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

Bettina H. Aten

This paper develops exploratory estimates of the spatial price differences for consumption goods and services at the U.S. state level. The estimates are built up 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 (place-to-place) 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 eover a fixed set of geographical areas, so that SPIs can only be directly estimated at 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

^{*} These are preliminary results, and should not be quoted without the author's permission. 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

lines, while others refer to single counties¹. 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.

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 nonmetropolitan 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

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.

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 counties².

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

 $^{^{2}}$ 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.

2003 results from Aten (2006) have been moved back to 2000 using the CPI-Urban price change for each area³. *Table 1* shows these SPIs and also the corresponding average rent for each area from the Census data.

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	
	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	

Table 1. Observed Price Levels and Rents by 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
	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 counties⁴, 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 make-up to control for geographic price differences⁵. 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

$$(i) \ln P_{i} = \sum_{j} \beta_{j} X_{j} + \varepsilon_{i}; \text{ (NonS)}$$

$$\varepsilon_{i} \approx N(0, \sigma^{2})$$

$$(ii) \ln P_{i} = \rho W \ln P_{i} + \sum_{j} \beta_{j} X_{j} + \varepsilon_{i}; \text{ (SLag)}$$

$$\varepsilon_{i} \approx N(0, \sigma^{2})$$

$$(iii) \ln P_{i} = \sum_{j} \beta_{j} X_{j} + \varepsilon_{i} \text{ (SErr)}$$

$$\varepsilon_{i} = \lambda W \varepsilon_{i} + \mu_{i};$$

$$\mu_{i} \approx N(0, \sigma^{2})$$

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

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

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.

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 autoregressive 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 otherwise⁶. 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 triangulation⁷, 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, respectively⁸. The use of spatial weight matrices

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: $(I-\lambda W)\ln P = (I-\lambda W)\ln P$

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 population⁹. 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.

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

 $[\]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- ρW) and (I- λW) 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).

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

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

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

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

 $\overline{PL}_{census} = \overline{PL}_{overlap} * Ratio$ where $\overline{PL}_{overlap} = \exp(\sum_{i \in overlap} w_i \ln PL_i / \sum_{i \in overlap} w_i)$

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 Rico¹⁰, 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.

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.

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.

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	-	С	С						
•									
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 * sig	nificant at	5% level						

Table 2. First Stage Regressions Base Models

** 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 Rbar² is a 'pseudo' R² 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 model¹¹. 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

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

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.



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 Region¹² 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.

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

Table 3. Rent Ratios and Bridged Price Levels

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)=(2)/(1)	Price Level* overlap (4)	Bridged Level census (5)=(3)*(4)
	5. South	578	686	0.84	0.96	0.81
	Atlantic 6. East South Central	482	506	0.95	0.86	0.81
	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-		449	460	0.98	0.82	0.80
Metro						
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.

		,, ,			
(n=3219)	Mean	CV	Range	Minimum	Maximum
Input Price levels	0.849	12%	0.71	0.69	1.40
-				(non-urban areas, KS)	(New York, NY)
Rent (\$)	\$442	30%	\$1,119	\$100	\$1,219
				(Kalawao ¹³ , HI)	(Santa Clara, CA)
Density*	51	909%	19,720	0.002	19,720
			,	(Yukon-Koyukuk, AK)	(New York, NY)
	1 / 1	. 1	.1 .	1 1 1 7 7 1 \	

Table 4. Input Data Summary

* 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.

rable 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	-	С	С					
Rbar ²	0.55	0.57	0.68					
MSE	135	100	95					

Table 5. Second Stage Regressions

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 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.

(n=3219)	Aean	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)
-		11.770 1.71		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)

Table 6. Summary of Predicted Price Levels

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 observations¹⁴, but this was not done here.

The county price level predictions from the SErr model are used in estimating the state price levels, shown graphically in *Figure 3*. The horizontal bars show the bridged input price levels while the individual points are the predicted levels using the SErr model coefficients. These have also been averaged within states, or there would be too many points (3219) to show on the graph.

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



Figure 3. Stage 2 Regression Inputs and Price Levels

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 7th highest rent level (1.24), a result that would be consistent with rent controls in effect.

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

Rank	By SPI (predicted)	SPI	Rank	By Rent (actual)	Rent (\$)	Rent Level	
3	California	1.222	3	New Jersey	762	1.34	
4	New Jersey	1.196	4	Alaska	746	1.31	
5	Massachusetts	1.151	5	Massachusetts	715	1.26	
6	New Hampshire	1.113	6	Nevada	711	1.25	
7	Alaska	1.104	7	New York	701	1.24	
8	District of Columbia	1.104	8	Connecticut	701	1.23	
9	Washington	1.073	9	Maryland	686	1.21	
10	Maryland	1.066	10	Colorado	680	1.20	
11	Illinois	1.061	11	Washington	667	1.17	
12	Colorado	1.050	12	Virginia	655	1.15	
13	Delaware	1.048	13	New Hampshire	647	1.14	
14	Connecticut	1.042	14	District of Columbia	646	1.14	
15	Florida	1.025	15	Florida	646	1.14	
16	Oregon	1.016	16	Delaware	646	1.14	
17	Minnesota	1.008	17	Arizona	626	1.10	
18	Virginia	1.007	18	Oregon	617	1.09	
19	Texas	0.994	19	Georgia	609	1.07	
20	Utah	0.988	20	Illinois	606	1.07	
21	Arizona	0.984	21	Utah	602	1.06	
22	Rhode Island	0.984	22	Texas	579	1.02	
23	Pennsylvania	0.980	23	Vermont	568	1.00	
24	Vermont	0.978	24	Minnesota	564	0.99	
25	Michigan	0.977	25	Rhode Island	560	0.98	
26	Georgia	0.976	26	North Carolina	559	0.98	
27	Nevada	0.972	27	Michigan	553	0.97	
28	Indiana	0.970	28	Wisconsin	539	0.95	
29	North Carolina	0.966	29	Pennsylvania	537	0.94	
30	New Mexico	0.959	30	Indiana	525	0.92	
31	Tennessee	0.955	31	South Carolina	521	0.92	
32	Wisconsin	0.955	32	Ohio	520	0.9	
33	Maine	0.954	33	New Mexico	513	0.90	
34	South Carolina	0.951	34	Tennessee	513	0.90	
35	Iowa	0.935	35	Idaho	511	0.90	
36	Nebraska	0.935	36	Maine	506	0.89	
37	Idaho	0.931	37	Kansas	496	0.87	
38	Ohio	0.931	38	Nebraska	487	0.86	
39	Louisiana	0.930	39	Missouri	482	0.85	
40	Kansas	0.929	40	Louisiana	470	0.83	
41	Arkansas	0.926	41	Iowa	468	0.82	
42	Montana	0.926	42	Oklahoma	459	0.81	
43	Mississippi	0.925	43	Alabama	456	0.80	
44	Kentucky	0.924	44	Arkansas	452	0.79	
45	Wyoming	0.924	45	Montana	450	0.79	
46	Alabama	0.920	46	Kentucky	448	0.79	
47	Oklahoma	0.919	47	Mississippi	446	0.78	
48	Missouri	0.917	48	Wyoming	446	0.78	
49	West Virginia	0.911	49	South Dakota	418	0.73	
50	South Dakota	0.908	50	West Virginia	406	0.73	

Rank	By SPI	SPI	Rank	v	Rent (\$)	Rent
	(predicted)			(actual)		Level
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
	ČV	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 as a whole. 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) model¹⁵.

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*).

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.



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 9th observation is the nearest neighbor to the first observation). However, W is not necessarily symmetric, as the nearest neighbor to the 9th 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), fifthorder (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 rents¹⁶, 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

¹⁶ Rents in the BLS include both Rents and Owner Equivalent Rents (for a more detailed description, see Aten [2006])

average were New Jersey, Massachusetts, New Hampshire, Alaska, and the District of Columbia. States with the lowest price level index were Puerto Rico¹⁷ 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%.

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 Bureau¹⁸. Future applications of the results should feed back into checks on the robustness of the methods developed in this paper. For example, one planned application is to adjust nominal personal income at the metropolitan or the state level to reflect differences in consumption prices. These adjusted incomes can then be compared to results obtained using unadjusted personal incomes.

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.

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.

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

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Obs /	Area	Area	County	State	County	Input	Predicted	Actual	Wtd Mean	
	Name	Code	Name		Fips	Plevel	Plevel	Rent (\$)	Rent* (\$)	
1 F	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	
	Boston	A103	York	ME	23031	1.116	1.088	677	755	
16		A103	Bristol	MD	25005	1.116	1.054	525	755	
17		A103	Essex	MD	25009	1.116	1.089	672	755	
18		A103	Middlesex	MD	25017	1.116	1.139	880	755	
19		A103	Norfolk	MD	25021	1.116	1.141	890	755	
20		A103	Plymouth	MD	25023	1.116	1.086	666	755	
21		A103	Suffolk	MD	25025	1.116	1.151	832	755	
22		A103	Worcester	MD	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	
	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	
	NY City	A109	Bronx	NY	36005	1.278	1.227	636	750	
34		A109	Kings New York	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	750 750	
37	NV ouburba	A109	Richmond	NY	36085	1.278	1.202	773	750	
	NY suburbs	A110	Fairfield	CT CT	9001	1.286	1.357	1157	893 803	
39 40		A110	Litchfield		9005	1.286	1.241	742	893 803	
40		A110	New Haven	CT	9009 36027	1.286	1.252	779	893 803	
41 42		A110	Dutchess Nassau	NY NY	36027 36059	1.286 1.286	1.235 1.312	717 991	893 893	
		A110						725	893 893	
43		A110	Orange	NY	36071 36070	1.286	1.237			
44		A110	Putnam Rockland	NY	36079 36087	1.286	1.293	932	893 803	
45 46		A110 A110	Rockland Suffolk	NY NY	36087 36103	1.286 1.286	1.289 1.305	912 971	893 893	
40 47		A110 A110	Westchester	NY	36103	1.286	1.305	869	893	
	NJ suburbs	A110 A111	Bergen	NY	36119	1.286	1.278	901	779	
40 1	NU SUDUIDS	A111 A111	Essex	NJ	34003 34013	1.140	1.165	901 681	779 779	
49 50		A111	Hudson	NJ	34013 34017	1.140	1.141	712	779	
50 51		A111 A111	Hunterdon	NJ	34017 34019	1.140	1.141	897	779 779	
52		A111 A111	Mercer	NJ	34019 34021	1.140	1.160	697 748	779	
52 53		A111 A111	Middlesex	NJ	34021	1.140	1.125	875	779	
53 54		A111 A111	Monmouth	NJ	34023 34025	1.140	1.137	784	779	
		A111 A111	Morris	NJ	34025 34027	1.140	1.133	784 920	779	
55 56		A111 A111	Ocean	NJ	34027 34029	1.140	1.160	920 824	779	
50			Uccall	UNI	54028	1.140	1.142	024	119	

Obs Area	Area	County	State	County	Input	Predicted	Actual	Wtd Mean
Name			Olule	Fips	Plevel	Plevel	Rent (\$)	Rent* (\$)
					-	-		(1)
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 Chica	-	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 Detro	it 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. Lo	uis 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 Cleve		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 Minne		Anoka	MN	27003	0.993	0.000	657	
107 101111	A211 A211	Carver	MN	27003	0.993	0.992	656	
108	A211 A211	Chisago	MN	27019	0.993	0.991	515	655
109	A211 A211	Dakota	MN	27025	0.993	1.013	754	655
111 112	A211	Hennepin	MN	27053	0.993	0.996	668 500	655 655
112	A211	Isanti	MN	27059	0.993	0.960	509	655

NameCodeNameFipsPlevel113A211RamseyMN271230.993114A211ScottMN271390.993115A211SherburneMN271410.993116A211WashingtonMN271630.993117A211WrightMN271710.993	Predicted Plevel 0.986 0.994 0.973 1.001 0.963 0.966	Actual Rent (\$) 615 667 568 701	Wtd Mean Rent* (\$) 655 655
113A211RamseyMN271230.993114A211ScottMN271390.993115A211SherburneMN271410.993116A211WashingtonMN271630.993117A211WrightMN271710.993	0.994 0.973 1.001 0.963	615 667 568	655
114A211ScottMN271390.993115A211SherburneMN271410.993116A211WashingtonMN271630.993117A211WrightMN271710.993	0.994 0.973 1.001 0.963	667 568	
115A211SherburneMN271410.993116A211WashingtonMN271630.993117A211WrightMN271710.993	0.973 1.001 0.963	568	655
116 A211 Washington MN 27163 0.993 117 A211 Wright MN 27171 0.993	1.001 0.963		
117 A211 Wright MN 27171 0.993	0.963	701	655
5			655
	0.966	521	655
118 A211 Pierce WI 55093 0.993		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	607 515	521
128 A213 Campbell KY 21037 0.874 129 A213 Gallatin KY 21077 0.874	0.872	515 416	521 521
	0.853	416 516	
130 A213 Grant KY 21081 0.874 131 A213 Kenton KY 21117 0.874	0.871 0.873	516	521 521
131 A213 Kenton KY 21117 0.874 132 A213 Pendleton KY 21191 0.874	0.873	520 416	521 521
132 A213 Pendleton KY 21191 0.874 133 A213 Brown OH 39015 0.874	0.853	416	521 521
133 A213 Brown OH 39015 0.874 134 A213 Butler OH 39017 0.874	0.858	442 567	521 521
134 A213 Buller OH 39017 0.874 135 A213 Clermont OH 39025 0.874	0.882	558	521 521
136 A213 Clemint OH 39025 0.874 136 A213 Hamilton OH 39061 0.874	0.871	498	521 521
137 A213 Warren OH 39061 0.874	0.888	498 605	521 521
137 A213 Walteri On 39103 0.674 138 Kansas City A214 Johnson KS 20091 0.860	0.885	716	576
139 A214 Johnson KS 20091 0.000 139 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

Obs Area	Area	County	State	County	Input	Predicted	Actual	Wtd Mean
Name	Code	Name		Fips	Plevel	Plevel	Rent (\$)	Rent* (\$)
100								
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 WV	51685	1.058	1.078	931	806 806
173 174	A312 A312	Berkeley Jefferson	WV	54003 54037	1.058 1.058	0.982 0.984	507 517	806 806
175 Baltimore	A312 A313	Anne Arundel	MD	24003	0.966	0.904	817	629
176 20101010	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	ТΧ	48085	0.971	1.003	823	659
183	A316	Dallas	ТΧ	48113	0.971	0.971	656	659
184	A316	Denton	ТΧ	48121	0.971	0.985	739	659
185	A316	Ellis	ТΧ	48139	0.971	0.956	603	659
186	A316	Henderson	ТΧ	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 TX	48397	0.971	0.986	747	659
193 194 Houston	A316	Tarrant Brazoria	TX TX	48439 48039	0.971	0.963	629 546	659
195	A318 A318	Chambers	TX	48039 48071	0.951 0.951	0.938 0.928	546 498	600 600
195	A318 A318	Fort Bend	TX	48071	0.951	0.928	490 748	600
197	A318	Galveston	TX	48167	0.951	0.947	589	600
198	A318	Harris	ТХ	48201	0.951	0.951	600	600
199	A318	Liberty	ТХ	48291	0.951	0.918	449	600
200	A318	Montgomery	ТХ	48339	0.951	0.953	623	600
201	A318	Waller	ТΧ	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	749 740
214	A319	Gwinnett	GA	13135	0.944	0.959	834	749 740
215 216	A319 A319	Henry Newton	GA GA	13151 13217	0.944 0.944	0.941 0.910	751 594	749 749
216	A319 A319	Paulding	GA GA	13217 13223	0.944	0.910	594 660	749 749
217	A319 A319	Pickens	GA GA	13223	0.944	0.923	480	749 749
218	A319 A319	Rockdale	GA GA	13227	0.944	0.888	480	749 749
219	A319 A319	Spalding	GA	13247	0.944	0.947	528	749
220	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
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Obs Area	Area	County	State	County	Input	Predicted	Actual	Wtd Mean
Name	Code	Name		Fips	Plevel	Plevel	Rent (\$)	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		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 53035	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
251 252	A425 A425	Columbia	OR OR	41009	0.977 0.977	0.964 0.958	608 578	665 665
252	A425 A425	Marion	OR	41047 41051	0.977	0.956	576 642	665
		Multnomah						
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 HI	53011	0.977	0.983	695	665
258 Honolulu	A426	Honolulu		15003	1.379	1.379	846	846
259 Anchorage	A427	Anchorage Municipal		2020	1.059	1.059	752	752
260 Phoenix	A429	Maricopa Binal	AZ	4013	0.929	0.930	677 514	672 672
261	A429	Pinal	AZ	4021	0.929	0.898	514	672
262 Denver	A433	Adams	CO CO	8001 8005	1.001	0.994	706 747	720 720
263	A433	Arapahoe	CO CO		1.001	1.003		
264	A433	Boulder		8013	1.001	1.028	861	720
265	A433	Denver	CO CO	8031 8035	1.001	0.989	652 1072	720 720
266 267	A433 A433	Douglas Jefferson	co	8035 8059	1.001 1.001	1.075 1.009	1072 772	720 720
267	A433 A433	Weld	co	8059 8123	1.001	0.966	572	720 720
269 MW Cs	D200	Jefferson	IL	17081	0.797	0.966	400	408
209 MW CS 270	D200 D200	Allen	i∟ KS	20001	0.797	0.795	400 353	408 408
270	D200 D200	Neosho	KS	20001	0.797	0.787	353	408 408
271 272	D200 D200	Rice	MN	20133	0.797	0.787	515	408 408
272 273	D200 D200	Brookings	SD	46011	0.797	0.815	389	408
273	D200 D200	Lake	SD SD	46011 46079	0.797		389 372	408 408
			SD SD			0.790		
275	D200	Moody	SD FL	46101	0.797	0.792	379	408
276 South Cs 277	D300	DeSoto	FL	12027	0.796	0.801	457	423
	D300	Hardee		12049 13031	0.796	0.799	444	423
278	D300	Bulloch	GA	13031	0.796	0.801	452	423
279 280	D300 D300	Burke	GA	13033	0.796	0.779	324	423
	UJUU	Jenkins	GA	13165	0.796	0.781	335	423

Obs Area	Area	County	State	County	Input	Predicted	Actual	Wtd Mean	
Name	Code	Name		Fips	Plevel	Plevel	Rent (\$)	Rent* (\$)	
	_	_						-	
281	D300	Screven	GA	13251	0.796	0.779	323		
282	D300	Pearl River	MS	28109	0.796	0.794	412		
283	D300	Hamblen	TN	47063	0.796	0.795	418		
284	D300	Jefferson	TN	47089	0.796	0.797	429		
285 West Cs	D400	Deschutes	OR	41017	0.879	0.890	641		
286	D400	Whitman	WA	53075	0.879	0.862	492		
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		
290	X100	Tolland	CT	9013	0.920	0.943	670		
291	X100	Windham	СТ	9015	0.920	0.922	566		
292	X100	Franklin	MA	25011	0.920	0.952	718		
293	X100	Hampden	MA	25013	0.920	0.915	531	551	
294	X100	Hampshire	MA	25015	0.920	0.939	653		
295	X100	Cayuga	NY	36011	0.920	0.907	489		
296	X100	Erie	NY	36029	0.920	0.913	520		
297	X100	Madison	NY	36053	0.920	0.910	505		
298	X100	Niagara	NY	36063	0.920	0.905	481		
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		
302	X100	Cambria	PA	42021	0.920	0.881	357		
303	X100	Mercer	PA	42085	0.920	0.899	448		
304	X100	Somerset	PA	42111	0.920	0.884	371	551	
305	X100	Chittenden	VT	50007	0.920	0.943	674		
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		
309	X200	Elkhart	IN	18039	0.851	0.848	542		
310	X200	Posey	IN	18129	0.851	0.827	426		
311	X200	Vanderburgh	IN	18163	0.851	0.834	459		
312	X200	Warrick	IN	18173	0.851	0.837	482		
313	X200	Henderson	KY	21101	0.851	0.825	416		
314	X200	Bay	MI	26017	0.851	0.829	436		
315	X200	Midland	MI	26111	0.851	0.841	505		
316	X200	Saginaw	MI	26145	0.851	0.838	485		
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		
321	X200	Fairfield	OH	39045	0.851	0.850	552		
322	X200	Franklin	OH	39049	0.851	0.861	595		
323	X200	Greene	OH	39057	0.851	0.859	600		
324	X200	Licking	OH	39089	0.851	0.842	510		
325	X200	Madison	OH	39097	0.851	0.844	520		
326	X200	Mahoning	OH	39099	0.851	0.833	458		
327	X200	Miami	OH	39109	0.851	0.846	529		
328	X200	Montgomery	OH	39113	0.851	0.847	532		
329	X200	Pickaway	OH	39129	0.851	0.839	494		
330	X200	Trumbull	OH	39155	0.851	0.835	470	547	
331	X200	Dane	WI	55025	0.851	0.869	656		
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		
336	X300	Lauderdale	AL	1077	0.866	0.840	428		

Obs Area	Area	County	State	County	Input	Predicted	Actual	Wtd Mean
Name	Code	Name		Fips	Plevel	Plevel	Rent (\$)	Rent* (\$)
337	X300	St. Clair	AL	1115	0.866	0.852	493	557
338	X300 X300	Shelby	AL	1115	0.866	0.883	493 659	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	12001	0.866	0.874	608	557
342	X300	Lee	FL	12000	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
371 372	X300 X300	Cherokee	SC SC	45021	0.866	0.836	405	557 557
372	X300 X300	Florence Greenville	SC	45041 45045	0.866 0.866	0.845 0.866	453 566	557 557
				45045	0.866			
374 375	X300 X300	Pickens Spartanburg	SC SC	45083	0.866	0.854 0.852	500 492	557 557
376	X300 X300	Hamilton	TN	47065	0.866	0.858	492 520	557
377	X300 X300	Marion	TN	47005	0.866	0.830	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	тх	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	ТΧ	48245	0.866	0.851	486	557
385	X300	Midland	ТΧ	48329	0.866	0.848	470	557
386	X300	Orange	ТΧ	48361	0.866	0.851	487	557
387	X300	Potter	ТΧ	48375	0.866	0.845	454	557
388	X300	Randall	ТΧ	48381	0.866	0.857	519	557
389	X300	Wilson	ТΧ	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
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Obs	Area	Area	County	State	County	Input	Predicted	Actual	Wtd Mean
	Name	Code	Name		Fips	Plevel	Plevel	Rent (\$)	Rent* (\$)
393		X300	Gloucester	VA	51073	0.866	0.862	547	557
393 394		X300	Goochland	VA VA	51075	0.866	0.876	622	557
394 395		X300 X300	Hanover	VA VA	51075	0.866	0.876	705	557 557
395 396		X300 X300					0.892		557 557
396 397		X300	Henrico	VA VA	51087 51093	0.866 0.866	0.855	685 507	557 557
			Isle of Wight						
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*	Rent*	Ratio	Price	Bridged
Clato	Census	Overlap	Census/Overlap	Level*	Level
	(\$)	(\$)	e en euero renap	Overlap	Census
	(1)	(2)	(3)=(1)/(2)	(4)	$(5) = (3)^*(4)$
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	740	0.00	4.04	
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 36 Ohio	417	EAE	0.02	0.07	0.04
	505	545	0.93	0.87	0.81
37 Oklahoma	465 601	494 659	0.94 0.91	0.85 0.97	0.80 0.89
38 Oregon	514	573		0.97	0.89
39 Pennsylvania 40 Rhode Island		575	0.90	0.94	0.04
40 Rhode Island 41 South Carolina	560 540	510	1.06	0.86	0.91
41 South Carolina 42 South Dakota	540 433	385	1.12	0.86	0.91
43 Tennessee	433 527	365 497	1.06	0.79	0.89
43 Termessee 44 Texas	527 571	497 611	0.93	0.85	0.90
45 Utah	603	604	1.00	0.94	0.86
46 Vermont	553	657	0.84	0.80	0.80
47 Virginia	619	741	0.84	0.94	0.81
48 Washington	640	741	0.88	1.04	0.92
49 West Virginia	407	510	0.80	0.98	0.32
50 Wisconsin	523	591	0.88	0.90	0.80
51 Wyoming	446	001	0.00	0.00	0.00
52 Puerto Rico	318				
	010				

* 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		0.98	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	1.07	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	1.19	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	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	0.93	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	0.89	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	0.92	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	0.89	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	1.04	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%