ESTIMATING THE INCOME ELASTICITY OF THE PROPERTY TAX BASE

John E. Anderson and *Shafiun N. Shimul,*
University of Nebraska-Lincoln

INTRODUCTION

ESTIMATES OF THE INCOME ELASTICITY OF THE property tax base are important for state and local governments to understand how fluctuations in income over time may affect property tax revenues. The experience of state and local governments during the Great Recession of 2008-09 and simultaneous financial markets crisis, when coupled with unprecedented declines in home values over the period 2007-11, make it more important than ever to have recent and accurate estimates. There is also concern over the run-up in agricultural land values in recent years, perhaps indicating the presence of a bubble in land prices. Accurate estimates of the income elasticity of property value should provide insight regarding the fundamentals in this asset market. To obtain accurate estimates of both long-run and short-run income elasticities, we employ panel time series methods that have not yet been used for this purpose.

In this paper we present methods by which short- and long-run elasticities are estimated using disaggregated local property value data. Applications of these methods are demonstrated using a panel of county-level data for the State of Nebraska over the period 1998-2011. Both ordinary least squares (OLS) and dynamic ordinary least squares (DOLS) methods are used to estimate long-run elasticities. Results obtained from models without income-county interaction terms indicate that the long-run income elasticity is approximately in the range of 0.57 to 0.67. Models that include income-county interaction terms yield similar estimates of the long-run income elasticity, but they also reveal striking county-specific effects that are highly variable.

To obtain short-run elasticities, a panel error-correction model is estimated. Results indicate that the adjustment process involves an approximate 5 percent (negative) response to an income shock in the subsequent year. Using estimates of short- and long-run elasticities, policy implications are investigated for local government units that rely heavily on the property tax.

RELATED LITERATURE

One of the earliest studies related to the topic of the income elasticity of state and local tax bases is the Groves and Kahn (1952) paper that implemented a simple regression model using a variety of subnational taxes from several states. They found taxes with low-income elasticities (between 0.0 and 0.8), such as the Wisconsin utility property tax, taxes with medium-income elasticities (from l.81 to 1.20), such as the Ohio sales tax, and taxes with high-income elasticities (in excess of 1.20), such as the Indiana, Maryland, Wisconsin, and North Carolina income taxes. Because their dependent variable in each case was the tax yield, however, their elasticity estimates include the effects of both changes in the tax bases and tax rates.

There is an extensive literature on the elasticity of state income and sales tax bases, summarized most recently in Bruce et al. (2006), and also including notable papers by Dye and McGuire (1991), and Fox and Campbell (1984). The Bruce et al. (2006) paper finds, for example, a long-run sales tax elasticity of 0.811 and a long-run personal income tax elasticity of 1.832. The literature on the elasticity of the property tax base is much more limited with the notable studies being Anderson (1991), Bridges (1964a, 1964b), Mikesell (1978), Sexton and Sexton (1986), and Sexton (1987). Anderson employed a panel data set for Michigan counties over the period 1973-88 and a log-linear regression model of property value on permanent income, finding a total income elasticity of 0.9394 for urban counties and 0.6448 for rural counties. His structural model provided estimates of the direct partial income elasticity of 0.6757 for Metropolitan Statistical Area (MSA) counties and substantially smaller elasticities for non-MSA counties, depending on the agricultural intensity of land use.

The Sexton and Sexton (1986) and Anderson (1991) studies distinguished between partial and total income elasticities of the property tax base by estimating a structural model that allows for a limited form of feedback. Those papers did not employ the now available methods of panel estimation, however. Hence, rather than focus on estimating partial and total income elasticities as they did, we focus on estimation of short- and long-run elasticity estimates using modern panel and dynamic estimation methods.

Estimation of both long-run and short-run elasticities using panel time series methods has received little attention to date. Bruce et al. (2006) have done so to estimate income elasticities of various tax bases, not including the property tax base. Hendershott et al. (2002) have used panel methods to estimate commercial real estate rents. A major contribution of the present paper is to apply panel estimation methods in the property tax context, thus advancing the state-of-the-art in estimating the income elasticity of the property tax base.

ESTIMATION MODELS

At the most basic level, the property tax base depends on the level of income generated in the economy. Suppose the natural log of the tax base in jurisdiction i at time t is designated as B_t^i and the natural log of income is I_t^i. The simplest model of the income elasticity is obtained from the regression equation,

$$(1) \quad B_t^i = \beta_0^i + \beta_1^i I_t^i + \varphi_t^i$$

where B_t^i is the estimated income elasticity.

Estimation of equation (1) using ordinary least squares method (OLS) runs the risk of several econometric problems, however. If the tax base and income time series are non-stationary there is the risk of obtaining spurious results. Of course, the risk of spurious results is eliminated if the series move together over time, as we would likely expect for aggregate property value and income. Fundamentally, the value of property is determined by the discounted present value of the future income stream generated by the property. Hence, we expect that fundamental relationship will eliminate the potential for spurious results

If the income regressor in equation (1) has a stochastic trend, i.e., has a unit root, there are several potential problems that may arise with OLS estimation. Stock and Watson (2011) indicate that the t-statistics estimated for a regressor using OLS may be non-normal causing the usual confidence intervals and hypotheses tests to be unreliable; and, there is a risk of obtaining a spurious regression result when the dependent and independent variables both have stochastic trends.

In order to estimate the long-run income elasticity of the tax base when the tax base and income are co-integrated (as we expect based on economic theory) and to be able to draw correct inferences based on the estimated t-statistics, econometricians have developed several estimators of the co-integrating coefficient. One such estimator is the dynamic OLS estimator (DOLS) that originates with Stock and Watson (1993). Bruce et al. (2006) suggest using the DOLS method to estimate the income elasticity of various tax bases. Using the DOLS method of estimation the long-run elasticity model is as follows.

$$(2) \quad B_t^i = \beta_0^i + \beta_1^i I_t^i + \Sigma_{g=-j}^{j} \gamma_g^i \Delta I_{t+g}^i + \varphi_t^i.$$

The estimate of coefficient β_1 gives the long-run elasticity of the tax base. The DOLS estimator of this coefficient is efficient in large samples. Furthermore, Stock and Watson (2011) report that statistical inferences regarding both β_1 and the γ_g using HAC standard errors are valid.

In order to estimate the short-run elasticity of the tax base, Bruce et al. (2006) suggest estimation of an error correction model (ECM). Changes in income may have an effect on the tax base that is not fully realized in the current period. There may be a substantial adjustment process that takes place over time. In this model deviations of the tax base from its long-run equilibrium value, denoted B_t^{i*}, are a function of income as well.

$$(3) \quad B_t^i - B_t^{i*} = \varepsilon_t^i = B_t^i - \beta_0^i - \beta_1^i I_t^i$$

In any time period, there are two short-run effects. The tax base can change due to a change in income or due to disequilibrium with respect to its long-run equilibrium level. Both of these effects are captured in the ECM:

$$(4) \quad B_t^i - B_{t-1}^i = \alpha_0^i + \alpha_1^i \left(I_t^i - I_{t-1}^i \right) + \alpha_2^i \varepsilon_{t-1}^i + \mu_t^i$$

In this model the α_1 parameter captures the immediate effect of a change in the log of personal income, or the short-run elasticity. This parameter estimate can then be compared to the long-run elasticity estimate of the coefficient β_1 in equation (2). The α_2 parameter estimate captures the adjustment process as the tax base moves toward its long-run equilibrium.

EMPIRICAL RESULTS

In order to estimate the income elasticity of the property tax base, property value data for each of the 93 counties of Nebraska were obtained from the Department of Revenue, Property Tax Division, for the period 1998-2011. County-level personal income data were obtained from the Bureau of Labor Statistics (BLS) for the same years.

Given that we are working with panel data, it is essential to check whether the dependent and independent variables are stationary. In our application, the dependent variable is the logarithm of property value, and the independent variable is the logarithm of personal income. If we find a unit root in either case we know that there is a stochastic trend in the series. The presence of a stochastic trend makes the OLS estimator have a non-normal distribution that causes the problems with hypothesis tests, confidence intervals, and forecasting noted above. On the issue of co-integration of the two series, property value and personal income, it is plausible on the basis of economic theory to believe that the series are co-integrated. We test for co-integration and use appropriate methods of estimation assuming that the series are co-integrated.

Sobel and Holcombe (1996) were the first researchers to recommend the use of time series methods to estimate the income elasticity of taxes in order to obtain unbiased estimates and consistent standard errors. They did not estimate the income elasticity of the property tax base, but they did suggest that their use of time series methods for aggregate national data on income and sales taxes might be even more relevant for state-level analysis where changes in both economic and population trends could play a more significant role affecting the time series properties of the data series. That suggestion may be even more relevant for sub-state level analysis, such as ours.

Panel unit root tests are reported in table 1. The results for the logarithm of property value are unambiguous. We cannot reject the hypothesis that this series has a unit root, either a common unit root process or individual unit root processes. The results for the logarithm of personal income, however, are ambiguous. The Levin, Lin and Chu

Table 1a
Panel Unit Root Tests

		Logarithm of Property Value		*Logarithm of Personal Income*	
Test Method	*Test Assumptions*	*Statistic*	*Probability Value*	*Statistic*	*Probability Value*
Levin, Lin and Chu t*	Common unit root process	6.7858	1.0000	-5.0326	0.0000
Im, Pesaran and Shin	Individual unit root processes	18.9185	1.0000	6.1981	1.0000
Augmented Dickey-Fuller	Individual unit root processes	35.1216	1.0000	79.4008	1.0000
Phillips-Perron	Individual unit root processes	84.6270	1.0000	93.7681	1.0000

Note: In all tests reported the null hypothesis assumes a unit root process.

Table 1b
Error-Correction-Based Co-integration Tests for Panel Data

Test Statistic	*Value*	*Z-Value*	*P-Value*
G_t	-1.533	-5.163	0.000
G_a	-1.855	4.130	1.000
P_t	-7.416	-2.136	0.016
P_a	-0.744	0.941	0.827

Note: Test statistics based on Westerlund (2007), with the null hypotheses of no co-integration. Tests implemented in Stata using methods outlined in Persyn and Westerlund (2008).

method, which assumes a common unit root, yields a test statistic for which we must reject the null hypothesis of a unit root. The remaining three tests, however, assume individual unit root processes and yield test statistics for which we cannot reject the hypothesis of unit roots. Given these results, we will use a DOLS estimation method, in addition to OLS, in order to deal with the non-stationary data.

Long-Run Elasticity Estimates

We begin with a simple model where we regress the logarithm of property value on the logarithm of personal income with county fixed effects, denoted as model 1. Table 1 reports the coefficient estimate for the long-run income elasticity as 0.67, which is statistically discernible. Model 2 is a similar regression with the inclusion of one-period lead and lag terms that are the changes in the logarithm of personal income. Inclusion of these terms makes the estimation DOLS. The DOLS estimation results in a somewhat smaller long-run income elasticity estimate of 0.57. The lagged change in income term is not statistically discernible, but the lead term is highly significant with a positive coefficient.

Model 3 is a more general version of model 1, with the inclusion of income-county interaction terms to allow estimation of county-specific income elasticities. Table 2 reports the interaction terms that are statistically significant at the 5 percent level or less (relative to county one, Adams County, which is the left out county). The estimated income elasticity for Adams County is 1.2071. For the other 92 counties, the estimated elasticity is the sum of the Adams County estimate plus the county-specific interaction term. Eleven counties have significant interaction terms, with four of those terms being positive (Cass, Dawes, Lancaster, and Sarpy counties) and the remaining seven terms (Arthur, Banner, Grant, Hayes, Hooker, Madison, and Wheeler counties) being negative. For reference, figure 1 presents a map of the State of Nebraska with counties labeled.

Model 4 is a more general version of model 2, with the inclusion of income-county interaction terms. In this case the estimated long-run income elasticity for Adams County is 0.86. For the remaining 92 counties the county-specific interaction term must be added to this figure. The lagged income variable in this model is not significant, but the lead income variable is positive and significant. Seven of the income-county interaction terms are statistically discernible, with four being positive (Cass, Colfax, Dawes, and Sarpy counties) and three being negative (Garfield, Hooker, and Wheeler counties).

The counties with significant interaction terms in models 3 and 4 fall into three general regional categories. First, there is a group of counties in the western Sandhills region of the state, including Aurthur, Banner, Dawes, Grant, Hayes, and Hooker counties. Second, there is a group of counties in the northeastern region of the state where a number of meat packing firms located in the 1990s, including Colfax, Garfield, Madison, and Wheeler counties. Finally, there are three counties that are in fast-growing urban areas near Omaha and Lincoln, including Cass, Lancaster, and Sarpy counties.

The counties in the Sandhills region generally have estimated interaction coefficients in model 3 approximately equal to minus one, indicating that the overall income elasticity of the property tax base is low (approximately 0.2, the difference between the overall estimated elasticity of 1.2 and the minus one interaction terms). The sole exception to this general pattern is the result for Dawes County where the interaction term is estimated to be approximately 1.6, indicating a very elastic relationship between income and property value. We have reason to question the general results for counties in the ranching area of the state, however. Sandhills counties, such as Arthur, Banner, Dawes, Grant, Hayes, and Hooker, may have unreliable income data since they are sparsely populated counties with the primary industry being ranching. Prior research using income measures for these counties gives reason to believe that ranchers may be able to report little formal income despite the fact that they have high wealth in the form of valuable ranch land. Consequently, the linkage between income and property value may be weak in those particular locations.

For the counties in the northeastern part of the state where meat packing firms expanded rapidly in the 1990s, the estimated elasticities are highly variable. Model 3 indicates that the combined elasticity for Madison County is approximately 0.1 (-1.1 plus 1.2), while that for Wheeler County is approximately -0.5 (-1.7 plus 1.2). Model 4 indicates that the combined income elasticities for the counties in this region are approximately: Colfax County 2.7 (1.8 plus 0.9), Garfield County

Table 2
Long-Run Income Elasticity Estimates

	Model 1 (OLS)	*Model 2 (DOLS)*	*Model 3 (OLS)*	*Model 4 (DOLS)*
Constant	13.0149[a] (0.2506)	13.9385[a] (0.3126)	8.7217[a] (0.3569)	10.6888[a] (0.4629)
Log of Personal Income	0.6702[a] (0.0261)	0.5734[a] (0.0325)	1.2071[a] (0.4558)	0.8641[c] (0.4870)
Lagged Change in Log of Personal Income		-0.0182 (0.0359)		-0.0204 (0.0314)
Leading Change in Log of Personal Income		0.2768[a] (0.0380)		0.2519[a] (0.0336)
Income-County Interactions:				
Arthur County			-0.9913[b] (0.4711)	
Banner County			-0.9752[b] (0.4685)	
Cass County			1.9019[a] (0.7387)	2.2235[a] (0.8547)
Colfax County				1.7942[b] (0.9065)
Dawes County			1.597[a] (0.6204)	2.5606[a] (0.7529)
Garfield County				-2.2613[a] (0.8237)
Grant County			-1.0465[b] (0.4815)	
Hayes County			-0.9501[b] (0.4628)	
Hooker County			-0.9710[b] (0.4852)	-1.169[b] (0.5326)
Lancaster County			2.692[b] (1.2921)	
Madison County			-1.1342[b] (0.4667)	
Sarpy County			2.745[a] (0.6157)	2.7908[a] (0.6865)
Wheeler County			-1.7523[a] (0.5197)	-1.3594[a] (0.5280)
Observations	1209	930	1209	930
F statistic	660.09[a]	110.05[a]	17.09[a]	9.34[a]

Superscripts a, b, and c indicate significance at the 1 percent, 5 percent, and 10 percent respectively.
Note: Only income-county interaction terms significant at the 5 percent level or lower are reported in this table.

Figure 1: **Map of Nebraska Counties**

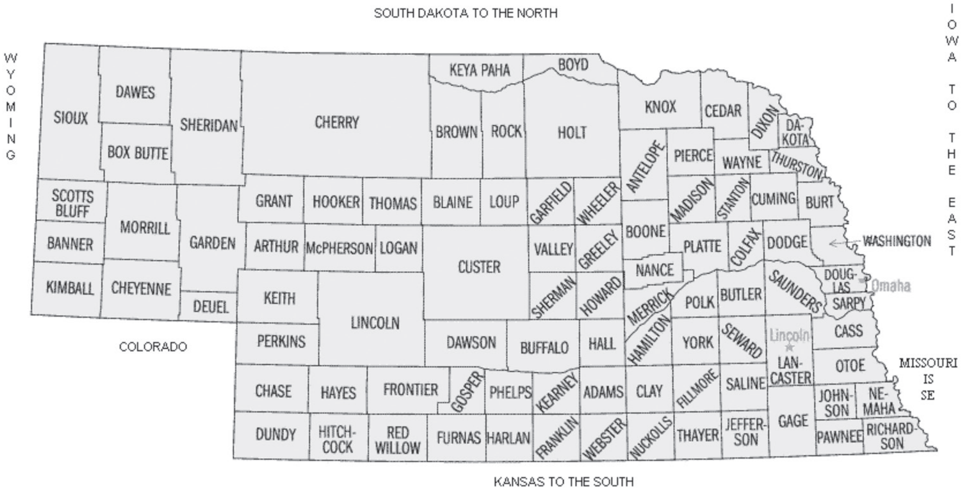

Table 3
Short-Run Elasticity Estimation using Error-Correction Model

	Model 1: Panel Estimation of Long-Run Elasticity and Fixed Effects to Estimate Short-Run Elasticity and Error-Correction Model	*Model 2: Pooled Estimation of Long-Run Elasticity and Fixed Effects to Estimate Short-Run Elasticity and Error-Correction Model*
	First Stage Estimation of Long-Run Elasticity	
Constant	13.0149[a]	-3.2130[a]
	(0.2506)	(1.5163)
Logarithm of Personal Income	0.6702[a]	2.3593[a]
	(0.0261)	(0.1578)
	Second Stage Estimation of Error-Correction Model (Panel with Fixed Effects)	
Constant	0.0371[a]	0.0369[a]
	(0.0015)	(0.0015)
Difference in Logarithm of Personal Income	-0.03712[a]	0.0113
	(0.0185)	(0.0193)
Adjustment Term	-0.0485[a]	-0.0512[a]
	(0.0161)	(0.0068)

-1.4 (-2.3 plus 0.9), and Wheeler County -0.4 (-1.3 plus 0.9).

Fast-growing urban and suburban counties Cass and Sarpy near Omaha and Lancaster County, the home of the state capitol in Lincoln, have large positive interaction terms in models 3 and 4. Model 3 results indicate that all three urban counties have large income elasticities. The combined elasticity estimate for Cass County is approximately 3.1 (1.9 plus 1.2), while for both Lancaster and Sarpy counties the combined elasticity estimates are approximately 3.9 (2.7 plus 1.2). Model 4 confirms similar results for Cass and Sarpy counties, but in this case the Lancaster County interaction term is not significant.

Short-Run and Error-Correction Estimates

Table 3 reports estimation of short-run elasticities and error-correction term. Model 1 estimates the short-run elasticity and the error-correction term using panel estimation methods with county fixed effects. The estimated short-run elasticity in this model (the estimated value of α_1 in equation (4)) is -0.037, indicating a negative income elasticity of approximately 4 percent. The negative and statistically discernible result is surprising. The estimated error correction term in this model (the estimated value of α_2 in equation (4)) is negative and statistically different from zero. This estimated coefficient indicates that when an income shock causes property values to deviate from their long-term equilibrium approximately 5 percent of the error is corrected in the following year.

Model 2 is similar to model 1 with the exception that the first stage equation is estimated using pooled rather than panel methods, as suggested by Hendershott et al. (2002). The second stage is then estimated using lagged residuals to run the error-correction model with panel regression methods as suggested by Hendershott et al. (2002). Results in this case indicate a positive short-run income elasticity of 0.01, although this result is not statistically discernible. The error-correction term in this model is -0.05, which is statistically discernible. The long-run elasticity estimate in the first stage of this estimation procedure yields an unrealistically large estimate, due to the pooled rather than panel estimation procedure employed in the first stage.

While the short-run income elasticities from both model estimates are near zero, both error-correction models indicate similar error-correction processes. Positive income shocks appear to be followed by an approximate 5 percent downward adjustment the first year following the income shock.

SUMMARY AND CONCLUSIONS

This paper reports on the use of panel time series methods to estimate both long-run and short-run income elasticities of the property tax base. Results of OLS estimation using a panel of Nebraska county level data over the period 1998-2011 indicate a long-run elasticity in the range of 0.57 to 0.67 – a somewhat inelastic response. The inclusion of county interaction terms in the OLS model reveals specific regional variation in the income elasticity estimates, with generally much larger elasticity estimates in the fast-growing urban counties and much lower elasticity estimates in the ranching region of the western Sandhills. Estimation using DOLS methods due to co-integration of the two series reveals a somewhat larger long-term income elasticity of 0.86, with substantial county-specific variation. Again, the urban counties outside of Omaha have much larger estimated income elasticities, while counties in the western ranching region have much smaller estimated elasticities.

There are several limitations of this research that should be pursued in future work on this topic. First, there are a limited number of years in panel data used in this study. A longer time series would be helpful in using panel time series methods, especially the error-correction model. This study used only one lag in the error-correction model estimation. With a longer time series available, more extensive investigation of various lag structures could be performed.

In consideration of the elasticity results obtained here it should be noted that the data used in this study are assessed values of property across the state of Nebraska. As such, these data do not directly and immediately reflect market values of property. Rather, they represent local assessors' views of property value for tax purposes. As indicated in Lutz (2008) and Lutz et al. (2011), there are numerous ways in which assessed values differ from market values. Time lags in assessment, as well as smoothing techniques used by local assessors, are built into these data. A study of the relationship between income, assessed values, and market values would be interesting but lies beyond the scope of the present study.

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