Telecommunications and Economic Activity: An Analysis of Granger Causality

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ABSTRACT: The pervasive role of telecommunications in contemporary commerce is well documented, and has dramatically increased the demand for services. Across the world, countries are seeking to improve telecommunications infrastructure and benefit from anticipated increases in economic activity, and a causal relation between the two is often tacitly assumed. This paper analyzes aggregate data at the national level to see if there is any empirical evidence that supports this assumption. We apply the well established Granger test for causality using time series data for levels of telecommunications infrastructure and economic activity from thirty countries. We find that the evidence for causality from levels of telecommunications infrastructure to economic activity is stronger than that for causality in the opposite direction. Moreover, this pattern appears to hold for both industrialized and developing economies, even though the former has strong service sectors that are heavily dependent on telecommunications. These findings provide additional insights into the complex relationship between telecommunications and economic activity. Some potential policy implications are also discussed. Granger causality tests have not seen much application in the IS literature, and we mention some IS research issues that may benefit from such analysis.

KEY WORDS AND PHRASES: economic activity, Granger causality, telecommunications infrastructure, telecommunications policy.

THE EXTENSIVE ROLE OF TELECOMMUNICATIONS in contemporary business, social, and political activity is well documented. In industrialized countries, new services are being rapidly introduced [28], and many developing countries are trying to also overcome chronic and acute deficiencies in basic infrastructure [33] through increased

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private sector participation [36]. In this context of a heightened role of telecommunications, the question, "Is there a causal relationship between levels of telecommunications infrastructure and economic activity?" is both relevant and interesting. Further, the literature indicates that many telecommunications policy and investment decisions are influenced by assumptions, albeit implicit, about causality in this relationship [31]. Unfortunately, empirical evidence on which to base these assumptions is scarce. This paper attempts to answer the foregoing causality question using data at the national level. Findings should contribute to our understanding of the relationship between telecommunications and business activity, and of assumptions that underlie telecommunications policy formulation.[1]

Why might one suspect a causal relationship between telecommunications and economic activity? Figure 1 summarizes the main reasons that have been suggested in the literature. As it shows, there are reasons to argue for causality in either direction. For instance, several case studies have demonstrated that improved telecommunications leads to more timely and widespread transfer of information needed for administration and commerce. Therefore, one can argue that increased telecommunications causes increased economic activity. Some examples that support this direction of causality follow:

- The RELCOM data network was set up in Russia [27] in April 1989, using just a MicroVAX and 286 PCs with dialup lines. Within three years, RELCOM was being used for market and business coordination within the country by about 7000 organizations and 200,000 users.
- The community services project in Peru [6] installed audioconferencing and public telephones to a small rural area using a satellite-based network. It was used by villagers to improve health, agricultural and educational activity.
- Telecommunications can reduce the time and expense associated with travel [8]. It enables organizations to lower their cost structure, enhance their value chain, and create new market mechanisms [5, 20, 24].

In the reverse direction, increased economic activity raises the intensity of information processing associated with coordination and control. This increases demand for more timely and accurate information. Greater economic activity also facilitates making the massive financial investments required for telecommunications growth. Together, these argue for a causal relationship from economic activity to telecommunications. Some examples that support this direction of causality follow:

- As agricultural development increases as a result of improved farming techniques, seeds, fertilizer, etc., the need to market surplus agricultural commodities arises, requiring reliable means of communicating rapidly over large distances.
- In the 1970s and 1980s, many oil surplus developing countries, such as Saudi Arabia, Venezuela, and Kuwait, undertook large investment programs in telecommunications based on oil revenues.
- As industrialized economies look at opportunities in developing countries, to tap emerging consumer markets or low-cost labor, the lack of telecommunica-

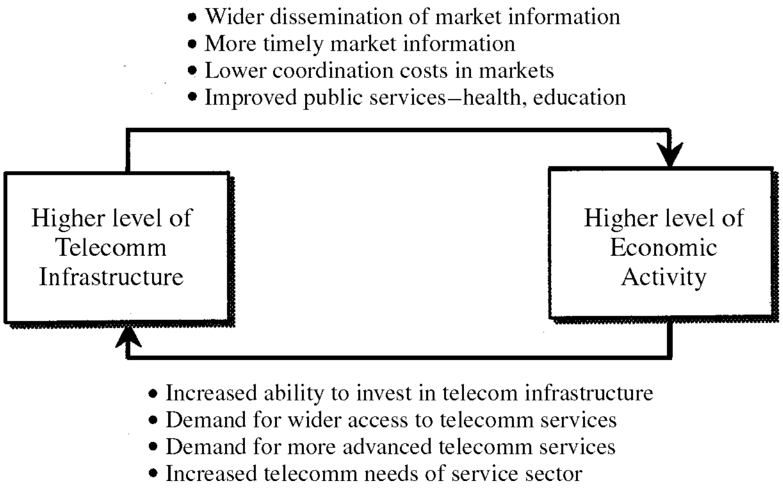


Figure 1. Causal Mechanisms Proposed in Literature

tions infrastructure can be a major deciding factor. To exploit global economic opportunities and thereby grow, many developing countries have to invest in their telecommunications infrastructure.

- The tertiary services sector is a major consumer of telecommunications, and as economic growth moves a country from agricultural to industrial to a service emphasis, the need for improved telecommunications becomes more acute.

While the preceding arguments are suggestive of causality, they are far from confirmatory. Further, even if causality does exist, these reasons do not allow one to conclude whether causality exists in only one direction or is bidirectional.

Earlier we alluded to causality assumptions underlying telecommunications policy. There are three groups of thinking in this regard [31]. The first group holds that telecommunications investments should be at levels lower than that suggested by market information arguments such as those mentioned earlier in this paper. They argue that there is a lack of evidence showing measurable economic effect. They fear that an increased urban-based economy would result, concentrating the benefits of growth in fewer people. They also argue that the economy may sometimes not be prepared to take advantage of advanced telecommunications technologies.[2]

The second group feels that telecommunications should grow as dictated by market forces, with free access to capital markets for investment funds.[3] A more activist third group contends that expansion and advancement in telecommunications infrastructure is a prime means of advancing a wide range of social and economic goals, including the delivery of health and education. This group supports the growth of telecommunications as dictated by market forces but, in addition, advocates intervention through regulation and policy, to promote telecommunication investments in selected areas. Clearly, the three lines of thinking make different implicit assumptions about causality. Without empirical evidence, however, it is hard to assess any of them.

At this point, it is appropriate to discuss the connection between investments in telecommunications infrastructure and the infrastructure itself, along with an explanation of our choice for operationalizing the telecommunications variable for causality analysis. First, investment is a periodic monetary flow, whereas the infrastructure itself represents a physical stock that results from a series of investments. In any case, the accumulated physical infrastructure in its entirety—not just the portion resulting from any one investment—is available to support economic activity in any given time period. Therefore, if a causal relationship is hypothesized, it should appropriately be between economic output levels and telecommunications infrastructure stock. The question that remains, then, is how best to measure this stock. Although details will follow shortly, at this stage we make a choice between two ways of measuring this stock: monetary and nonmonetary. The monetary approach would require one to keep a running total of periodic investments in telecommunications infrastructure. Since we propose to carry out a multicountry analysis, there are problems of currency conversion and inflationary effects, particularly for developing countries. Besides, the accounting rules for what is included in monetary estimates of telecommunications investments vary from country to country [33]. We therefore prefer to use nonmonetary measures to represent telecommunications infrastructure stock. The specifics of these measures will be discussed in the "Results" section.

As the preceding discussion suggests, although the role of telecommunications in economic activity is extensive, the relationship between the two is complex and not fully understood. We believe an empirical analysis of causality provides evidence, lacking heretofore in the literature, for a more complete understanding of this important relationship. In a nutshell then, the specific research question addressed by this paper is as follows:

> Is there a causal relationship between levels of telecommunications infrastructure and economic activity, and, if so, what is the direction of causality?

Next we review the literature on the relationship between telecommunications and economic growth. Some of the philosophical issues in establishing causality are also discussed here. Following that we describe the specific methodology used in this paper for analyzing causality and associated technical issues. Empirical results are then presented and discussed. Some implications of the findings are discussed in the conclusion of the paper.

Literature Review

THERE HAS BEEN LONG-STANDING RESEARCH INTEREST in the relationship between telecommunications and economic activity. Several studies have observed strong *correlation* between levels of economic activity and telecommunications infrastructure for individual countries over time, as well as for a cross section of countries at the same point in time. An early study by the CCITT (Consultative Committee on International Telephone and Telegraph) examined the correlation between per capita GDP and the number of telephone lines per 100 persons for a cross section of thirty industrialized and developing countries in the years 1955, 1960, and 1965 [7]. They found very high correlation coefficients, and estimated parameters did not vary much across the three years. This same study also examined this relationship for individual countries across several years and found the same strong correlation between levels of economic activity and telecommunications infrastructure.

Other studies have extended these early models by using more elaborate measures for telecommunications infrastructure and/or economic activity. Bebee and Gilling [4] used per capita GDP generated by the secondary and tertiary sectors of a country's economy since these sectors are the heaviest users of telecommunications. They also constructed a more complex estimate of telephone infrastructure using the number of telephone sets per 100 literate persons over 15 years of age, number of business telephones per 100 nonagricultural persons, and the average annual number of calls per telephone. Their findings of strong correlation were similar to those of earlier studies. Instead of telephone lines, some studies have used the density of telex lines as the measure of telecommunications infrastructure.

Some recent studies have developed multiple regression models with economic activity as the dependent variable and several infrastructure components—such as telecommunications, energy, and transportation—as explanatory variables [12]. Once again, strong correlation between telecommunications infrastructure levels and economic activity is observed. Other studies that examine this same correlation, but using different measures for the two variables, include [19, 34, 37]. While such aggregate correlation analysis is useful in showing that telecommunications and economic activity levels are somehow linked, it is subject to important limitations. One of those is the *inability to infer causality from any of the observed correlations.*

The simple concept that X causes Y raises subtle issues that go beyond econometrics. In the physical sciences, experiments can be repeatedly performed under controlled conditions to directly test suggested causal mechanisms. However, given the nonexperimental nature of most economic data, it is difficult and often impossible to determine cause-and-effect relationships from the available data in the strict philosophical sense. Since conflicting causal mechanisms may be proposed, a concept of "causality" has been developed in the economics literature that can be tested with statistical tools and that has seen considerable usage in recent years.

The concept, called Granger causality [15], can be informally described as follows. It begins with time series data on the two variables of interest—economic activity and telecommunications infrastructure levels, in our case. First, one builds a model to predict one variable, say economic activity, using only its own history—that is, one develops an autoregressive model of the variable. If adding the second variable—telecommunications, in this case—to the autoregressive model significantly improves the ability to predict economic activity levels, one says that telecommunications Granger-causes economic activity. By reversing the roles of the two variables, one can similarly examine whether economic activity Granger-causes telecommunications levels.

Basics of Granger Causality: Does X Granger-cause Y?

1. Build autoregressive model for Y—that is, predict Y as well as possible using only its own history.
2. Add some past history of X to autoregressive model of Y.
3. *If this addition improves the ability to predict Y in a statistically significant way, then X Granger-causes Y. Otherwise, there is no evidence of Granger causality from X to Y.*

Whether the Granger definition of causality is consistent with causality definitions in a strict philosophical sense has been debated in the literature [14]. However, it has been used widely in several different areas. For instance it has been used to test the money–income relationship [32]. Ashley et al. have found evidence that aggregate national sales Granger-causes advertising, but advertising does not Granger-cause aggregate sales [2]. Granger tests of the sales–advertising relationship have been reported extensively in the literature [22, 38]. Other relationships that have been examined include those between population and growth [21], technology partnerships and intensity of research & development activity [9], export levels and economic growth [25], fiscal policy variables and economic growth [30], and level of futures trading and stock price volatility [10]. However, the Granger test has not seen much application in the IS literature.

Methodology

IN THIS SECTION WE FIRST PRESENT TECHNICAL DETAILS of the methods and tests associated with Granger causality. Following that is a description of the measures used for the two variables and the countries included in the data set. Thirty countries are included, and for each country we have yearly data on economic activity and telecommunications infrastructure levels for at least 24 years.[4] Based on our prior discussion of possible causal mechanisms (summarized in Figure 1), and the practical aspects of analyzing economic data for causality, we test the following two hypotheses for each country:

H_a: The level of economic activity in any year Granger-causes the level of telecommunications infrastructure in a subsequent year.

H_b: The level of telecommunications infrastructure in any year Granger-causes the level of economic activity in a subsequent year.

The null hypothesis in each case is that there is no such causal relationship. For each country, both hypotheses could be false, one of them could be true, or both could be true.

Recall that Granger causality analysis begins with time series data on the two variables of interest. For a given country, let:

y(t) = economic activity level in year t
x(t) = telecommunications infrastructure level in year t

The specific measures used for the two variables will be developed shortly and are not necessary to present the method. Several different statistical tests have been devised to operationalize the notion of Granger causality, and they have different data requirements and discriminatory power. *We are particularly interested in small sample properties of the tests, since the time series for a country consists of 24 to at most 34 observations.* A detailed discussion of the small sample properties can be found in [16], where three different tests are compared. We use the Granger test in this study since it was found to have desirable small sample properties, and required fewer data points than the modified Sims test. The Granger test of causality is based on the OLS estimation of :

$$y(t) = \sum_{j=1}^{K} a(j)\,y(t-j) + \sum_{j=1}^{M} b(j)\,x(t-j) + \alpha + \varepsilon(t),$$

where $\varepsilon(t)$ is a white-noise term, and a is a constant. The test of the hypothesis that telecommunications infrastructure levels do not Granger-cause economic activity levels is that $b(j) = 0$ for $j = 1,2,\ldots,M$. The lagged dependent variables constitute an autoregressive representation for series $y(t)$. The Granger test statistic is calculated by estimating the above equation in both constrained (i.e., $b(j) = 0$, $j = 1,2,\ldots,M$) and unconstrained forms, and then taking the ratio

$$F_1 = \frac{(SSE_c - SSE_u)/(DFE_c - DFE_u)}{SSE_u / DFE_u},$$

where SSE and DFE stand for error sum of squares and degrees of freedom, respectively. The above ratio has an F distribution with $[(DFE_c - DFE_u), DFE_u]$ degrees of freedom, and can be used to test the null hypothesis mentioned above [16]. A similar test can be done for the claim that "economic activity level does not Granger-cause telecommunications infrastructure levels" by reversing the roles of $x(t)$ and $y(t)$ in Equation 1.

Before this F-ratio can be computed, however, the two time series for each country have to be "preconditioned" to meet the requirements of Equation 1. Notice that Equation 1 is a pure autoregressive process with no deterministic trend and that the error term $\varepsilon(t)$ is white noise. However, the time series for national economic activity and telecommunications infrastructure show distinct upward trends for every country. One would naturally expect these two items to grow steadily over time, albeit at different rates for different countries. We use the standard technique of differencing to remove trends, and Dickey–Fuller tests [13] to check for the presence of unit roots in the differenced series. For example, a first-order autoregressive representation of the series $y(t)$ is:

$$y(t) = a_1 * y(t-1) + \varepsilon(t) \tag{2}$$

where $\varepsilon(t)$ is a white-noise error term. Subtracting $y(t-1)$ from each side results in

$$y(t) - y(t-1) = a_1 * y(t-1) - y(t-1) + \varepsilon(t),$$

or alternatively,

$$\Delta y(t) = \gamma * y(t-1) + \varepsilon(t), \tag{3}$$

where $\Delta y(t)$ is the first difference of the series and $\gamma = (a_1 - 1)$. Testing the unit root hypothesis that $a_1 = 1$ is the same as testing for $\gamma = 0$ in Equation 3. Thus, the Dickey–Fuller test consists of estimating the value of γ in Equation 3 using OLS, and then checking for the null hypothesis that $\gamma = 0$. The distribution of the statistic is not the standard *t*-distribution, and Dickey and Fuller found in their Monte Carlo studies that the critical values for the test statistic depend on sample size. The above method can be easily extended to check for more than one unit root. For instance, if two unit roots are suspected, one needs to regress the second difference of the series against the lagged values of its first difference.

Once the series y(t) and x(t) have been appropriately differenced to remove trends and checked for the presence of unit roots, the next step is to determine an appropriate lag structure for an autoregressive representation of the differenced series in the form of Equation 1. We know the lag structure is appropriate when the error terms of the autoregressive representation approximate white noise. We used three different tests simultaneously to check for white noise error terms [29]. First, using the IDENTIFY option in the SAS ARIMA procedure, we visually checked the autocorrelation function of the residuals out to lag = 6 and compared the Ljung-Box statistic for this lag against the appropriate critical value of the χ^2 distribution. Second, we carried out spectral analysis on the residuals, and used Bartletts' Kolmogorov–Smirnov statistic and Fisher's Kappa statistic to check for their "whiteness." Once the appropriate lag structure was determined for Equation 1, the ratio F_1 mentioned above was computed by performing constrained and unconstrained OLS estimation using the autoregressive specification of the differenced series. A detailed flowchart of the complete process is shown in Figure 2.

The detailed sequence of steps just described can be recalled more easily as the three broad steps shown along the left margin in Figure 2. Step 1 essentially removes deterministic trends from the time series using differencing. When the coefficient g is not statistically different from zero, we know that trends have been removed and Step 1 terminates. Step 2 consists of determining an appropriate lag structure for the autoregressive time series. When the residuals are statistically white as determined by the tests indicated in Figure 2, we know that we have the appropriate lag structure. Therefore, at the end of step 2, we have a time series model that meets the structural requirements of the Granger test model stated earlier in Equation 1. In step 3, we perform the constrained and unconstrained estimations on the model resulting from step 2 and use the corresponding F-test to determine presence of causality.

Having summarized the procedure, it is useful to discuss an aspect of the Granger tests that has a bearing on the interpretation of results. As seen earlier, the Granger tests involve two variables: economic activity and telecommunications infrastructure levels. However, economic activity is correlated with other variables too, as the growth literature has clearly shown [3]. Similarly, telecommunications investments and infrastruc-

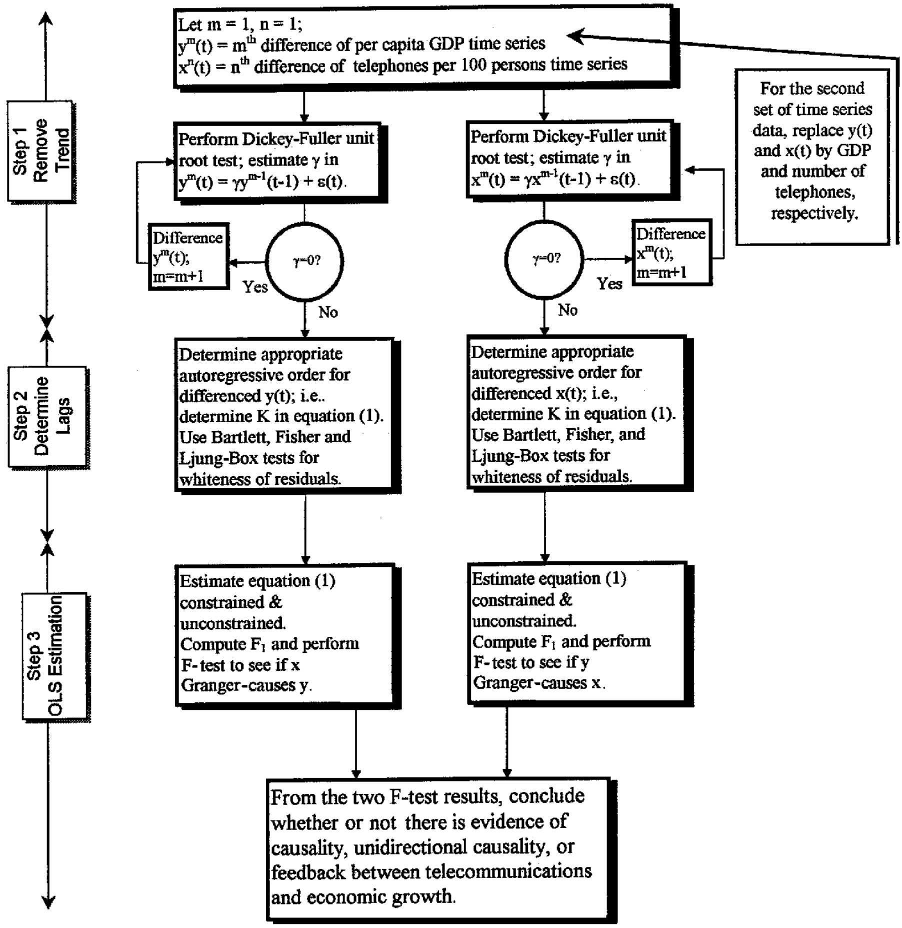


Figure 2. Flowchart for Telecommunications Causality Analysis

ture levels are determined by several factors. For instance, in many countries, the government wholly owns the telecommunications industry. Therefore, infrastructure levels are highly influenced or even decided by government policies. At first glance, it may appear that the effects of these different drivers of the two variables are ignored in our analysis. Recall, however, that the Granger test involves first setting up an *autoregressive* time series, where we model economic activity using only its own history. Therefore, although they are not explicitly identified, the influence of other drivers is implicitly included in an autoregressive specification since we first try to explain the variable in terms of its own past history.[5] If adding the second variable, telecommunications level, to this autoregressive model results in a statistically significant improvement, this improvement occurs in the presence of the influence of other drivers. A similar argument can be made with respect to telecommunications infrastructure levels. If adding economic activity to an autoregressive representation of telecommunications results in a statistically significant improvement, this improvement has occurred in the presence of other drivers, including government regulation and policy regarding telecommunications. Hence the causality findings to be presented in the final section reflect the impact of telecommunications without ignoring effects of other variables associated with economic activity.

Measures Used

We collected time series data for 15 developing countries and 15 industrialized nations. For each of these countries, we have data from at least 1970–1993. For some countries, it was possible to construct somewhat longer time series, but the longest sequence ranges from 1960–1993. Two different measures, total and per capita GDP, measured in constant 1987 dollars, were used to represent the level of economic activity for a given country in any year. This data is obtained from tables published by the United Nations [1].[6] Aggregate measures, such as GDP, are well established in the economic growth literature [3].

Similarly, we use two distinct measures for telecommunications infrastructure level—the total number of telephones and the number of telephones per 100 persons. For the early years of most countries—and, until fairly recent times in the case of many developing countries—these two measures reflected only wireline telephone services. However, many industrialized nations have developed a substantial base of cellular subscribers since the 1980s. Over the last five years of our time series, several developing countries have also experienced substantial growth in cellular telephony.[7] We have *included* cellular subscribers in the measure of telecommunications infrastructure in the specific years and countries where such service was made available.[8]

For each country analyzed in this paper, therefore, we have two sets of observations, each set consisting of two time series. The first set consists of per capita GDP in 1987 dollars and number of telephones per 100 persons. The second set is not standardized by population, and consists of total GDP in 1987 dollars and the total number of telephones.

Notation for the time series variables is as follows:

PHONES_PER_100 = Telephones per 100 individuals (including cellular where applicable)

TOTAL_PHONES = Total number of telephones (including cellular where applicable)

PERCAPGDP = Per capita GDP in 1987 dollars

GDP = Total GDP in 1987 dollars

We expect relatively consistent findings from each set, although differences in population growth rates may affect the strength of the findings. The four separate measures used for the two variables under study, although well established in the literature, have some limitations. These issues and other limitations of the study are discussed in detail after results of the analysis have been presented.

Some of the correlation studies cited earlier in the paper (e.g., [7]) examined the relationship between logarithmic transformations of the two variables. This may be appropriate if the relationship between the two variables is nonlinear and of the general form $y = a*x^b$. If one considers x to be an input in the production of y, then this functional form can also reflect characteristics of a production function, such as diminishing returns. We therefore also created a separate data set, paralleling the first, the only difference being that the second set was built using logarithmic transformations of the levels of economic activity and telecommunications infrastructure. The Granger tests were also applied separately to the transformed variables and the findings are reported along with those obtained using the original variables.

Country Selection

We collected time series data for thirty countries, divided into two groups as follows:

Developing Countries:

Argentina, Brazil, Chile, Colombia, India, Indonesia, Malaysia, Mexico, Panama, Paraguay, Peru, Philippines, Thailand, Uruguay, Venezuela

Industrialized Countries:

Australia, Canada, Denmark, Finland, France, Hong Kong, Italy, Japan, Korea, New Zealand, Singapore, South Africa, Sweden, United Kingdom, United States of America

The motivation for forming two groups—developing and industrialized countries—independent of the specific countries in each, is as follows. The primary sector (agriculture, mining) is a significant segment of the economy in developing countries along with the secondary sector (manufacturing) in many cases. In contrast, a distinctive characteristic of industrialized countries is the presence of a growing tertiary sector (service). Further, the chronic disparities in telecommunications infrastructure between the two groups are well documented [31]. Most developing countries still do not have well established policy-making or regulatory bodies in the area of telecommunications. In view of the sectoral and institutional differences, it is interesting to see whether the evidence of causality is significantly different across the two groups. As with measures, the limitations of choosing this specific set of countries are discussed subsequently.

Results

IN THIS SECTION, WE PRESENT THE RESULTS of our statistical analysis, together with a discussion of their implications for evidence of causality. Detailed numerical statistics are presented in tabular format, but we also present the same results in graphical format for easy interpretation by the reader.

Statistical Results

Table 1 presents results of the Granger tests using times series data for the two variables—telecommunications and economic activity. Table 2 presents the same analysis using logarithmic transformations of the two variables. The two tables are therefore identical in structure, which is as follows. The first column lists country names, with the first fifteen being the developing countries. The remaining columns are divided into two groups. The first group analyzes causality from telecommunications to economic activity levels, while the second group analyzes causality in the opposite direction. Each group shows results of the Granger test applied separately to the standardized and absolute value time series data. For example, in Table 1, headings for the first group of columns read "PHONES_PER_100–>PERCAPGDP" and "TOTAL_PHONES–>GDP" for the standardized and absolute values, respectively.

Statistical significance of the tests is shown in the columns labeled "SIG." When both test results—that is, with standardized as well as absolute values—are significant at the 10 percent level,[9] the SIG column shows two asterisks (**). When only one of the tests is significant, just one asterisk (*) is used. The SIG column is left blank when neither test is significant at the 10 percent level. Therefore the asterisks should not be interpreted as signifying different levels of statistical significance. They only indicate whether both tests, one test, or neither test was significant at the 10 percent level. The reader can therefore get a sense of the causality findings simply by focusing on the two SIG columns in Tables 1 and 2.

An alternate representation of these findings is shown in Figures 3 and 4. These two figures exclude all numerical details of Tables 1 and 2 and summarize only the statistical significance of the Granger tests. Each data point in Figures 3 and 4 represents a country and its x and y coordinates represents the Granger F-test probability value using standardized and absolute data, respectively. In effect they summarize the main findings of our analysis. They are also visually more convenient to absorb and will be used in the following discussion. The reader can always refer back to Tables 1 and 2 for numerical corroboration. We have used logarithmic scales in Figures 3 and 4 for better visual separation of data points since the cutoff significance level is 10 percent. (With a linear scale, all statistically significant data points would be condensed into a small portion around the southwest corner of each graph, making it hard to observe any patterns.)

Discussion of Results

The following observations readily emerge from Figures 3 and 4. First, despite some dispersion, a 45-degree trend is apparent in all four charts. This indicates that the absolute and standardized data sets yield reasonably consistent findings on the whole, with both the original and log-transformed variables. This consistency is reassuring in view of the aggregated nature of data used in the analysis. The southwest quadrant of each chart represents countries for which the Granger causality tests were significant using both absolute and standardized data sets. The northwest and southeast

Table 1. Granger-Causality Test Results Using Original Variables

	PHONES_PER_100 $\nRightarrow$ PERCAPGDP					TOTAL_PHONES $\nRightarrow$ GDP				PERCAPGDP $\nRightarrow$ PHONES_PER_100					GDP $\nRightarrow$ TOTAL_PHONES			
Country	DF1	DF2	Fval	Prob	SIG	DF1	DF2	Fval	Prob	DF1	DF2	Fval	Prob	SIG	DF1	DF2	Fval	Prob
Argentina	2	28	3.21	0.06	**	3	27	2.52	0.08	1	27	0.90	0.35		3	27	1.59	0.21
Brazil	1	27	3.53	0.07	**	1	29	3.01	0.09	2	26	0.67	0.52	*	2	26	3.00	0.07
Chile	1	22	2.99	0.1	**	1	22	4.27	0.05	3	16	0.91	0.46		3	16	1.00	0.42
Colombia	2	16	3.26	0.07	**	2	16	4.32	0.03	1	16	3.11	0.10	**	1	19	2.98	0.10
India	1	29	1.14	0.3	**	1	29	5.34	0.03	1	29	1.73	0.20		1	29	2.10	0.16
Indonesia	1	19	4.11	0.06	**	1	19	5.60	0.03	1	19	6.10	0.02	**	1	19	8.67	0.01
Malaysia	1	23	1.1	0.31		1	22	1.63	0.22	1	22	5.35	0.03	**	1	22	7.67	0.01
Mexico	1	19	0.34	0.57		1	19	0.46	0.50	1	19	0.19	0.67		2	16	0.11	0.90
Panama	1	20	3.1	0.09	*	1	20	1.71	0.21	1	20	3.12	0.09	**	2	17	2.89	0.08
Paraguay	1	20	3.29	0.08	**	3	14	2.99	0.07	1	19	0.10	0.75		1	19	0.04	0.85
Peru	1	23	3.48	0.07	*	2	20	0.28	0.76	1	23	2.55	0.12	*	1	23	5.29	0.03
Philippines	2	16	4.31	0.03	**	2	16	3.33	0.06	1	19	0.16	0.69		2	16	0.15	0.86
Thailand	2	16	4.58	0.03	**	2	16	5.83	0.01	1	19	3.00	0.10	*	1	19	2.41	0.14
Uruguay	3	13	0.28	0.84		3	13	0.36	0.79	2	16	0.16	0.86		1	19	0.05	0.82
Venezuela	1	21	3.72	0.07	**	1	21	4.61	0.04	1	21	3.10	0.09	*	1	21	0.47	0.50

Continued

Table 1. Granger-Causality Test Results Using Original Variables (Continued)

	PHONES_PER_100 ⇒PERCAPGDP					TOTAL_PHONES ⇒GDP				PERCAPGDP ⇒PHONES_PER_100					GDP ⇒TOTAL_PHONES			
Country	DF1	DF2	Fval	Prob	SIG	DF1	DF2	Fval	Prob	DF1	DF2	Fval	Prob	SIG	DF1	DF2	Fval	Prob
Australia	1	20	3.09	0.09	**	1	22	4.01	0.06	2	19	0.50	0.61		2	19	1.07	0.36
Canada	2	18	0.45	0.64		1	21	0.20	0.66	1	21	0.76	0.39		1	21	0.60	0.45
Denmark	3	20	2.48	0.09	**	3	20	4.07	0.02	3	26	0.35	0.79		1	26	0.26	0.62
Finland	1	19	0.44	0.52		1	19	0.87	0.36	2	16	7.14	0.01	**	2	16	9.00	0.00
France	1	19	0.14	0.71		1	19	0.10	0.76	2	16	0.20	0.82		2	16	0.13	0.88
Hong Kong	2	16	0.9	0.43		1	19	0.39	0.54	2	16	0.80	0.47		2	16	1.20	0.33
Italy	2	18	1.91	0.18	*	2	18	4.01	0.04	1	19	0.52	0.48		1	21	0.57	0.46
Japan	2	16	2.74	0.09	**	2	16	2.65	0.10	2	16	1.31	0.30		2	16	1.09	0.36
Korea	1	19	3.88	0.06	**	1	19	4.90	0.04	1	19	0.07	0.79		1	19	0.15	0.70
New Zealand	3	13	7.91	0	**	3	13	5.98	0.01	1	19	1.74	0.20	*	1	19	3.18	0.09
Singapore	1	24	0.45	0.51		1	24	1.29	0.27	1	24	0.49	0.49		1	24	1.64	0.21
South Africa	1	19	0.23	0.64		1	19	1.58	0.22	1	19	1.58	0.22		1	19	1.25	0.28
Sweden	2	20	2.99	0.07	**	1	23	3.23	0.09	1	23	6.90	0.02	**	1	23	7.17	0.01
UK	1	23	0.83	0.37		1	23	0.79	0.38	1	23	0.34	0.56		1	23	0.27	0.61
USA	1	24	3.08	0.09	**	1	24	3.53	0.07	1	24	0.50	0.49		1	24	0.37	0.55

Note: **DF1, DF2:** Degrees of freedom associated with Fval (numerator & denominator). **Fval:** F-ratio of Granger test from constrained and unconstrained OLS estimation of time series. **Prob:** Probability of F-distribution with DF1 and DF2 degrees of freedom being greater than Fval. **SIG:** whether Fval is significant at the 10% level. Two stars (**) indicates that Fval is significant for both standardized as well as absolute time series. One star (*) indicates significance for only one series, but not both.

Table 2. Granger-Causality Test Results Using Logarithmic Transformations of Variables

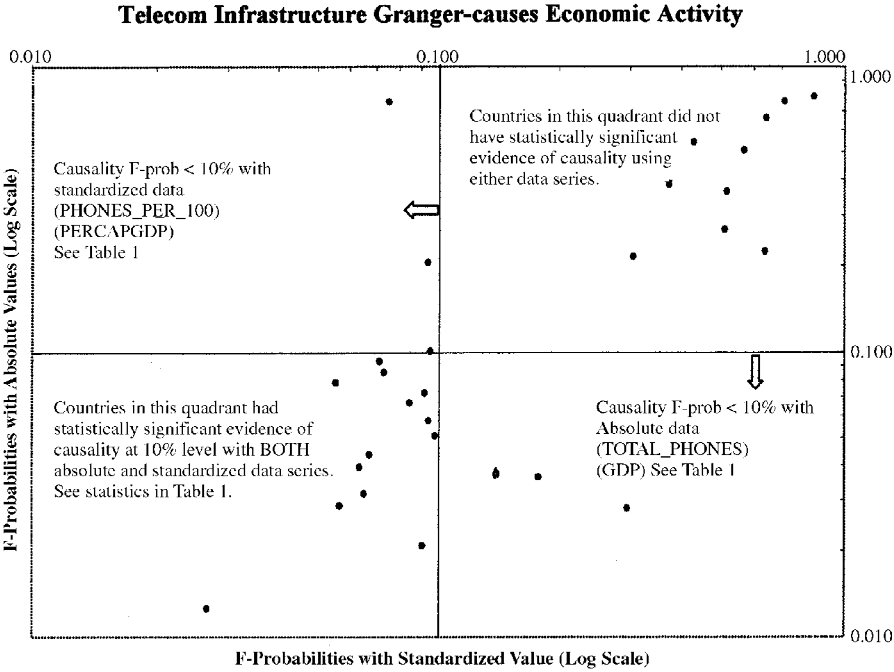
COUNTRY	PHONES_PER_100 ⇒ PERCAPGDP					TOTAL_PHONES ⇒ GDP				PERCAPGDP ⇒ PHONES_PER_100					GDP ⇒ TOTAL_PHONES			
LOG(Var)	DF1	DF2	Fval	Prob	SIG	DF1	DF2	Fval	Prob	DF1	DF2	Fval	Prob	SIG	DF1	DF2	Fval	Prob
Argentina	2	26	3.23	0.06	**	1	27	4.15	0.05	2	26	0.70	0.51		1	27	0.53	0.47
Brazil	1	27	2.98	0.10	**	1	27	3.01	0.09	2	22	3.01	0.07	**	2	22	3.08	0.07
Chile	1	22	3.08	0.09	**	1	22	3.23	0.09	1	22	1.24	0.28		1	22	1.33	0.26
Colombia	1	19	3.00	0.10	**	1	19	3.11	0.09	2	16	2.10	0.16		2	16	2.20	0.14
India	2	26	3.20	0.06	*	2	26	1.44	0.25	2	26	1.16	0.33		2	26	1.16	0.33
Indonesia	1	19	2.78	0.11	*	2	18	3.22	0.06	1	19	3.44	0.08	*	1	19	1.72	0.20
Malaysia	1	23	0.08	0.79		1	22	0.09	0.77	1	22	0.98	0.33		1	22	3.01	0.10
Mexico	1	19	1.76	0.20	*	1	19	3.26	0.09	1	19	0.26	0.62		1	19	0.39	0.54
Panama	1	20	0.06	0.81		1	20	0.11	0.74	1	20	3.03	0.10	**	1	20	4.01	0.06
Paraguay	1	20	4.00	0.06	**	1	20	3.18	0.09	1	19	1.29	0.27		1	19	1.21	0.29
Peru	4	14	1.06	0.41		1	23	0.40	0.53	2	20	0.47	0.63		2	20	0.50	0.62
Philippines	2	16	5.39	0.02	**	2	16	5.63	0.01	1	19	0.91	0.35		2	16	0.23	0.80
Thailand	1	19	8.28	0.01	**	1	19	8.53	0.01	2	16	2.97	0.08	*	2	16	1.21	0.33
Uruguay	1	19	2.03	0.17		1	19	2.00	0.17	2	16	0.63	0.55		1	19	1.26	0.28
Venezuela	1	21	3.02	0.10	**	1	21	3.19	0.09	1	21	0.26	0.62		1	21	0.35	0.56

Continued

Table 2. Granger-Causality Test Results Using Logarithmic Transformations of Variables (Continued)

COUNTRY	PHONES_PER_100 ⇒PERCAPGDP					TOTAL_PHONES ⇒GDP				PERCAPGDP ⇒PHONES_PER_100					GDP ⇒TOTAL_PHONES			
LOG(Var)	DF1	DF2	Fval	Prob	SIG	DF1	DF2	Fval	Prob	DF1	DF2	Fval	Prob	SIG	DF1	DF2	Fval	Prob
Australia	1	20	3.19	0.09	**	1	22	2.99	0.10	1	22	0.35	0.56		2	19	0.25	0.79
Canada	1	21	0.61	0.44		1	21	0.79	0.38	1	21	2.10	0.16		1	21	2.78	0.11
Denmark	5	18	2.30	0.09	**	5	18	2.32	0.09	1	26	0.04	0.85		1	26	0.01	0.93
Finland	1	19	0.25	0.62		2	16	0.39	0.69	2	16	3.27	0.06	**	2	16	10.40	0.00
France	1	19	0.28	0.60		1	19	0.24	0.63	2	16	1.15	0.34		2	16	1.48	0.26
Hong Kong	2	16	1.51	0.25		2	16	1.07	0.37	2	16	3.46	0.06	**	2	16	3.22	0.07
Italy	2	18	1.27	0.30		2	18	1.27	0.30	2	18	0.54	0.59		1	21	0.04	0.84
Japan	2	16	2.78	0.09	**	2	16	2.80	0.09	2	16	2.65	0.10	**	2	16	3.17	0.07
Korea	4	14	1.36	0.30	*	2	16	3.45	0.06	2	16	0.99	0.39		2	16	1.37	0.28
New Zealand	3	13	5.72	0.01	**	1	19	3.23	0.09	1	19	2.73	0.11	*	1	19	6.09	0.02
Singapore	3	18	0.15	0.93		2	21	0.15	0.87	1	24	0.00	0.96		1	24	0.04	0.85
South Africa	1	19	0.09	0.76		1	19	0.11	0.74	1	19	1.04	0.32		1	19	1.26	0.28
Sweden	2	20	3.20	0.06	**	2	20	3.30	0.06	1	23	5.77	0.02	**	1	23	6.36	0.02
UK	1	23	0.96	0.34		1	23	0.92	0.35	1	23	0.74	0.40		1	23	0.80	0.38
USA	2	21	2.91	0.08	**	1	24	3.03	0.09	1	24	1.29	0.27		1	24	1.33	0.26

Note: **DF1, DF2:** Degrees of freedom associated with Fval (numerator & denominator). **Fval:** F-ratio of Granger test from constrained and unconstrained OLS estimation of time series. **Prob:** Probability of F-distribution with DF1 and DF2 degrees of freedom being greater than Fval. **SIG:** whether Fval is significant at the 10% level. Two stars (**) indicates that Fval is significant for both standardized as well as absolute time series. One star (*) indicates significance for only one series, but not both.



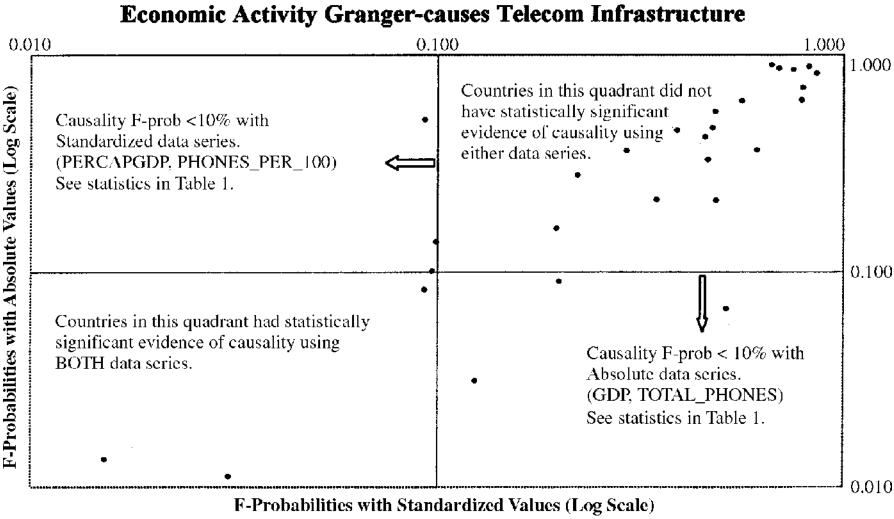
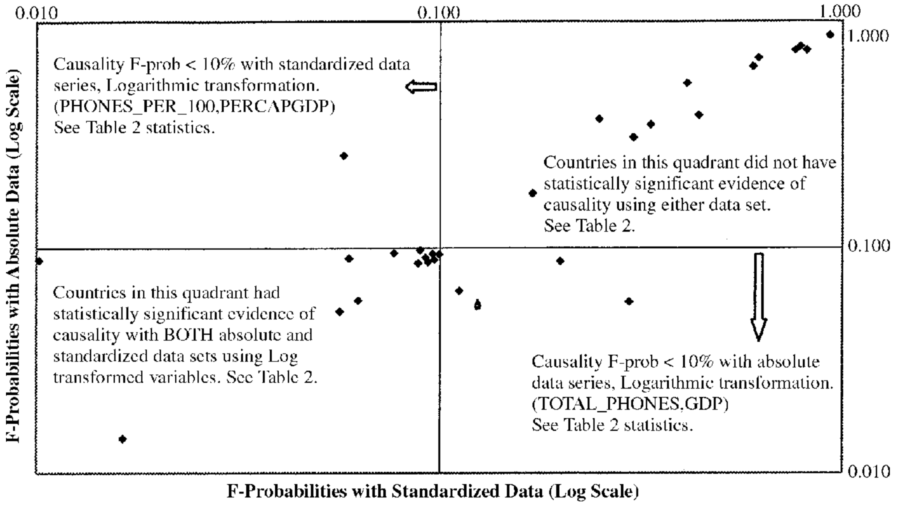


Figure 3. Direction of Causality—Evidence Using Original Variables

quadrants represent weaker causality findings where only one of the datasets—either standardized or absolute value—yielded statistically significant results. The north-east quadrant represents countries with no statistically significant causality findings.

A comparison of the two charts in Figure 3 indicates that evidence for causality from telecommunications to economic activity is substantially stronger than that for causality in the opposite direction. There are fifteen data points in the statistically

Telecom Infrastructure Granger-causes Economic Activity
Log-Transformed Time Series Variables



Economic Activity Granger-causes Telecom Infrastructure
Log-Transformed Time Series Variables

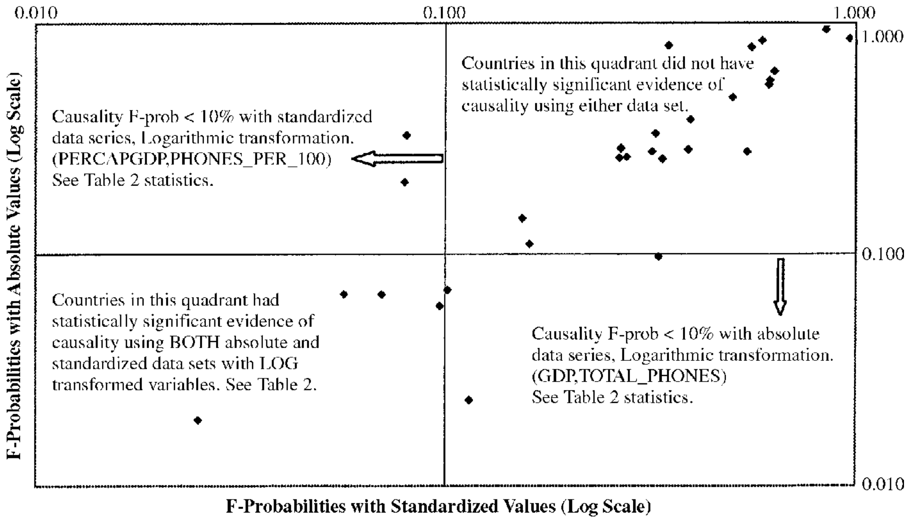


Figure 4. Direction of Causality—Evidence Using Transformed Variables

significant southwest quadrant of the first chart compared to four data points in the same quadrant of the second chart. The same pattern can be seen in the southwest quadrants of the two charts that comprise Figure 4. Further, from Tables 1 and 2, it can be seen that the causality relationship from telecommunications to economic activity is more or less equally prevalent among developing and industrialized countries. These findings are summarized in the box below.

- There is *reasonable evidence* of a causal relationship *from* telecommunications infrastructure *to* economic activity levels.
- There is some evidence of a causal relationship *from* levels of economic activity *to* telecommunications infrastructure but the evidence is significantly weaker.
- This pattern of directionality is substantially the same for industrialized and developing countries.

Our finding that the directionality pattern remains the same for industrialized and developing countries is somewhat unexpected. In fact, given their low infrastructure levels[10] and imprecision in reporting national statistics, it was not clear whether causality evidence might be masked by noise for developing countries. As noted earlier in the paper, the service sector is much more significant in industrialized as compared to developing countries. This sector is a heavier user of telecommunications compared to the agricultural or industrial sectors of an economy. Hence it was somewhat surprising to see the same pattern of causality in both sets of countries. Also, the causal mechanisms summarized earlier in Figure 1 would suggest that there ought to be stronger evidence of causality *from* economic activity *to* telecommunications levels in industrialized countries. However, we find that evidence to be very weak for both sets of countries.

We conclude this section by noting that while the general patterns of causality in Tables 1 and 2 are largely the same in aggregate—that is, both tables show the same patterns stated in the preceding results box—there is greater consistency between the two tables in the evidence for causality in one direction as opposed to the other. Specifically, the evidence for causality from telecommunications to economic activity in Tables 1 and 2 is quite consistent. For causality evidence in the opposite direction, however, there are four countries (out of thirty) for which one table said "not significant" while the other said "significant."[11] However, this discrepancy is usually not as drastic as it first appears. For instance, in the case of Columbia, the F-probabilities in Table 1 are (0.10, 0.10) resulting in "**" for statistical significance. In Table 2 the F-probabilities for Columbia are (0.14, 0.16), resulting in a finding "not significant." Note, however, that the F-probabilities are not widely different in the two tables.

Limitations and Concluding Remarks

The relationship between telecommunications infrastructure and economic activity is complex, but also significant given its extensive role in contemporary commerce. Our results contribute to further understanding of this relationship by suggesting that there is reasonable evidence for causality in one direction but not the other. These findings are moderated by limitations of the data and by measurement limitations discussed elsewhere in the paper. Some of the data quality limitations will be eased as more telecommunications statistics become available in the future. We point out some of these limitations and then discuss potential contributions of the findings.

Limitations

The first limitation is one of developing an appropriate measure for the variables of interest. As previously mentioned, the two measures of economic activity, GDP and per capita GDP, are well established in the growth literature. Nevertheless, they have one limitation that is relevant to this study. The extent of telecommunications usage by different sectors of the economy—agricultural, manufacturing, and service—is known to be significantly different, the service sector being the heaviest user. An aggregate measure of economic activity may mask differential impacts of the technology. Unfortunately, such disaggregated economic data are not consistently reported for most countries, making it difficult to arrive at general conclusions about sector-specific impact.

Our measure of telecommunications infrastructure levels has limitations as applied to *industrialized* nations. We have used TOTAL_PHONES and PHONES_PER_100, which represent wireline and wireless penetration levels for a given country. As mentioned earlier in the paper, this measure is a reasonable representation of telecommunications infrastructure levels for most developing countries. It is not so for industrialized countries, where other advanced services—such as leased lines, frame relay and ATM circuits—are available. Nevertheless, for those industrialized countries where data are available, PHONES_PER_100 or TOTAL_PHONES appears to be correlated to levels of these advanced infrastructure components. However, there is wholly insufficient data in the publicly available United Nations compilations to estimate a functional relationship between PHONES_PER_100 and other infrastructure components that is statistically valid *over a wide range* of PHONES_PER_100 values and countries.

Even if this data were available for most countries, there is the separate issue of whether to develop a single composite index of telecommunications infrastructure or to use a multidimensional index. Since the measurement units for the different infrastructure components are noncommensurate, a single composite index, while simplifying causality analysis, would be difficult to develop. A multidimensional index would be more representative of the infrastructure, but would make causality analysis considerably more complex. One consequence of this shortcoming in our measure is that while our causality findings for developing countries can be reasonably interpreted as applying to their complete infrastructure, the causality findings for industrialized countries should be interpreted in the context of so-called *basic* infrastructure. This shortcoming may also be a factor behind our finding the same asymmetric causality pattern for both developing and industrialized countries.

We should emphasize that "basic" should not be interpreted as an insignificant component of overall telecommunications infrastructure, thereby perhaps diluting the perceived significance of the findings for industrialized countries. In fact, basic infrastructure represents the most extensive component of the overall telecommunications infrastructure of any country. The terms "basic" and "nonbasic" are simply standard terms used in the telecommunications policy literature (see [31], for example) to distinguish between certain types of services. Historically, the so-called basic infrastructure carried voice, whereas nonbasic referred to emerging technology/services that mostly carried data traffic. The two were handled separately for policy purposes. However, over time, basic infrastructure has been increasingly used to carry data as well. Newer technologies, such as ATM and xDSL, carry voice as well as data traffic, blurring the original distinction between the two infrastructure components. Therefore, the impact of these newer technologies would in fact be included, albeit indirectly and partially, in the PHONES_PER_100 and TOTAL_PHONES values for the latter years in our time series data. In short, while PHONES_PER_100 and TOTAL_PHONES have limitations for industrialized countries, they are not quite as deficient in representing overall infrastructure levels as might appear at first glance.

A second limitation of using PHONES_PER_100 or TOTAL_PHONES—and this applies to industrialized as well as developing countries—is that these two measures do not capture infrastructure reliability. Two countries could both have, say, PHONES_PER_100 = 15, but one may be much more reliable than the other. There is substantial *anecdotal* evidence that countries with low PHONES_PER_100 levels generally also tend to have poorer network reliability. Therefore we would expect positive correlation between PHONES_PER_100/TOTAL_PHONES and infrastructure reliability measures. However, reliability data has never been publicly reported for most countries in any systematic way. Only very recently, from about 1996, did the ITU suggest that individual countries report reliability measurements. Even so, as of 1997, most countries still do not publicly report them. For this reason, it will be difficult to include reliability estimates into causality analysis for some time.

Apart from the specific measures used, identifying a suitable set of countries presented special challenges. The United Nations publications cited earlier in the paper report telecommunications statistics for over two hundred countries. However, there are significant gaps in the reported data, particularly for developing countries. As a result, there are some prominent omissions, such as China and Israel. For this reason too, no developing countries from Africa could be included. Infrastructure data on former Soviet republics are also very scarce. So there are some geographic gaps in the set of countries selected for analysis, but they are mainly in the developing country group. These constraints resulted in our selecting a total of thirty countries. Nevertheless, it is a reasonably large number to observe any causality patterns that may exist across countries.

One limitation that can be addressed as new data become available is the 10 percent significance level used for testing the causality hypotheses. Given the number of parameters being estimated for the time series—especially the unconstrained one—we need many more years of data to obtain higher degrees of freedom in the F-tests. Although the amount of missing data in recent publications continues to decrease, some areas of the world are still deficient in their reporting of statistics. As a result, it will perhaps become possible to construct longer time series, but only for a limited number of countries.

The foregoing discussion documents some of the general issues of data quality and measurement of variables that make it difficult to arrive at more conclusive findings regarding causality between telecommunications and economic activity. Data quality can be addressed by severely limiting the country set that is analyzed, but then the results may not hold outside that limited set. The difficulty of determining appropriate measures to operationalize telecommunications infrastructure and economic activity will affect any study in this area. Clearly, multiple studies will be necessary to get more complete evidence of the causality effects being studied. Our study makes an initial contribution to this body of evidence.

Findings and Contribution

Causality issues arise continually in IS research. For instance, the relationship between IT infrastructure levels and organizational performance or structure has been the object of some interest in the literature [11, 18]. The growth of international information systems has been associated with growth in global trade. Is there a causal relation? To the best of our knowledge, the Granger test methodology used in this paper has not seen any application in the IS literature. We believe that one contribution of this paper lies in introducing this method to the IS research literature by applying it to a substantive problem from the domain. The method has been widely used in several other domains and could be a useful addition to the set of tools employed to study IS problems. For instance, a similar Granger approach could be used to test for causality between IT infrastructure levels and organizational performance at the level of individual firms. Results would complement correlational findings reported in the literature. The IT productivity paradox is well documented [23]. That literature suggests that part of the paradox may stem from limitations in measurement and analysis. Given that data on IT investment levels are now being reported more frequently, the Granger analysis approach may offer another way to examine the IT investment value question.

The two main findings of our empirical analysis were as follows. First, the evidence for causality from telecommunications to economic activity levels was substantially stronger than evidence for causality in the opposite direction. Second, this causality pattern was substantially the same for both industrialized and developing countries. These findings contribute to our understanding of the complex relationship between telecommunications and economic activity levels by first uncovering empirical evidence of causality. There was no basis for making inferences of causality from past correlational studies. Early in this paper, we noted that informal arguments existed to support causality hypotheses in either direction. Our findings offer support, albeit indirectly, for the suggested causal mechanisms from telecommunications to economic activity, but they are inconclusive regarding causal mechanisms in the opposite direction. Nevertheless, the finding of asymmetry in evidence for causality suggests some policy implications.

In terms of policy, our finding of a causal link from telecommunications to economic activity levels suggests that market mechanisms for expanding telecommunications infrastructure might be augmented by specific incentives to guide telecommunications growth within a country in targeted ways. One example would be in the area of spatial distribution of telecommunications services. It is well known that within any one country there is spatial unevenness in the distribution of telecommunications infrastructure. This unevenness is more pronounced in developing countries, but can also be seen in industrialized countries. This spatial unevenness in infrastructure correlates well with spatial unevenness in economic activity levels. Our causality findings argue that improved telecommunications infrastructure would increase economic activity levels in depressed areas. Therefore, incentives can be provided to build out infrastructure to areas that are underserved, or to promote otherwise costly wireless technologies that would enable service to be extended to underserved areas in a timely manner.

The vital role of policy in the telecommunications sector has been extensively documented [26, 35, 36]. Policy makers in this sector seek to balance the efficiencies derived from market mechanisms against achieving desirable, but possibly inefficient, social goals. Even as countries across the world proceed to liberalize their telecommunications sector, the pace at which this is occurring varies widely. As noted earlier in the paper, there is some disagreement among policy makers as to how aggressively to promote (or throttle) market forces in this sector. The causality findings in this paper can help inform that debate and the resulting actions that are taken in specific circumstances.

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NOTES

1. Implementing policy is widely recognized as being critical to harnessing private sector resources for telecommunications infrastructure growth [36].

2. For example, if the computing sector is weak, and organizations do not use information systems extensively, advanced data communications services would remain underutilized.

3. A minimum amount of regulation is called for to ensure widespread access to basic services and to protect the public interest.

4. For some countries, it was possible to construct longer time series depending on the availability of data. The longest series is 34 years long, but most are between 24 and 29 years.

5. Our study, therefore, does not cover the impact of any *specific policy decision* for a country. One way to study the impact of specific regulatory policies would be to do event studies—that is, a before-and-after analysis on a country-by-country basis. But then it would be harder to compare effects across multiple countries.

6. These statistics are published biennially by the United Nations. Only one of those serial publications is listed in the bibliography.

7. For instance, Chile doubled the number of cellular subscribers between 1992 and 1993. While the absolute magnitudes of growth in cellular subscribers are still quite small for most developing countries, the growth rates have been impressive.

8. For example, India did not have cellular service until after 1993, the end point of our time series. So in our time series for India, the telecommunications measure included only wireline services. Chile, on the other hand, reports cellular service starting in 1989. So in the time series for Chile, the telecommunications measure included cellular subscribers from 1989 to 1993.

9. Statistical analyses frequently use cutoff values of 1 percent and 5 percent to test hypotheses. However, since telecomm infrastructure data are only reported annually, it is difficult to

get the sample sizes necessary for that level of confirmation. As such, statistical analyses of telecommunications infrastructure sometimes need to use a critical value of 10 percent, the highest value that is still considered acceptable [17].

10. For example, the telephone densities for India and Sweden are approximately 1 per 100 persons and 40 per 100 persons, respectively.

11. These countries are Colombia, Malaysia, Hong Kong, and Japan.

References

1. *Annuaire Statistique de l'Union Internationale des Télécommunications*. Geneva: ITU, 1994.

2. Ashley, R.; Granger, C.W.J.; and Schmalensee, R. Advertising and aggregate consumption: an analysis of causality. *Econometrica, 48,* 5 (1980), 1149–1168.

3. Barro, R.J., and Sala-i-Martin, X. *Economic Growth.* New York: McGraw-Hill, 1995.

4. Bebee, E.L., and Gilling, E.T.W. Telecommunications and economic development: a model for planning and policymaking. *Telecommunications Journal, 43,* 8 (1976), 537–543.

5. Benjamin, R., and Wigand, R. Electronic markets and virtual value chains on the information superhighway. *Sloan Management Review, 36,* 2 (Winter 1995), 62–73.

6. Block, C.H. Satellite linkages and rural development. In H.E. Hudson (ed.), *New Directions in Satellite Communications*. Norwood, MA: Artech House, 1985.

7. CCITT. *GAS-5 Handbook: Economic Studies at the National Level in the Field of Telecommunications.* Geneva: CCITT, 1968.

8. Clark, D., and Unwin, K. Telecommunications and travel: potential impact in rural areas. *Regional Studies, 15* (1981), 47–56.

9. Colombo, M.G., and Garrone, P. Technological cooperative agreements and firm's R&D intensity: a note on causality relations. *Research Policy, 25,* 6 (1996), 923–932.

10. Darrat, A.F., and Rahman, S. Has futures trading activity caused stock price volatility? *Journal of Futures Markets, 15,* 5 (1995), 537–557.

11. Dewan, S.; Michael, S.C., and Min, C. Firm characteristics and investments in information technology: scale and scope effects. *Information Systems Research, 9,* 3 (1998), 219–232.

12. Dholakia, R.R., and Harlam, B. Telecommunications and economic development: econometric analysis of the US experience. *Telecommunications Policy, 18,* 6 (1994), 470–477.

13. Dickey, D., and Fuller, W.A. Distribution of the estimates for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74* (June 1979), 427–431.

14. Geweke, J. Inference and causality in economic time series models. In Z. Griliches (ed.), *Handbook of Econometrics,* vol. II, Amsterdam: North-Holland, 1984, pp. 1102–1103.

15. Granger, C. Investigating causal relations by econometric models and cross spectral methods. *Econometrica, 37* (1969), 424–438.

16. Guilkey, D.K., and Salemi, M.K. Small sample properties of three tests for Granger causal ordering in a bivariate stochastic system. *Review of Economics and Statistics, 64,* 4 (1982), 668–680.

17. Gujarati, D.N. *Basic Econometrics.* New York: McGraw-Hill, 1995.

18. Gurbaxani, V., and Whang, S. The impact of information systems on organizations and markets. *Communications of the ACM, 34,* 1 (1991), 59–73.

19. Jipp, A. Wealth of nations and telephone density. *Telecommunications Journal* (July 1963), 199–201.

20. Kambil, A., and Short, J.E. Electronic integration and business network redesign: a roles-linkage perspective. *Journal of Management Information Systems, 10,* 4 (Spring 1994), 59–83.

21. Kapuria-Foreman, V. Population and growth causality in developing countries. *Journal of Developing Areas, 29,* 4 (1995), 531–540.

22. Leach, D.F., and Reekie, W.D. A natural experiment of the effect of advertising on sales: the SASOL case. *Applied Economics, 28,* 9 (1996), 1081–1091.

23. Lucas, H.C. *Information Technology and The Productivity Paradox.* New York: Oxford University Press, 1999.

24. Malone, T.W.; Yates, J.; and Benjamin, R. Electronic markets and electronic hierarchies. *Communications of the ACM, 30,* 6 (1987), 484–497.

25. McCarville, M., and Nadozie, E. Causality tests of export-led growth: the case of Mexico. *Atlantic Economic Journal, 23,* 2 (1995), 140–145.

26. Miller, N.P. Regulation: reconciling policy objectives. In B. Wellenius and P. Stern (eds.), *Implementing Reforms in the Telecommunications Sector: Lessons from Experience.* Washington, DC: World Bank, 1994, pp. 485–504.

27. Press, L. Developing networks in less industrialized nations. *IEEE Computer, 28,* 6 (1995), 66–71.

28. Riezenman, M.J. Technology 1999 analysis & forecast: communications. *IEEE Spectrum, 36,* 1 (1999), 29–35.

29. SAS. *SAS ETS Manual.* Cary, NC: SAS Institute, 1996.

30. Saunders, P.J. A Granger causality approach to investigating the impact of fiscal policy on the U.S. economy: 1970.I–1990.III. *Studies in Economics & Finance, 16,* 1 (1995), 3–22.

31. Saunders, R.J.; Warford, J.J.; and Wellenius, B. *Telecommunications and Economic Development.* Baltimore: Johns Hopkins Press, 1994.

32. Sims, C.A. Money, income and causality. *American Economic Review, 62* (1972), 540–552.

33. *Statistical Yearbook: Annuaire Statistique.* New York: United Nations, 1972–1994.

34. Taylor, L.D. *Telecommunications Demand: A Survey and Critique.* Cambridge, MA: Ballinger, 1980.

35. Townsend, D.N. The vital role of regulation in the telecommunications sector. In B. Wellenius and P. Stern (eds.), *Implementing Reforms in the Telecommunications Sector: Lessons from Experience.* Washington, DC: World Bank, 1994, pp. 505–510.

36. Wellenius, B., and Stern, P. (eds.) *Implementing Reforms in the Telecommunications Sector: Lessons from Experience.* Washington, DC: World Bank, 1994.

37. Yatrakis, P.G. Determinants of the demand for international telecommunications. *Telecommunications Journal, 39* (1972), 732–746.

38. Zanias, G.P. The long run, causality, and forecasting in the advertising-sales relationship. *Journal of Forecasting, 13,* 7 (1994), 601–610.