

Inter-county Spillovers in California's Ports and Roads Infrastructure

Final Report

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ABSTRACT

Using county-level data, we analyze the impact of county-level ports infrastructure investment for the state of California. Estimating county-level production functions for the manufacturing and retail trade industries, we include the level of ports infrastructure stocks in own and neighboring counties as shift variables in the production function. As another form of county interdependency, we also test for and find significant evidence of spatial autocorrelation, and we accordingly adapt our model. We find positive impacts from county-level port investment on manufacturing output, while we find mixed spillover effects of port investment in neighboring counties. Counties with large ports experience negative spillovers from increases in neighboring counties' ports infrastructure. On the other hand, some counties with smaller ports experience significantly positive spillovers from additional neighboring counties' ports infrastructure stocks, while others with smaller ports experience no significant impact from changes in neighbors' ports. We find unambiguous positive spillover effects from ports infrastructure on the retail trade sector in adjacent counties.

TABLE OF CONTENTS

1. Introduction	1
2. Data and Descriptive Statistics	2
2A. Ports Investment	3
2B. Roads Investment	5
2C. Gross State Product	7
2D. County-level Employment and Payroll	9
3. Model and Results	11
3A. Results: All Counties Manufacturing Sector	14
3B. Results: All Counties Retail Trade Sector	17
4. Conclusions and Recommendations	19
5. Implementation	20
6. Appendix A: Data Description	21
9. References	23

LIST OF FIGURES AND TABLES

Table 1: Average Annual Port Capital Spending, 1998-1005

Table 2: Port Capital Stock

Figure 1: Percent Growth Rate in Capital Stock

Table 3: Roads Investment, 2005

Figure 2: Real Gross State Product, 1997-2005

Figure 3: Real Gross State Product for Manufacturing, Retail Trade, and Wholesale Trade

Figure 4: Year to Year Percent Change in Nominal GSP

Table 4: Percent Change in Total Employment, 1998-2005

Table 5: Percent Change in Nominal Payroll, 1998-2005

Table 6: Elasticities Evaluated at the Mean of the Data for the Entire Sample,
Manufacturing

Table 7: Mean of Ports Elasticities for Individual Ports Counties

Table 8: Elasticities Evaluated at the Mean of the Data for the Entire Sample, Retail
Trade

DISCLOSURE

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1. Introduction

California is home to three of the nation's top container ports (Los Angeles, Long Beach, and Oakland), which have experienced considerable growth in the volume of containers handled in the past decade, due to the increased reliance on trans-Pacific trade routes. Projections show that the demand for services at Los Angeles and Long Beach could double between 2005 and 2020. Whether these projections will be borne out depends on trade patterns, availability of alternative ports of call, and the ability of the terminal operators to handle more containers. Currently, 40 percent of trade from Asia enters the US through the Ports of Los Angeles and Long Beach (hereafter referred to as the San Pedro Bay ports). Containerships currently on order from Asian shipbuilders have capacity of more than 8000 TEUs (twenty foot equivalent units, the standard measure of container size). These "Post Panamax" ships are too large to move from Asia to Eastern US ports through the Panama Canal. Asian trade could be diverted to East Coast or Gulf ports through the Suez Canal or by utilizing smaller ships through the Panama Canal. The amount of available divergence is dependent on congestion and cost issues at California ports.

As the West Coast ports (like most US ports) are landlord ports where city government owns the port land and lease terminals out to operators, the ability of the terminals to handle increased throughput is a function of using existing space more productively, constraints on labor rules, and the ability of ports to expand and improve facilities. Ports must conduct environmental impact reports for any changes to existing facilities, which must then be approved by the relevant local, county, and state government authorities. There have notably been no environmental impact reports

approved in the past 5 years by either of the San Pedro Bay ports, mainly due to increased pressure on city officials by environmental groups and environmental regulatory authorities. This has led to considerable tensions between the groups who focus on the negative externalities generated by ports and operators of “trade-dependent” groups (primarily shippers and transportation providers) who focus on the employment and economic benefits of the ports. At the center of this debate is the fact that negative externalities from the ports tend to be experienced locally, while the positive externalities are felt locally, regionally, and nationally.

In an earlier study, Cohen and Monaco (2007) estimate interstate spillover effects from ports and roads infrastructure. They find that ports infrastructure investment reduces manufacturing costs within a state, but also find evidence of diseconomies of scale from ports investment in a neighbor state. In this study, we focus on county-level analysis of ports and roads infrastructure investment for the state of California. Estimating county-level production functions for the manufacturing industry we find positive impacts from county-level port investment on manufacturing output. The effects of investment by neighboring counties is mixed, with positive effects felt by some counties that have small ports and negative effects felt by counties that have larger ports. Likewise, we find mixed spillover effects of port investment in neighboring counties on counties that have no ports.

2. Data and Descriptive Statistics

For our analysis, we use county level data on output, capital, and employment from 1998-2005. Data on employment and personal income by industry was obtained

from the Bureau of Economic Analysis. Data on ports and roads annual investment by county was obtained from State and Local Public Finance statistics, published by the U.S. Census Bureau. Data on capital spending in the manufacturing industry for California was obtained from Annual Survey of Manufactures and apportioned to the county level using gross county product in manufacturing. Data on private investment for wholesale trade and retail trade industries was obtained from the Annual Capital Expenditures Survey and, as this is a national statistic, was apportioned first to the state of California using state GDP and then apportioned to the counties using county output for each industry. See the data appendix for additional details on the data construction.

2A. Ports Investment

As would be expected, the largest investment in ports infrastructure is in Los Angeles County. Table 1 presents average annual nominal capital spending for the five largest California ports.

Table 1: Average Annual Port Capital Spending, 1998-2005

	Port Name	Average
Los Angeles, CA	Los Angeles and Long Beach	\$319,420,364
Alameda, CA	Oakland	\$95,890,545
San Diego, CA	San Diego	\$29,070,200
San Francisco, CA	San Francisco	\$16,421,455
San Joaquin, CA	Stockton	\$5,182,667

The average annual investment in LA county is over three times that of the next largest county (Alameda), which is not surprising given the relative size of the San Pedro Bay ports and the Port of Oakland. Though not shown, Sacramento and Ventura (Port

Hueneme) counties are beginning to invest increasing funds in their ports, though these increases in investment came towards the end of the time span covered by this study.

Port Hueneme, in particular, has invested large sums over the past three years to attract ro-ro operations (involved in auto transport) away from the San Pedro Bay ports.

Sacramento is working to establish itself as an alternative to the Port of Oakland since it has fewer problems with road congestion in the county.

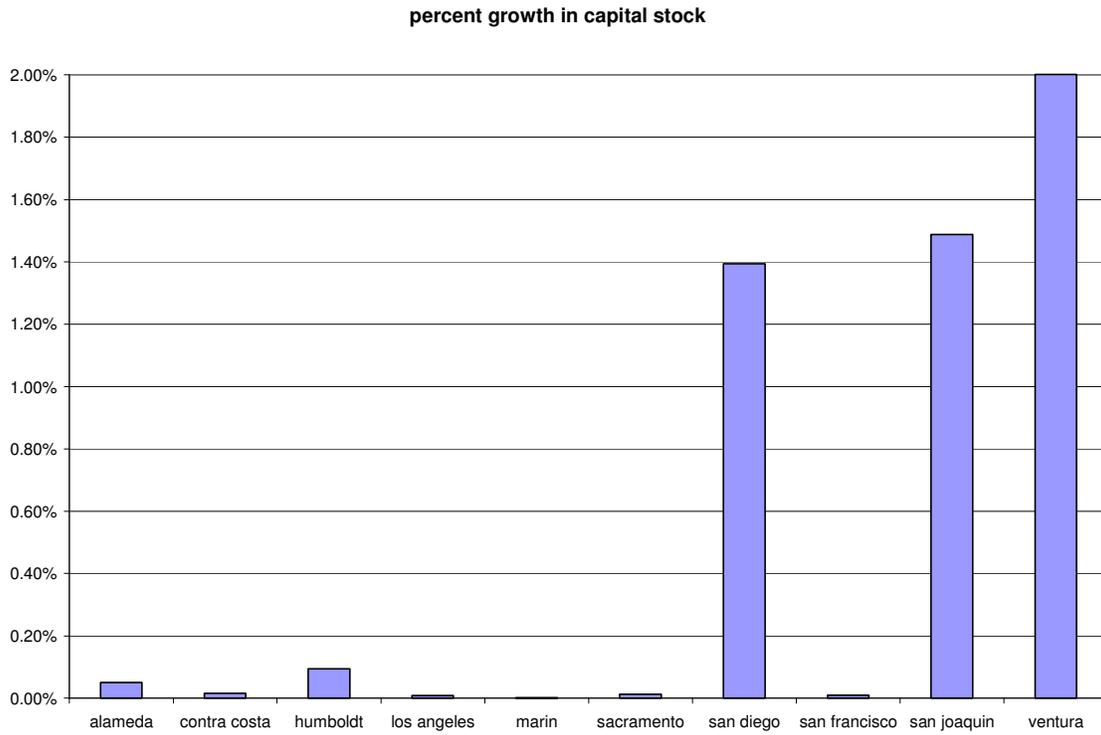
We transform the capital investment data into capital stock measures using the method described in Appendix A and present the average capital stock over the period 1998-2005 (in thousands of 2000 dollars) in Table 2.

Table 2: Port Capital Stock

County Name	Average Port Capital Stock
Los Angeles	\$4,241,038
Alameda	\$183,567
San Francisco	\$171,758
Contra Costa	\$14,156
san Mateo	\$5,029
Sacramento	\$3,657
San Diego	\$1,784
San Joaquin	\$151
Humboldt	\$58
Ventura	\$10

These data on capital stock reinforce the data presented in Table 1; there is a great deal of dispersion in the value of port capital stock by county. Some of the smaller ports are left off the charts entirely, which can obscure the fact that these ports tend to be the fastest growing, as evidenced by the growth rates presented in Figure 3 below.

Figure 1: Percent Growth Rate in Capital Stock (1998-2005)



2B. Roads Investment

Table 3 presents data on roads investment in 2005 for the ten counties with the highest levels of roads investment.

Table 3: Roads Investment, 2005

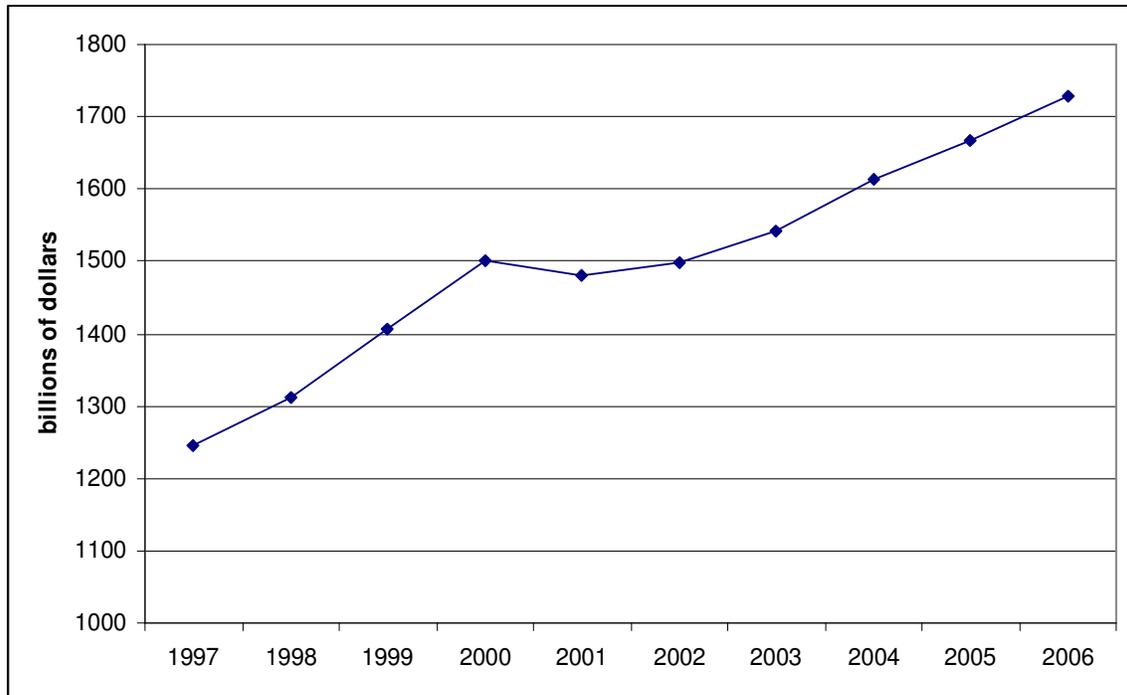
County	Roads Investment (in thousands)	Per Capita Roads Investment	Port in County	Ports in Adjacent Counties
Yolo	\$57,972	\$308.22	none	Sacramento
San Francisco	\$106,866	\$143.63	San Francisco	Redwood
Sacramento	\$194,068	\$141.17	Sacramento	Stockton
Santa Clara	\$197,771	\$114.23	none	Redwood
Alameda	\$88,561	\$60.77	Oakland	Stockton
San Diego	\$148,944	\$50.64	San Diego	None
Orange	\$129,953	\$43.29	none	Los Angeles, Long Beach, San Diego
Riverside	\$57,113	\$28.18	none	San Diego
Los Angeles	\$267,950	\$26.93	Los Angeles, Long Beach	Ventura
San Bernardino	\$51,881	\$25.95	none	Los Angeles, Long Beach

There is less dispersion in these figures than we see in ports investment. Los Angeles has a significant investment in its roads on an annual basis, but what is notable is that all of these counties either house a port or are adjacent to a port. The increased roads investment, especially in the ports-adjacent counties, is likely in response to the increased importance of these counties in goods movement and international trade, as well as the general increase in population. In the case of Riverside and San Bernardino counties, warehouses and distribution centers for wholesalers, retailers (and the third party providers that provide services to manufacturers, retailers and wholesalers) are locating in this region, referred to as the “Inland Empire,” rather than Los Angeles and Orange counties. This is occurring simultaneously with the rise in housing availability in these counties.

2C. Gross State Product

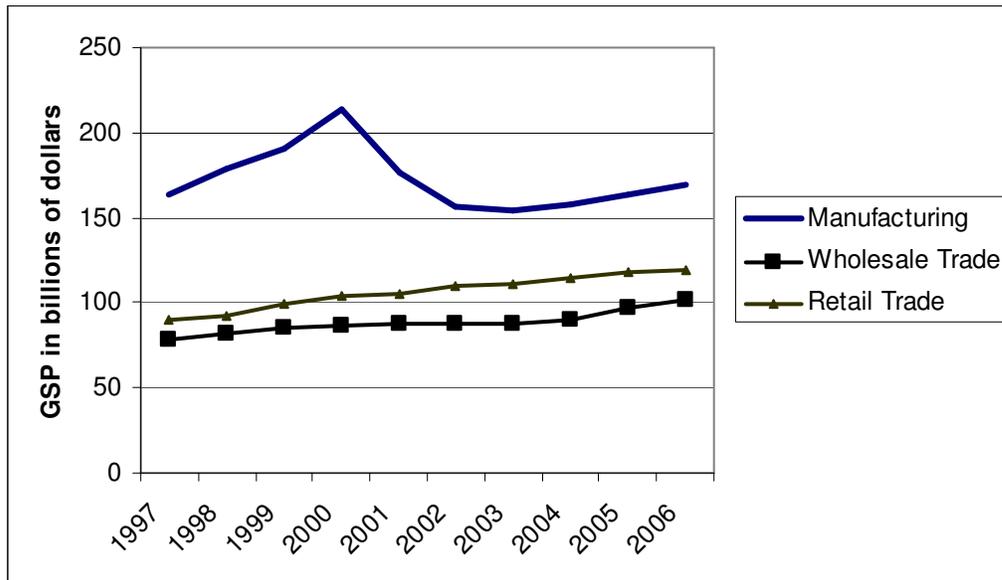
Figure 2 presents nominal gross state product (a measure of economic activity analogous to GDP, but measured at the state level) for California from 1997-2005.

Figure 2: Real Gross State Product: 1997-2005 (in billions of 2005 dollars)



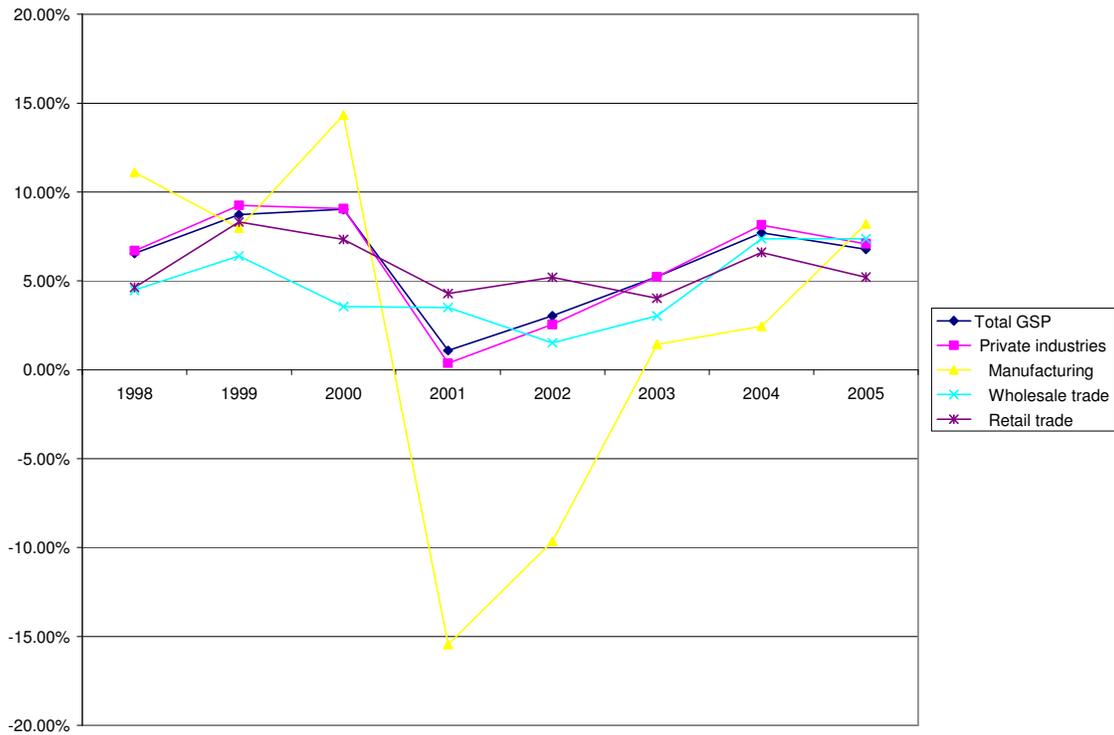
It is evident from this picture that nominal GSP reflects what we know about the economy over the last decade – fast growth in the late 1990s, slowdown in 2000-2002, and recovery after 2003. What is more interesting is to examine the same measures for specific industries, namely those that are the focus of this study, which are presented in Figure 3.

Figure 3: GSP for Manufacturing, Retail Trade, and Wholesale Trade



What is clear from figure 3 is that the growth in wholesale and retail trade provided much needed state economic activity after the decline of manufacturing after 2000. Figure 4 presents the percentage change in nominal GSP growth overall and by industry from 1998-2005.

Figure 4: Year to Year Percent Change in Nominal GSP



2D. County-level Employment and Payroll

Since there are far too many counties to display the level of employment and payroll for each county, we split counties into “port” and “nonport” categories. We classify “port” counties as those counties directly adjacent to those with a port (it should be noted that since ports locate along waterways it is often the case that counties that contain ports are also adjacent to other counties with ports – an example would be Alameda, San Francisco, and Oakland in Northern California). Nonport counties do not contain ports, nor are they adjacent to a county with a port.

We see preliminary evidence of increased economic activity in trade-related industries in counties that house a port. Table 4 presents the percentage growth in employment by industry divided by “non port” and “port” status.

Table 4: Percentage Change in Total Employment (1998-2005)

	Non Port	Port
Total Employment	10.6%	18.7% *
Retail Trade	10.5%	20.9% *
Wholesale Trade	8.9%	10.1%
Manufacturing	-8.0%	-1.7%

* - significant at the 5 percent level

Both total employment and employment in retail trade grew faster in counties with ports or port-adjacent over this time period. There is also a slower decline in manufacturing employment, though this is not significant at the 5 percent level.

Table 5 presents the percentage change in nominal payroll by industry over the same period. Again, we see higher payroll growth rates in port and port-adjacent counties than in non-port counties. This growth in payroll exceeds the percentage change in employment, suggesting that the mean wage increased in these sectors. The increased demand for workers in retail and wholesale trade sectors is due to the overall growth in the population as well as job growth in other sectors.

Table 5: Percent Growth in Nominal Payroll, 1998-2005

	Non Port	Port
Total Employment	45.5%	58.1% *
Retail Trade	42.8%	53.8% *
Wholesale Trade	29.1%	54.8% *
Manufacturing	13.2%	19.9% *

* - significant at the 5 percent level

3. Model and Results

To quantify the relationship between ports and roads infrastructure and county level output, we use a production function approach, test for first order spatial correlation, and, finding evidence of spatial autocorrelation, incorporate this into the model through a spatial Cochrane-Orcutt transformation. First, we estimated a Cobb-Douglas production function, but the implied elasticities were implausible. Thus, we chose to estimate a more sophisticated, flexible functional form, which is a variation of a translog production function. The advantage of the translog production function is that it does not impose a priori assumptions on the elasticity of production or the elasticity of substitution between inputs. The primary disadvantage is the sheer number of parameters which must be estimated, often resulting in multicollinearity. Indeed, when we tried incorporating both linear and quadratic terms, there was apparent multicollinearity that resulted in insignificant quadratic terms. Thus, we chose to drop the quadratic terms, and our functional form can be written as follows:

$$\begin{aligned}
(1) \quad \ln Y_{n,t} = & \sum_n \beta_n D_{n,t} + \beta_K \ln K_{n,t} + \beta_L \ln L_{n,t} + \beta_P \ln P_{n,t} + \beta_R \ln R_{n,t} + \beta_{WP} \ln WP_{n,t} + \\
& \eta_t t + \beta_{KL} \ln K_{n,t} \ln L_{n,t} + \beta_{KP} \ln K_{n,t} \ln P_{n,t} + \beta_{KR} \ln K_{n,t} \ln R_{n,t} + \beta_{KWP} \ln K_{n,t} \ln WP_{n,t} \\
& + \beta_{LP} \ln L_{n,t} \ln P_{n,t} + \beta_{LR} \ln L_{n,t} \ln R_{n,t} + \beta_{LWP} \ln L_{n,t} \ln WP_{n,t} + \beta_{PR} \ln P_{n,t} \ln R_{n,t} \\
& + \beta_{PWP} \ln P_{n,t} \ln WP_{n,t} + \beta_{RWP} \ln R_{n,t} \ln WP_{n,t} + \eta_{tK} t \ln K_{n,t} + \eta_{tL} t \ln L_{n,t} + \eta_{tWP} t \ln WP_{n,t} \\
& + \nu_{n,t}
\end{aligned}$$

where Y is county-level output, K represents the stock of private capital in county n at time t , L is the level of employment, P is the stock of ports infrastructure, WP is the weighted average of neighboring counties' ports infrastructure, R is the stock of roads infrastructure, and t is the time trend ($t=1,2,\dots,8$ corresponds to the years of the sample, 1998-2005). The variables $D_{n,t}$ are county fixed effects. All other variables except t and R are in natural logarithms. Including R in natural logarithms led to some implausible elasticity estimates. Details of the data construction are in the Data Appendix. The error terms are assumed to be spatially autocorrelated, and in matrix notation in the form $\nu_{n,t} = \rho W\nu_{n,t} + \gamma$, where $\gamma \sim N(0, \sigma_n^2 I)$ and I is a 464 by 464 identity matrix. Thus, we allow for heteroskedasticity, which we adapt for in the regression with a White Robust procedure. We also assume that there are zero covariances among the error terms across observations. Our assumption of spatial autocorrelation is based on the results of the Kelejian and Robinson (1992) test for spatial autocorrelation, for which we strongly reject the null hypothesis of no spatial autocorrelation (P-Value=.0222). While we also allow for first-order time series autocorrelation in addition to spatial autocorrelation, in the form introduced by Cohen and Morrison Paul (2004), the time-series autocorrelation coefficient parameter estimate in our model was statistically insignificant. Thus, we present here only the latter results. Incorporating more sophisticated modeling of space-time processes is beyond the scope of this paper but is a topic for future research.

In addition to incorporating spatial autocorrelation, we allow for spatial lags in ports infrastructure. Namely, WP represents the weighted average of neighboring counties' ports infrastructure. The individual elements of the spatial weights matrix, represented by the matrix W in both the error structure and the spatial lag, are the inverse of the number of contiguous neighbor counties. In other words, $w_{i,j} = 1/k$, where k is the number of contiguous neighbors of county i. Also, we follow the traditional approach of imposing that the sum over all j of $w_{i,j}$ equals 1, for every row i in the matrix W.

We estimate the production function by Ordinary Least Squares, using the “robust” heteroskedasticity procedure with TSP software, and then correct for the possibility of spatial autocorrelated errors with a Maximum Likelihood estimation procedure. Lee (2004) has shown that Maximum Likelihood estimation yields consistent parameter estimates for the spatial autocorrelation coefficients. After obtaining the spatial autocorrelation adjusted results (we find that the parameter estimate for $\rho = .041046$), we calculate elasticities of output with respect to each of the inputs. It is also worth noting that our R-squared measure for the final model is .975.

For the ports variable, the elasticity of output with respect to own-county ports can be obtained as the partial derivative, $\epsilon_{Y,P} = \partial \ln Y / \partial \ln P = [\partial Y / \partial P][P/Y]$. Similarly, the elasticity of output in a particular county with respect to ports in neighboring counties can be written as $\epsilon_{Y,WP} = \partial \ln Y / \partial \ln WP = [\partial Y / \partial WP][WP/Y]$. Analogous to $\epsilon_{Y,P}$ is $\epsilon_{Y,R} = [\partial \ln Y / \partial \ln R] = [\partial Y / \partial R][R/Y]$, which is the percentage change in output resulting from a one percentage change in roads infrastructure within the same county.

We also calculate elasticities of output with respect to the other inputs (private capital, labor, and the time trend). For the entire sample we first calculate the mean of

each variable over all counties and years, and then we evaluate the elasticities at the mean of the data. These results for the manufacturing sector are presented in Table 5. For the individual counties we also calculate the mean of each county's elasticities over all years of the sample. While only a few of the elasticities are statistically significant when evaluated at the mean of the data for all counties, many of them are significant when the mean is taken over the individual counties. For this reason, in Table 6 we focus on the ports elasticity estimates based on the mean over the individual counties for the manufacturing sector. This approach also captures more cross-county heterogeneity that is obscured in the overall estimates.¹

3A. Results: All Counties Manufacturing Sector

We calculate elasticities of output with respect to each of the inputs (private capital and labor), and the shift variables (roads, ports, neighboring counties' ports, and time trend). For the entire sample we evaluate each of the elasticity measures at the mean of the data, and calculate the standard errors using the Delta method in TSP. Table 6 shows the elasticity estimates for the specification in equation (1) that adjusts for spatial autocorrelation. We find that $\epsilon_{Y,L} = 0.758$ and is significant, while $\epsilon_{Y,K} = 0.358$ and is insignificant. Also, $\epsilon_{Y,WP} = 0.167$ and is significant (t-statistic=2.08), while $\epsilon_{Y,P} = 0.031$ and is insignificant. The estimates for all counties imply a large (greater than 1) but insignificant $\epsilon_{Y,R}$ estimate. The implausible magnitude of this elasticity may be the result of some outliers that are affecting the mean of the data. $\epsilon_{Y,t}$ is about 0.05 and is highly

¹ Since they are not crucial in the interpretation of the results, a table of the regression parameter estimates is available upon request from the authors.

significant, implying a notable increase in output over time after accounting for all other variables that affect output.

Table 6: Elasticities Evaluated at Mean of the Data for Entire Sample

Parameter	Estimate	Std. Error	t-statistic	P-value
$\epsilon_{Y,R}$	1.06245	0.79169	1.34201	[0.180]
$\epsilon_{Y,L}$	0.757671	0.28166	2.69002	[0.007]
$\epsilon_{Y,K}$	0.357673	0.267994	1.33463	[0.182]
$\epsilon_{Y,WP}$	0.167183	0.080307	2.0818	[0.037]
$\epsilon_{Y,P}$	0.031032	0.030773	1.00841	[0.313]
$\epsilon_{Y,t}$	0.048617	0.016872	2.88157	[0.004]

While it is useful to assess the elasticities evaluated at the mean of the data for the entire sample, additional insights may be apparent from evaluating the elasticities at each data point, then looking at the means and standard deviations for individual counties. For the individual counties we calculate the mean of each county's elasticities over all years of the sample. When we calculate the individual elasticities for each data point and then average over each of the 58 counties for all 8 years of the sample, we observe some interesting patterns in the own ports and neighboring ports elasticities.

Table 7: Mean of the Ports Elasticities for Individual Port Counties

County	Own-Ports Elasticity ($\epsilon_{Y,P}$)	Neighbor Ports Elasticity ($\epsilon_{Y,WP}$)
Major Ports		
Los Angeles	1.20 (0.050)	-0.058 (0.045)
Alameda	0.680 (0.009)	-0.119 (0.008)
San Diego	0.796 (0.023)	-0.0002 (0.02)
Smaller Ports		
Ventura	0.404 (0.011)	0.040 (0.004)
San Francisco	0.446 (0.009)	0.083 (0.014)
San Joaquin	0.306 (0.002)	-0.004 (0.013)

Sacramento	0.515 (0.009)	-0.016 (0.007)
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(standard errors presented in parentheses)

What is notable in Table 7 is the fact that for major ports, own port elasticity is positive (and greater than one in the case of Los Angeles County), while neighbor ports elasticity is negative. For these counties, increasing ports investment leads to higher levels of manufacturing output, however, this effect is offset if neighboring counties increase their ports investment (the neighboring ports effects are substantially smaller than own-ports effects). Since there are no large ports in adjacent counties, this implies that as smaller ports grow this may adversely affect industries in counties with larger ports. This is sensible as smaller ports (such as the Port of Hueneme, in Ventura County, which is adjacent to Los Angeles County) market themselves as less congested alternatives to the larger ports and encourage businesses to relocate some operations to areas adjacent to the smaller, growing ports.

We see a mixed pattern in the smaller ports. For all of these smaller ports, greater port investment in a particular county leads to additional manufacturing output in that county. With the exception of the Port of Sacramento and San Joaquin, manufacturing output in these counties reacts positively to increased ports investment in the neighboring counties. We may see this as businesses locate in counties that have proximity to two ports, which gives them more transportation options. Due to the lack of available land, it may make sense for firms to locate in counties with smaller ports, even if they use the ports service from the larger ports in the adjacent counties. For example, firms may locate in Ventura County since wages and land are generally cheaper than in Los Angeles

County, even if they use the services available from the Ports of Los Angeles and Long Beach.

Finally, we find mixed results for spillover effects in counties that have no significant international trade ports, but are located adjacent to counties with ports. Focusing on Southern California, we find that $\epsilon_{Y,WP} = 0.026$ for Orange County (with a standard error of 0.024) and 0.018 for Riverside County (standard error 0.010), but $\epsilon_{Y,P} = -0.019$ for San Bernardino County (standard error 0.002). This may reflect the fact that firms are only beginning to locate major facilities in San Bernardino and our data ends in 2005. It does suggest that there are positive spillovers from port activities in adjacent counties.

3B. Results: All Counties Retail Trade Sector

We next estimate the same model for the retail trade sector as well as the wholesale trade sector. Unfortunately the results for the wholesale trade sector did not yield sensible results, undoubtedly due to data problems with constructing the private capital stock in this sector. For the purpose of this report, we only present the results for retail trade.

Table 8: Elasticities Evaluated at Mean of the Data for Entire Sample

Parameter	Estimate	Std. Error	t-statistic	P-value
$\epsilon_{Y,R}$	0.510656	0.235738	2.16620	[0.030]
$\epsilon_{Y,L}$	0.344126	0.092922	3.70337	[0.000]
$\epsilon_{Y,K}$	1.40859	0.508879	2.76802	[0.006]
$\epsilon_{Y,WP}$	0.228284	0.045981	4.96476	[0.000]
$\epsilon_{Y,P}$	0.495554	0.536957	0.922893	[0.356]
$\epsilon_{Y,t}$	0.012066	0.077451	0.155788	[0.876]

These results differ somewhat from those for the manufacturing sector. First, we find that roads investment and capital investment are both positive and significant (unlike for the manufacturing sector, where the elasticities were not statistically significant). Increasing roads infrastructure in the county by 1% will result in a 0.5% increase in retail trade output for that county.

Like the case of the manufacturing sector, we find that output in the retail trade sector for a county will grow when its neighbors increase their ports investment. It is notable that the same is not true of own ports investment, which is not statistically significant. This implies that firms in the ports county do not benefit as much as firms in neighboring counties; thus, the benefits from ports investment accrue to neighboring counties in a larger way than own counties. This may be due to adjacent counties becoming attractive as retail trade centers, drawing on nearby wholesale trade and transportation resources, but characterized by relatively cheaper land values than in counties containing ports.

4. Conclusions and Recommendations

There is currently considerable debate over the positive and negative spillover effects from port-related activities in Southern California. Clearly there are pollution and congestion problems resulting from the ships, trucks, and trains involved in port operations, however, the ports provide attractive amenities for firms that locate in port counties and the adjacent counties in order to be close to the transportation center.

Using county-level data for the State of California from 1998-2005, we estimate a production function for the manufacturing and retail trade industries. We find that there are positive and significant impacts of port investment on county manufacturing output. The magnitude of these effects is largest for the largest ports (located in Los Angeles, Alameda, and Oakland counties). We also find that investment in ports has positive spillover effects on manufacturing in adjacent counties that have small ports. This may be due to the access firms have to multiple transportation options. Finally, we find both positive and negative spillovers from ports investment on the manufacturing sector for counties adjacent to ports that do not have their own ports.

In the case of the retail trade sector, we find that own ports investment does not have a significant positive effect on the retail trade industry in the county. However, we find an unambiguous positive and significant effect of neighboring ports investment on the retail trade sector in a county adjacent to a port.

For both models we also find significant evidence of another form of spatial interdependencies, namely, spatial autocorrelation. We adapt our model for spatial autocorrelation with a spatial Cochrane-Orcutt transformation, assuming that counties

neighboring a particular county are given equal weight. In future work we plan to explore alternative spatial weights matrices, as well as the possibility of higher order spatial autocorrelation. Also, since we are using panel data, we anticipate there may be a need to address space-time autocorrelation processes.

The next step in this research is to estimate incorporate airports infrastructure investment into the mode. Time sensitive goods are often shipped to the U.S. via air freight to major transportation hubs and then distributed to their final destination. In California, the value of freight sent into LAX rivals that of the largest container ports in the state. Since the shippers typically use both ocean and air freight transportation to move their goods into the U.S. ports and airports may have a complementary relationship.

5. IMPLEMENTATION

While these are preliminary results, which should be augmented by further studies that incorporate other statistical techniques, they reinforce the findings of other studies that find significant spillover effects from ports investment on adjoining counties. We suggest that policy-makers can use these numbers to generate estimates of the impact of additional ports facilities on their neighbors. These can also augment recommendations made by regional governments in their “regional goods movement” plans, recognizing the potential benefits that accrue from both roads and ports investment for counties and their neighbors.

6. Appendix A: Data Description

Roads capital stock: A state-level roads capital stock measure for 1997 ($R_{s,j,1997}$), in thousands of 2000 dollars, was constructed using the perpetual inventory method, with 1995 as the base year and an assumed depreciation rate of 5%. The base year capital value was taken from Cohen and Paul (2004), and the investment level in 1995 was taken as real state roads spending in 1995. The nominal state roads spending in 1995 was from the Census Bureau's State Public Finances publication (www.census.gov/govs/www/state.html). After obtaining a series for the state roads capital stock, the state's roads capital stock was apportioned to the counties using the following formula (see Da Silva Costa, et. al., 1987 for another application of this approach): $R_{c,i,t} = R_{s,i,t} * [R_{c,j,1997}/R_{s,j,1997}]$, where $R_{c,i,t}$ is county roads stock in county i in year t , and $R_{s,j,t}$ is state roads stock in state j in year t , $R_{c,j,1997}$ is the county c 's real roads investment in 1997, and $R_{s,j,1997}$ is the state's real roads investment in 1997. The county roads stocks are calculated with this approach for the years 1998-2005.

Ports capital stock: The county level stocks estimates (thousands of 2000 dollars) were calculated for each year, using the formula: $P_{c,i,t} = P_{s,j,t} * [P_{c,i,t0}/P_{s,j,t0}]$, where $P_{c,i,t}$ represents ports capital stock in county i in year t , $P_{s,j,t}$ is the state level ports capital stock in time t , $P_{c,i,t0}$ is the county ports real investment in county i in the earliest year of ports spending in that county, and $P_{s,j,t0}$ is the total real state ports spending in the earliest year of county c 's ports spending. The county ports capital stocks are calculated with this approach for the years 1998-2005.

Investment deflators for roads and ports capital stocks: from Government Gross Investment, Structures, State & Local, from the BEA table called "NIPA Table".

Output (manufacturing): County output (millions of 2000 dollars) is obtained by multiplying state gross domestic product by the ratio of county personal income to state personal income. According to Boarnet (1996), this is “consistent with the methodology used by the Southern California Association of Governments to estimate county product within their region (page 16).”

Employment (manufacturing): Data on the county-level number of workers were obtained from the Bureau of Economic Analysis website.

Private capital stock (manufacturing): County spending on fixed assets were given by the ratio of county personal income to state personal income, multiplied by the state-level capital spending. County fixed assets were then obtained via the perpetual inventory method, with 1997 as the base year. Depreciation was assumed to be 5%. The initial (1997) capital stock estimate was given as the inverse of the depreciation rate times the average of annual county level fixed asset spending in the years 1995-1997. The capital spending deflator was from the Bureau of Labor Statistics (www.bls.gov/mfp/mprodload.htm).

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