TRANSPORTATION INFRASTRUCTURE AND ECONOMIC ACTIVITY: EVIDENCE USING VECTOR AUTOREGRESSION, ERROR CORRECTION AND DIRECTED ACYCLIC GRAPHS

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Word Count: 5915
Tables and Figures: 5 Tables and 1 Figure

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ABSTRACT

Prior analysis regarding transportation infrastructure has often focused on the aggregate effects of public investment on economic growth or activity, usually at a national or state level. Modeling efforts that attempt to treat all counties as equivalent units, while assuming a homogeneous modeling structure for all the units, may miss important information regarding the statistical and causal relationships between economic activity and transportation infrastructure. This study examines the interrelationships between infrastructure and activity using two Washington State highway infrastructure datasets in combination with county-level employment, wage and establishment numbers for several industrial sectors for a subset of counties from 1990 to 2004. Estimations using vector autoregressions, error correction models and directed acyclic graphs are made. The results show that the relationships between infrastructure investment and economic activity are often weak and are not uniform in effect.

INTRODUCTION

The question of public investment in transportation infrastructure is one of the oldest and most controversial since the ratification of the U.S. Constitution. The largest recent public infrastructure investment in transportation occurred as a result of the 1956 Interstate Highway Act and the subsequent authorization of the Department of Transportation in 1968. Holtz-Eakin (1993) estimated that almost 34.5 percent of all public capital investment has been in street and highway infrastructure resulting in approximately $127 billion in infrastructure investment since 1960 (Bureau of Transportation Statistics, 2006).

In the last fifteen years there has been increasing focus on the issue of infrastructure investment and its impact on the economy. Lakshmanan and Chatterjee (2005) note several types of infrastructure effects that are realized over different time scales. Brown (1999a; 1999b) posits highway investment as reducing transportation costs that then facilitates development of local area economies through changes in the scale and scope of the local economy. A study by Washington State University (Gillis, et al, 1994) interviewed nearly 650 business establishments in Washington and found that investment designed to improve freight efficiency and proximity to existing infrastructure was deemed “critical” for new development. Much of the prior analysis regarding infrastructure has focused on the aggregate effects of public investment on economic growth or on development, usually at a national or state level. Modeling efforts that attempt to treat all counties as equivalent units, while assuming a homogeneous modeling structure for all the units, may miss important information regarding the statistical and causal relationships between economic activity and transportation infrastructure.

LITERATURE REVIEW

Gramlich (1994) identifies public infrastructure capital as “large capital intensive natural monopolies such as highways, other transportation facilities, water and sewer lines, and communication systems.” An alternative definition simply states public infrastructure is the tangible capital stock owned by the public sector. The first recent study examining the role of public capital infrastructure on economic growth was Aschauer (1989), which found a positive relationship between investment and economic productivity. Additional studies were conducted by Munnell (1990; 1992), which appeared to confirm Aschauer’s original findings. Tatom (1991) and Dalenberg and Partridge (1995; 1997) challenged the results of Aschauer and Munnell indicating they had overstated the impact of public capital investment on economic growth. Instead, they found that the positive benefits of public investment were either small or statistically insignificant. This has led Fisher (1997) in a comprehensive review of the topic to conclude that “*some* public services clearly have a positive effect on *some* measures of economic development in *some* cases” (emphasis in the original).

One commonality shared by these studies is that they all use a production function modeling approach. As noted in Fisher (1997) most of these studies are also aggregated at the state level, while a few, such as Dalenberg and Partridge (1995), Luce (1994) and Reynolds and Maki (1990), examine local areas. Reynolds and Maki specifically examine labor market areas, which are associated with particular metropolitan areas.

Fox and Porca (2001) note infrastructure is commonly held to be public investment that improves the productivity of the private sector, but the investment may also be viewed in terms of services rendered. A similar concept is noted in Lakshmanan and Anderson (2002), where the authors detail the linkages between transportation policy, information technologies, infrastructure investment and economic activity associated with (freight) transportation services.

In most prior studies, relevant variables are derived from highly aggregated data such as total highway spending or total public capital as measured in highway miles. Economic development indicators include such measures as state gross product, employment, foreign investment, number of new plants or personal income. The production function analysis approach relies heavily on aggregated data, even for estimations done at the local level. Accordingly, estimation results using disaggregated data may provide additional information on local conditions resulting from infrastructure investment.

An alternative, cost-focused approach in examining public transportation investment was undertaken by Chandra and Thompson (2000) who examined the impact of investment in rural highways on non-urban counties in the U.S. between 1969 and 1993. The authors proceed from the hypothesis that highway capital may provide benefits to specific industries within a region over competitors in other regions. A model is developed in which multiple routes exist in the transportation network with customers and firms located at various positions on the network. The model predicts the impact on firm growth within a region due to lowered transportation costs through the mechanism of market area expansion or contraction. Further, they assume empirically that lower transportation costs will occur on those routes that receive infrastructure investment. The authors then estimate an empirical fixed-effects econometric model with county-level earnings determined by Standard Industrial Classification (SIC) codes as the outcome variable with a matrix of highway construction variables as the primary input.

One possible shortcoming in the approach used by Chandra and Thompson is the assumption of homogeneity within counties. Counties are not uniformly shaped structures of equal area spaced regularly across the landscape. *A priori* one would not expect that transportation infrastructure would have an equally beneficial effect on all locations within a county, or an equally deleterious effect on counties that do not receive infrastructure investment but have locations proximate to the investment. Instead, one would expect that intra-county and inter-county effects that are a function of proximity to the infrastructure would exist.

Spatial interaction models are another method of assessing infrastructure impacts on economic activity. These models seek to approximate processes that happen over space; regarding transportation, they usually model commodity or traffic flows in a networked space. Examples of such models are outlined in Haynes and Fotheringham (1984) and in Fotheringham, et al (2004). Spatial interaction models approximate changes in economic activity resulting from infrastructure improvements by assessing the changes in flows between locations in the spatial network. These changes in flows, or accessibility, can be associated with increases in factor productivity (Fox and Porca, 2001).

Spatial interaction models are particularly well suited for estimating the economic impacts of transportation infrastructure investment if the origin and destination traffic counts are known, or can be reliably estimated. Two recent examples of accessibility measure analysis can be found in Baradaran and Ramjerdi (2001), which examines locational accessibility of European cities, and in Vachal, et al (2004) where accessibility measures are used to inform a set of transportation quality indices for non-urban/rural communities in the United States. In the absence of the required parameter data, the applicability of these models lessens considerably.

A final consideration in the estimation of infrastructure investment impacts on economic activity is the nature of the causal relationship. Economic development may induce investment in transportation infrastructure, infrastructure investments may accommodate expansion of economic activity, or it may be a mix of both effects. In order to examine and estimate changes in economic activity due to infrastructure investment, an empirical model describing the system must first be developed. Variables of interest could be changes in total employment in the area, changes in employment by industry classification, changes in total personal income, income by industry, changes in population, the number of business openings or closings and changes in area property values at the census tract level. As noted in a recent study by Smith, et al (2002), the cause-effect relationship between transportation investment and economic activity may also change over time. As a result, the causal relationship between infrastructure investment and economic activity is not straightforward and may involve feedbacks with autoregressive components, simultaneity and various leading and lagging effects between the variables in the system. In order to ascertain the nature of these interrelationships different estimation and statistical inference techniques need to be considered and employed.

METHODOLOGY

Due to the simultaneity, endogeneity and autoregressive properties that are likely to be present in the variables of interest, the modeling format chosen to examine these interrelationships is a vector autoregression (VAR). VARs are quite common in applied econometrics, but their use in infrastructure analysis has been limited. Two recent examples are in Sturm, et al (1999) that examines long-term output effects from infrastructure investment and Kawakami and Doi (2004) which uses a VAR and vector error correction (VEC) framework to examine the economic effects of investment in port infrastructure in Japan. The estimation framework proceeds as a VAR/VEC model with associated impulse response functions (IRFs). Additional information on any direct causal relationships may be obtained from the implementation of Directed Acyclic Graphs (DAGs) using the residual correlation matrix of the VEC/VAR estimation (Bessler, et al, 2002).

The VAR model consists of a series of Ordinary Least Squares (OLS) regressions in which each dependent variable is a function of the independent variables and lagged values of the dependent and independent variables and includes an uncorrelated error term. In addition, due to the assumption of endogeneity, the response variables are also associated independent variables for the other variables in the system (Enders, 1995). VARs are particularly adept at describing the data involved in a system and in forecasting. However, causal or correlative identification of the structure of a system must rely upon economic theory (Stock and Watson, 2001). Here, the IRFs refer more specifically to the historical association between the variables in the system. A variant of the VAR model is the vector error correction model (VECM). This family of VARs allows for nonstationary variables that are cointegrated in a stationary form. By implication it is assumed that the error terms of the VAR system of equations are also stationary (Enders, 1995).

Associated with VAR estimation is the notion of Granger causality (Granger, 1969), which is a measure of statistical association between two variables. This statistical measure has been criticized as weak, and perhaps misleading (Garrison, 1988; Toda and Phillips, 1993). The danger in this measure is the temptation to fall into the logical fallacy of *post hoc ergo prompter hoc*, in which correlation between two variables is given the erroneous implication of causation simply due to the realization of one variable prior to the occurrence of another variable. Due to the ambiguity surrounding measures of Granger causation, these statistics will not be considered in this study.

STUDY AREAS

This study proposes to examine the effects of transportation infrastructure at the local level over time and differentiating these effects by the type of highway infrastructure and the rural-urban character of the county. Counties in Washington State were first identified as major urban, small urban, or rural. This characterization is based upon the U.S. Office of Management and Budget urban-rural classifications and then further identified using the Rural Urban Commuting Area (RUCA) area definitions (Washington State Department of Health, 2006). Large urban counties are those with urban populations greater than 100,000, while small urban counties have urbanized populations between 25,000 and 100,000. Rural counties are defined as those counties that do not have urbanized population concentrations greater than 25,000. Infrastructure was then broken down as major highway or minor highway based upon annual traffic count volumes for the primary traffic arterials in the county (Peterson, et al, 2004). A county-highway combination such as urban-major highway, rural-major highway, etc., further differentiates the counties. Table 1 provides a listing of the counties, their designation and the associated highway types.

DATA

Broad economic activity variables from the US Census Bureau's Quarterly Census of Employment and Wages (QCEW) for 1990 through Q1 of 2005 were used to measure economic changes at the county level. This dataset provides information on levels of employment, average wages and the number of establishments according to SIC or NAICS business activity classifications. The industrial classes deemed to be most affected by transportation infrastructure were agriculture production, mining, manufacturing, retail, wholesale trade, construction and warehousing/transportation. This dataset was chosen due to temporal contiguity with two infrastructure databases obtained from the Washington State Department of Transportation. These are the Construction Contract Information System (CCIS) and the Capital Program Management System (CPMS). Both datasets have information on infrastructure expenditures, including locations and types of completed investments from 1991 through 2004. Using a joined dataset, a cumulative infrastructure value was calculated for each county comprising maintenance and repair projects or new capacity and connectivity construction projects. For capital projects crossing county lines, the investment amount was pro-rated using the ratio of in-county highway miles to the total highway miles affected by the project.

EMPIRICAL MODEL AND STATISTICAL MEASURES

Using the economic data in concert with cumulative investment, separate VAR systems of equations were created for each county-industry combination. The basic form of the VAR model is

$$Bx_{it} = \Gamma_0 + \Gamma_1 x_{jt} + \Gamma_2 x_{i,jt-1} + \varepsilon_t \qquad (1)$$

x_{it} is a matrix of the dependent variables at time t, x_{jt} is a matrix of contemporaneous values of the independent variables and $x_{i,jt-1}$ is a matrix of the lagged values of the dependent and independent variables. B and the Γ's are matrices of parameters to be estimated, while ε_t is a matrix of serially uncorrelated error terms (Enders, 1995).

Two important components of VAR estimation are the determination of series stationarity and the appropriate lag length for each series. Dickey-Fuller and Augmented Dickey-Fuller tests were run for each county-industry pair. It was found that each series was stationary in first differences, or integrated of order 1. Lag length was determined using Lutkepohlized (Lutkepohl, 1990) estimates of the Likelihood Ratio, Akaike Information Criterion, Forecast Predicted Error, Bayes Information Criterion and the Hannan and Quinn Information Criterion. The lag length chosen for each model used a "consensus of the statistics" approach. If there was no consensus lag length, the default was the lag length determined by the Likelihood Ratio statistic. Table 2 provides the lag lengths used in the VAR estimations for each county-industry pair.

One problem that may exist within the VAR framework described above is the presence of cointegrated variables. In estimating the VAR relationship, the differences in realizations of the variables may be written as

$$\Delta X_{it} = \Pi_0 + \Pi X_{it-1} + \sum_{i=1}^{n} \Pi_n \Delta X_{it-n} + \varepsilon_t \qquad (2)$$

where Π_0 is a vector of intercept terms that may enter the system in the cointegrating vector or as a time trend, Π_n is a set of coefficient matrices, and Π is a non-zero matrix of elements Π_{in} (Enders, 1995). If Π =0, then the VAR representation noted in equation (1) is valid in first differences. However if $\Pi \neq 0$, then the system has an error correction model (VECM) form which implies that

$$\Delta X_{it} = \Pi X_{it-1} + \varepsilon_t \qquad (3)$$

and the estimation of the VAR model will be mis-specified (Johansen, 1988; Enders, 1995). In order to test for cointegration between variables, we examine the rank of Π (Johansen and Juselius, 1990). The rank of the Π matrix is equal to the number of cointegrating vectors, r, in the system and is affected by how the Π_0 term enters the system. The trace statistics test the null hypothesis of r cointegrating vectors against the alternative of p cointegrating vectors, where p = the number of variables in x_{it}. Results for the trace test statistics are provided for each county in Table 3; the critical values are taken from Osterwald-Lenum (1992). The notation "c.v. (1)" and "c.v. (2)" refer to the critical values for the case of an intercept term inside the cointegrating equation, and for the case of an intercept outside the cointegrating equation, respectively.

The cointegration rank results indicate that the arbitrary use of a single model framework for the estimation of the relationships between economic activity and transportation infrastructure is problematic and may lead to incorrectly specified models and/or problems with statistical inference applied uniformly to all counties within a state. One possible result is that the models are likely to be underspecified due to the absence of other explanatory variables in the system.

VAR/VEC estimation produces output conducive to analysis by means of impulse response functions (IRFs). While IRFs are often used as a forecast estimation tool (Enders, 1995; Stock and Watson, 2001), they can also be used to understand the interrelationships that exist between variables in a system. IRFs rely upon the information contained in the error structure of the variables in a VAR or VECM system. These errors are often viewed as indicators of "innovation accounting" (Bessler, 2002), in which the error structure reflects the responses of variables in the system due to shocks, or innovations, in one of the other system variables. Since the IRFs are created using the VAR/VEC error structures they track the historical responses of the change in direction of the movement of variables in a system due to changes in the other variables. In this regard, the IRFs are similar to measures of cross-elasticities of the response variables in the presence of a one percent increase in the impulse variable. While an IRF is a forecast of probable future response, these forecasts are based upon historical actuals. IRFs then describe how a system has responded in the past and how the system variables are interrelated.

One other technique useful for determining causal relationships that can be estimated in the VAR framework is the implementation of directed graphs (Glymour, et al, 1987; Yu, et al, 2006). Directed graphs can be implemented using the error correlation matrix of the VECMs or the residual covariance structure of a VAR (Spirtes, et al, 1993). Due to the likely presence of feedbacks within the systems of variables being estimated here, a directed cyclic structural equation model (SEM) graph incorporating the errors in the system may provide insight into the causal relationships between the different variables. However, the causal interpretation of recursive SEM's is not straightforward (Scheines, et al, 1998). An alternative graph format uses non-recursive or acyclic, directed graphs (Scheines, et al, 1998; Yu, et al, 2006) although this form often eliminates causal relationships subject to feedbacks. Use of the directed acyclic graph framework does provide a restricted case for causal analysis. As in Yu, et al (2006), the estimation of the directed graphs uses the TETRAD[1] software program.

The output of the DAG is a pattern that contains directed and undirected edges. The pattern may contain edges such that $X \rightarrow Y$, $X \leftarrow Y$, implying causal relations, or $X - Y$, an edge where there is a relation between the variables but causation is not straightforward. This case indicates simultaneity, or correlation without causation (Scheines, et al, 1998). The applicability of the results from DAGs may not be fully informed in those cases in which simultaneity is in effect, but such results are indicative of the existence of a probable causal relationship (Scheines, et al, 1998). A good, compact overview of directed acyclic graphs can be found in Bessler, et al (2002), while a more extensive treatment is provided in Spirtes, et al (1993).

ESTIMATION RESULTS

Tables 4 and 5 present the different estimation results for the counties in the study. The different economic variables are noted in the tables with the extensions *_est*, *_emp* and *_w*, which represent establishments, employment and wages, respectively; cumulative infrastructure investment uses the variable *cuminv*. Not every industry is estimated in the same manner for every county due to variability in the presence or absence of cointegrating vectors in the data. If cointegrating vectors were found in the system of variables, the estimation proceeded using a VECM framework. Several of the counties did not have significant numbers of observations for some of the industrial classes in question, so the statistical relationships between economic activity in those sectors and infrastructure investment are unknown. The VARs/VECMs were estimated in deltas – as changes in the levels of the variables. The statistical data estimates the impact of changes in economic variables due to changes in infrastructure investment and vice versa. Statistical significance is determined at the 90% significance level ($p<0.10$) unless otherwise stated. Significant VAR and VEC results for investment and economic activity are presented in Table 4.

The Construction sector has the most consistent results across all of the counties. Investment and economic variables are significant in five of the seven counties: Grays Harbor, Lincoln, Pend Oreille, Spokane and Yakima. The agricultural production sector is found to be significant for all the economic variables and investment in four of the counties. Notably, the exceptions are in Grant, Grays Harbor and Yakima counties, which are major agricultural (including forestry) producing counties in Washington State.

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[1] TETRAD is a free software download available from the Department of Philosophy at Carnegie Mellon University at http://www.phil.cmu.edu/projects/tetrad/ (accessed May 17, 2006). The estimation routines for this study used the TETRAD III version of the software. The primary researchers are Peter Spirtes, Clark Glymour and Richard Scheines. TETRAD III implements the same PC algorithm used in TETRAD II as noted in Spirtes, et al (1993) and in Bessler, et al (2002).

This may be due to the fact that the sectors dominate the local economies of each county and are not as responsive to changes in transportation infrastructure investment.

The results for the other sectors are generally mixed. Several county-industry pairs indicate all four system variables were significant, while others show only a few of the economic variables are associated with changes in infrastructure investment. The most common significant economic variable in these truncated systems is the sectoral wage rate (Clark-Mining, Grant-Retail and Warehousing, Grays Harbor-Manufacturing and Retail, Lincoln-Wholesale, Spokane-Wholesale and Yakima-Warehousing. Employment is also found to be significantly associated with infrastructure investment in several of the county-industry pairs. The numbers of establishments within a county-sector pairing are found to be significant in association with infrastructure investment only in the presence of the sectoral employment and wage variables. Finally, most of the systems indicating a significant association between economic activity and infrastructure investment have long lag periods, usually on the order of 11 or 12 months. These long lag periods may indicate that industries do not alter their business, employment and wage decisions immediately in response to changes in transportation investment, but accommodate these changes over a longer time horizon. This would also suggest that transportation demand driven changes in infrastructure investment take time to be implemented and have a significant impact on local economies. Finally, the R^2 values are generally quite good in those systems in which all of the variables are significant. R^2 values decline substantially in the presence of only one or two significant economic variables. These results indicate that the VAR/VEC system variables explain quite a bit of the variation in each system, but that other unspecified variables also contribute significantly to the systems.

In Table 5 which presents the DAG results, an arrow indicates a causal relationship, while a "—" indicates that the exact causal nature cannot be determined. Such an ambiguity in the system suggests the presence of feedbacks between the variables in which current levels of the variables, or rates of change, are dependent upon previous, lagged values of the other variables in the relationship. For example, if the relationship is noted as establishments – investment, the implication would be that changes in the number of establishments in a sector is responsive to prior changes in infrastructure investment, which, in turn, spurs a response in infrastructure expenditures as a result of the change in the number of establishments, or that the relationships may be simultaneously reinforcing. The statistical level of significance for the presence of a causal relationship is set at 0.05.

As a result of the likely presence of simultaneity in the systems of variables, the DAG results indicating significant causal relationships between infrastructure and economic activity are far fewer than the VAR/VEC results. Only six relationships are discovered using the DAG process, three indicating a direct causal relationship and three providing unclear results. Investment is found to influence Retail sector employment in Clark County and Construction sector employment in Grant County. Investment is also found to be a causal driver of establishment numbers in the Spokane Warehousing sector, while a probable simultaneous relationship is noted between Agricultural Production employment and investment in Yakima County. Interestingly, VAR/VEC estimations do not indicate significant statistical associations for any of these county-industry pairs. No causal relationships were found for any of the sectors in Grays Harbor and Lincoln counties.

Two relationships are discovered for Pend Oreille County: one between Retail establishments and investment and another between Construction sector wages and investment. Only the Construction result is substantiated by the results of the VAR/VEC estimation. A further examination of the VAR/VEC results, the DAG and the IRFs for this sector is detailed below.

The final piece of analysis involves the use of Impulse Response Functions (IRFs). Combined with the results achieved in the VAR/VEC estimations, the IRFs provide information on the direction and magnitude of response to changes in one of the other system variables. A graph of the IRF provides an impulse and a response variable. As the study is concerned with the interrelationship between changes in economic activity and infrastructure investment, a cumulative measure is more appropriate to measure the persistence of the effects of changes to the system over time (Andrews and Chen, 1994). A cumulative IRF (CIRF) measures the amount of time it takes for a variable to converge (in this case, $\Delta = 0$, or no change), subsequent to a shock in the system (Marques, 2004). If an IRF does not trend back towards 0 over the period, the system has either permanently shifted, perhaps to a new equilibrium point, or the adjustment period is longer than the time period under consideration. The systems estimated in this study allowed for a maximum lag period of 12 months. For the measures of persistence an additional 12 months was allowed in estimating the CIRFs, for a total of 24 months. CIRF results are presented below for one industry-county economic variable pairing: Construction sector wages and infrastructure investment in Pend Oreille County, as part of an extended example comparing the significant VAR/VEC, DAG and IRF results.

Pend Oreille County Construction Sector CIRF

Pend Oreille County is a primarily rural county located in the forests and mountains of northeastern Washington State. Transportation infrastructure is primarily from small state highways and county or forest service roads. Pend Oreille County also features one of a handful of small border crossings into Canada that exist in eastern Washington.

Based upon the results of the VAR/VEC and DAG routines, Construction sector wages and infrastructure investment in the county are characterized by the presence of simultaneity and a probable dual-causal relationship existing over a lagged period of 12 months. An examination of the CIRFs for these variables in Figure 1 provides some visual confirmation of this interrelationship.

The CIRF of wage effects on infrastructure investment indicates that increases in the sector wage rate are associated with a permanent increase in infrastructure investment. This increase peaks after 15 months and then declines through month 24. At the same time, an increase in infrastructure expenditures is associated with a modest decline in the wage rate for the first 5 to 6 months after a change, which is then followed by a permanent increase in the wage rate out to 24 months. It should be noted that the changes in the wage rate are quite modest: a 1 percent change in the rate of investment translates into a change in the wage rate of 0.00015 dollars after 18 months.

DISCUSSION AND CONCLUSION

The primary implications of this study are that counties are heterogeneous units that display remarkable diversity in economic responses to transportation infrastructure investment, and that infrastructure investment, at least during the 1990's and early 2000's, does little to alter already existing trends in economic activity within counties. Transportation infrastructure then appears to accommodate economic activity, but does little to reverse industry sector downturns, or create substantial, long-term opportunities for expansion of a county's economic base.

The VAR and VECM results indicate that connections exist between many of the economic system variables and the cumulative level of investment in transportation. However, the variation amongst the county-industry pairs examined in this study is still substantial. The results also indicate the causal relationships between infrastructure and economic activity are not straightforward, but involve interactions between varying leads and lags of the system variables. The large amounts of unexplained variation in the system also point to other processes determining changes in economic activity, such as secular, industry-wide trends, and infrastructure investment, perhaps as the result of political activity such as lobbying that is separate from changes in the economic base of a county.

Directed acyclic graph results established that no direct causal relationships between infrastructure and economic activity could be detected in most of the various county-industry pairs. Where relationships are established, the results are often ambiguous and indicate again the presence of systemic feedbacks. The results appear to be a confirmation Fisher's (1997) conclusion noted above: *some* transportation infrastructure investments have *some* effect on *some* economic indicators in *some* locations in Washington State.

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LIST OF TABLES AND FIGURES

TABLE 1 Study Counties, Types and Highway Types

County	Type	Highway Type
Clark	large urban	major highway
Grant	rural	major highway
Grays Harbor	rural	minor highway
Lincoln	rural	major highway
Pend Oreille	rural	minor highway
Spokane	large urban	major highway
Yakima	small urban	major highway

TABLE 2 VAR/VEC Lag Lengths and Test Statistics by County and Industry

County	Industry	Lag Length	Statistic
Clark	Ag.Prod.	11	LR, FPE, AIC, HQIC
	Mining	3	FPE, AIC
	Construct.	9	FPE, AIC
	Manuf.	3	FPE, AIC, HQIC
	Wholesale	3	FPE, AIC
	Retail	12	LR, FPE,AIC
	Whse/Trans.	10	FPE, AIC
Grant	Ag.Prod.	11	FPE, AIC, HQIC
	Mining	N/A	
	Construct.	1	FPE, AIC, BIC
	Manuf.	4	FPE, AIC
	Wholesale	12	LR, AIC
	Retail	3	FPE, AIC
	Whse/Trans.	12	LR, FPE, AIC
Grays Harbor	Ag.Prod.	6	FPE, AIC
	Mining	N/A	
	Construct.	6	FPE, AIC
	Manuf.	3	FPE, AIC, HQIC
	Wholesale	N/A	
	Retail	12	LR, FPE, AIC
	Whse/Trans.	1	FPE, AIC, HQIC, BIC
Lincoln	Ag.Prod.	12	LR, FPE, AIC, HQIC
	Mining	N/A	
	Construct.	9	LR, FPE, AIC
	Manuf.	9	FPE, AIC
	Wholesale	12	LR, FPE, AIC
	Retail	1	FPE, AIC, HQIC, BIC
	Whse/Trans.	3	FPE, AIC
Pend Oreille	Ag.Prod.	12	LR, AIC
	Mining	N/A	
	Construct.	12	LR, AIC
	Manuf.	10	LR
	Wholesale	N/A	
	Retail	1	FPE, AIC, HQIC, BIC
	Whse/Trans.	12	LR, FPE, AIC, HQIC
Spokane	Ag.Prod.	11	LR, FPE, AIC
	Mining	1	FPE, AIC, HQIC, BIC
	Construct.	12	LR, FPE, AIC, HQIC
	Manuf.	9	FPE, AIC
	Wholesale	1	FPE, AIC, HQIC, BIC
	Retail	12	LR, FPE, AIC
	Whse/Trans.	12	LR
Yakima	Ag.Prod.	11	LR, FPE, AIC
	Mining	N/A	
	Construct.	12	LR, FPE, AIC, HQIC
	Manuf.	12	LR
	Wholesale	11	FPE, AIC
	Retail	12	LR, FPE, AIC
	Whse/Trans.	11	LR, FPE, AIC, HQIC

A notation of N/A indicates that there were either no observations for that county-industry pair, or that the number of observations was insufficient to create lagged values.

TABLE 3 Trace Test Statistics of Cointegration Rank by County

County	Industry Rank (r)	Ag. Prod. Trace	Mining Trace	Const. Trace	Manuf. Trace	Whole. Trace	Retail Trace	Whse. Trace	c.v. (1)	c.v. (2)
Clark	r = 0	56.21	58.04	42.68	72.93	86.8	42.01	44.56	53.12	47.21
	r ≤ 1	27.92	23.54	18.66	29.13	22.67	16.51	24.52	34.91	29.68
	r ≤ 2	6.93	10.8	7.87	9.83	5.82	4.52	7.8	19.96	15.41
	Rank	1	1	0	1	1	0	0		
Grant	r = 0	38.94		40.08	42.46	47.17	67.36	70	53.12	47.21
	r ≤ 1	20.88		16.75	19.71	22.4	16.42	36.69	34.91	29.68
	r ≤ 2	7.07		2.64	4.87	5.48	4.5	16.66	19.96	15.41
	Rank	0	N/A	0	0	0	1	1		
Grays Harbor	r = 0	32.48		89.57	54.52		53.98	46.85	53.12	47.21
	r ≤ 1	11.82		44.84	30.79		26.46	20.89	34.91	29.68
	r ≤ 2	4.44		14.91	11.72		5.59	1.28	19.96	15.41
	Rank	0	N/A	2	1	N/A	1	0		
Lincoln	r = 0	48.59		43.76	32.7	61.28	31.82	149.65	53.12	47.21
	r ≤ 1	20.61		20.46	13.64	29.54	10.72	62.19	34.91	29.68
	r ≤ 2	7.92		6.93	4.51	6.76	0.45	9.35	19.96	15.41
	Rank	0/1	N/A	0	0	1	0	2		
Pend Oreille	r = 0	42.96		52.22	62.37		37.26	51.98	53.12	47.21
	r ≤ 1	20.27		21.76	25.68		16.39	19.36	34.91	29.68
	r ≤ 2	4.98		2.47	10.31		4.66	3.28	19.96	15.41
	Rank	0	N/A	0/1	1	N/A	0	0/1		
Spokane	r = 0	49.91	39.66	49.58	40.95	50.33	61.83	91.42	53.12	47.21
	r ≤ 1	20.98	19.96	26.04	15.7	22.21	29.64	46.03	34.91	29.68
	r ≤ 2	7.81	7.23	12.71	7.81	4.02	15.02	15.88	19.96	15.41
	Rank	0/1	0	0/1	0	0/1	1	2		
Yakima	r = 0	103.48		81.73	44.16	39.5	51.99	41.11	53.12	47.21
	r ≤ 1	44.92		27.24	18.16	21.47	22.85	16.73	34.91	29.68
	r ≤ 2	18.3		8.86	7.41	8.9	7.28	5.95	19.96	15.41
	Rank	1	N/A	1	0	0	0/1	0		

TABLE 4 Significant VAR and VECM Results By County

County	Equation	R-sq	chi2	P
Clark	D_min_oil_w	0.17	34.99	0.00
	D_cuminv	0.09	16.51	0.09
	D.whse_trans_emp	0.46	146.30	0.00
	D.whse_trans_w	0.54	202.04	0.00
	D.whse_trans_est	0.39	110.09	0.00
	D.cuminv	0.40	110.45	0.00
County	**Equation**	**R-sq**	**chi2**	**P**
Grant	D.agprod_emp	0.93	2026.36	0.00
	D.agprod_w	0.79	524.07	0.00
	D.agprod_est	0.52	152.82	0.00
	D.cuminv	0.30	60.69	0.05
	D.whole_emp	0.56	181.92	0.00
	D.whole_w	0.73	387.94	0.00
	D.whole_est	0.38	88.67	0.00
	D.cuminv	0.34	71.88	0.01
	D_retail_w	0.29	56.96	0.00
	D_cuminv	0.19	33.11	0.00
	D_whse_trans_w	0.62	160.98	0.00
	D_cuminv	0.49	93.46	0.00
County	**Equation**	**R-sq**	**chi2**	**P**
Grays Harbor	D_construc~p	0.39	87.87	0.00
	D_construc~w	0.47	117.70	0.00
	D_construc~t	0.24	42.38	0.01
	D_cuminv	0.34	71.08	0.00
	D_manuf_w	0.65	278.18	0.00
	D_cuminv	0.30	62.18	0.00
	D_retail_emp	0.62	173.43	0.00
	D_retail_w	0.57	142.11	0.00
	D_cuminv	0.48	99.89	0.00
County	**Equation**	**R-sq**	**chi2**	**P**
Lincoln	D_agprod_emp	0.87	596.63	0.00
	D_agprod_w	0.69	193.23	0.00
	D_agprod_est	0.67	179.26	0.00
	D_cuminv	0.58	123.93	0.00
	D.construct_emp	0.45	110.55	0.00
	D.construct_w	0.54	162.77	0.00
	D.construct_est	0.36	76.08	0.00
	D.cuminv	0.51	139.92	0.00
	D.manuf_emp	0.57	176.84	0.00
	D.manuf_w	0.69	308.34	0.00
	D.manuf_est	0.30	59.16	0.01
	D.cuminv	0.34	70.45	0.00
	D_whole_emp	0.53	113.82	0.00
	D_whole_w	0.48	95.03	0.00
	D_cuminv	0.36	57.41	0.01

County	Equation	R-sq	chi2	P
Pend Oreille	D.agprod_emp	0.60	179.80	0.00
	D.agprod_w	0.65	227.68	0.00
	D.agprod_est	0.57	158.98	0.00
	D.cuminv	0.37	70.85	0.02
	D_construct_emp	0.53	85.65	0.00
	D_construct_w	0.63	131.84	0.00
	D_construct_est	0.60	112.38	0.00
	D_cuminv	0.49	71.68	0.01
	D_manuf_emp	0.47	79.25	0.00
	D_manuf_w	0.68	189.26	0.00
	D_manuf_est	0.58	124.62	0.00
	D_cuminv	0.40	59.61	0.00

County	Equation	R-sq	chi2	P
Spokane	D_agprod_emp	0.68	208.85	0.00
	D_agprod_w	0.62	159.58	0.00
	D_agprod_est	0.36	56.27	0.07
	D_cuminv	0.46	82.01	0.00
	D.min_oil_emp	0.06	9.76	0.04
	D.cuminv	0.07	11.06	0.03
	D_construct_emp	0.91	924.72	0.00
	D_construct_w	0.90	816.33	0.00
	D_construct_est	0.52	101.25	0.00
	D_cuminv	0.48	86.26	0.00
	D.manuf_emp	0.38	85.93	0.00
	D.manuf_w	0.79	515.34	0.00
	D.manuf_est	0.38	87.80	0.00
	D.cuminv	0.26	49.04	0.07
	D_whole_w	0.14	23.73	0.00
	D_cuminv	0.10	16.52	0.00
	D_retail_emp	0.70	217.65	0.00
	D_cuminv	0.40	61.24	0.07

County	Equation	R-sq	chi2	P
Yakima	D_construct_emp	0.86	537.05	0.00
	D_construct_w	0.86	542.04	0.00
	D_construct_est	0.42	64.94	0.03
	D_cuminv	0.49	87.57	0.00
	D.whse_trans_emp	0.76	423.97	0.00
	D.whse_trans_w	0.86	835.93	0.00
	D.cuminv	0.35	73.94	0.00

TABLE 5 Significant Directed Acyclic Graph Results

County	Industry	Causal Relationship
Clark	Retail	investment --> employment
Grant	Construction	investment --> employment
Grays Harbor		none
Lincoln		none
Pend Oreille	Construction	wages -- investment
Pend Oreille	Retail	establishments -- investment
Spokane	Warehousing/Transport	investment --> establishments
Yakima	Agricultural Production	employment -- investment

FIGURE 1 Impulse and Response Functions: Investment and Construction Wages in Pend Oreille County