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Investigating State Appropriations and Net Tuition Revenue for Public Higher Education: A Vector Error-Correction Modeling Approach

IHELG Monograph

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Investigating State Appropriations and Net Tuition Revenue for Public Higher Education:

A Vector Error-Correction Modeling Approach

A paper presented at the
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by

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Abstract

This paper demonstrates the use of vector-error correction modeling, within a dynamic panel analytical framework, to examine the relationship between state appropriations and net tuition revenue for public higher education. This study uses panel data from 50 states covering 26 years. The findings from this paper show that in the short-run, tuition revenue at public higher education institutions is negatively influenced by state appropriations. This study finds no evidence that the long-term trend in net tuition revenue is altered permanently by shocks in state appropriations.

Introduction

The growth in state appropriations to public higher education has been reduced substantially over the past few years. This decline has been well publicized in higher education industry news outlets such as *The Chronicle of Higher Education* (e.g., Keldermen, 2009) and *The NEA Almanac of Higher Education* (e.g., Zumeta, 2003, 2009). Numerous reports (e.g., Mortenson, 2008; State Higher Education Executive Officers, 2007, 2008) have also documented what appears to be a secular downward trend in state support for higher education and an increase in tuition as a source of revenue. Additionally, scholars have discussed the reduction in state support for public higher education and the implications for college affordability (Trombley, 2003) and access (e.g., Keller, 2006; Rizzo, 2006). Given the reduced growth in state funding for higher education and the need to maintain quality in such areas as instruction and student support, the importance of other sources of revenue, such as tuition, will become increasing important to public higher education institutions (Hearn, 2003). Some researchers (Koshal & Koshal, 2000) suggest there is an interdependent relationship between the state appropriations and the level of tuition at public higher education institutions.

Although it has been reported (e.g., Heller, 2006; Zumeta, 2009) that state appropriations are being replaced by tuition as revenue at colleges and universities, less attention has been paid to examining the short- and long-term relationship between state appropriations and the extent to which gains in net tuition revenue offset losses in state support at public colleges and universities. While they have documented the rise in net tuition revenue over the past few years, most reports (e.g., Redd, 2000; Davis, 2003) have focused on private rather than public higher education. Similarly, the bulk of the research has examined net tuition revenue within the context of tuition discounting (e.g., Martin, 2002; Massa & Parker, 2007) and enrollment management with respect to the impact low-income transfer students have on revenue at private higher education institutions (e.g., Dowd, Cheslock, & Melguizo, 2008) or the relationship between state funding and tuition at public institutions in one state (e.g., Blake, 2006).

[Insert Figure 1 about here]

Between 1982 and 2006, adjusting for inflation, state appropriations per full-time equivalent (FTE) student to public higher education has remained virtually unchanged while net tuition revenue per FTE student has increased slightly (see Figure 1). Analyses of trends in state appropriations and net tuition revenue (e.g., State Higher Education Executive Officers, 2006, 2007; Heller, 2006) have been confined to descriptive statistics that do not take into account the possible spurious relationship between and endogenous nature of these variables, as well as the effect of other unobservable variables across states. Moreover, no known studies have used statistical techniques that distinguish between short- and long-term changes or the proportion by which the long-term disequilibrium (or imbalance) in the state appropriations and net tuition revenue are being corrected in each time period.

This study addresses the limitations of prior analyses by employing vector error-correction and dynamic panel modeling techniques, to demonstrate how higher education analysts can better distinguish between the short- and long-term effects of changes in state appropriations on net tuition revenue (and net tuition revenue on state appropriations) for public higher education. In addition to taking into account possible endogeneity and heterogeneity, these combined techniques also enable analysts to determine the extent to which short-term changes in state appropriations and net tuition revenue adjust to their respective long-term trends.

Conceptual Framework

This study uses a conceptual framework that is grounded in resource dependency theory (Pfeffer, 1997; Pfeffer & Salancik, 1978; Scott, 1995). Resource dependency theory endeavors to explain how organizations strive to address a loss of resources from one external source with a gain from another external source. Applied to this study, resource dependency theory is the conceptual backdrop of public higher education's need to offset reductions in state support by increases in tuition revenue. Among other things, resource dependency theory posits that an organization can quickly respond to changes in the external environment, given its relationship to that environment. With respect to public higher education institutions, their external environment is comprised of the state and the market. Aspects of the state environment include state support for higher education reflected by financial resources provided to institutions and students. The market for public colleges and universities is partly reflected by the demand from students, manifested in tuition revenue.

Research Design

Using panel data and employing vector error-correction (VEC) and dynamic panel modeling (DPM) techniques, we ask the following research questions:

1. In the short-run, what is the relationship between changes in state

appropriations per FTE student and changes in net tuition revenue per FTE student to public higher education institutions?

2. In the long-run, what is the relationship between in state appropriations per FTE student and net tuition revenue per FTE student at public higher education institutions?

Data and Variables

This study uses a times-series/cross-sectional (TSCS), otherwise known as dynamic panel data. The data cover 50 states from 1982 to 2006, yielding an analytic sample size of 1,250 state-year observations.

This paper considers two models: model-1 with state appropriations to public higher education per full-time equivalent (FTE) student as a dependent variable and model-2 with net tuition revenue to public higher education per FTE student as a dependent variable. These data were downloaded from the State Higher Education Executive Officers Association website.

The independent variables are lags of the dependent variables, total state taxes per capita, per capita income, and Pell grant revenue per FTE student. The tax and income data were downloaded from the U.S. Bureau of Economic Analysis website. The Pell grant data were downloaded from the Postsecondary Education Opportunity website. As recommended by Arellano (2003), year dummy variables (1983 – 2006)

[Insert Table 1 about here]

are also included in the analysis. Table 1 displays the list of variables and their respective descriptive statistics. For easier interpretation of the results, all continuous variables are log transformed. This transformation allows one to interpret changes in the variables in terms of percentages.

Notations

The paper uses lowercase bold letters and uppercase bold letters to represent vectors and matrices, respectively. The scalar variables are represented by lowercase italicized letters.

Analytical Framework

This paper uses vector error-correction (VEC) models within a dynamic panel (DPM) analytical framework. VEC models are parameterized vector autoregressive (VAR) models, which are simply regression models with lagged dependent variables as independent variables modeled analytically as:

$$y_t = c + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \ldots\ldots + \beta_n y_{t-n} + \varepsilon_t \qquad (1),$$

where y_t is a dependent variable depending upon values of the same variable in n prior time periods (t-1), (t-2)….. (t-n) and ε_t is an error term. Equation 1 may also include other variables, in which case it reflects a multivariate VAR involving the use of two or more series of data measured over time.

An example of a multivariate VAR with two variables with a lag of two time periods (n=2) is reflected as:

$$y_{1,t} = c_1 + \beta_{11} y_{1,t-1} + \beta_{12} y_{1,t-2} + \beta_{13} y_{2,t-1} + \beta_{14} y_{2,t-2} + \varepsilon_{1,t} \qquad (2),$$

$$y_{2,t} = c_2 + \beta_{21} y_{1,t-1} + \beta_{22} y_{1,t-2} + \beta_{23} y_{2,t-1} + \beta_{24} y_{2,t-2} + \varepsilon_{2,t} \qquad (3).$$

VEC models are re-parameterized multivariate VAR models (Equations 2 and 3) and reflected as (Refer to Appendix-A for detailed derivation):

$$\Delta y_{1,t} = c_1 + \alpha_{11}\Delta y_{1,t-1} + \alpha_{12}\Delta y_{2,t-1} + \eta_1(y_{1,t-2} - y_{2,t-2}) + \theta_1 y_{2,t-2} + \varepsilon_{1,t} \quad (4),$$

$$\Delta y_{2,t} = c_2 + \alpha_{21}\Delta y_{1,t-1} + \alpha_{22}\Delta y_{2,t-1} + \eta_2(y_{2,t-2} - y_{1,t-2}) + \theta_2 y_{1,t-2} + \varepsilon_{2,t} \quad (5),$$

where $\alpha_{11} = (\beta_{11} - 1)$, $\alpha_{12} = \beta_{13}$, $\eta_1 = (\beta_{11} + \beta_{12} - 1)$, $\theta_1 = (\beta_{11} + \beta_{12} + \beta_{13} + \beta_{14} - 1)$, $\alpha_{21} = \beta_{21}$, $\alpha_{22} = (\beta_{23} - 1)$, $\eta_2 = (\beta_{23} + \beta_{24} - 1)$, $\theta_2 = (\beta_{21} + \beta_{22} + \beta_{23} + \beta_{24} - 1)$, and Δ is a change operator such that Δy_t is $y_t - y_{t-1}$. In Equations 4 and 5, η_1 and η_2 are the estimated coefficients of adjustment parameters, also known as error-correction (EC) parameters. The statistical significance of the EC parameters provides evidence of a dynamic or cointegrating relationship between y_1 and y_2. If the EC parameters are statistically significant and negative, the values of y_1 and y_2 are diverging toward their respective long-term trend. Therefore, the use of VEC models allows analysts to examine short-run effects, long-run effects, and the adjustment of short-run “shocks” or effects to long-run equilibrium or trends. For example, VEC models are used by economists to examine the short- and long-term relationship between national economic growth and measures of educational attainment (e.g., Asteriou & Agiomirgianakis, 2001; Francis & Iyare, 2006; de Meulemeester & Rochat, 1995) as well as the short-term and long-term demand for higher education (e.g., Canton & de Jong, 2005).

Because this study uses dynamic panel data, the VEC models are calibrated using dynamic panel modeling (DPM) techniques. DPM techniques take into account, through the use of lags and differences, endogeneity and unobserved state heterogeneity (such as history, culture, and politics) that may produce biased parameter estimates. According to several econometricians (Arellano & Bover, 1995; Blundell & Bond, 1998), the use of lags of the differenced values of endogenous variables and values of exogenous variables as instruments increases asymptotic efficiency and robustness of parameter estimates. VEC models within a DPM analytical framework are represented as:

$$\Delta y_{1,t} = c_1 + \alpha_{11}\Delta y_{1,t-1} + \alpha_{12}\Delta y_{2,t-1} + \eta_1(y_{1,t-2} - y_{2,t-2}) + \theta_1 y_{2,t-2} + \boldsymbol{\gamma}_1\mathbf{x}_t + \lambda_{1,t} + \varepsilon_{1,t} \quad (6),$$

$$\Delta y_{2,t} = c_2 + \alpha_{21}\Delta y_{1,t-1} + \alpha_{22}\Delta y_{2,t-1} + \eta_2(y_{2,t-2} - y_{1,t-2}) + \theta_2 y_{1,t-2} + \boldsymbol{\gamma}_2\mathbf{x}_t + \lambda_{2,t} + \varepsilon_{2,t} \quad (7),$$

where $\lambda_{1,t}$ and $\lambda_{2,t}$ are time-specific effects, $\mathbf{x}_t$ is a vector of exogenous variables, and $\boldsymbol{\gamma}_1$ and $\boldsymbol{\gamma}_2$ are the vectors of coefficients associated with vector $\mathbf{x}_t$ in Equations 6 and 7, respectively.

Consistent with and using some terms from Yasar and colleagues (2006), the link between the VAR models (Equations 4 and 5) and the VEC models (Equation 6 and 7) can be expressed within a dynamic panel modeling framework as follows:

$$\Delta y_{1,i,t} = \alpha_{11,i}\Delta y_{1,i,t-1} + \alpha_{12,i}\Delta y_{2,i,t-1} + \eta_{1,i}(y_{1,i,t-2} - y_{2,i,t-2}) + \theta_{1,i} y_{2,i,t-2}$$
$$+ \boldsymbol{\gamma}_{1,i}\mathbf{x}_{i,t} + \phi_{1,i} + \lambda_{1,t} + \varepsilon_{1,i,t} \quad (8),$$

$$\Delta y_{2,i,t} = \alpha_{21,i}\Delta y_{1,i,t-1} + \alpha_{22,i}\Delta y_{2,i,t-1} + \eta_{2,i}(y_{2,i,t-2} - y_{1,i,t-2}) + \theta_{2,i} y_{1,i,t-2}$$
$$+ \boldsymbol{\gamma}_{2,i}\mathbf{x}_{i,t} + \phi_{2,i} + \lambda_{2,t} + \varepsilon_{2,i,t} \quad (9),$$

where the constants c_1 and c_2 are absorbed in constants $\phi_{1,i}$ and $\phi_{2,i}$, respectively with $\phi_{1,i}$ and $\phi_{2,i}$ as unobserved time-invariant state-specific effects, $\lambda_{1,t}$ and $\lambda_{2,t}$ are time-specific effects, i is a state, y_1 is state appropriations per FTE student, y_2 is net tuition revenue per FTE student, $\mathbf{x}_{i,t}$ is a vector of exogenous variables that includes total state taxes per capita, per capita income, and Pell grant revenue per FTE student, and $\boldsymbol{\gamma}_{1,i}$ and $\boldsymbol{\gamma}_{2,i}$ are the vectors of coefficients associated with vector $\mathbf{x}_{i,t}$ in Equations 8 and 9, respectively. Within this analytical framework, Equations 8 and 9 are estimated via system Generalized Method of Moments (GMM) estimation techniques (Arellano & Bover, 1995; Blundell & Bond, 1998)[1]. This study uses a dynamic-fixed effects panel model estimated through a system of equations via GMM techniques or otherwise known as system GMM. Using system GMM, instrumental variables are created using the lags of the differenced values of the endogenous variables and the values of the exogenous variables present in the model to reduce endogenous variable bias. As demonstrated by other scholars (Arellano & Bover, 1995; Bludell & Bond, 1998), dynamic fixed-effect panel models provide more robust and less biased estimates when endogenous, lagged, and lagged dependent variables are included as explanatory variables in the model.

When including a lagged dependent variable as an independent variable, OLS regression techniques tend to produce upwardly biased parameter estimates (Kiviet, 1995). On the other hand, fixed-effects regression tends to generate downwardly biased estimates (Nickell, 1981). According to researchers (Arellano & Bover, 1995; Blundell & Bond, 1998), regression models via GMM techniques tend to produce parameter estimates that lie between estimates produced by OLS regression and fixed-effects regression models with lagged dependent variables as independent variables. The use of GMM techniques also generate instrumental variables under orthogonal conditions (i.e. the cross-products of the regressors with errors are set to zero), thus reducing the chance of spurious results[1]. System GMM involves the use of lags of the differenced values of the endogenous variables and values of the exogenous variables. The use of these instruments increases asymptotic efficiency and robustness of parameter estimates from small samples and short time periods (Arellano & Bover, 1995; Blundell & Bond, 1998). Although econometricians explicitly utilize system GMM techniques, within a dynamic

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[1] To conduct the analysis, this we utilize the Stata program, xtabond2. For a detailed explanation on the use of xtabond2, see Roodman (2004).

panel modeling analytic framework, few higher education researchers (e.g., Rizzo, 2006; Titus, 2009) have employed this technique. Because it uses vector error-correction models within a dynamic panel modeling analytic framework, this study implicitly utilizes system GMM techniques.

Prior to estimating the VEC models (Equations 8 and 9), several statistical tests are carried out. These tests include panel unit root tests and error-correction-based panel cointegration tests. Panel unit root tests, using the Hadri (2000) technique, are conducted to uncover non-stationary characteristics of the data in this study. The null hypothesis for the panel unit root Hadri (2000) test is a stationary time series in all states with an alternative hypothesis of a unit root (or non-stationary around a trend) in all states. The results indicate that both state appropriations per FTE student and net tuition revenue per FTE student are non-stationary around a trend. According to Wooldridge (2001), the use of (ordinary least square) OLS regression techniques with non-stationary data may produce spurious results.

[Insert Table 2 here]

To determine if the use of VEC modeling techniques is warranted, an error-correction-based panel cointegration test is conducted. The Westerlund (2007) error-correction-based panel cointegration test determines the number of lags to include in VEC model when using panel data.[2] As shown in Table 2, the results of the Westerlund error-correction-based panel cointegration tests reveal that a maximum of two lags should be used for the endogenous variables (y_1 and y_2) in the VEC models as reflected above in Equations 8 and 9.

Table 2 also indicates that the Westerlund (2007) error-correction-based panel cointegration tests reveal that cointegration is present in the data, specifically between state appropriations per FTE student and net tuition revenue per FTE student. This suggests that a linear combination of state appropriations and net tuition revenue is stationary and error-correction (EC) parameters can be estimated via a VEC model.

Prior to estimating the VEC models (Equations 8 and 9), a panel unit root test is performed. Using a technique recommended by Hadri (2000), a panel unit root test is conducted to uncover non-stationary characteristics of the data in this study. In other words, the results of the Hadri panel unit root test allows one to discern whether the series depart from their mean in the entire sample within each state and time period. The Hadri panel unit root test takes into account homogeneous or heterogeneous serially correlated error terms as well as a time trend. [3] The null hypothesis for the Hadri panel unit root test is a stationary time series in all states with an alternative hypothesis of a unit root (or non-stationary around a trend) in all states. Prior to performing the Hadri panel unit root tests, the data series are lagged by two years, based on the results from the Westerlund error-correction-based panel cointegration test shown in Table 2.

[Insert Table 3 about here]

As revealed in Table 3, the results from Hadri panel unit root tests indicate that even taking in account homogeneous or heterogeneous serially correlated error terms as well as a time trend, the null hypotheses of stationarity for both variables are rejected at the 1% significance level. This finding suggests that both state appropriations per FTE student and net tuition revenue per FTE student are non-stationary around a trend.

According to Wooldridge (2001), the use of ordinary least square (OLS) regression techniques to analyze non-stationary data may produce spurious results. (See appendix B)

In this study, two VEC models are estimated. The first model, based on Equation 8, examines how state appropriations per FTE student are influenced by net tuition revenue per FTE student. The second model, based on Equation 9, examines how net tuition revenue per FTE student is affected by state appropriations per FTE student. The estimation of the two models separately enables analysts to determine if one time series is useful in forecasting another, or what is known as Granger causality (Granger, 1969).

Using a method advocated by Granger (1988), the short-term effects are calculated by summing the coefficients of the lagged differenced independent variables. Short-term effects of state appropriations per FTE student and net tuition revenue per FTE student are calculated for net tuition revenue per FTE student and state appropriations per FTE student, respectively. Following Yasar and colleagues (2006), the long-term coefficients are calculated by subtracting the ratio of the estimated coefficients of the lag values of state appropriations per FTE student and net tuition revenue per FTE student to the estimated coefficient of the respective EC parameters from one.

Limitations

Because it focuses on demonstrating the use of VEC models while utilizing state-level panel data, this paper does not address institution-level variables that may also influence state appropriations per FTE student and net revenue tuition revenue per FTE student. At the institutional level, state appropriations may be influenced by academic program mix. Net tuition revenue within a state may be influenced by institutional autonomy, with respect to setting tuition levels, and the amount of institutional financial aid expenditures. This paper does not address the possible long-run equilibrium relationships that may exist between states or institutions, otherwise known as “between cointegration” (Anderson, et al., 2006). Addressing these limitations is beyond the scope of this paper.

[Insert Table 4 about here]

Results

For purpose of comparison, results from OLS regression and fixed-effects models are shown in Appendix B. However, it should be noted that while the parameter estimates from the models in Table 4, should fall within the range of respective parameter estimates in Table B1 and Table B2, OLS regression models with differences typically produce parameter estimates with a downward bias and hence are not strictly comparable. Additionally, the regression results in Tables B1 and B2 do not take into account possible endogeneity bias shown to be present in the parameter estimates generated using OLS and fixed-effects techniques.

The vector error-correction models within a dynamic panel analytic framework is warranted as evidenced by the Arellano-Bond (A-B) test statistics for the two models shown in Table 4 (Arellano & Bond, 1991, 1998). The A-B test statistics indicate that while first-order serial correlation in the first-differenced residuals is statistically significant, second-order serial correlation is not statistically significant. The results of the A-B-tests are also consistent with the results from the Hadri panel unit root tests. Consequently the DFEP models are appropriately specified.

Generated by VEC and DPM, via system techniques, Table 4 shows that Pell grants per FTE students (beta = 0.188, $p < 0.01$) and state per capita income (beta = 1.181, $p <$

0.001) positively impact state appropriations but has no impact on net tuition revenue. Albeit speculative, the positive association between state appropriations and Pell grants may be explained by the following. As student financial need increases, reflected by a rise in Pell grant awards, states increase appropriations to higher education in an effort to prevent substantial increases in tuition rates.

The results in Table 4 also reveal that in both models, the estimated EC parameters are negative and statistically significant, indicating that changes in both state appropriations per FTE student and net tuition revenue per FTE student adjust to their respective long-run trends. In each time-period, state appropriations partially adjusts to its long-run trend by 26% (beta = -0.262, $p < 0.001$). In each short-run period, net tuition revenue partially also adjusts by 26% to its long-run trend but is marginally statistically significant (beta = -0.263, $p < 0.10$).

[Insert Table 5 about here]

The calculated short-run and long-run coefficients for state appropriations per FTE student and net tuition revenue per FTE student are shown in Table 5. The results in Table 5 reveal that, in the short-run, the changes in state appropriations are not related to changes in net tuition revenue. Table 5 also shows that in the short-run, net tuition revenue is negatively influenced by state appropriations (beta = -0.216, $p < 0.05$). However, the results in Table 5 indicate that in the long-run, net tuition revenue is not related to state appropriations.

Although not shown, the Granger-causality coefficients were estimated from the VAR models (i.e. equations 2 and 3) and are consistent with the long-run effect computed from the VEC models (i.e. equations 8 and 9). Together, the results from the VEC models suggest that, over the long run, changes in state appropriations cannot be used to forecast changes in net tuition revenue nor can changes in net tuition revenue be relied on to predict changes in state appropriations.

Conclusions

Several conclusions can be drawn from the results of this paper. First, this paper demonstrated the use of vector error-correction (VEC) models within a dynamic panel modeling (DPM) analytical framework enables analysts to determine the relationship between state appropriations and net tuition revenue over the short- and long-run taking into account possible endogeneity bias and unobserved state heterogeneity.

Second, the results from this paper suggest that in the short-run, net tuition revenue is negatively influenced by state appropriations but state appropriation is not influenced by net tuition revenue. This finding shows that in the short-run, for every 10 percent increase in state appropriations, net tuition revenue decreases by only two percent. Therefore, the results in this paper imply that, in the short-run, increases in net tuition revenue do not offset declines in state appropriations to public higher education. Public higher education tuition revenue does not fully adjust to short-run changes to state appropriations. This finding suggest that with respect to cuts in appropriations and short term responses via net tuition revenue, public higher education is forever playing "catch up" with respect the loss in state appropriations.

Third, the results in this paper also show there is no evidence that over the long-term, state appropriations and net tuition revenues are inter-related. These findings may point to the long-term implications for the overall quality of public higher education as total revenue per FTE student declines. In the future, the extent to which individual states are able to increase state appropriations to higher education may be constrained by their political economy, particularly voter-initiated pressure with respect to tax rates and overall budgetary expenditures (Archibald & Feldman, 2006).

Fourth, the results from this study show there is no evidence that suggests changes in state appropriations or net tuition revenue are altered permanently by shock in the state economy, as measured by per capita income. Although this paper has provided some evidence that federal, specifically Pell grants, and state appropriations for public higher may not be out of sync, more research is needed in this area.

To analyze the how both changes in state appropriations or net tuition revenue are affected by per capita income and other variables, this study employed an advanced statistical technique, vector error-correction (VEC) modeling techniques within a dynamic panel modeling analytic framework. These techniques allow for more rigorous statistical analyses than was previously provided by various reports in their attempts to explain the changes in and the relationship between state appropriations and net tuition revenue.

Implications

The focus of this study has been how advanced statistical techniques can help us to further our understanding of the relationship between state appropriations and net tuition revenue for public higher education across states and over time. Because this study utilizes VEC and dynamic panel modeling techniques, this paper has several implications for methods. First, the use panel data and VEC modeling techniques within a dynamic analytical framework demonstrates how higher education analysts can appropriately distinguish between long- and short-run effects of changes in state appropriations and net tuition revenue for public higher education while taking possible endogeneity bias and unobserved heterogeneity into account.

Second, the results of this study suggest that prior analyses with respect to the relationship between state appropriations and net tuition revenue may lack precision and suffer from possible estimation bias. This study shows that utilizing vector error-correction models within a dynamic panel analytic framework, via system GMM techniques, decreases the likelihood of producing biased results and making inferences with respect to spurious relationships between variables of interest such as state appropriations and net tuition revenue.

Third, this paper advances our understanding of how VEC and DPM techniques can be used to understand the dynamic relationships among variables when utilizing TSCS or panel data. Higher education researchers are increasingly calling for the use of panel data in the study of higher education. This paper demonstrates the use of appropriate statistical techniques when utilizing panel data. In the future, to examine how changes in finance policies such as net tuition revenue and institutional financial aid are related, these techniques could be applied to panel data on higher education institutions within particular states of interest.

Fourth, the findings from this paper may have implications for the application of resource dependency theory to state higher education finance. The results of this paper provide evidence that a long-run relationship exists between state appropriations and net tuition revenue to public higher education but not direction of causation in the long-run. The findings from this paper also show that, in both the short- and long-run, public higher education institutions do not adjust to changes in their external environments, namely state appropriations, by systematically adjusting upwardly to changes in net tuition revenue. On the other hand, at least in the short-run, public higher education may be adjusting downwardly to net tuition revenue in response to temporary upward adjustments in state appropriations. This asymmetry in resource adjustment may reflect non-economic constraints such as state political pressure to limit tuition increases as opposed to institutional inability to secure more market-based resources such as tuition revenue.

Fifth, the results from this paper have possible implications for informing state higher education finance policy debates. The findings from this paper can be viewed within the context of states that are facing future choices with respect to financing public higher education. These choices, exacerbated by projected structural deficits in state budgets, and presumed to related, include less state funding of public higher education and increases in tuition at public higher education institutions. This paper provides evidence that such choice may be mutually exclusive or in other words, one may not necessarily influence the other, at least not in the long run. Therefore, while it is important to discuss the impact of reduced state support for public higher education, such discussions should be based on more rigorous analysis of the available data such as that which is provided in this paper.

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Table 1. Descriptive statistics of variables used in the analyses.

Variables	Average	Standard Deviation	Minimum	Maximum
State appropriations per FTE student	$4,759	$1,765	$1,545	$13,425
Net tuition revenue per FTE student	$2,325	$1,577	$262	$10,818
Total state taxes per capita	$54	$32	$2.9	$151
Pell grant revenue per FTE student	$0.47	$0.28	$0.06	$4.96
State per capita income	$24,699	$5,001	$13,736	$44,266

Table 2: Westerlund (2007) Error-Correction-Based Panel Cointegration Tests – State appropriations per FTE Student and Net Tuition Revenue per FTE Student

	Error correction for state appropriations & net tuition
	Z-statistics
Individual states (cross-sectional) (G_τ)	-5.753***
Individual states (cross-sectional) (G_α)	-0.153
All States (pooled) (P_τ)	-2.918**
All States (pooled) (P_α)	-3.154**
Average lag length	2 years

+p< 0.10, *p< 0.05, **p < 0.01, ***p <0.001

Table 3: Hadri Test for Panel Unit Root - State Appropriations per FTE and Net Tuition Revenue per FTE student, lagged two years

	State appropriations per FTE student	Net tuition revenue per FTE student
	Z-statistics	
Homoskedastic Across Units		
Time Trend Unit Root (Z_{τ})	36.584***	40.447***
Individual Unit Root (Z_{μ})	90.341***	98.776***
Heteroskedastic Across Units		
Time Trend Unit Root (Z_{τ})	32.256***	37.761***
Individual Unit Root (Z_{μ})	87.340***	96.213***

+p< 0.10, *p< 0.05, **p < 0.01, ***p <0.001

Table 4. Vector Error-Correction Model (Within a Dynamic Panel Model Analytical Framework) Results: Estimated Coefficients and Standard Errors, (1982 – 2006)

	Dependent Variables for	
Independent Variables	*Model-1: Change in State Appropriations per FTE Student*	*Model-2: Change in Net Tuition Revenue per FTE Student*
Constant	-9.339**	4.344
	(3.589)	(12.940)
State Appropriations per FTE Student		
Lagged 1-Year Change in Appropriations per FTE Student	-0.350****	-0.253
	(0.076)	(0.184)
Lagged 2-Year Change in Appropriations per FTE Student	-0.030	0.037
	(0.062)	(0.259)
2-Year Lagged Net Tuition Revenue per FTE Student		-0.494
		(0.589)
Net Tuition Revenue per FTE Student		
Lagged 1-Year Change in Net Tuition Revenue per FTE Student	-0.116*	-0.141*
	(0.061)	(0.081)
Lagged 2-Year Change in Net Tuition Revenue per FTE Student	-0.008	-0.160
	(0.036)	(0.111)
2-Year Lagged State Appropriations per FTE Student	-0.312**	
	(0.134)	
Exogenous variables		
State Taxes per capita	-0.017	-0.014
	(0.052)	(0.062)
Pell Grants per FTE Student	0.188**	-0.052
	(0.084)	(0.185)
Per Capita Income	1.181***	-0.007
	(0.342)	(0.782)
Error-Correction (EC) Parameter	-0.262***	-0.263+
	(0.096)	(0.128)
Year Dummies	Yes	Yes
Number of States	50	50
Number of Observations	1,100	1,100
Number of Instruments	39	35
Arellano-Bond Test for AR1	-4.81****	-3.34***
Arellano-Bond Test for AR2	-0.63	-1.41

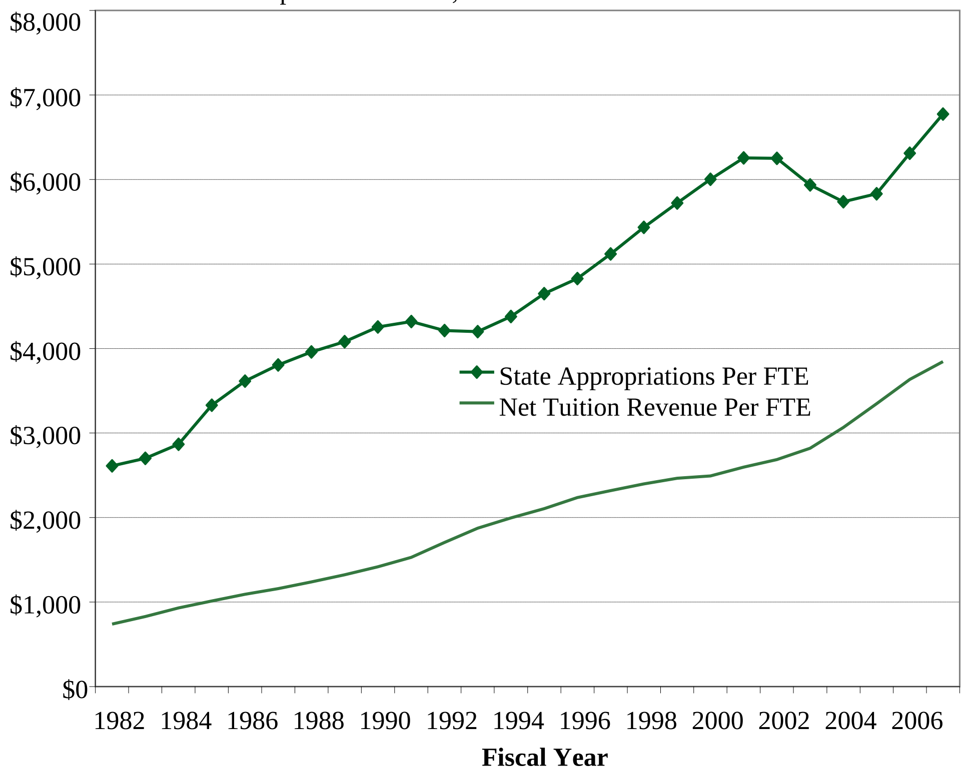
The standard errors, corrected for small samples (Windmeijer, 2004), are in parenthesis.
Note: The panel models are estimated using the Arellano-Bond two-step system GMM method.
The Stata module, xtabond2 was used to generate estimates above.
+p< 0.10, *p< 0.05, **p < 0.01, ***p <0.001

Table 5. State Appropriations per FTE Student and Net Tuition Revenue per FTE Student: Calculated Short-Run and Long-Run Coefficients and Standard Errors, Based on Results in Table 1 (1982 – 2006)

	Dependent Variables of models considered in this paper	
Independent Variables – Calculated Coefficients	*Model-1: State Appropriations per FTE Student*	*Model-2: Net Tuition Revenue per FTE Student*
Net Tuition Revenue per FTE Student		
Short-run effect	-0.124	
	(0.069)	
Long-run effect	-0.189	
	(0.184)	
State Appropriations per FTE Student		
Short-run effect		-0.216*
		(0.118)
Long-run effect		-0.875
		(1.480)

Note: Standard errors for the long-run coefficients were calculated by dividing the calculated long-run coefficients by the value of the respective *F* statistics (not shown), are in parenthesis.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Figure 1. Public Higher Education State Appropriations per FTE Student and Net Tuition Revenue per FTE Student, Fiscal Years 1982-2006



Source: State Higher Education Executive Officers.

Appendix-A

Consider an example of a multivariate VAR with two variables with a lag of two time periods. The analytic equations of such a VAR model can be reflected in Equations A.1 and A.2 as:

$$y_{1,t} = c_1 + \beta_{11} y_{1,t-1} + \beta_{12} y_{1,t-2} + \beta_{13} y_{2,t-1} + \beta_{14} y_{2,t-2} + \varepsilon_{1,t} \quad \text{(A.1)},$$

$$y_{2,t} = c_2 + \beta_{21} y_{1,t-1} + \beta_{22} y_{1,t-2} + \beta_{23} y_{2,t-1} + \beta_{24} y_{2,t-2} + \varepsilon_{2,t} \quad \text{(A.2)}.$$

Equations (A.1) and (A.2) can be written in the matrix notation as:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{1,t-2} \\ y_{2,t-1} \\ y_{2,t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \quad \text{(A.3)}$$

Or $\mathbf{y}_t = \mathbf{c} + \mathbf{B}\mathbf{z}_t + \mathbf{e}_t$ (A.4)

where $\mathbf{y}_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix}$, $\mathbf{c} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix}$, $\mathbf{e}_t = \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}$, $\mathbf{z}_t = \begin{bmatrix} y_{1,t-1} \\ y_{1,t-2} \\ y_{2,t-1} \\ y_{2,t-2} \end{bmatrix}$,

and $\mathbf{B} = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \end{bmatrix}$.

VEC model can be obtained by re-parameterizing multivariate VAR model of equation (A.4). To this end, let us rewrite (A.1) by adding and subtracting some terms as below:

$$y_{1,t} - y_{1,t-1} = c_1 + (\beta_{11} y_{1,t-1} - y_{1,t-1}) - (\beta_{11} y_{1,t-2} - y_{1,t-2}) + (\beta_{11} y_{1,t-2} - y_{1,t-2}) + \beta_{12} y_{1,t-2}$$
$$+ \beta_{13} y_{2,t-1} - \beta_{13} y_{2,t-2} + \beta_{13} y_{2,t-2} + \beta_{14} y_{2,t-2} + \varepsilon_{1,t}$$

$$\Rightarrow \quad \Delta y_{1,t} = c_1 + (\beta_{11} - 1)\Delta y_{1,t-1} + (\beta_{11} + \beta_{12} - 1) y_{1,t-2} + \beta_{13} \Delta y_{2,t-1} + (\beta_{13} + \beta_{14}) y_{2,t-2} + \varepsilon_{1,t}$$

$$\Rightarrow \quad \Delta y_{1,t} = c_1 + (\beta_{11} - 1)\Delta y_{1,t-1} + (\beta_{11} + \beta_{12} - 1) y_{1,t-2} - (\beta_{11} + \beta_{12} - 1) y_{2,t-2} + (\beta_{11} + \beta_{12} - 1) y_{2,t-2}$$
$$+ \beta_{13} \Delta y_{2,t-1} + (\beta_{13} + \beta_{14}) y_{2,t-2} + \varepsilon_{1,t}$$

$$\Rightarrow \quad \Delta y_{1,t} = c_1 + (\beta_{11} - 1)\Delta y_{1,t-1} + (\beta_{11} + \beta_{12} - 1)(y_{1,t-2} - y_{2,t-2}) + \beta_{13}\Delta y_{2,t-1}$$

$$+ (\beta_{13} + \beta_{14} - \beta_{11} - \beta_{12} + 1) y_{2,t-2} + \varepsilon_{1,t}$$

$$\Rightarrow \quad \Delta y_{1,t} = c_1 + \alpha_{11}\Delta y_{1,t-1} + \alpha_{12}\Delta y_{2,t-1} + \eta_1 (y_{1,t-2} - y_{2,t-2}) + \theta_1 y_{2,t-2} + \varepsilon_{1,t} \qquad \text{(A.5),}$$

where $\alpha_{11} = (\beta_{11} - 1)$, $\alpha_{12} = \beta_{13}$, $\eta_1 = (\beta_{11} + \beta_{12} - 1)$, $\theta_1 = (\beta_{11} + \beta_{12} + \beta_{13} + \beta_{14} - 1)$, and Δ is a change operator such that Δy_t is $y_t - y_{t-1}$.

Similarly, we can re-parameterize equation (A.2) as below

$$\Delta y_{2,t} = c_2 + \alpha_{21}\Delta y_{1,t-1} + \alpha_{22}\Delta y_{2,t-1} + \eta_2 (y_{2,t-2} - y_{1,t-2}) + \theta_2 y_{1,t-2} + \varepsilon_{2,t} \qquad \text{(A.6),}$$

where $\alpha_{21} = \beta_{21}$, $\alpha_{22} = (\beta_{23} - 1)$, $\eta_2 = (\beta_{23} + \beta_{24} - 1)$, and $\theta_2 = (\beta_{21} + \beta_{22} + \beta_{23} + \beta_{24} - 1)$.

Appendix B

Table B1. Pooled OLS Regression Analysis: Estimated Coefficient and Standard Errors, (1982-2006)

	Dependent Variables for	
Independent Variables	*Model-1: Change in State Appropriations per FTE Student*	*Model-2: Change in Net Tuition Revenue per FTE Student*
Constant	-0.175	-0.160
	(0.128)	(0.158)
State Appropriations per FTE Student		
Lagged 1-Year Change in Appropriations per FTE Student	-0.120***	-0.128**
	(0.041)	(0.048)
Lagged 2-Year Change in Appropriations per FTE Student	-0.040	-0.035
	(0.044)	(0.038)
2-Year Lagged Net Tuition Revenue per FTE Student		-0.028
		(0.017)
Net Tuition Revenue per FTE Student		
Lagged 1-Year Change in Net Tuition Revenue per FTE Student	-0.073***	-0.070
	(0.023)	(0.059)
Lagged 2-Year Change in Net Tuition Revenue per FTE Student	0.013	-0.020
	(0.028)	(0.033)
2-Year Lagged State Appropriations per FTE Student	-0.065****	
	(0.012)	
Exogenous variables		
State Taxes per capita	0.002	0.006*
	(0.002)	(0.003)
Pell Grants per FTE Student	0.005	0.002
	(0.006)	(0.006)
Per Capita Income	0.068****	0.030
	(0.016)	(0.023)
Error-Correction (EC) Parameter	-0.047****	-0.019
	(0.010)	(0.007)
Year Dummies	Yes	Yes
Number of States	50	50
Number of Observations	1,100	1,100
R^2	0.258****	0.078****

Note: The robust standard errors, adjusted for state clusters (50), are in parenthesis.
+*p*< 0.10, **p*< 0.05, ***p* < 0.01, ****p* <0.001

Table B2. Fixed-Effects Regression Analysis: Estimated Coefficient and Standard Errors, (1982-2006)

Independent Variables	Dependent Variables for *Model-1: Change in State Appropriations per FTE Student*	Dependent Variables for *Model-2: Change in Net Tuition Revenue per FTE Student*
Constant	-1.666**	1.565
	(0.742)	(1.188)
State Appropriations per FTE Student		
Lagged 1-Year Change in Appropriations per FTE Student	-0.274****	-0.125**
	(0.048)	(0.049)
Lagged 2-Year Change in Appropriations per FTE Student	0.037	-0.043
	(0.045)	(0.042)
2-Year Lagged Net Tuition Revenue per FTE Student		-0.231****
		(0.054)
Net Tuition Revenue per FTE Student		
Lagged 1-Year Change in Net Tuition Revenue per FTE Student	-0.073***	-0.187***
	(0.024)	(0.060)
Lagged 2-Year Change in Net Tuition Revenue per FTE Student	0.000	0.044
	(0.029)	(0.037)
2-Year Lagged State Appropriations per FTE Student	-0.317****	
	(0.037)	
Exogenous variables		
State Taxes per capita	0.014	-0.048
	(0.018)	(0.034)
Pell Grants per FTE Student	0.036***	0.012
	(0.013)	(0.019)
Per Capita Income	0.429****	0.055
	(0.084)	(0.118)
Error-Correction (EC) Parameter	-0.297****	-0.211****
	(0.032)	(0.031)
Year Dummies	Yes	Yes
Number of States	50	50
Number of Observations	1,100	1,100
Overall R^2	0.106****	0.009****

Note: The robust standard errors, adjusted for state clusters (50), are in parenthesis.
+p< 0.10, *p< 0.05, **p < 0.01, ***p <0.001

Endnotes

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[1]On a more technical note, GMM seeks to find conditions under which the assumptions about the *functions* of the disturbance error and the explanatory variables that would result in the moment conditions ensuring valid instruments. For a technical exposition of GMM techniques, see Greene (2003).

[2]For a more detailed explanation of the Westerlund error-correction-based panel cointegration test, see Westerlund (2007) and Persyn and Westerlund (2008).

[3]See Hadri (2000) for a full description of the technique.