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Are the Pacific Island Economies Growth Failures?

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Abstract

Many Pacific Island economies have found it difficult to achieve sustained economic growth and hence sustained improvements in living standards. But what is required to establish whether the Pacific Island economies are growth failures is a valid counterfactual. In this paper, matching methods based on the propensity score are used to find the most appropriate set of comparator countries for the Pacific Island economies. The paper also pays close attention to geography as a fundamental growth constraint facing Pacific Island countries since they are some of the most remote in the world. The results show that ignoring spatial autocorrelation, whereby economic growth rates depend on the growth rates of neighbouring countries, biases estimates of how slowly the Pacific Island economies have grown conditional on other growth determinants. The propensity score matching methods also emphasis the fragility of empirical claims about a significantly slower growth of Pacific Island economies.

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I. Introduction

Many Pacific Island economies have found it difficult to achieve sustained economic growth and hence sustained improvements in living standards. For example, Sampson (2005) finds that after controlling for OECD membership and whether a country is an oil exporter, the Pacific states grew more slowly than countries in any other region of the world over 1995-2003.[2] This is despite high per capita inflows of external finance, in the form of both overseas aid and remittances. Consequently, many experts are critical of this apparently poor performance, placing the blame on poor institutions (Chand, 2001), aid inflows (Hughes, 2003), bad policy settings (Chand, 2003; Gosarevski, Hughes and Windybank, 2004) and especially governance failures. According to estimates made by Duncan (2005), in the absence of poor governance, per capita GDP in Papua New Guinea (PNG) would have been double what it actually was in 2003 and one-third higher for Fiji.

The problem with such claims is that although good governance helps economic growth on average there are plenty of exceptions, so it is neither a necessary nor sufficient condition. A case in point is Italy, which is:

> "…notorious for its political instability, inflation, massive public debt, and clientelism. Its political and economic institutions are often derided and labelled dysfunctional. Yet, in historical perspective, the country has frequently performed better than its more stable and "efficient" European neighbours…"
>
> Tolliday (2000), pp. 241

A closer example is New Zealand, which despite comprehensive economic reform and textbook management since the mid-1980s still has only a mediocre growth experience (McCann, 2006). Hence the reverse could also hold: despite Pacific Island countries doing many things wrong, they perhaps would not have grown any faster doing things right. The difficulty of examining this claim, compared with the ease of observing the growth anomaly that is Italy, is that simple comparisons with neighbouring countries are unlikely to be valid. The Pacific Island countries differ dramatically in terms of scale, remoteness and insularity when compared to their neighbouring countries on the Pacific rim.

Hence what is required to establish whether the Pacific Island economies are growth failures is a valid counterfactual. In this paper, matching methods based on the propensity score are used to find the most appropriate set of comparator countries for the Pacific Island economies. This propensity score summarises the effects of many different growth determinants to find the countries outside of the Pacific Islands that are most like those in the Pacific (i.e., those that have a similar counterfactual probability of being in the Pacific). These quasi-experimental propensity score methods are popular in medical sciences and labour economics but also are increasingly used for cross-country research in both economics (Persson and Tabellini, 2002) and political science (King and Zeng, 2006). The need for a counterfactual is also understood by Duncan (2005), who uses Mauritius as a comparator to Fiji and Botswana as a comparator to PNG.[3] The results reported here may help to see how

[2] This may reflect a change from earlier periods. Armstrong and Read (2002) find a significantly higher growth rate over 1980-93 for 'small' countries (defined as population below three million) in the East Asia and Pacific (EAP) region than in the rest of the world. Since 23 of their 27 EAP countries were Pacific Islands, the faster growth rate amongst small countries in the EAP region likely reflected good growth performance of Pacific Island countries, at least on average.

[3] Duncan also uses estimates from regression methods, which implicitly force all countries in a sample to be comparators for a specific country, regardless of their dissimilarity.

this ad hoc selection of comparators does compared with the results from more formal propensity score methods.

The second contribution of the current paper is that it pays close attention to geography as a fundamental growth constraint that Pacific Island countries have little control over. In addition to using comprehensive measures of remoteness in growth models, the paper also recognises that economic growth rates may depend on the growth rates of nearby countries. This *spatial autocorrelation* can arise because nearby countries have unobserved factors in common (e.g., climate, topography, access to major world markets) and because of interaction between one country and another (e.g. through common customs borders and cross-border flows of goods, capital and labour) so that growth depends on the growth rate of neighbouring countries. The first model, of unobserved common factors, is known as a *spatial error* model while the second, of unaccounted for interactions, is a *spatial lag* model. Ignoring these lags can bias coefficient estimates since the omitted autocorrelation enters through the systematic part of the model (Anselin, 1988).

Surprisingly, despite the spatial nature of cross-country data on economic growth rates there is little mention of spatial autocorrelation in the literature. The main results are due to Conley and Ligon (2003) who find that the hypothesis of independent growth rates for countries that are less than 2000 miles from each other can be rejected.[4] The literature on the economic performance of small states (Easterly and Kraay, 2000; Armstrong and Read, 2002, 2006) also ignores this spatial autocorrelation, despite the fact that small states are clustered in the Caribbean and Pacific oceans, so spatial interactions are likely to have a substantial effect on estimates of the effects of "smallness". Similarly, none of the studies of slow growth in the Pacific have yet accounted for possible spatial effects despite the geographic clustering (by definition) of the countries in this region.

Therefore this paper starts with a cross-country growth regression that incorporates various geographic and other causal factors mentioned in the literature on small and Pacific states. The model is then subjected to various tests for spatial autocorrelation, following which more robust spatial models are estimated. The propensity score matching methods are then introduced. As yet there is no way to incorporate spatial effects into propensity score matching models, so the two extensions to the literature discussed here – using propensity scores to find a suitable comparator and accounting for spatial autocorrelation -- are applied separately. There is no reason to expect offsetting biases from a failure of previous studies to recognise either of these two extensions, so results for each can independently raise doubts about the robustness of conclusions about growth failures in the Pacific.

2. Previous Literature

There is a growing literature on the economies of small and Pacific states. This literature argues that the most important vulnerabilities of small island developing countries are small size, remoteness and insularity, disaster proneness, environmental fragility, and dependence on foreign sources of finance and demographic changes (Briguglio, 1995). Small size means a small domestic market and dependence on export markets and a narrow range of products, limited ability to influence prices, limited ability to exploit economies of scale, limitations on domestic competition, and problems of public administration (e.g. small labour force from

[4] They also use other distance metrics, including the cost of airfares from one country to another and the cost of shipping a 20 kilogram parcel via UPS. There is a significant positive spatial correlation between the growth rates of countries where this UPS distance was less than US$270 and where the airfare distance was less than US$1100.

which to draw experienced and efficient administrators). Insularity and remoteness give rise to problems associated with transport and communications such as high per-unit transport costs, uncertainties of supply, and the need to hold relatively large stocks. Proneness to natural disasters is a problem since the impact of a given disaster covers relatively more of a small country.

Despite these apparent disadvantages, Easterly and Kraay (2000) find that small states have the same range of growth experiences as other states. Their results are based on a dataset of 157 countries, 33 of which are small states (defined by population below one million).[5] They also find that there is no growth difference for small states after controlling for their region in the world, whether an oil producer, and whether an OECD member. The absence of a clear growth disadvantage of small states is due to offsetting effects of openness to international trade, which is favourable to growth, and greater output volatility, which harms average growth rates. This output volatility is partly due to the relatively larger terms of trade shocks experienced by small states.

Bertram (2004) finds that the level of GDP per capita of small island economies depends directly on the GDP per capita of their metropolitan patron and on the strength of their political ties with the metropolitan patron. Specifically, using a sample of 60 small island states and territories (defined by population less than three million), the elasticity of island per capita GDP with respect to metropolitan per capita GDP is estimated to be 0.56. For a more restricted sample of 20 Pacific Island states and territories (which excludes PNG and Hawaii) it appears that being politically fully integrated with a patron economy in the global core added about US$6,016 to per capita income. Put another way, Bertram and Karagedikli (2004) show that on average across the Pacific islands region, politically integrated units exhibit per capita incomes nine times higher than sovereign island states (including both Hawaii and PNG – it is three times larger if these two units are excluded). Similarly, Armstrong and Read (2000) compare the economic performance of dependent territories with that of ‘small’ sovereign states (based on a population less than three million). For a sample of 105 entities, 41 of which are dependent territories, they show that dependent territories have higher GNP per capita than the sovereign states, even when controlling for a range of other factors such as economic structure, island status, and aid transfers.

Armstrong and Read (2006) examine the impact of insularity, remoteness, being an archipelago, and being mountainous on the economic performance of ‘small’ states (defined as those less than five million people). They measure remoteness as the great circle distance from the capital city of each small state to the nearest one of three global economic hubs (Tokyo, Japan; Washington or Los Angeles, USA; and Brussels, EU). The Pacific states are more likely to be smaller, islands, archipelagos, remote, and mountainous than other small states. However, they conclude that neither small size itself, being an island, being mountainous nor being archipelagos is a serious handicap for the small Pacific states. Remoteness, however, almost certainly is. It is therefore useful to describe just how economically remote the Pacific Island countries are before moving into the main analysis.

[5] Only four of the 33 were from the Pacific (Fiji, Solomon Islands, Vanuatu and Samoa). Sampson (2005) shows that this conclusion is not robust to changes in sample coverage and time period. Specifically, after adding another 21 small states (8 from the Pacific) and changing the time period to 1995-2003, Sampson finds that small states have average annual growth rates that are 0.8 percentage points lower than for other states.

3. How Remote Are the Pacific Island Economies?

There are several measures of country remoteness. The most comprehensive used here is based on a detailed matrix of bilateral distances for 219 countries. These distance calculations require information on geographical coordinates for each country and this means that some assumptions are needed since countries are much larger than a single point. The assumption used here is that for smaller countries the coordinates of the capital city are sufficient. For larger countries, within-country city-level data are used to calculate the geographic distribution of population inside each country, and a population weighted centroid is used to proxy for the location of the country. The between country distances are calculated with the great circle formula, which uses latitude and longitude and an estimate of the circumference of the earth (which changes slightly from the poles to the equator). The distance of each Pacific Island country to each of the other 218 countries is then weighted by either (i) the GDP of each of those 218 countries or (ii) the population of each of those 218 countries.[6]

Table 1: Potential Market Remoteness Measures for the Pacific and Caribbean Islands

Island Group	2003 GDP-weighted distance (km)	GDP-weighted distance rank (2003)	Population-weighted distance rank (2003)	GDP-weighted distance rank (1988)
Micronesia	10377	176	146	179
Polynesia	11942	207	201	208
Melanesia	11972	207	170	208
Pacific Islands (mean)	11456	197	176	199
Caribbean (mean)	8103	100	176	98

Source: Summary averages from country-level results reported in the Appendix. Distances are the weighted average distances from each island group to every other country in the world, weighted either by each country's GDP or population. The location of each country is based on population-weighted centroids for larger countries and location of capital city for smaller countries. The rank is out of 219 countries, with #1 the most accessible, #219 most remote. The Caribbean countries are the island members of the list presented in Appendix A of Armstrong and Read (2002).

Table 1 reports the average distances for each of the three groups of Pacific Island countries. These averages are derived from the more detailed country-level estimates of average GDP-weighted or population-weighted distance that are reported in Appendix Table 1. The average Pacific Island country is 11,500 kilometres from any other randomly selected country (with the bilateral distance weighted by the other country's GDP). Micronesian countries are slightly less remote than either Polynesian or Melanesian countries, due to their Northerly location and the fact that more of the world's GDP is in the Northern Hemisphere. Out of the 219 countries for whom this calculation has been made, the Melanesian and Polynesian countries have an average rank as the 207th most remote, while the Micronesian countries have an average rank of 176th most remote (shown in column 2 of Table 1).

It should be emphasised that island location itself is not necessarily a cause of disadvantage for this remoteness measure, which is based on potential accessibility to the world's centres of GDP. (Other measures that take into account *actual* travel possibilities are examined below.) Indeed, the country that is least remote by this metric is also an island – the location of the Faeroe Islands in the North Atlantic gives them the shortest average distance (5660 kilometres) to all other countries of the world, as weighted by GDP. A perhaps more relevant comparison is with the Caribbean islands, whose average distance from the rest of the world's GDP (8100 kilometres) is only 70 percent of the average distance that the Pacific Island countries face. In terms of ranking, the average Caribbean island is the 100th most

[6] GDP-weighted great circle average distance to all other countries has also been used as a measure of remoteness by Silva and Tenreyro (2006).

remote country, compared with the average Pacific Island country which is the 197th most remote.

The final two columns of Table 1 report the rankings for two different measures of distance – one using population weights rather than GDP and one using GDP 15 years earlier.[7] The results in the third column suggest that Pacific Island countries, and especially Micronesia, are less remote from population centres than they are from the centres of the world's GDP. In fact, on average they have the same remoteness rank as the Caribbean countries when distances are weighted by population. The values in the final column suggest a slight decline in potential remoteness for Pacific Island countries over the 15 years from 1988 to 2003. Their average remoteness rank declined from 209th to 207th, no doubt due to the rising share of world GDP located in East Asia, which potentially benefits Micronesia especially.

Whether proximity to rich (or populous) countries equals actual accessibility depends on transport links. In this regard the Pacific Island countries appear more disadvantaged than island countries in other parts of the world. While the Pacific Island countries are, on average, 40 percent further from the locations of world GDP than the island states in the Caribbean they are much further away in terms of airfare-based measures of distance (Table 2).

Table 2: Air Fare Measures of Market Remoteness for the Pacific and Caribbean Islands

Island Group	Average cost of fares to three key metropolitan cities (US$)	Average fare to closest of three key metropolitan cities (US$)	Average fare to most distant of three key metropolitan cities (US$)
Micronesia	1773	1768	1361
Polynesia	1067	727	1699
Melanesia	905	585	1586
Pacific Islands (mean)	1289	1084	1534
Caribbean (mean)	545	395	902

Source: Summary averages from country-level results reported in the Appendix. The three metropolitan cities for the Pacific Islands are Auckland, San Francisco and Sydney. For the Caribbean the three cities are Miami, New York and London. Fares are for one-way, economy class travel, booked on Travelocity for Feb 3, 2007.

On average, travelling from a Caribbean island to any one of three main metropolitan cities with strong links to the Caribbean (Miami, New York and London) costs US$545. A similar calculation for the Pacific Islands, but with Auckland, San Francisco and Sydney as the metropolitan cities, gives an average fare of US$1289. Thus, by this metric the Pacific Island countries are 140 percent more remote than the Caribbean islands.[8] The cost disadvantage is even more apparent when considering travel to the closest metropolitan city, which is likely to act as a deterrent to both freer movement of labour (e.g. seasonal migration schemes) and the export of services to in-bound tourists.

Table 2 also indicates considerable variation *within* the Pacific, with the patterns of accessibility reversing from those for potential market remoteness. Specifically, while Micronesia is closer to the centres of world GDP the cost of travel from Micronesia is higher than for either Polynesia or Melanesia. Moreover, while Micronesia is closest to Sydney and furthest from San Francisco the travel costs are higher to the closer location than to the

[7] The column headed "2003" relates to GDP averaged over the 2002-2004 period, while the "1988" estimates are for the average of the 1987-1989 period.
[8] 1289/545=2.37.

further location. Presumably this reflects the larger volume of air travel from Micronesia to and from the U.S. This example serves as a warning that the potential market access and distance measures used elsewhere in the paper are imperfect proxies for more economic concepts of distance. However, such imperfect proxies have to be relied upon because of limited availability of data on better economic proxies for distance.[9]

4. Data and Model Specification

This section describes the variables used in the cross-country growth model which is applied to a cross section of 174 countries over 1987-2003. The 15 Pacific Island countries in this sample (listed in Table 5) have, on average, grown more slowly in per capita terms than have other countries over the 1987-2003 period. This result holds even more strongly when restricting the comparison to other 'small' countries (defined by population below three million). Whether this gap (and its statistical significance) persists after accounting for the greater remoteness and other characteristics of Pacific Island countries can only be answered with the regression models.

The selection of explanatory variables to be used in the model is guided by the results of previous studies of economic growth in either 'small' or Pacific Island economies, especially Easterly and Kraay (2000), Bertram (2004) and Armstrong and Read (2006). In addition to the distance measures described above in Table 1 the other geographic variables included in the models are indicators for Pacific Island countries and for landlocked countries. The next set of variables relate to population. The literature uses several thresholds for defining 'small' countries, ranging from sizes of 1-5 million. To provide more generality a continuous (log) population variable is used. The logarithm of land area for each country is also included in the model. This implicitly gives a measure of population density, which may affect economic growth by allowing easier knowledge spillovers and lower per capita infrastructure costs but may also have negative effects due to congestion and competition for resources, especially on small atolls.

In the literature, greater trade openness and volatility of output growth of small countries appear to be offsetting factors affecting growth (Easterly and Kraay, 2000). Both are included in the model. Sovereign status and a history of colonization are important geopolitical factors affecting growth. Similarly, if the country is a former colony, how fast the colonial power grows seems to matter (Bertram, 2004). A final factor likely to be relevant in hindering growth, at least in Melanesia, is language diversity. This diversity may increase the transactions costs of internal commerce, and raise the costs and lower the returns to human capital formation. Language diversity is also a proxy for ethnic fractionalization which may lead to more group conflict (Alesina et al., 2003).

A comparison of average characteristics across the three groups of countries in Table 3 shows that the Pacific Island countries face a number of structural disadvantages in addition to being very remote. Their population and land area are much smaller than for other states, even when comparing just with states whose population is less than three million. Hence they are likely to suffer from limited domestic markets, a factor shown by Redding and Venables (2004) to be a significant determinant of income. They are also less open to international

[9] Even in the Conley and Ligon (2002) study, where 'economic distance' is proxied by the cost of sending a 20 kilogram package by UPS between the capital cities of country pairs, only a limited number of pairs (*n*=26) were obtained which were then used as 'hubs' for completing the matrix of shipping costs from all countries to all other countries. For measures of distance based on airfares, Conley and Ligon chose 15 hub cities.

trade, which may reflect protectionist policy choices,[10] but could also be due to their greater remoteness causing transport costs to be a more significant source of 'natural protection'. The Pacific countries also have greater language diversity, which is likely to hinder growth (Alesina et al., 2003). Finally, they are more likely to have been colonized than other countries (although not other small countries) and their last colonizing country grows slower on average than the colonizing country for small states if other parts of the world.

Table 3: Description of Data Used in Regressions

	Pacific Islands	Other Countries	Non-Pacific Small
Average annual growth rate of GDP per capita (US$), 1987-2003	0.020 (0.023)[a]	0.022 (0.034)	0.027 (0.030)
GDP-weighted average distance to all other countries in 1987-89 ('000 kilometres)	11.632 (0.793)	8.234 (1.764)	8.429 (1.592)
Change in GDP-weighted average distance to all other countries between 1988-2003 (kilometres)	-141.767 (8.519)	67.054 (87.999)	83.302 (61.793)
Population, average over 1987-2003 (logarithm of '000s)	4.704 (1.688)	8.849 (1.920)	6.306 (1.240)
Land area (logarithm of square kilometres)	7.455 (2.755)	11.697 (2.507)	9.041 (2.710)
Landlocked country (=1, otherwise = 0)	0.000 (0.000)	0.201 (0.402)	0.150 (0.362)
Openness to trade, exports plus imports as a share of GDP 1987-2003	0.715 (0.181)	0.945 (0.695)	1.442 (0.990)
Volatility, standard deviation of annual GDP growth, 1988-2003	0.114 (0.071)	0.149 (0.121)	0.111 (0.115)
Language diversity, number of languages spoken by at least 20 percent of the population	1.867 (0.743)	1.629 (0.784)	1.775 (0.698)
Never a colony (=1, otherwise = 0)	0.067 (0.258)	0.170 (0.377)	0.025 (0.158)
Colonizer growth rate, GDP per capita growth rate (1987-2003) of last colonizing country	0.031 (0.012)	0.034 (0.012)	0.042 (0.014)
Number of countries	15	159	40

Source: World Bank and Asian Development Bank for data on GDP, growth rates, population, openness and volatility. Data on land area, whether landlocked, language diversity and colonizers are from a database constructed by the Centre d'Etudes Prospectives et d'Informations Internationales.
[a] Small countries defined as having average population less than 3 million, outside the Pacific Islands region.
[b] Standard deviations in ( )

On the other hand, some factors appear to be favourable to faster growth in the Pacific Island countries than elsewhere. First, between 1988 and 2003 they have become closer to the centres of world GDP due to the rising share of world GDP produced in the surrounding countries, and particularly in Asia. In contrast, other countries and especially other small countries have become further away from the centres of world GDP.[11] Second, none of the Pacific Island countries are landlocked, which is typically found to be an impediment to

[10] These act as an indirect tax on exports by raising the relative price of non-traded goods, in addition to their direct effect in reducing imports, so could potentially have a large impact on trade openness.
[11] However, while the change in remoteness is less than 200 kilometres, the gap in remoteness between the Pacific and other small countries remains over 3000 kilometres.

growth (Hausmann, 2001). Finally, the volatility of their growth rates, which has been shown to reduce average growth (Easterly and Kraay, 2000) is no different than for other small states and is less than for the full set of non-Pacific Island countries.

5. Basic Regression Results

The results of estimating the cross-country growth model with Ordinary Least Squares (OLS) are reported in Table 4. This estimator does not take account of any spatial autocorrelation in country growth rates. A lack of testing for (and treatment of) spatial autocorrelation is typical of the recent cross-country growth literature, with the notable exception of Conley and Ligon (2003). Instead the literature simply relies on using standard errors that are meant to be robust to heteroscedasticity of unknown form – an approach also followed in this table. (Detailed diagnostic testing for spatial autocorrelation is presented in Section 7 below).

Table 4: OLS Regression Estimates of Long Run Growth Equations

	Explanatory Factors				
	Geographic constraints	Population density	Trade and stabilization	Political and social	All Factors
Pacific Island country (=1, otherwise=0)	-0.182 (2.80)**	-0.058 (0.91)	-0.039 (0.75)	0.018 (0.29)	-0.146 (1.67)+
GDP-weighted distance (1987-89)	-0.187 (2.46)*				-0.136 (1.63)
Change in GDP-weighted distance (2003 minus 1988)	-0.403 (5.48)**				-0.326 (4.17)**
Landlocked country	-0.138 (1.75)+				-0.095 (1.28)
Population		0.484 (3.70)**			0.215 (1.60)
Land area		-0.676 (5.89)**			-0.246 (1.77)+
Openness to trade			0.169 (2.88)**		0.131 (2.23)*
Volatility of per capita GDP growth rate			-0.406 (5.32)**		-0.345 (4.99)**
Language diversity				-0.220 (2.86)**	-0.171 (2.80)**
Never a colony				0.087 (1.05)	-0.038 (0.55)
Colonizer growth rate				0.224 (2.21)*	0.102 (1.27)
Constant	0.000 (0.00)	-0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)
R-squared	0.149	0.136	0.215	0.086	0.394
Log-likelihood	-232.411	-234.649	-225.304	-238.607	-202.890

Note: Standardized (beta) coefficients are reported, showing the effect of a one standard deviation increase in the explanatory variable on the standard deviation of average per capita GDP growth over 1987-2003, for *N*=174 countries. Definitions for all variables are reported in Table 3.
Heteroscedasticity robust *t*-statistics in ( ). + significant at 10%; *at 5%; **at 1%

The results in Table 4 are broken into five columns, where the first four each deal with a particular set of factors likely to affect growth rates and finally all factors are considered at once. A dummy variable for the Pacific Island countries is included in each of these five models, to give average growth rates in the region conditional on each set of factors. To aid cross-factor comparisons of magnitudes, the coefficients are estimated from standardized variables so that each refers to the effect of a standard deviation increase in the explanatory factor on the standard deviation of growth rates.

While the remoteness of the Pacific Island countries might be expected to excuse part of their lower growth, in fact once geographic constraints are taken into account the Pacific Island countries appear to grow more slowly (column 1, Table 4). The reason is that the negative effect of remoteness (-0.18) is outweighed by the effect of the change in GDP-weighted distance between 1988 and 2003 (-0.42). Recall from Table 1 that the Pacific Island countries became 'closer' to the centres of world GDP over this period, due especially to the economic rise of Asia. In addition, none of the Pacific Island countries are landlocked, which gives a further reason for expecting faster growth. Since the Pacific Island countries, on average, did not grow as fast as the geographic factors predict the dummy variable for the Pacific registers a negative, significant coefficient.

These results suggest a 'potential growth failure' due to the Pacific Island countries not fully exploiting the opportunity provided by being close to where the greatest gains were made in the global economy. But it must be stressed that the distance measures are based on *potential* market access. Suitable transport and trade systems need to be in place to turn this potential into actual market access. In other words, being close to a rapidly growing region may be of little use if there is no cheap, easy, or reliable way to get to that region. The average airfares in Table 2 have already shown that actual remoteness of the Pacific Islands is greater than what potential remoteness measures indicate. It could likewise be the case that actual remoteness did not fall by the extent that the potential remoteness calculations suggest.[12]

When account is taken of each of the other groups of factors in Table 4 (population and land area; trade and stabilisation; and political and social) there is no significant Pacific Island effect. In other words, one cannot reject the hypothesis that the Pacific Island countries grew at the rate that would be expected once account is taken of their smaller size (both population and area), level of trade openness and growth volatility, language diversity and the growth rate of their colonizers. However, such inferences rely on ignoring the effects of remoteness and other geographic factors (which are re-introduced in column 5).

In terms of the individual coefficients in columns 2-4, the largest effects on average growth rates for this sample of 174 countries appear to be population (larger is better), land area (smaller, meaning greater density, is better), growth volatility (more is bad for average growth rates), language diversity (more is bad for average growth) and the growth rate of the last colonizing country (faster is better).[13] While openness to trade is also statistically significant the magnitude of its positive coefficient is smaller than for the other factors mentioned above.

When geographic factors are combined with all of the other factors in the regression model, the average growth rates of the Pacific Island are significantly lower than for other countries. While the effect is statistically significant at only the 10 percent level, it is nevertheless suggestive of a growth failure since so many of the constraints that bind in the Pacific

[12] This would require comparing average airfares (and shipping rates) from the 1987-89 period with the current period and such data are not available for this project.
[13] All of these effects are of course *ceteris paribus.*

(remoteness, low openness to trade, high language diversity, slow growth of colonial powers) have been accounted for.

Of course this coefficient of -0.15 for the slower average growth rate of Pacific Island countries, conditional on all the other factors in Table 4, hides a variety of country-level experiences. The results for individual countries are summarised in Table 5, in the form of residuals giving deviations of actual from predicted growth rates. The two countries that have done worst, in the sense of growing more slowly than predicted, are PNG and the Solomon Islands. The two that have done the best are Samoa and the Cook Islands.

Table 5: Deviation from Predicted Average GDP per capita Growth Rates for Pacific Island Countries

Lower than predicted average growth rates		Higher than predicted average growth rates	
Country	Residual	Country	Residual
Papua New Guinea	-1.28	Samoa	1.66
Solomon Islands	-1.16	Cook Islands	0.82
Palau	-0.50	Vanuatu	0.40
Nauru	-0.31	Fiji	0.39
French Polynesia	-0.23	Federated States of Micronesia	0.14
Tonga	-0.09	Kiribati	0.14
Marshall Islands	-0.05	New Caledonia	0.08
Tuvalu	-0.01		

Source: Author's calculation from regression results reported in the last column of Table 4. Values of the residuals are for standard deviations of average growth rates.

According to typically applied standards, the model in the last column of Table 4 seems to be quite successful. It explains 39 percent of the cross-country variation in economic growth rates. The usual problem of heteroscedasticity in cross-sectional data should be mitigated by using robust standard errors. Almost all of the explanatory variables are statistically significant and have signs that accord with expectations. However such conclusions may be premature because the OLS estimates do not account for spatial autocorrelation. The methods for detecting and treating such spatial autocorrelation are described in the next section.

6. Methods of Measuring for Spatial Effects in Cross-Country Growth Regressions

As noted above, economic growth rates are likely to be (positively) spatially autocorrelated. More generally, positive spatial autocorrelation occurs when high or low values for a random variable tend to cluster in space. Such a sample contains less information than an uncorrelated one so inference errors may occur if this is not accounted for. Moreover, ignoring these spatial interactions may also cause omitted variable bias (Anselin and Bera, 1998). This potential for bias depends on whether spatial effects enter through the systematic part of the model (*aka* a spatial lag model), the disturbances (*aka* a spatial error model) or both.

A key issue in adjusting for this spatial autocorrelation is that some structure has to be imposed on the data. While it is hypothetically possible for the growth rate of a country to be influenced by the growth rates of all countries in the world, as a practical matter many of these bilateral relationships are likely to be zero (e.g. how does economic growth in Rwanda affect growth in Kiribati?) Moreover, not all of these potential interactions can be estimated. For example, with a cross-sectional sample of size N there would be $N \times N$ correlations to estimate along with the β and σ^2 parameters of a standard regression model, which exceeds the number of observations.

A *spatial weight matrix* is one way of imposing the required structure on the study of spatial autocorrelation. This is an $N \times N$ positive and symmetric matrix which exogenously determines for each observation (row) which locations (columns) belong in its neighbourhood. For non-neighbours, $w_{ij}=0$, while for neighbours the weights are either $w_{ij}=1$ (binary weights) or a function of something else, such as: $w_{ij} = 1/d_{ij}$ where d_{ij} is the distance between observations i and j (inverse distance weights). The diagonal elements of the weights matrix are conventionally set to zero, and typically standardised such that the elements of a row sum to one (Anselin and Bera, 1998). Hence, the spatial weight matrix allows all of the interactions between observation i and each of its neighbours to be parameterized in the form of a weighted average. Specifically, for some random variable of interest z, each element of the spatially lagged variable Wz equals $\sum_j w_{ij} z_j$ which is a weighted average of the z values in the neighbourhood of point i.

The spatial weight matrix is used by both main approaches for incorporating spatial effects into regression models: the *spatial lag* model and the *spatial error* model. With a spatial lag model the growth rate of each country is affected by the spatially weighted average of growth rates of other nearby countries, even after controlling for observable factors that might be common for the countries, such as measures of remoteness or dummy variables for belonging to a particular region of the world. In contrast, the spatial error model is based on the assumption that spatially-varying omitted factors show up in the model's disturbances, causing the disturbance for one observation to be correlated with a spatially weighted average of neighbouring disturbances.

Formally, the spatial lag model is defined as:

$$Y = \rho WY + X\beta + \varepsilon \qquad (1)$$

where Y is an $N\times 1$ vector of observations on the dependent variable, WY is the spatially lagged dependent variable, X is an $N\times k$ matrix of explanatory variables, ε is a vector of errors, β is the vector of regression parameters and ρ is the spatial autoregressive parameter. Although equation (1) looks like a dynamic model from time-series econometrics, one key difference causes OLS to always be an inconsistent estimator of the spatial lag model. In the time-series context, if there is no serial correlation in the errors, ε_t there will be no correlation between y_{t-1} and ε_t and OLS will be a consistent estimator. In contrast, $(WY)_i$ is always correlated with both ε_i and the error term at all other locations. Hence, OLS is not consistent for the spatial lag model and either a maximum likelihood or instrumental variables estimator is needed (Anselin, 1988).

In contrast to the spatial lag model, the spatial error model is defined as:

$$\begin{aligned} Y &= X\beta + \varepsilon \\ \varepsilon &= \lambda W\varepsilon + \mu \end{aligned} \qquad (3)$$

where λ is the spatial autoregressive coefficient, μ is a vector of errors that are assumed to be independently and identically distributed and the other variables and parameters are as defined in equation (1). In this model, the error for one observation depends on a weighted average of the errors for neighbouring observations, with λ measuring the strength of this relationship.

It is clear that both equations (1) and (3) are restricted versions of a more general spatial autoregressive model with autoregressive disturbances:

$$Y = \rho W_1 Y + X\beta + \varepsilon$$
$$\varepsilon = \lambda W_2 \varepsilon + u \quad (4)$$

It may therefore seem preferable to always begin with a model like equation (4) and test in a general-to-specific way to see if either equation (3) or equation (1) are data-acceptable. Indeed, equation (4) could always be the starting point for cross-sectional regressions because the standard OLS regression model:

$$Y = X\beta + \varepsilon \quad (5)$$

is just a special case with ρ=λ=0. However, spatial models are much more computationally demanding and for most econometric software there are limits on the sample sizes that they can accommodate. Moreover, they have to be estimated by methods such as instrumental variables and maximum likelihood that require additional assumptions.

It is possible to use Lagrange Multiplier (LM) tests for spatial autocorrelation, which only need the restricted model to be estimated. Therefore it is common in the spatial econometrics literature to start with an OLS model and use the residuals from that model to test against spatial alternatives. In addition to these LM tests, Moran's I test, which has some parallels with the Durbin-Watson statistic, is also widely used (Anselin and Bera, 1998). For a row-standardized spatial weight matrix, Moran's I can be expressed as:

$$I = \frac{\mathbf{e}'\mathbf{We}}{\mathbf{e}'\mathbf{e}} \quad (6)$$

where $\mathbf{e}$ is a vector of OLS residuals and $\mathbf{W}$ is the spatial weight matrix. Moran's I is asymptotically normally distributed with mean $-1/(N-1)$ and its statistical significance can be evaluated from a standardized normal table. A feature of Moran's I is that the alternative hypothesis does not specify the process generating the autocorrelated disturbances. However, there is a simple intuition for Moran's I because for any variable $\mathbf{z}$ in deviation from mean form, I is equivalent to the slope coefficient in a linear regression of $\mathbf{Wz}$ on $\mathbf{z}$ (Anselin, 1995).

The LM tests are based on explicitly specified alternative hypotheses. For testing OLS against the spatial error model (λ=0) the test statistic is:

$$LM_\lambda = \left[\mathbf{e}'\mathbf{We}/\hat{\sigma}^2\right]^2 / T \quad (7)$$

where $T = tr(W' + W)W$ and LM_λ is distributed as χ^2 with 1 degree of freedom. For testing OLS against the spatial lag model (ρ=0) the test statistic is:

$$LM_\rho = \left[\mathbf{e}'\mathbf{WY}/\hat{\sigma}^2\right]^2 / T_1 \quad (8)$$

where $T_1 = (\mathbf{WX}\hat{\beta})'\mathbf{M}(\mathbf{WX}\hat{\beta})/\hat{\sigma}^2 + T$ and $\mathbf{M} = \mathbf{I} - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$. One difficulty with both LM_λ and LM_ρ is that they each have power against the other alternative. In other words, when testing λ=0, LM_λ responds to nonzero ρ and when testing ρ=0, LM_ρ responds to nonzero λ. To test in the possible presence of both spatial error and spatial lags, Anselin et al. (1996) develop specification tests for spatial lags that are robust to ignored spatial errors and tests for spatial errors that are robust to ignored spatial lags. These tests denoted LM_λ^* and LM_ρ^* should be used when both LM_λ and LM_ρ are statistically significant.

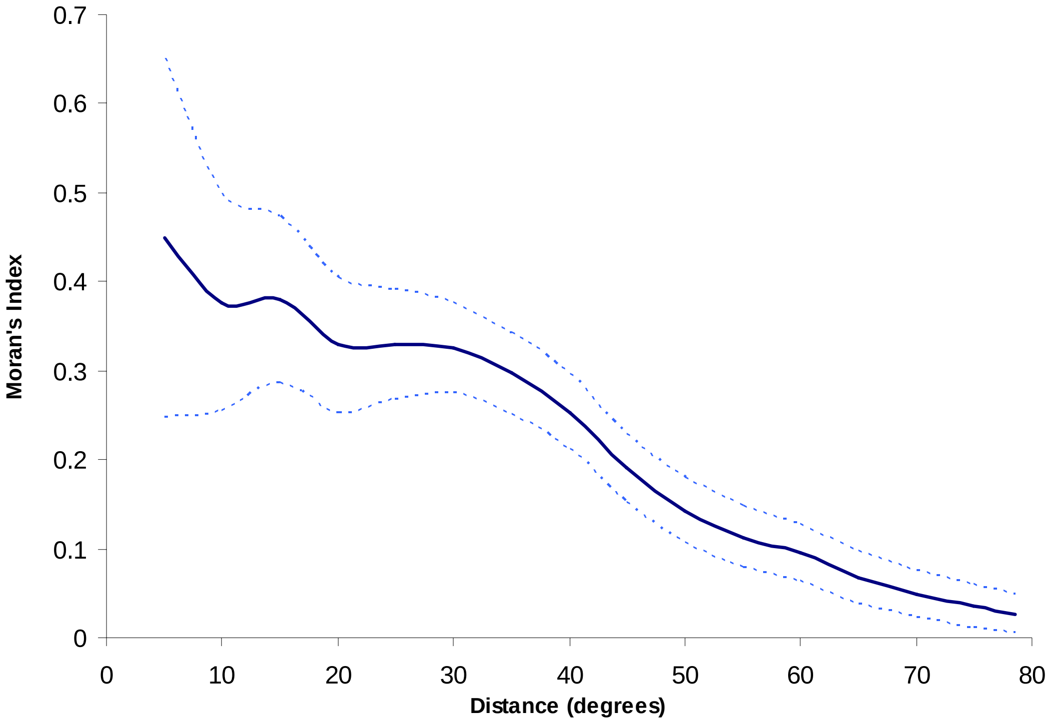
All five of the spatial autocorrelation tests described here are used in the current study. Depending on the outcome of the specification tests, the cross-country model of growth rates will be re-estimated in either the spatial lag or spatial error framework.

7. Results of Testing for Spatial Autocorrelation Effects

A spatial weights matrix is needed to test for spatial autocorrelation in the residuals of the growth model reported in the last column of Table 4. In turn, this requires a measure of distance between countries, so latitude and longitude coordinates for each country's capital city were used. According to this metric the minimum distance between capital cities was 0.1 degrees (11 kilometres), which is between Kinshasa (Dem. Republic of the Congo) and Brazzaville (Republic of the Congo) who are located on opposite banks of the Congo River. While this is clearly an imperfect proxy, since the centre of these two countries (in either population or economic terms) is clearly further apart, it is hopefully sufficiently accurate for indicating which countries are 'nearby'. The median distance for the 174 countries in the estimation sample is 78.6 degrees (8,700 kilometres). One factor when forming a spatial weight matrix is to avoid "islands" that have no neighbours. The largest minimum distance was 23.5 degrees (2,560 kilometres) for New Zealand. Therefore the estimation only considers weight matrices where the neighbourhood ranges from 25 to 75 degrees which is the span from the minimum feasible neighbourhood to the median distance between countries.

Two methods are used to get a preliminary view of any spatial autocorrelation in the sample. First, Moran's Index was calculated using weight matrices based on varying neighbourhood sizes. These ranged from five degrees to 78.6 degrees (the median) and the results are illustrated in Figure 1. When countries within a five degree radius of location *i* are considered as the neighbourhood, Moran's I=0.45 and it is statistically significant (p<0.01). In other words, a regression of the spatially weighted average growth rate within this neighbourhood, WY on the growth rate of each country, Y, would have a statistically significant coefficient of 0.45. The strength of the spatial autocorrelation declines as the neighbourhood is defined to include a larger area but even at the median distance Moran's I is still statistically significant.

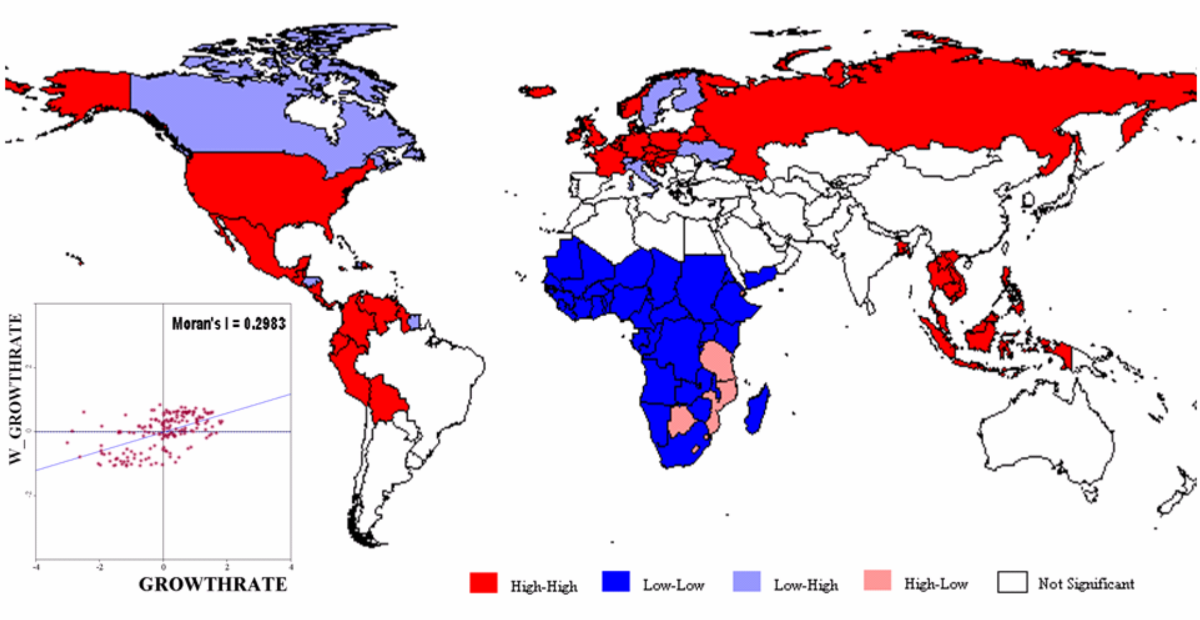
Figure 1: Spatial Correlation in Cross-Country Average Economic Growth Rates, 1987-2003



Source: Author's calculation using Moran's *I* statistic described in the text. Broken lines are +/- 2 std errors. One degree of distance is approximately 110 kilometres.

Second, a cluster map of local spatial autocorrelation was constructed using the GeoDa software (Anselin, Syabri and Kho, 2006). The map in Figure 2 indicates the countries with significant ($p<0.05$) local spatial autocorrelation for each location. Both high-high and low-low clusters are evidence of positive spatial autocorrelation. Recalling that Moran's Index can be found from a regression of the spatially weighted average growth rate of neighbours, WY on the growth rate of each country, Y, the high-high clusters correspond to countries in the positive-positive ('northeast') quadrant of a Moran scatterplot, which has WY on the y-axis and Y on the x-axis. The low-low clusters correspond to the negative-negative quadrant. Negative spatial autocorrelation would be indicated by a preponderance of high-low and low-high clusters. The countries where no colour is displayed on the map have no statistically significant local spatial autocorrelation.

Figure 2: Cluster Map for Local Spatial Autocorrelation in Country Average Economic Growth Rates, 1987-2003



Source: Author's calculation using GeoDa software based on weight matrix with countries within 35 degrees of each other as 'neighbours'.

The map in Figure 2 shows that most of Africa has significant low-low clusters of economic growth. In contrast, much of Europe, the United States and parts of Latin America, and much of Southeast Asia have significant high-high clusters. This clustering is not consistent with the spatial randomness that estimation methods like OLS require. Indeed, because there are very few high-low and low-high combinations the cluster map is indicative of significant positive spatial autocorrelation in country average GDP growth rates. The Moran scatter plot also shows this positive spatial autocorrelation, based on the positive relationship between the spatially weighted average growth rate of neighbours, W_GROWTHRATE and the GROWTHRATE of each country.

To see whether this spatial autocorrelation in growth rates is also transmitted to the residuals of the OLS estimates of the growth model, the tests described in Section 6 are used. Two different types of weights – binary and inverse distance – are used for neighbourhoods varying from 25 to 75 degrees. According to these tests there is substantial evidence of misspecification in the OLS results (Table 6).

Table 6: Specification Tests for Spatial Autocorrelation in the OLS Residuals of the Cross-Country Growth Regression

Type of weighting matrix	Moran's I	LM_{λ}	LM^{*}_{λ}	LM_{ρ}	LM^{*}_{ρ}
Binary weights					
25 degree neighbourhood	5.979***	19.545***	0.489	31.925***	12.869***
35 degree neighbourhood	7.688***	25.557***	0.434	44.875***	19.752***
45 degree neighbourhood	6.424***	14.711***	0.006	21.447***	6.742***
55 degree neighbourhood	4.894***	7.165***	0.007	10.334***	3.177
65 degree neighbourhood	3.789***	3.436*	0.025	4.802**	1.391
75 degree neighbourhood	2.727***	0.902	0.001	1.123	0.221
Inverse distance weights					
25 degree neighbourhood	5.980***	22.070***	0.009	29.465***	7.403***
35 degree neighbourhood	7.107***	28.263***	0.025	39.936***	11.698***
45 degree neighbourhood	7.037***	26.041***	0.029	35.877***	9.866***
55 degree neighbourhood	6.748***	22.999***	0.018	33.572***	10.591***
65 degree neighbourhood	6.501***	20.896***	0.176	32.049***	11.329***
75 degree neighbourhood	6.388***	19.571***	0.346	31.051***	11.825***

Note: ***=p<0.01, **=p<0.05, *=p<0.10.

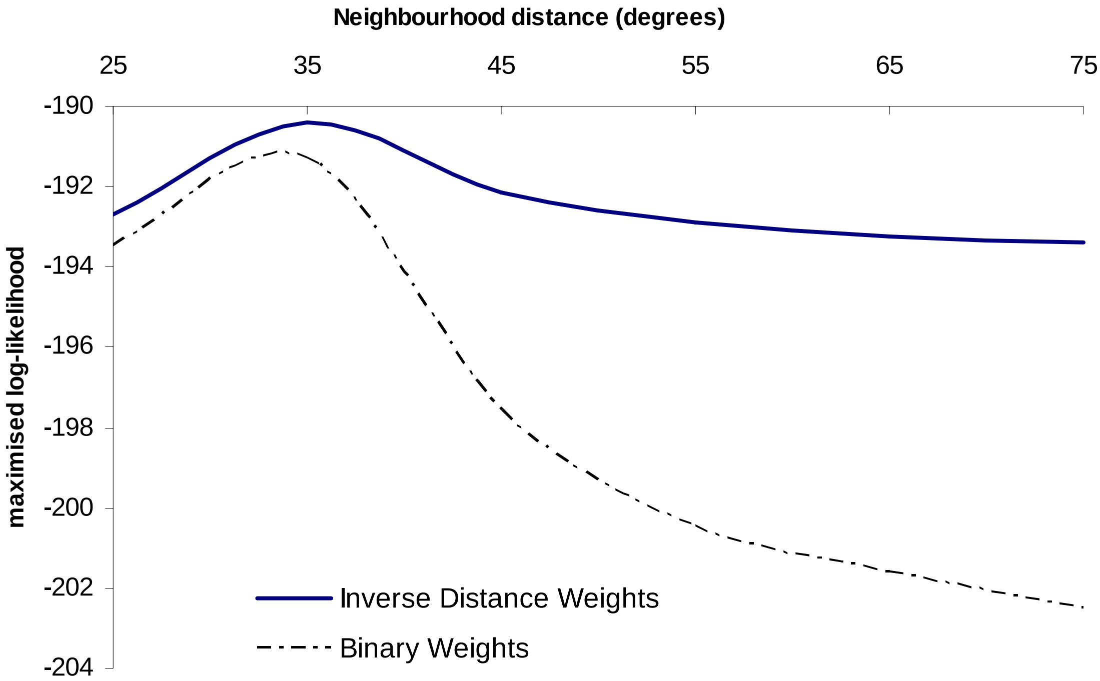
Both the LM_{λ} and the LM_{ρ} tests are statistically significant, except when binary weights are used with large neighbourhoods (>45 degrees). Hence it is necessary to use the specification tests for spatial lags that are robust to unaccounted for spatial errors, and the tests for spatial errors that are robust to ignored spatial lags. According to these robust tests there is no evidence in favour of the spatial error model (i.e., the values of LM^{*}_{λ} are always below the threshold for statistical significance). However the restriction that $\rho=0$ is decisively rejected even when the neighborhood extends all the way to the median distance between countries (at least when inverse distance weights are used).

In other words, the OLS estimates of the growth model in Table 4 are likely to be biased because they omit a relevant variable – the spatially weighted average growth rate of nearby countries. The appropriate specification is instead the spatial lag model. The test results in Table 6 suggest that plausible candidates for constructing this spatial lag (i.e., for being 'nearby') are at least countries that are within 25 degrees (2800 kilometres) all the way up to countries that are within 75 degrees (8300 kilometres).

8. Spatial Regression Results

In light of the above results about the misspecification of the growth model when OLS is used as the estimator, a variety of spatial lag and spatial error models were estimated. Six neighbourhood sizes were chosen, ranging from the minimum feasible (to prevent "islands" with no neighbours) of 25 degrees to a maximum of 75 degrees which is almost the median distance between countries in the sample. Both binary and inverse distance weights were considered. A comparison of the maximised log likelihoods of the resulting models indicated that there was better performance when the spatial weight matrix was based on inverse distance rather than a simple 0/1 set of binary weights. There was also evidence that a neighbourhood size of 35 degrees gave the best fit (Figure 3). This neighbourhood of approximately 3900 kilometres is similar to the finding of Conley and Ligon that the spatial autocorrelation between country's growth rates is highest at around 2000 miles (3200 kilometres).

Figure 3: Log-Likelihood Values for Spatial Lag Regression Models with Binary and Inverse Distance Spatial Weight Matrices and Neighbourhoods of Different Sizes



Source: Author's calculation using spatial regression methods described in the text.

Table 7 contains a comparison of the previously presented OLS results with those of the spatial lag model (based on inverse distance weights with neighbourhoods of 25, 35, and 75 degrees and binary weights for a neighbourhood of 35 degrees). The preferred estimates (based on the results in Figure 3) use inverse distance weights and a neighbourhood of 35 degrees. According to the maximum likelihood estimates for this model, $\rho=0.54$, with a standard error of 0.09. In other words, the spatially weighted average growth rate of countries within a radius of 35 degrees (3900 kilometres) exerts a considerable effect on the GDP growth rate of the country at location *i*, even after controlling for remoteness, other geographic constraints, population, openness and volatility and social and political factors.

The use of the spatial lag model has a dramatic effect on the coefficient on the Pacific Islands dummy variable, which is the focus of attention. This coefficient now is only one-half as large as in the OLS estimates and is statistically insignificant. The same fall in magnitude and statistical significance of the dummy variable for Pacific Island countries occurs when the spatial lag model is estimated with the other weights matrices and neighbourhoods.

In contrast to the fragility of the result for the Pacific Islands dummy variable, several of the other growth determinants appear to have almost exactly the same effect in the spatial lag model as they had in the OLS estimates. These more robust variables include land area, openness to trade and the volatility of the growth rate. The positive effect of population becomes even more apparent in the spatial lag results than it was with OLS. Some of the other variables, including language diversity and the change in GDP-weighted distance between 1988 and 2003 become smaller but are still statistically significant. This may reflect the fact that these variables are also somewhat spatially clustered. Thus it appears that geographic variables, including regional dummies, are susceptible to misspecification from a failure to include relevant spatial lags in cross-country growth models.

Table 7: OLS and Spatial Lag Regression Estimates of Long Run Growth Equations

	OLS	Inverse-distance weights, neighbourhood:			Binary wght
	regression	25 degrees	35 degrees	75 degrees	35 degrees
Pacific Island country (=1, otherwise=0)	-0.146 (1.67)+	-0.069 (0.86)	-0.066 (0.81)	-0.100 (1.19)	-0.058 (0.68)
GDP-weighted distance (1987-89)	-0.136 (1.63)	-0.043 (0.56)	-0.037 (0.50)	-0.065 (0.86)	-0.032 (0.42)
Change in GDP-weighted distance (2003 minus 1988)	-0.326 (4.17)**	-0.154 (2.00)*	-0.134 (1.74)+	-0.183 (2.51)*	-0.121 (1.57)
Landlocked country	-0.095 (1.28)	-0.049 (0.73)	-0.047 (0.71)	-0.058 (0.86)	-0.046 (0.67)
Population	0.215 (1.60)	0.274 (2.09)*	0.265 (2.16)*	0.275 (2.23)*	0.273 (2.22)*
Land area	-0.246 (1.77)+	-0.256 (1.92)+	-0.254 (2.04)*	-0.252 (1.98)*	-0.268 (2.15)*
Openness to trade	0.131 (2.23)*	0.117 (2.23)*	0.112 (2.17)*	0.133 (2.43)*	0.115 (2.15)*
Volatility of per capita GDP growth rate	-0.345 (4.99)**	-0.338 (5.06)**	-0.324 (4.78)**	-0.325 (4.95)**	-0.315 (4.54)**
Language diversity	-0.171 (2.80)**	-0.111 (2.13)*	-0.107 (2.07)*	-0.121 (2.29)*	-0.112 (2.17)*
Never a colony	-0.038 (0.55)	-0.078 (1.17)	-0.073 (1.11)	-0.053 (0.81)	-0.059 (0.89)
Colonizer growth rate	0.102 (1.27)	0.065 (0.82)	0.072 (0.97)	0.078 (1.05)	0.081 (1.10)
Spatial weighted average of neighbors' growth rates	n.a.	0.440 (5.19)**	0.538 (6.00)**	0.657 (5.51)**	0.594 (5.99)**
Constant	0.000 (0.00)	-0.015 (0.27)	-0.006 (0.11)	0.006 (0.10)	0.013 (0.25)
R-squared[a]	0.394	0.475	0.491	0.471	0.483
Log-likelihood	-202.890	-192.708	-190.410	-193.366	-191.304

Note: Standardized (beta) coefficients are reported, showing the effect of a one standard deviation increase in the explanatory variable on the standard deviation of average per capita GDP growth over 1987-2003, for N=174 countries. Definitions for all variables are reported in Table 3.
Robust t-statistics in ( ). + significant at 10%; *at 5%; **at 1%; for spatial regression robust z-statistics in ( ).
[a] For spatial lag models the squared correlation between actual and predicted values is reported.

9. Results from Matching Estimators

The results in Sections 7 and 8 suggest that claims of growth failure in the Pacific Island countries are not robust. Specifically, once interactions between the growth rates of nearby countries are accounted for, there is only a small (less than 0.1 of a standard deviation) and statistically insignificant effect of being a Pacific Island country on the average growth rate of GDP per capita. In this section, the issue of appropriate comparators for evaluating the counterfactual growth rate of the Pacific Island countries is studied. Recall that previous approaches either use regression methods (including Section 8) or ad hoc selections of comparators. The regression methods implicitly force all countries in a sample to be comparators for a specific country, regardless of their dissimilarity. The ad hoc selecting of comparators, such as done by Duncan (2005) in using Botswana and Mauritius for PNG and Fiji, may not yield the same counterfactual growth comparisons as more formal methods like propensity score matching.

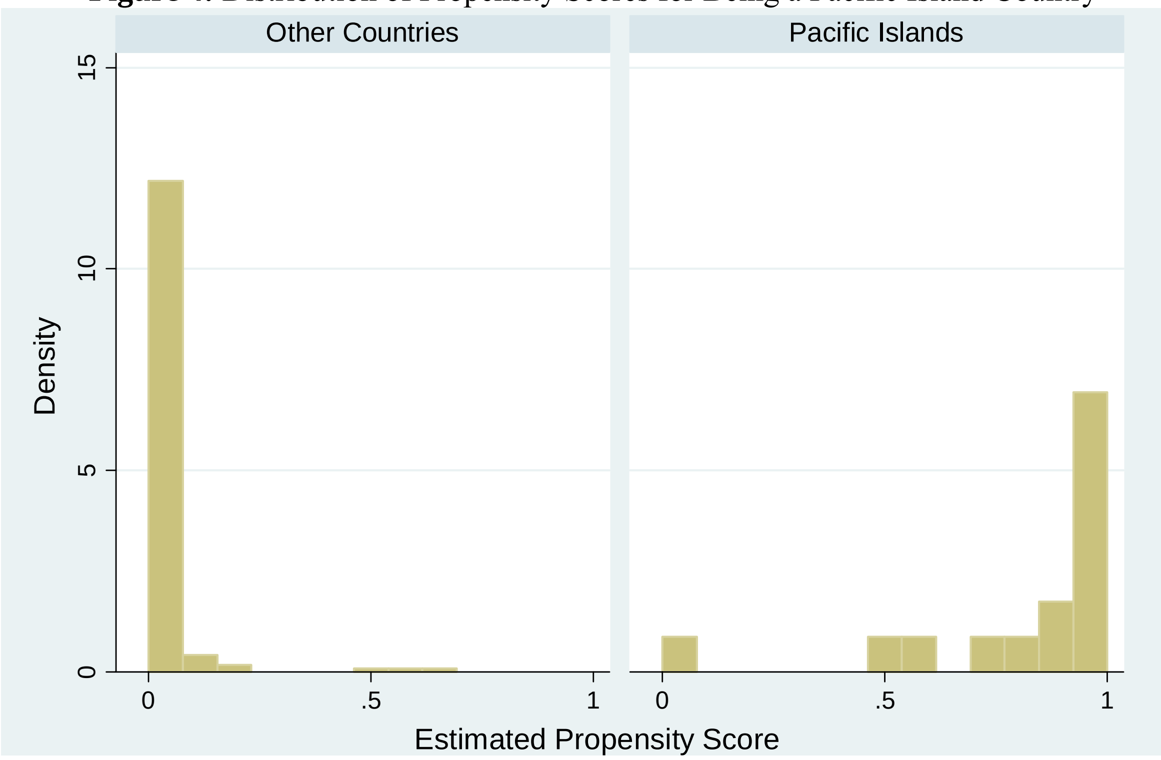
In order to construct a propensity score it is necessary to have a probabilistic (probit) model showing the characteristics most closely associated with the propensity to be a Pacific Island country. The following model explains over 80 percent of the variation in the 0/1 variable denoting which of the sample of 174 countries are Pacific Island countries (PIC):

$$PIC = -5.87 + 1.00GDP\_DISTANCE - 0.77LOGPOP - 1.03INDEPENDENT$$

(2.10) (3.30) (3.10) (1.03)

where z-statistics are in ( ). The explanatory variables are the GDP-weighted distance in 2003, the logarithm of each country's population and a dummy variable for whether the country is politically an independent state. The coefficients show that Pacific Island countries are more remote, have smaller populations and are less likely to be politically independent. Based on this equation, the propensity for each country to be a Pacific Island country is estimated, with the results shown in Figure 4.

Figure 4: Distribution of Propensity Scores for Being a Pacific Island Country



It is readily apparent from the left-hand panel of Figure 4 that most countries outside of the Pacific Islands have zero probability of being a Pacific Island country, according to the factors in the model generating the propensity scores. Because of this dissimilarity, these countries are not necessarily good comparators. Who are the good comparators? The only propensity scores from the non- Pacific Island countries that exceed 0.25 are for New Zealand (0.69), Timor Leste (0.54) and the Seychelles (0.53). In other words these are the countries that are most like the Pacific Islands in terms of remoteness, population and political autonomy. So researchers searching for counterfactuals of how the Pacific Island countries might have grown if they had adopted different policies would do better to look at the growth experience of these three comparators than at some other countries chosen in an ad hoc manner. For the record, the average annual growth rate of these three comparators was 3.1 percent over 1987-2003 (or 3.0 percent if weighting by the propensity scores).

Of the two comparators used by Duncan (2005) Mauritius has the fourth highest propensity score (0.23) amongst the non- Pacific Island countries, while Botswana has the 11th highest score (0.07). Thus they can be considered reasonable but not necessarily the best choices of comparators. Does the use of ad hoc methods of selecting comparators matter? The average growth rate of Mauritius and Botswana was 4.0 percent per year (4.6 percent if weighted by the propensity score). In contrast, if all 11 non- Pacific Island countries that have propensity scores at least as high as Botswana are used, the average growth rates are only 2.9 percent (or 3.0 percent weighting by the propensity score). So a more systematic method of selecting comparators would lead to a lower counterfactual growth rate for evaluating how badly the Pacific Island countries have done.

The other feature apparent from Figure 4 is the considerable heterogeneity amongst the Pacific Island countries. The histogram for the propensity scores in the right hand panel shows that most Pacific Island countries have a 100 percent probability of being in the 'treatment group' (that is, of being a Pacific Island country). However, one country (PNG) has a very low probability. This reflects the difficultly of grouping PNG with the rest of the Pacific Islands, at least in terms of population size. This heterogeneity within the treatment group provides further reason for expecting differences between the treatment and control groups (the comparator countries) to not necessarily be statistically significant.

An attempt to examine such differences formally is presented in Table 8. Two types of comparisons are made. The first compares the average growth rate of the 15 Pacific Island countries (the 'treatment group') and 14 other countries who share a 'common support'. This condition limits the comparisons to countries where there are overlapping propensity scores in the treatment and control groups. The second comparison all of the159 non- Pacific Island countries, many of whom have a propensity to be a Pacific Island country which is lower than that estimated for any of the treatment group. In both cases, the so-called *kernel matching* method is used. Each treated country is matched with a weighted average of all control group countries within a certain propensity score distance, with weights declining in that distance. In other words, the counterfactual average growth rate of the control group of countries places most weight on the non- Pacific Island countries with the highest propensity scores.

Table 8: Treatment Effects Estimates of Difference in Average per capita GDP Growth Rate Between Pacific Island and Other Countries

	Restricting to Common Support	Using All Countries
Number of countries in treatment group	15	15
Number of countries in control group	14	159
Difference in mean average growth rate (Treatment minus control)	-0.004	-0.004
Standard error of difference	0.009	0.009
t-statistics	0.41	0.41

Source: Author's calculations from data described in text.
Standard errors are based on 100 bootstrapped replications.

Both types of treatment effects reported in Table 8 are small (-0.004) and statistically insignificant. In other words, using this flexible propensity score method, there is no firm evidence that the Pacific Island countries grew more slowly over 1987-2003 than did an appropriate group of comparator countries.

10. Conclusions

The existing literature suggests that the Pacific Island economies are growth failures. A number of expert diagnoses for these failures are available and in many cases discuss genuine problems of poor governance and weak economic policy. However, it is less clear how quickly the Pacific Island countries would grow in the absence of these problems. These countries face a number of fundamental constraints on growth, especially related to their remoteness from centres of world GDP.

The results reported in this paper provide some reason for doubting the counterfactual claims of how well the Pacific Island countries would grow following the adoption of better policies. The two failings of the existing literature that are considered here are the use of ad hoc methods for selecting comparator countries and the ignoring of spatial effects whereby interactions between the growth rates of nearby countries are not accounted for. In both cases, once improved methods are used – spatial lag models for dealing with the dependence on neighbouring country growth rates and propensity score matching for selecting comparators – the hypothesis that per capita GDP growth in the Pacific Island countries is lower than in other countries is rejected.

The strong spatial effects – and especially that they occur through the systematic rather than the random part of the regression model – also imply the need for a regional focus in any solutions to actual or perceived growth problems in the Pacific. In the preferred spatial regression model the average growth rate of neighbouring countries directly enters into the equation predicting the growth of a specific country (rather than these spatial effects simply being proxies for unobserved characteristics that are common to neighbouring countries, which would enter through the random part of the regression model). Thus it is hard for a single country to have a strong growth performance if it is surrounded by other countries with much more modest growth. In other words, targeting growth impediments in a single country, say the Solomon Islands, will not get to the bottom of a slow growth problem if nothing is done about the neighbouring countries.

References

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., and Wacziarg, R. (2003) Diversity, *Journal of Economic Growth* 8(2): 155-194.

Anselin, L. (1988) *Spatial Econometrics: Methods and Models* Dordrecht: Kluwer Academic Publishers.

Anselin, L. (1995) *SpaceStat, A Software Program for the Analysis of Spatial Data, Version 1.80*. Regional Research Institute, West Virginia University, Morgantown, WV.

Anselin, L. and Bera, J. (1998) “Spatial dependence in linear regression models with an introduction to spatial econometrics” in A. Ullah and D. Giles (eds) *Handbook of Applied Economic Statistics* New York: Marcel Dekker, pp. 237-289.

Anselin, L., Bera, J., Florax, R., and Yoon, M. (1996) “Simple diagnostic tests for spatial dependence” *Regional Science and Urban Economics* 26(1): 77-104.

Anselin, L., Syabri, I., and Kho, Y. (2006) GeoDa, an introduction to spatial data analysis, *Geographical Analysis* 38(1): 5-22.

Armstrong, H. and Read, R. (2000) Comparing the economic performance of dependent territories and sovereign micro-states, *Economic Development and Cultural Change* 48(2): 285–306.

Armstrong, H. and Read. R. (2002) “The Phantom of Liberty? Economic Growth and the Vulnerability of Small States” *Journal of International Development* 14(4): 435-458.

Armstrong, H. and Read, R. (2006) Geographical ‘handicaps’ and small states: some implications for the Pacific from a global perspective, *Asia Pacific Viewpoint* 47(1): 79-92.

Asian Development Bank (2006) *Key Indicators 2006*, Manila.

AusAID. (2006) *Pacific 2020 Challenges and Opportunities for Growth*, Canberra.

Bertram, G. (2004) On the convergence of small island economies with their metropolitan patrons, *World Development* 32(2): 343–364.

Bertram, G. and Karagedikli, O. (2004) Core-periphery linkages and income in small Pacific Island economies, in J. Poot (ed) *On the Edge of the Global Economy* Edgar Elgar, Cheltenham, pp. 106-121.

Briguglio, L. (1995) Small island developing states and their economic vulnerabilities, *World Development* 23(10): 1615–1632.

Chand, S. (2001). Lessons for development from Pacific island countries. *Pacific Economic Bulletin, 16*(1), 95-108.

Chand, S. (2003). Economic trends in the Pacific island countries. *Pacific Economic Bulletin,* *18*(1), 1-15.

Conley, T. and Ligon, E. (2002) Economic distance and cross-country spillovers, *Journal of Economic Growth* 7(2): 157-187.

Duncan, R. (2005) Quantitative assessment of the cost of governance failure in Fiji Islands, Nauru, Papua New Guinea and Solomon Islands, *Working Paper* No. 6, Asian Development Bank—Commonwealth Secretariat Joint Report to the Pacific Islands Forum Secretariat on Toward a New Pacific Regionalism.

Easterly, W. and Kraay, A. (2000) Small states, small problems? Income, growth and volatility in small states, *World Development* 28(11): 2013-2027.

Gosarevski, S., Hughes, H., and Windybank, S. (2004). Is Papua New Guinea viable? *Pacific Economic Bulletin, 19*(1), 134-145.

Hausmann, R. (2001). Prisoners of geography, *Foreign Policy* 122(1):44-53.

Hughes, H. (2003). Aid has failed the Pacific. *Issue Analysis, 33*, Centre for Independent Studies, Sydney.

King, G., and Zeng, L. (2007) When can history be our guide? The pitfalls of counterfactual inference, *International Studies Quarterly* (forthcoming).

McCann, P. (2006) New Zealand and its regions in the global economy: an economic geography perspective, *Keynote Address* 47th Annual Conference of the New Zealand Association of Economists, Wellington.

Persson, T., and Tabellini, G. (2002) Do constitutions cause large governments? Quasi-experimental evidence, *European Economic Review* 46(4-5): 908-918.

Redding, S. and Venables, A. (2004) Economic geography and international inequality, *Journal of International Economics* 62(1): 53-82.

Sampson, T. (2005) Notes on the economic performance of small states 1995-2003, *Working Paper* No. 2, Asian Development Bank—Commonwealth Secretariat Joint Report to the Pacific Islands Forum Secretariat on Toward a New Pacific Regionalism.

Silva, J. and Tenreyro, S. (2006) The log of gravity, *Review of Economics and Statistics* 88(4): 641-658.

Tolliday, S (2000) Introduction:enterprise and state in the Italian “economic miracle” *Enterprise and Society* 1(2): 241-248.

World Bank (2006a) *At Home and Away: Expanding Job Opportunities for Pacific Islanders Through Labour Mobility* The World Bank: Washington, D.C.

Appendix Tables

Appendix Table 1: Remoteness Measures for the Pacific Islands

	ISO Code	2003 GDP-weighted distance (km)	GDP-weighted distance rank (2003)	Population-weighted distance rank (2003)	GDP-weighted distance rank (1988)
Cook Islands	COK	12264	213	210	213
Fiji	FJI	12218	211	193	211
Federated States of Micronesia	FSM	10301	173	150	178
Kiribati	KIR	10809	185	161	187
Marshall Islands	MHL	10335	176	156	179
Northern Mariana Islands	MNP	9669	163	130	166
New Caledonia	NCL	12501	215	176	215
Niue	NIU	12246	212	209	212
Nauru	NRU	10943	188	159	190
Palau	PLW	10205	171	119	175
Papua New Guinea	PNG	11407	195	153	200
French Polynesia	PYF	11873	206	212	207
Solomon Islands	SLB	11574	203	158	204
Tokelau	TKL	11528	200	197	202
Tonga	TON	12410	214	204	214
Tuvalu	TUV	11479	198	181	201
Vanuatu	VUT	12160	210	170	210
Wallis and Futuna	WLF	11860	205	196	208
Samoa	WSM	11874	207	201	209
Unweighted average		11456	197	176	199

Source: Author's calculation from World Bank GDP and population data. Distances are the weighted average distances from each country in the row stub to every other country in the world, where the location of each country is based on population-weighted centroids for larger countries and location of capital city for smaller countries. The rank is out of 219 countries, with #1 the most accessible, #219 most remote.

Appendix Table 2: Remoteness Measures for the Caribbean Islands

	ISO Code	2003 GDP-weighted distance (km)	GDP-weighted distance rank (2003)	Population-weighted distance rank (2003)	GDP-weighted distance rank (1988)
Aruba	ABW	8370	116	192	117
Anguilla	AIA	7908	85	165	80
Netherlands Antilles	ANT	8334	114	189	113
Antigua and Barbuda	ATG	7991	90	166	87
Bahamas	BHS	7391	70	164	69
Barbados	BRB	8291	112	174	109
Cayman Islands	CYM	7874	79	187	83
Dominica	DMA	8121	102	172	98
Guadaloupe	GLP	8055	95	169	94
Grenada	GRD	8371	117	182	115
Jamaica	JAM	7952	88	186	88
St Kitts and Nevis	KNA	8003	93	163	90
St Lucia	LCA	8227	106	175	106
Martinique	MTQ	8178	105	173	101
Trinidad and Tobago	TTO	8502	126	185	122
St Vincent and Grenadines	VCT	8291	111	178	110
British Virgin Islands	VGB	7892	83	167	79
Unweighted average		8103	100	176	98

Source: Author's calculation from World Bank GDP and population data. Distances are the weighted average distances from each country in the row stub to every other country in the world, where the location of each country is based on population-weighted centroids for larger countries and location of capital city for smaller countries. The rank is out of 219 countries, with #1 the most accessible, #219 most remote.

Appendix Table 3: Air Fares in the Pacific

	Origin	Destination City AKL	SFO	SYD
Papua New Guinea	POM	904	3227	754
Solomon Islands	HIR	670	1418	1079
Fiji	NAN	248	793	276
Vanuatu	VLI	259	905	324
Samoa	APW	306	2720	473
Tonga	TBU	190	777	354
Cook Islands	RAR	248	950	367
French Polynesia	PPT	2165	2349	1906
Palau	ROR	2054	1434	1357
FSM	TKK	3221	1041	3039
Northern Marianas	SPN	1648	946	1166
Guam	GUM	1834	1191	1086
Marshall Islands	KWA	na	2191	na

Source: Fares obtained from Travelocity on November 24, 2006 for one-way, economy class travel on Feb 3, 2007. Fares are in US$. No fares could be obtained for travel from either Tuvalu or Kiribati.

Appendix Table 4: Air Fares from the Caribbean Islands

	Origin	Destination City Miami	New York	London
St Lucia	SLU	572	494	734
St Kitts Nevis	NEV	426	354	1002
Dominica	DOM	392	323	989
Barbados	BGI	494	419	780
Trindad and Tobago	POS	337	401	837
Aruba	AUA	376	227	894
Jamaica	KIN	239	324	752
Antigua and Barbuda	ANU	344	297	720
Bahamas	NAS	170	165	941
Cayman Islands	GCM	267	272	986
Grenada	GND	588	516	na
Guadaloupe	PTP	594	530	1328
Martinique	FTF	590	526	1018
Netherlands Antilles	CUR	246	330	706
St Vincent	SVD	393	328	908
Virgin Islands	STT	294	229	936

Source: Fares obtained from Travelocity on November 24, 2006 for one-way, economy class travel on Feb 3, 2007. Fares are in US$.