.860	0.845	496	576
142		A214	Cass	MO	29037	0.860	0.847	515	576
143		A214	Clay	MO	29047	0.860	0.861	589	576
144		A214	Clinton	MO	29049	0.860	0.833	434	576
145		A214	Jackson	MO	29095	0.860	0.853	538	576
146		A214	Lafayette	MO	29107	0.860	0.829	416	576
147		A214	Platte	MO	29165	0.860	0.873	652	576
148		A214	Ray	MO	29177	0.860	0.834	443	576
149	DC	A312	District of Columbia	DC	11001	1.058	1.031	646	806
150		A312	Calvert	MD	24009	1.058	1.046	804	806
151		A312	Charles	MD	24017	1.058	1.054	838	806
152		A312	Frederick	MD	24021	1.058	1.032	740	806
153		A312	Montgomery	MD	24031	1.058	1.078	934	806
154		A312	Prince George's	MD	24033	1.058	1.037	756	806
155		A312	Washington	MD	24043	1.058	0.978	489	806
156		A312	Arlington	VA	51013	1.058	1.098	946	806
157		A312	Clarke	VA	51043	1.058	1.006	620	806
158		A312	Culpeper	VA	51047	1.058	0.998	586	806
159		A312	Fairfax	VA	51059	1.058	1.100	1027	806
160		A312	Fauquier	VA	51061	1.058	1.034	748	806
161		A312	King George	VA	51099	1.058	1.008	631	806
162		A312	Loudoun	VA	51107	1.058	1.088	988	806
163		A312	Prince William	VA	51153	1.058	1.060	863	806
164		A312	Spotsylvania	VA	51177	1.058	1.049	815	806
165		A312	Stafford	VA	51179	1.058	1.059	861	806
166		A312	Warren	VA	51187	1.058	0.988	539	806
167		A312	Alexandria City	VA	51510	1.058	1.089	880	806
168		A312	Fairfax City	VA	51600	1.058	1.090	976	806

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	1.058	1.098	991	806
170		A312	Fredericksburg City	VA	51630	1.058	1.020	663	806
171		A312	Manassas City	VA	51683	1.058	1.055	826	806
172		A312	Manassas Park City	VA	51685	1.058	1.078	931	806
173		A312	Berkeley	WV	54003	1.058	0.982	507	806
174		A312	Jefferson	WV	54037	1.058	0.984	517	806
175	Baltimore	A313	Anne Arundel	MD	24003	0.966	0.999	817	629
176		A313	Baltimore	MD	24005	0.966	0.969	672	629
177		A313	Carroll	MD	24013	0.966	0.961	642	629
178		A313	Harford	MD	24025	0.966	0.965	658	629
179		A313	Howard	MD	24027	0.966	1.016	895	629
180		A313	Queen Anne's	MD	24035	0.966	0.963	649	629
181		A313	Baltimore City	MD	24510	0.966	0.945	506	629
182	Dallas	A316	Collin	TX	48085	0.971	1.003	823	659
183		A316	Dallas	TX	48113	0.971	0.971	656	659
184		A316	Denton	TX	48121	0.971	0.985	739	659
185		A316	Ellis	TX	48139	0.971	0.956	603	659
186		A316	Henderson	TX	48213	0.971	0.927	463	659
187		A316	Hood	TX	48221	0.971	0.945	552	659
188		A316	Hunt	TX	48231	0.971	0.931	480	659
189		A316	Johnson	TX	48251	0.971	0.945	550	659
190		A316	Kaufman	TX	48257	0.971	0.943	541	659
191		A316	Parker	TX	48367	0.971	0.946	554	659
192		A316	Rockwall	TX	48397	0.971	0.986	747	659
193		A316	Tarrant	TX	48439	0.971	0.963	629	659
194	Houston	A318	Brazoria	TX	48039	0.951	0.938	546	600
195		A318	Chambers	TX	48071	0.951	0.928	498	600
196		A318	Fort Bend	TX	48157	0.951	0.979	748	600
197		A318	Galveston	TX	48167	0.951	0.947	589	600
198		A318	Harris	TX	48201	0.951	0.951	600	600
199		A318	Liberty	TX	48291	0.951	0.918	449	600
200		A318	Montgomery	TX	48339	0.951	0.953	623	600
201		A318	Waller	TX	48473	0.951	0.926	488	600
202	Atlanta	A319	Barrow	GA	13013	0.944	0.909	590	749
203		A319	Bartow	GA	13015	0.944	0.909	588	749
204		A319	Carroll	GA	13045	0.944	0.891	498	749
205		A319	Cherokee	GA	13057	0.944	0.943	758	749
206		A319	Clayton	GA	13063	0.944	0.933	700	749
207		A319	Cobb	GA	13067	0.944	0.957	820	749
208		A319	Coweta	GA	13077	0.944	0.918	636	749
209		A319	DeKalb	GA	13089	0.944	0.949	774	749
210		A319	Douglas	GA	13097	0.944	0.941	748	749
211		A319	Fayette	GA	13113	0.944	0.974	911	749
212		A319	Forsyth	GA	13117	0.944	0.931	700	749
213		A319	Fulton	GA	13121	0.944	0.941	736	749
214		A319	Gwinnett	GA	13135	0.944	0.959	834	749
215		A319	Henry	GA	13151	0.944	0.941	751	749
216		A319	Newton	GA	13217	0.944	0.910	594	749
217		A319	Paulding	GA	13223	0.944	0.923	660	749
218		A319	Pickens	GA	13227	0.944	0.888	480	749
219		A319	Rockdale	GA	13247	0.944	0.947	777	749
220		A319	Spalding	GA	13255	0.944	0.897	528	749
221		A319	Walton	GA	13297	0.944	0.904	564	749
222	Miami	A320	Broward	FL	12011	1.017	1.031	765	701
223		A320	Miami-Dade	FL	12086	1.017	1.009	664	701
224	Tampa	A321	Hernando	FL	12053	0.920	0.906	561	617

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	0.920	0.922	636	617
226		A321	Pasco	FL	12101	0.920	0.899	522	617
227		A321	Pinellas	FL	12103	0.920	0.921	620	617
228	Los Angeles	A419	Los Angeles	CA	6037	1.197	1.197	721	721
229	Greater LA	A420	Orange	CA	6059	1.068	1.101	947	804
230		A420	Riverside	CA	6065	1.068	1.033	669	804
231		A420	San Bernardino	CA	6071	1.068	1.030	654	804
232		A420	Ventura	CA	6111	1.068	1.090	919	804
233	San Francisco	A422	Alameda	CA	6001	1.343	1.295	884	1017
234		A422	Contra Costa	CA	6013	1.343	1.307	935	1017
235		A422	Marin	CA	6041	1.343	1.386	1208	1017
236		A422	Napa	CA	6055	1.343	1.277	830	1017
237		A422	San Francisco	CA	6075	1.343	1.378	1021	1017
238		A422	San Mateo	CA	6081	1.343	1.383	1194	1017
239		A422	Santa Clara	CA	6085	1.343	1.390	1219	1017
240		A422	Santa Cruz	CA	6087	1.343	1.320	982	1017
241		A422	Solano	CA	6095	1.343	1.272	811	1017
242		A422	Sonoma	CA	6097	1.343	1.291	881	1017
243	Seattle	A423	Island	WA	53029	1.054	1.044	697	735
244		A423	King	WA	53033	1.054	1.064	781	735
245		A423	Kitsap	WA	53035	1.054	1.037	665	735
246		A423	Pierce	WA	53053	1.054	1.028	626	735
247		A423	Snohomish	WA	53061	1.054	1.062	778	735
248		A423	Thurston	WA	53067	1.054	1.035	658	735
249	San Diego	A424	San Diego	CA	6073	1.144	1.144	783	783
250	Portland	A425	Clackamas	OR	41005	0.977	0.987	716	665
251		A425	Columbia	OR	41009	0.977	0.964	608	665
252		A425	Marion	OR	41047	0.977	0.958	578	665
253		A425	Multnomah	OR	41051	0.977	0.973	642	665
254		A425	Polk	OR	41053	0.977	0.953	557	665
255		A425	Washington	OR	41067	0.977	0.991	732	665
256		A425	Yamhill	OR	41071	0.977	0.969	631	665
257		A425	Clark	WA	53011	0.977	0.983	695	665
258	Honolulu	A426	Honolulu	HI	15003	1.379	1.379	846	846
259	Anchorage	A427	Anchorage Municipality	AK	2020	1.059	1.059	752	752
260	Phoenix	A429	Maricopa	AZ	4013	0.929	0.930	677	672
261		A429	Pinal	AZ	4021	0.929	0.898	514	672
262	Denver	A433	Adams	CO	8001	1.001	0.994	706	720
263		A433	Arapahoe	CO	8005	1.001	1.003	747	720
264		A433	Boulder	CO	8013	1.001	1.028	861	720
265		A433	Denver	CO	8031	1.001	0.989	652	720
266		A433	Douglas	CO	8035	1.001	1.075	1072	720
267		A433	Jefferson	CO	8059	1.001	1.009	772	720
268		A433	Weld	CO	8123	1.001	0.966	572	720
269	MW Cs	D200	Jefferson	IL	17081	0.797	0.795	400	408
270		D200	Allen	KS	20001	0.797	0.787	353	408
271		D200	Neosho	KS	20133	0.797	0.787	351	408
272		D200	Rice	MN	27131	0.797	0.815	515	408
273		D200	Brookings	SD	46011	0.797	0.793	389	408
274		D200	Lake	SD	46079	0.797	0.790	372	408
275		D200	Moody	SD	46101	0.797	0.792	379	408
276	South Cs	D300	DeSoto	FL	12027	0.796	0.801	457	423
277		D300	Hardee	FL	12049	0.796	0.799	444	423
278		D300	Bulloch	GA	13031	0.796	0.801	452	423
279		D300	Burke	GA	13033	0.796	0.779	324	423
280		D300	Jenkins	GA	13165	0.796	0.781	335	423

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	0.796	0.779	323	423
282		D300	Pearl River	MS	28109	0.796	0.794	412	423
283		D300	Hamblen	TN	47063	0.796	0.795	418	423
284		D300	Jefferson	TN	47089	0.796	0.797	429	423
285	West Cs	D400	Deschutes	OR	41017	0.879	0.890	641	576
286		D400	Whitman	WA	53075	0.879	0.862	492	576
287	NE Bs	X100	Hartford	CT	9003	0.920	0.955	728	551
288		X100	Middlesex	CT	9007	0.920	0.947	691	551
289		X100	New London	CT	9011	0.920	0.943	674	551
290		X100	Tolland	CT	9013	0.920	0.943	670	551
291		X100	Windham	CT	9015	0.920	0.922	566	551
292		X100	Franklin	MA	25011	0.920	0.952	718	551
293		X100	Hampden	MA	25013	0.920	0.915	531	551
294		X100	Hampshire	MA	25015	0.920	0.939	653	551
295		X100	Cayuga	NY	36011	0.920	0.907	489	551
296		X100	Erie	NY	36029	0.920	0.913	520	551
297		X100	Madison	NY	36053	0.920	0.910	505	551
298		X100	Niagara	NY	36063	0.920	0.905	481	551
299		X100	Onondaga	NY	36067	0.920	0.919	551	551
300		X100	Oswego	NY	36075	0.920	0.910	507	551
301		X100	Berks	PA	42011	0.920	0.916	538	551
302		X100	Cambria	PA	42021	0.920	0.881	357	551
303		X100	Mercer	PA	42085	0.920	0.899	448	551
304		X100	Somerset	PA	42111	0.920	0.884	371	551
305		X100	Chittenden	VT	50007	0.920	0.943	674	551
306		X100	Franklin	VT	50011	0.920	0.920	556	551
307		X100	Grand Isle	VT	50013	0.920	0.920	557	551
308	MW Bs	X200	Macon	IL	17115	0.851	0.831	449	547
309		X200	Elkhart	IN	18039	0.851	0.848	542	547
310		X200	Posey	IN	18129	0.851	0.827	426	547
311		X200	Vanderburgh	IN	18163	0.851	0.834	459	547
312		X200	Warrick	IN	18173	0.851	0.837	482	547
313		X200	Henderson	KY	21101	0.851	0.825	416	547
314		X200	Bay	MI	26017	0.851	0.829	436	547
315		X200	Midland	MI	26111	0.851	0.841	505	547
316		X200	Saginaw	MI	26145	0.851	0.838	485	547
317		X200	Lancaster	NE	31109	0.851	0.844	515	547
318		X200	Clark	OH	39023	0.851	0.839	491	547
319		X200	Columbiana	OH	39029	0.851	0.828	431	547
320		X200	Delaware	OH	39041	0.851	0.867	646	547
321		X200	Fairfield	OH	39045	0.851	0.850	552	547
322		X200	Franklin	OH	39049	0.851	0.861	595	547
323		X200	Greene	OH	39057	0.851	0.859	600	547
324		X200	Licking	OH	39089	0.851	0.842	510	547
325		X200	Madison	OH	39097	0.851	0.844	520	547
326		X200	Mahoning	OH	39099	0.851	0.833	458	547
327		X200	Miami	OH	39109	0.851	0.846	529	547
328		X200	Montgomery	OH	39113	0.851	0.847	532	547
329		X200	Pickaway	OH	39129	0.851	0.839	494	547
330		X200	Trumbull	OH	39155	0.851	0.835	470	547
331		X200	Dane	WI	55025	0.851	0.869	656	547
332		X200	Marathon	WI	55073	0.851	0.839	495	547
333	South Bs	X300	Blount	AL	1009	0.866	0.834	390	557
334		X300	Colbert	AL	1033	0.866	0.837	412	557
335		X300	Jefferson	AL	1073	0.866	0.857	515	557
336		X300	Lauderdale	AL	1077	0.866	0.840	428	557

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	0.866	0.852	493	557
338		X300	Shelby	AL	1117	0.866	0.883	659	557
339		X300	Jefferson	AR	5069	0.866	0.847	464	557
340		X300	Alachua	FL	12001	0.866	0.867	569	557
341		X300	Brevard	FL	12009	0.866	0.874	608	557
342		X300	Lee	FL	12071	0.866	0.883	655	557
343		X300	Marion	FL	12083	0.866	0.857	518	557
344		X300	Catoosa	GA	13047	0.866	0.852	489	557
345		X300	Dade	GA	13083	0.866	0.837	410	557
346		X300	Dougherty	GA	13095	0.866	0.850	480	557
347		X300	Lee	GA	13177	0.866	0.868	581	557
348		X300	Walker	GA	13295	0.866	0.843	442	557
349		X300	Acadia	LA	22001	0.866	0.823	333	557
350		X300	Ascension	LA	22005	0.866	0.846	459	557
351		X300	East Baton Rouge	LA	22033	0.866	0.859	524	557
352		X300	Lafayette	LA	22055	0.866	0.852	489	557
353		X300	Livingston	LA	22063	0.866	0.852	490	557
354		X300	St. Landry	LA	22097	0.866	0.821	317	557
355		X300	St. Martin	LA	22099	0.866	0.827	352	557
356		X300	West Baton Rouge	LA	22121	0.866	0.843	445	557
357		X300	Chatham	NC	37037	0.866	0.865	561	557
358		X300	Currituck	NC	37053	0.866	0.870	587	557
359		X300	Durham	NC	37063	0.866	0.885	665	557
360		X300	Franklin	NC	37069	0.866	0.853	496	557
361		X300	Johnston	NC	37101	0.866	0.852	492	557
362		X300	Orange	NC	37135	0.866	0.889	690	557
363		X300	Wake	NC	37183	0.866	0.901	750	557
364		X300	Canadian	OK	40017	0.866	0.858	523	557
365		X300	Cleveland	OK	40027	0.866	0.861	538	557
366		X300	Logan	OK	40083	0.866	0.837	408	557
367		X300	McClain	OK	40087	0.866	0.842	439	557
368		X300	Oklahoma	OK	40109	0.866	0.852	488	557
369		X300	Pottawatomie	OK	40125	0.866	0.842	438	557
370		X300	Anderson	SC	45007	0.866	0.847	465	557
371		X300	Cherokee	SC	45021	0.866	0.836	405	557
372		X300	Florence	SC	45041	0.866	0.845	453	557
373		X300	Greenville	SC	45045	0.866	0.866	566	557
374		X300	Pickens	SC	45077	0.866	0.854	500	557
375		X300	Spartanburg	SC	45083	0.866	0.852	492	557
376		X300	Hamilton	TN	47065	0.866	0.858	520	557
377		X300	Marion	TN	47115	0.866	0.840	426	557
378		X300	Bexar	TX	48029	0.866	0.869	576	557
379		X300	Cameron	TX	48061	0.866	0.839	420	557
380		X300	Comal	TX	48091	0.866	0.878	633	557
381		X300	Ector	TX	48135	0.866	0.838	417	557
382		X300	Guadalupe	TX	48187	0.866	0.857	519	557
383		X300	Hardin	TX	48199	0.866	0.851	488	557
384		X300	Jefferson	TX	48245	0.866	0.851	486	557
385		X300	Midland	TX	48329	0.866	0.848	470	557
386		X300	Orange	TX	48361	0.866	0.851	487	557
387		X300	Potter	TX	48375	0.866	0.845	454	557
388		X300	Randall	TX	48381	0.866	0.857	519	557
389		X300	Wilson	TX	48493	0.866	0.842	436	557
390		X300	Charles City	VA	51036	0.866	0.839	422	557
391		X300	Chesterfield	VA	51041	0.866	0.894	713	557
392		X300	Dinwiddie	VA	51053	0.866	0.866	569	557

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	0.866	0.862	547	557
394		X300	Goochland	VA	51075	0.866	0.876	622	557
395		X300	Hanover	VA	51085	0.866	0.892	705	557
396		X300	Henrico	VA	51087	0.866	0.889	685	557
397		X300	Isle of Wight	VA	51093	0.866	0.855	507	557
398		X300	James City	VA	51095	0.866	0.887	676	557
399		X300	Mathews	VA	51115	0.866	0.853	498	557
400		X300	New Kent	VA	51127	0.866	0.870	587	557
401		X300	Powhatan	VA	51145	0.866	0.881	650	557
402		X300	Prince George	VA	51149	0.866	0.877	627	557
403		X300	York	VA	51199	0.866	0.900	745	557
404		X300	Chesapeake City	VA	51550	0.866	0.883	657	557
405		X300	Colonial Heights City	VA	51570	0.866	0.882	640	557
406		X300	Hampton City	VA	51650	0.866	0.878	616	557
407		X300	Hopewell City	VA	51670	0.866	0.859	516	557
408		X300	Newport News City	VA	51700	0.866	0.871	576	557
409		X300	Norfolk City	VA	51710	0.866	0.870	554	557
410		X300	Petersburg City	VA	51730	0.866	0.855	499	557
411		X300	Poquoson City	VA	51735	0.866	0.907	785	557
412		X300	Portsmouth City	VA	51740	0.866	0.867	556	557
413		X300	Richmond City	VA	51760	0.866	0.870	559	557
414		X300	Suffolk City	VA	51800	0.866	0.855	509	557
415		X300	Virginia Beach City	VA	51810	0.866	0.901	747	557
416		X300	Williamsburg City	VA	51830	0.866	0.881	637	557
417	West Bs	X499	Mohave	AZ	4015	0.876	0.857	563	661
418		X499	Yuma	AZ	4027	0.876	0.852	536	661
419		X499	Butte	CA	6007	0.876	0.858	566	661
420		X499	Stanislaus	CA	6099	0.876	0.868	620	661
421		X499	Ada	ID	16001	0.876	0.868	622	661
422		X499	Canyon	ID	16027	0.876	0.849	516	661
423		X499	Clark	NV	32003	0.876	0.889	732	661
424		X499	Nye	NV	32023	0.876	0.853	542	661
425		X499	Utah	VT	49049	0.876	0.865	604	661

* Weighted mean rent by Area

Appendix Table A2. Rent Ratios and Bridged Price Levels

	State	Rent* Census ($) (1)	Rent* Overlap ($) (2)	Ratio Census/Overlap (3)=(1)/(2)	Price Level* Overlap (4)	Bridged Level Census (5) = (3)*(4)
1	Alabama	455	510	0.89	0.86	0.76
2	Alaska	746	752	0.99	1.06	1.05
3	Arizona	615	662	0.93	0.92	0.86
4	Arkansas	465	464	1.00	0.85	0.85
5	California	753	811	0.93	1.19	1.11
6	Colorado	665	720	0.92	1.00	0.92
7	Connecticut	687	776	0.89	1.08	0.95
8	Delaware	610	686	0.89	1.01	0.90
9	District of Columb	646	646	1.00	1.03	1.03
10	Florida	646	656	0.99	0.96	0.95
11	Georgia	548	723	0.76	0.94	0.71
12	Hawaii	787	846	0.93	1.38	1.28
13	Idaho	497	594	0.84	0.86	0.72
14	Illinois	585	662	0.88	1.03	0.91
15	Indiana	530	531	1.00	0.94	0.93
16	Iowa	484				
17	Kansas	490	617	0.80	0.87	0.69
18	Kentucky	454	515	0.88	0.87	0.77
19	Louisiana	477	479	1.00	0.85	0.85
20	Maine	504	677	0.74	1.09	0.81
21	Maryland	668	700	0.95	1.00	0.96
22	Massachusetts	696	738	0.94	1.10	1.03
23	Michigan	540	588	0.92	0.93	0.85
24	Minnesota	543	655	0.83	0.99	0.82
25	Mississippi	460	412	1.11	0.79	0.88
26	Missouri	468	540	0.87	0.86	0.75
27	Montana	458				
28	Nebraska	499	515	0.97	0.84	0.82
29	Nevada	704	729	0.97	0.89	0.86
30	New Hampshire	625	698	0.90	1.09	0.98
31	New Jersey	747	762	0.98	1.12	1.09
32	New Mexico	521				
33	New York	666	743	0.90	1.24	1.11
34	North Carolina	563	690	0.82	0.89	0.73
35	North Dakota	417				
36	Ohio	505	545	0.93	0.87	0.81
37	Oklahoma	465	494	0.94	0.85	0.80
38	Oregon	601	659	0.91	0.97	0.89
39	Pennsylvania	514	573	0.90	0.94	0.84
40	Rhode Island	560				
41	South Carolina	540	510	1.06	0.86	0.91
42	South Dakota	433	385	1.12	0.79	0.89
43	Tennessee	527	497	1.06	0.85	0.90
44	Texas	571	611	0.93	0.94	0.88
45	Utah	603	604	1.00	0.86	0.86
46	Vermont	553	657	0.84	0.94	0.79
47	Virginia	619	741	0.84	0.96	0.81
48	Washington	640	727	0.88	1.04	0.92
49	West Virginia	407	510	0.80	0.98	0.78
50	Wisconsin	523	591	0.88	0.90	0.80
51	Wyoming	446				
52	Puerto Rico	318				

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

Appendix Table A3. SPIs using different models and weight matrices

	State	Freq		Rent	PL 38	Plevel	SERR	SLAG	OLS				SERR				
						Input				N1	N3	N5	N7	N9	N11	DUMS	UNCON
				(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
1	Alabama	67		0.81	0.90	0.87	0.92	0.90	0.90	0.91	0.92	0.92	0.92	0.92	0.92	0.89	0.89
2	Alaska	27		1.32	1.09	1.16	1.10	1.13	1.13	1.12	1.11	1.10	1.10	1.10	1.11	1.14	1.14
3	Arizona	15		1.11	0.96	0.99	0.98	1.00	1.00	0.99	0.99	0.98	0.98	0.98	0.99	1.00	1.01
4	Arkansas	75		0.80	0.90	0.93	0.93	0.90	0.90	0.92	0.92	0.93	0.93	0.93	0.92	0.89	0.89
5	California	58		1.36	1.23	1.29	1.22	1.25	1.25	1.23	1.22	1.22	1.22	1.22	1.22	1.23	1.24
6	Colorado	63		1.20	1.03	1.07	1.05	1.07	1.07	1.06	1.05	1.05	1.05	1.05	1.05	1.07	1.08
7	Connecticut	8		1.24	1.14	1.07	1.04	1.06	1.06	1.05	1.04	1.04	1.04	1.04	1.04	1.04	1.04
8	Delaware	3		1.14	1.04	1.07	1.05	1.06	1.06	1.05	1.05	1.05	1.05	1.05	1.05	1.03	1.03
9	District of Columbia	1		1.14	1.09	1.13	1.10	1.12	1.12	1.11	1.10	1.10	1.10	1.11	1.11	1.10	1.11
10	Florida	67		1.14	0.99	1.05	1.03	1.04	1.04	1.03	1.03	1.02	1.03	1.03	1.03	1.00	1.00
11	Georgia	159		1.08	0.97	0.92	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.96	0.96
12	Hawaii	5		1.44	1.43	1.49	1.35	1.39	1.39	1.37	1.36	1.35	1.36	1.36	1.36	1.37	1.38
13	Idaho	44		0.90	0.91	0.85	0.93	0.92	0.92	0.93	0.93	0.93	0.93	0.93	0.93	0.98	0.98
14	Illinois	102		1.07	1.07	1.10	1.06	1.07	1.07	1.06	1.06	1.06	1.06	1.06	1.06	1.05	1.05
15	Indiana	92		0.93	0.99	1.03	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.95	0.93
16	Iowa	99		0.83		0.83	0.94	0.91	0.91	0.93	0.93	0.94	0.93	0.93	0.93	0.91	0.88
17	Kansas	105		0.88	0.89	0.81	0.93	0.92	0.92	0.92	0.93	0.93	0.93	0.93	0.93	0.91	0.89
18	Kentucky	120		0.79	0.90	0.85	0.92	0.91	0.91	0.92	0.92	0.92	0.92	0.92	0.92	0.89	0.90
19	Louisiana	64		0.83	0.90	0.93	0.93	0.92	0.92	0.93	0.93	0.93	0.93	0.93	0.93	0.90	0.90
20	Maine	16		0.89	1.15	0.91	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	1.00	1.01
21	Maryland	24		1.21	1.04	1.10	1.07	1.08	1.08	1.07	1.07	1.07	1.07	1.07	1.07	1.06	1.06
22	Massachusetts	14		1.26	1.13	1.19	1.15	1.17	1.17	1.16	1.15	1.15	1.15	1.15	1.15	1.15	1.16
23	Michigan	83		0.98	0.96	0.99	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.96	0.95
24	Minnesota	87		1.00	1.02	1.02	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.00	0.99
25	Mississippi	82		0.79	0.82	0.97	0.93	0.89	0.89	0.92	0.92	0.93	0.92	0.92	0.92	0.89	0.89
26	Missouri	115		0.85	0.89	0.89	0.92	0.91	0.91	0.91	0.92	0.92	0.92	0.92	0.92	0.91	0.89
27	Montana	56		0.80		0.90	0.93	0.91	0.91	0.92	0.92	0.93	0.93	0.92	0.92	1.01	1.01
28	Nebraska	93		0.86	0.88	0.90	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.91	0.89
29	Nevada	17		1.26	0.91	0.97	0.97	0.99	0.99	0.98	0.97	0.97	0.97	0.97	0.97	0.99	0.99
30	New Hampshire	10		1.14	1.15	1.16	1.11	1.12	1.12	1.12	1.11	1.11	1.11	1.11	1.11	1.12	1.13
31	New Jersey	21		1.35	1.15	1.23	1.20	1.22	1.22	1.20	1.20	1.20	1.20	1.20	1.20	1.19	1.20
32	New Mexico	33		0.91		0.90	0.96	0.95	0.95	0.96	0.96	0.96	0.96	0.96	0.96	1.04	1.04
33	New York	62		1.24	1.28	1.33	1.25	1.27	1.27	1.26	1.25	1.25	1.25	1.25	1.25	1.26	1.27
34	North Carolina	100		0.99	0.90	0.83	0.97	0.96	0.96	0.97	0.97	0.97	0.97	0.97	0.97	0.93	0.93
35	North Dakota	53		0.71		0.83	0.90	0.89	0.89	0.89	0.90	0.90	0.90	0.90	0.90	0.89	0.85
36	Ohio	88		0.92	0.90	0.94	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.92	0.92
37	Oklahoma	77		0.81	0.90	0.90	0.92	0.91	0.91	0.91	0.92	0.92	0.92	0.92	0.92	0.89	0.90
38	Oregon	36		1.09	1.01	1.03	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.04	1.05

Appendix Table A3. SPIs using different models and weight matrices

	State	Freq		Rent	PL 38	Plevel	SERR	SLAG	OLS				SERR				
						Input				N1	N3	N5	N7	N9	N11	DUMS	UNCON
				(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
39	Pennsylvania	67		0.95	0.97	0.99	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	1.00	1.01
40	Rhode Island	5		0.99		1.04	0.98	1.02	1.02	0.99	0.99	0.98	0.98	0.98	0.98	1.03	1.05
41	South Carolina	46		0.92	0.90	0.98	0.95	0.94	0.94	0.95	0.95	0.95	0.95	0.95	0.95	0.92	0.92
42	South Dakota	66		0.74	0.82	0.97	0.91	0.89	0.89	0.90	0.91	0.91	0.91	0.91	0.91	0.89	0.85
43	Tennessee	95		0.91	0.88	0.98	0.96	0.95	0.95	0.95	0.96	0.96	0.95	0.95	0.95	0.92	0.92
44	Texas	254		1.02	0.98	1.01	0.99	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.97	0.98
45	Utah	29		1.06	0.91	0.95	0.99	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99	1.05	1.05
46	Vermont	14		1.00	0.95	0.92	0.98	0.97	0.97	0.98	0.98	0.98	0.98	0.98	0.98	1.01	1.02
47	Virginia	135		1.16	0.98	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	0.99	1.00
48	Washington	39		1.18	1.08	1.11	1.07	1.09	1.09	1.08	1.07	1.07	1.07	1.07	1.07	1.09	1.10
49	West Virginia	55		0.72	1.09	0.88	0.91	0.87	0.87	0.90	0.91	0.91	0.91	0.91	0.91	0.88	0.88
50	Wisconsin	72		0.95	0.93	0.94	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.96	0.96	0.94	0.93
51	Wyoming	23		0.79		0.90	0.92	0.90	0.90	0.91	0.92	0.92	0.92	0.92	0.92	1.01	1.01
52	Puerto Rico	78		0.55		0.89	0.87	0.82	0.82	0.85	0.86	0.87	0.87	0.87	0.87	0.84	0.86
	sum	3219	mean	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	max	254		1.44	1.43	1.49	1.35	1.39	1.39	1.37	1.36	1.35	1.36	1.36	1.36	1.37	1.38
	min	1		0.55	0.82	0.81	0.87	0.82	0.82	0.85	0.86	0.87	0.87	0.87	0.87	0.84	0.85
	range	253		0.89	0.60	0.68	0.49	0.57	0.57	0.52	0.50	0.49	0.49	0.49	0.49	0.53	0.53
	stdev	46.4		0.20	0.13	0.14	0.10	0.11	0.11	0.10	0.10	0.10	0.10	0.10	0.10	0.11	0.11
	cv	1.4%		20%	13%	14%	10%	11%	11%	10%	10%	10%	10%	10%	10%	11%	11%

Appendix Table A4. SPIs for Total Personal Income by State

State Name		Personal Income 2000 (thousands of dollars)			Rank		Difference
		Nominal	**Adjusted**	**SPI**	**Nominal**	**Adjusted**	**(Nom-Adj)**
California	CA	1103841912	933811835	1.182	1	1	0
Texas	TX	593139424	623963379	0.951	3	2	1
New York	NY	663005163	552255301	1.201	2	3	-1
Florida	FL	457539355	466884903	0.980	4	4	0
Illinois	IL	400373280	392679343	1.020	5	5	0
Pennsylvania	PA	364837901	387407410	0.942	6	6	0
Ohio	OH	320538414	359689169	0.891	8	7	1
Michigan	MI	294226742	313691244	0.938	9	8	1
New Jersey	NJ	323553551	281906976	1.148	7	9	-2
Georgia	GA	230355758	246014993	0.936	11	10	1
North Carolina	NC	218668022	237315466	0.921	13	11	2
Virginia	VA	220845445	225260122	0.980	12	12	0
Massachusetts	MA	240208628	217634935	1.104	10	13	-3
Washington	WA	187853404	181912374	1.033	14	14	0
Indiana	IN	165285059	178422009	0.926	16	15	1
Maryland	MD	181957207	176532750	1.031	15	16	-1
Missouri	MO	152722183	173616320	0.880	19	17	2
Wisconsin	WI	153547595	168068593	0.914	18	18	0
Minnesota	MN	157963755	163548860	0.966	17	19	-2
Tennessee	TN	148833423	163152647	0.912	20	20	0
Colorado	CO	144393687	142739771	1.012	21	21	0
Connecticut	CT	141570257	141185761	1.003	22	22	0
Arizona	AZ	132557859	140618690	0.943	23	23	0
Alabama	AL	105806693	120466056	0.878	24	24	0
Louisiana	LA	103150742	116193250	0.888	25	25	0
Kentucky	KY	98845348	112233741	0.881	26	26	0
South Carolina	SC	98270171	108509074	0.906	27	27	0
Oregon	OR	96401727	99035404	0.973	28	28	0
Oklahoma	OK	84310444	95960303	0.879	29	29	0
Iowa	IA	77762743	87406131	0.890	30	30	0
Kansas	KS	74569739	83952828	0.888	31	31	0
Mississippi	MS	59836915	67723562	0.884	33	32	1
Arkansas	AR	58726196	66358221	0.885	34	33	1
Nevada	NV	61427864	65807525	0.933	32	34	-2
Utah	UT	53561211	56379827	0.950	35	35	0
Nebraska	NE	47328771	52898021	0.895	36	36	0
West Virginia	WV	39582040	45548530	0.869	39	37	2
New Mexico	NM	40318443	43819399	0.920	38	38	0
New Hampshire	NH	41429037	38798247	1.068	37	39	-2
Maine	ME	33173133	36248456	0.915	41	40	1
Idaho	ID	31289782	35058898	0.892	42	41	1
Rhode Island	RI	30696701	32341281	0.949	43	42	1
Hawaii	HI	34450883	26488855	1.301	40	43	-3
Delaware	DE	24276962	24263704	1.001	44	44	0
Montana	MT	20716220	23464664	0.883	46	45	1
South Dakota	SD	19437807	22401558	0.868	47	46	1
District of Columbia	DC	23102223	21871262	1.056	45	47	-2
North Dakota	ND	16096687	18781528	0.857	50	48	2
Vermont	VT	16883009	18035324	0.936	49	49	0
Alaska	AK	18741427	17830661	1.051	48	50	-2
Wyoming	WY	14063058	15884839	0.885	51	51	0
United States		**8422074000**	**8422074000**	**1**			