On the Relationship between Telecommunications Investment and Economic Growth in the United States

RICHARD O. BEIL, GEORGE S. FORD, AND JOHN D. JACKSON*

Abstract: Using a time series of fifty years, the relationships between investment by telecommunications firms and Gross Domestic Product in the United States are examined. Granger-Sims causality tests are conducted, with proper allowance for both the non-stationarity of the data and lag length. These tests indicate that investment by telecommunications firms is caused by, but does not cause, economic activity, and the findings are robust across lag lengths. The evidence suggests that policies aimed at stimulating the U.S. economy by accelerating investment in the telecommunications sector may not be successful.

The longest economic expansion is U.S. history ended in early 2001 (NBER 2002). As the economy languishes, the pressure for stimulus intensifies. Near the top of potential industrial interventions to jump-start economic growth is telecommunications, its status driven by regulatory instability and the nation's current fascination with the Internet. Proposals to stimulate investment in this particular sector of the economy are numerous and vary widely, typically involving either more or less competition or more or less regulation.

Implicit in the proposals to stimulate investment in the telecommunications industry is the assumption that such investment *causes* economic growth. The purpose of this analysis is to address this seemingly critical issue – does investment by telecommunications firms cause economic growth, or, alternately, does economic growth cause such investment? Some insight into the true nature of this relationship could shed considerable light on important questions concerning both economic and telecommunications policy.

While causal relationships are ideally determined by theoretical means, economic theory provides three plausible causality scenarios between investment and output. The first is based on a simple aggregate production function, where output is typically modeled as a function of the private capital stock, the amount of labor employed, and government spending. The classic example of such a model was proposed by Ram (1986), now a standard tool in the analysis of economic development. In this type model, output is "caused" by investment or, similarly, changes in the capital stock.

This particular causal view is contradicted by a second and alternative explanation known as the acceleration principle. Cullem (1988) provides a recent application. For this alternative, the level of investment is determined by the change in aggregate income, so that the causal relationship flows from output to investment, but not vice versa.

Finally, it is possible for the causal relationship to go both ways. When the causal relationships hold jointly, the effect of one relation feeds back onto the other, and the other then feeds back onto the one, and so forth (Röller and Waverman 2002).

* Beil and Jackson: Department of Economics, Auburn University, Alabama 36849. Ford: Z-Tel Communications, Inc., Tampa, Florida 33602.

With theoretical ambiguity, empirical methods are required to determine which of the three views, if any, are best supported by the data. To this end, an empirical model of causality is applied to a long series of data on investment by telecommunications firm and Gross Domestic Product in the United States. The causality tests confirm that economic output causes telecommunications investment, but investment by telecommunications firms does not cause output. This finding is robust across alternative lag specifications.

Empirical Framework

Recent studies evaluating the relationship of telecommunications infrastructure or investment to economic activity include Madden and Savage (1998) and Röller and Waverman (2002). Both studies employ panel data consisting of many countries, but neither study considers the unique relationship within the U.S and the former excludes the U.S. altogether. Average effects measured using many diverse economies may not hold for any particular economy in the sample. A U.S. specific analysis focused on telecommunications investment made by telecommunications firms can provide more insight for domestic policy purposes.

Additionally, earlier studies typically find that that any positive relationship between investment and economic activity is limited to lower income economies (Jipp 1963; Madden and Savage 1998), which would likely not apply to the US. While Röller and Waverman (2002) find that the correlation of investment and growth is higher in economies with relatively high telephone penetration rates. Though their theoretical structure *assumes* a particular causal relationship, their empirical methodology contemplates correlation only and not causation, except to the extent the results are not inconsistent with their theory.

According to Granger (1969), and similarly Sims (1972), the causal relationship between two variables can be determined by examining the way they move with respect to each other over time. Some variable X causes another variable Y_t if, given a universe of information on all factors affecting both X_t and Y_t, the present value of Y (i.e. Y_t) can be predicted better using past values of X (i.e. X_t, $i = 1, \ldots n$) than by not using them. In a statistical sense, this means that the mean squared (prediction) errors of Y, given all information affecting $\{Y_t\}$ except information on $\{X_t\}$ — call this information set $\{A_t\}$, i.e. MSE = $\sigma^2(Y_t | A_t)$ — is larger than the mean square (predictions) error of Y, given information on both $\{A_t\}$ and $\{X_t\}$, i.e. MSB = $\sigma^2(Y_t | A_t, X_t)$. Thus, "Granger causality" states that X causes Y if

$$\sigma^2(Y_t|A_t, X_t) < \sigma^2(Y_t|A_t) \ .$$

Since a significant reduction in error variance will result within a least squares framework when a statistically significant variable (or set of variables) is added to the model, a simple statistical test for this requirement is available.

Because Wold's theorem states that any stationary time series can be characterized by a self-deterministic component and a moving average process of possibly infinite order (i.e., an auto-regressive process), then if $\{Y\}$ is stationary, it is possible for $\{A\}$ to include only past values of Y. Thus, if $\{X_t\}$ and $\{Y_t\}$ are a pair of linear covariance stationary time series processes, then each can be written, respectively, as

$$(1) \qquad X_t = \sum_{j=1}^{k} \alpha_j X_{t-j} + \sum_{j=1}^{m} \beta_j Y_{t-j} + \varepsilon_t$$

and

$$(2) \qquad Y_t = \sum_{j=1}^{r} \gamma_j X_{t-j} + \sum_{j=1}^{s} \delta_j Y_{t-j} + \mu_t \, .$$

According to Granger and Sims, causality tests based on these models are then straightforward: (i) X causes Y if $H_0^1: \gamma_1 \ldots = \gamma_r = 0$ can be rejected; (ii) Y causes X if $H_0^2: \beta_1 = \ldots = \beta_m = 0$ can be rejected; (iii) there is feedback between X and Y if H_0^1 and H_0^2 are both rejected; and

(iv) X and Y are independent if neither H_0^1 nor H_0^2 is rejected.

As long as the two series are stationary, the tests required by the procedure are traditional F-tests of the joint hypotheses implied in (i) through (iv). The null hypotheses to be tested assume the relevant parameters are jointly zero, so the null being tested is one of Granger non-causality rather than one of Granger causality. This is desirable since rejection of the null provides the strong inference that, say, X does indeed cause Y. The Granger test, then, involves three steps: 1) find a stationary series of X and Y; 2) estimate equations (1) and (2); and 3) test the joint significance of the coefficient vectors γ and β.

Data and Results

Our Granger test employs 50 years of data (1947 through 1996) on real Gross Domestic Product (*GDP*) and real U.S. telecommunications investment by telecommunications firms (*INV*). The U.S. Bureau of Economic Analysis' National Accounts Data and Detailed Fixed Assets Tables include the two series. The series also are specified in per-capita terms (*GDPc*) and (*INVc*).

Based on the Augmented Dickey-Fuller and Phillips-Perron tests (both with a null of non-stationarity), the series are non-stationary in their levels, but stationary in their first differences (i.e., the series are I(1)). Summary statistics from these tests are provided in Table 1. Due to these tests, we use first differences (indicated by Δ) for the causality test. While there are Granger methods for non-stationary series, such procedures are not necessary for our data.

It is well known that lag length can affect the results of causality tests. Standard practice calls for selecting a lag length that minimizes information criterion such as the Akaike Information Criterion (AIC). This task is accomplished by choosing a maximum lag length M and estimating regressions for all possible combinations of lag lengths (M^2 regressions), then selecting the lag combination with the lowest information criterion (or criteria). Our procedure, based on an M of 10, always selected a single lag for the *GDP* series, but varied lag lengths for the *INV* series.

TABLE 1 –UNIT ROOT TESTS

	Augmented Dickey-Fuller	Phillips-Perron
INV	1.34	2.82
Δ*INV*	-4.23*	-5.56*
GDP	2.38	8.37
Δ*GDP*	-4.38*	-4.98*
INVc	0.48	1.39
Δ*INVc*	-5.04*	-5.97*
GDPc	0.72	2.16
Δ*GDPc*	-5.41*	-6.20*

* Statistically significant at the 5% level.

The F-statistics of the Granger-Sims causality tests are summarized in Table 2. Results from the AIC-selected lag lengths (underlined in the table), and their immediately adjacent lag values, are presented. The null hypothesis of the Granger-Sims test is "non-causation," thus higher values for the F-statistic are required to reject the null. Statistical significance is indicated in the table at the 5 and 10% levels.

The causality test provides strong evidence that economic output causes investment by telecommunications firms. For the AIC-selected lag length (Δ*GDP* one lag, Δ*INC* five lags), the null hypothesis of non-causality is easily rejected with F = 5.03 and 4.37 (critical F-values are 4.07. In fact, the null is rejected at the 5 or 10% significance level for all six lag structures summarized in Table 2.

Alternately, the null hypothesis that investment by telecommunications firms does not cause economic output is never rejected. At the AIC-selected lag structure, the F-statistics are only 1.18 and 1.39, both of which are well below the critical F-value of 4.05 and 2.81, respectively.

To further evaluate the effect of lag length, the causality tests were conducted using all lag combinations up to six lags for both *GDP* and both *INV* series. The null hypothesis that *GDP* does not cause *INV* was rejected 28 times, or

45% of the total tests. Alternately, the null hypothesis that *INV* does not cause *GDP* was rejected only once and only at the 10% level (1.6% of the total tests).

Conclusions

Based on investment and GDP data for the period 1947 to 1996, Granger-Sims causality tests indicate that investment telecommunications in the telecommunications industry is caused by, but does not cause, economic activity. These results paint a picture of telecom executives as good businessmen – they observe a potential market, indicated by rising incomes, and invest in the physical capital required to meet that demand.

Not observed is the "Field of Dreams" type result in which "if you (the telecom companies) build it (make telecom investments), they (the customers, as measured by their purchasing power) will come." These findings suggest efforts to stimulate the economy by accelerating investment in the telecommunications sector may not be successful in the U.S. Higher levels of investment in the telecommunications sector require a return to economic expansion or, at least, stability.

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TABLE 2. SUMMARY OF RESULTS FROM GRANGER CAUSALITY TESTS

(F-Statistics for Non-Causality)

H_0: ΔGDP *does not cause* ΔINV			H_0: $\Delta GDPc$ *does not cause* $\Delta INVc$		
Variable(Lag)	$\Delta GDP(1)$	$\Delta GDP(2)$	Variable(Lag)	$\Delta GDPc(1)$	$\Delta GDPc(2)$
$\Delta INV(4)$	8.68*	4.34*	$\Delta INVc(4)$	7.78*	4.10*
$\Delta INV(5)$	<u>5.03*</u>	2.76**	$\Delta INVc(5)$	<u>4.37*</u>	2.69**
$\Delta INV(6)$	4.54*	2.42**	$\Delta INVc(6)$	4.13*	2.52**
H_0: ΔINV *does not cause* ΔGDP			H_0: $\Delta INVc$ *does not cause* $\Delta GDPc$		
Variable(Lag)	$\Delta GDP(1)$	$\Delta GDP(2)$	Variable(Lag)	$\Delta GDPc(1)$	$\Delta GDPc(2)$
…	…	…	$\Delta INVc(2)$	1.54	1.17
$\Delta INV(1)$	<u>1.18</u>	0.88	$\Delta INVc(3)$	<u>1.39</u>	1.41
$\Delta INV(2)$	0.95	0.93	$\Delta INVc(4)$	1.32	1.21

* Statistically significant at the 5% level.
** Statistically significant at the 10% level.

Appendix							
Year	Real Tel. Inv.	Real GDP	Population	Year	Real Tel. Inv.	Real GDP	Population
1947	5210	1516.4	0.145	1972	19371	3990.5	0.211
1948	6229	1571.4	0.148	1973	23395	4151.1	0.213
1949	5063	1546.5	0.150	1974	23489	4062	0.215
1950	5048	1753.9	0.153	1975	21006	4167.2	0.217
1951	4636	1843.3	0.155	1976	22371	4357.4	0.219
1952	5403	1940.2	0.158	1977	28396	4576.1	0.221
1953	6047	1947.8	0.161	1978	33127	4876	0.224
1954	5807	2000.9	0.164	1979	34919	4942.6	0.226
1955	6646	2130.1	0.166	1980	35159	4936.6	0.229
1956	8457	2170.4	0.169	1981	35273	4997.1	0.231
1957	8082	2176	0.172	1982	34676	4915.6	0.233
1958	6695	2226.5	0.175	1983	33054	5286.8	0.235
1959	7532	2339.1	0.178	1984	33222	5583.1	0.237
1960	9278	2352.9	0.182	1985	34572	5806	0.239
1961	9272	2500.4	0.185	1986	38675	5969.5	0.242
1962	10241	2603.3	0.188	1987	38244	6234.4	0.244
1963	11297	2739.4	0.190	1988	39647	6465.2	0.246
1964	11369	2879.5	0.193	1989	37383	6633.5	0.248
1965	13186	3123.6	0.195	1990	37975	6664.2	0.251
1966	13958	3261.8	0.197	1991	37954	6720.9	0.255
1967	13700	3338.3	0.200	1992	44263	6990.6	0.258
1968	15000	3504.1	0.202	1993	44447	7168.7	0.261
1969	17361	3571.4	0.204	1994	47937	7461.1	0.264
1970	19437	3566.5	0.206	1995	48569	7621.9	0.268
1971	19278	3723.8	0.209	1996	54508	7931.3	0.271

Source. Bureau of Economic Analysis (www.bea.gov).