Public investment in transportation and communication and growth: A dynamic panel approach*

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Abstract

This paper investigates the relationship between public investment in transportation and communication and economic growth using traditional instrumental estimation and a mixed fixed and random coefficient approach in the context of a dynamic panel framework. We find that there is a dynamic effect of public investment in transportation and communication on economic growth and its impact is positive. In comparison with earlier studies, our estimated coefficients are somewhat lower. However, for the reverse causal relationship proposed by the investment acceleration hypothesis, we find that there is significant heterogeneity across countries and our empirical study does not support the presence of reverse causality.

1 Introduction

The recent explosion of work on externality based growth models has generated a number of models linking government spending with the economy's long run growth; see Barro (1990) and Barro and Sala-i-Martin (1995, 1999). This has, in turn, sparked a number of empirical studies on the relationship between the size of government (both at aggregate and disaggregate levels) and economic growth. Examples include Barro (1990, 1991), Barro and Sala-i-Martin (1995, 1999), Easterly and Rebelo (1993), Cashin (1995), Deverajan, Swaroop and Zou (1996), Kocherlakota and Yi (1996, 1997), Agell, Lindh and Ohlsson (1997), Mendoza, Milesi-Ferretti, and Aseaet (1997), Miller and Ressek (1997), Kneller, Bleany and Gemmell (1999), and Gupta, Clements, Baldacci, and Mulas-Granados (2002), among others.

There is, however, conflicting evidence in the literature regarding the question as to how the composition of government expenditure affects economic growth. In particular, on the relationship between public investment in transportation and communication (infrastructure) and economic growth, there has been a mixed picture. Aschauer (1989) finds that core infrastructure – streets, highways, airports, mass transit, and other public capital – has the most explanatory power for private-sector productivity in the United States over the period 1949 - 1985. In a cross-country study, Easterly and Rebelo (1993) find, using the pooled regressions, that only public investment in transportation and communication (hereafter T&C) among the sectorial components of government investment, is consistently positively correlated with growth with a very high coefficient (between 0.59 and 0.66). On the other hand, Deverajan *et al.* (1996) find, from the study of 43 developing countries over 20 years, that transport and communication expenditures have a negative correlation with per-capita real GDP growth. Miller and Russek (1997) report that the estimated coefficient for the ratio of transportation and communication expenditure to GDP is positive but not statistically significant for 23 developing countries.

Why does this previous literature provide conflicting results? A theoretical perspective and recent econometric literature on the panel data analysis for developing countries direct our attention to addressing this question. First of all, it takes time for public investment in T&C to affect growth and thus, a consideration of time is important for investigating the effect of infrastructure on growth. From this point of view, a dynamic model might be more desirable than a contemporaneous cross-section analysis. Secondly, in practice, it is often difficult to find good instruments in the traditional instrumental panel approach. Kiviet (1995) shows that panel data models that use instrumental variable estimation often lead to poor finite sample efficiency and to biased estimates. Thirdly, as pointed out in Weinhold (1999), and Nair-Reichert and Weinhold (2001), the instrumental approach imposes the assumption, widespread in the panel causality literature, that the coefficients on the explanatory variables are equal across units in the panel and thus potential bias might be induced by heterogeneity of the cross section units. From these points of view, a more careful investigation is warranted for addressing the relationship.

The purpose of this paper is to revisit and examine the causal relationship between public investment in T&C and economic growth, bearing the time consideration and the econometric issues in mind. In exploring this end, our study is different from the previous literature on several grounds. First of all, we consider a dynamic panel model using a much richer data set for 15 developing countries over 1970 to 1987. Secondly, we not only employ an instrumental approach, but also apply the mixed fixed and random coefficients model (hereafter MFR) of Weinhold (1999) and Nair-Reichert and Weinhold (2001) to avoid biased parameter estimates resulting from cross-sectional heterogeneity. Thirdly, following the accelerating effect of output on investment as in Clark (1979) and Wagner's law (the tendency for government expenditure to be higher at higher level of per capita GDP), we examine reverse causality in which public investments in T&C follow growth and thus rapid growth leads to higher investments in this sector.[1]

Our results confirm and extend the conclusion of earlier study that public investment in T&C Granger causes economic growth. The estimated coefficients in our study are somewhat lower, whereas the sizes of the coefficients are disturbingly high in Easterly and Rebelo (1993). Furthermore, although we allow heterogeneity of dynamics in the developing country panel, the estimation results of the MFR model still support a causal relation from public investment in T&C to growth. However, from both approaches, instrumental estimation and the MFR model, we do not find evidence of reverse causality. In particular, the estimation results of MFR model indicate that there is a great deal of heterogeneity across countries in the reverse causal relationship. The plan of the paper is as follows. Section 2 discusses a methodology used in this panel study and Section 3 reports empirical results. Concluding remarks are offered in Section 4.

2 Methodology

In their study of the effect of public investment in T&C on growth, Easterly and Rebelo (1993) use instrumental variable estimation to avoid the joint endogeneity of the two variables and the possibility of reverse causality. However, since the size of the coefficient is disturbingly high (a coefficient of 2) and their analysis of decade averages implies only two data points per country, their results on causality from infrastructure to growth cast doubt on the validity of the procedure. On the other hand, Devarajan *et al.* (1996) use pooled regressions with the choice of a five-year forward moving average of per-capita real GDP growth to reflect the fact that public expenditures often take time before their effects register on output growth, to eliminate short-term fluctuations induced by shifts

[1] Musgrave (1969, p.74) mentions that the most plausible formulation of Wagner's hypothesis appears to be in terms of a positive correlation between the share of government expenditure in GDP and income per capita. Also, there is a large body of literature on Wagner's law, which includes Gandhi (1971), Abizadeh and Gray (1985) and Ram (1987), among others.

in public expenditure, and to increase the number of time series observations in the panel data. However, their analysis does not consider any potential bias resulting from the heterogeneity in the cross-country panel for developing countries. Furthermore, as public investment in T&C takes time before its effect on output growth can be registered, an appropriate model should consider dynamic adjustment over time and ignoring the dynamic aspect of the data is not only a loss of potentially important information but can lead to serious misspecification biases in the estimation.

Our study tries to avoid these potential weaknesses and considers a dynamic panel framework in which we reflect the effect of public investment in T&C on growth over time and incorporate heterogeneous behaviour of cross-units into model estimation. In a dynamic panel data model, we can not use the pooling regression or the Least Squares Dummy Variable (LSDV) estimation method due to the bias resulting from the correlation between the lagged dependent variables and the error term as shown in Nickell (1981), Anderson and Hsiao (1981, 1982), Hsiao (1986) and Kiviet (1995), among others.[2] The usual approach for dealing with this problem is to first-difference the data to remove the fixed effects and then estimate the model using instruments. Holtz-Eakin *et al.* (1988) adopt this approach in a framework for testing Granger causality in panels and suggest using a time-varying set of instruments that includes both differences and levels. Following Holtz-Eakin *et al.* (1988), we consider a bivariate dynamic panel model:

$$y_{it} = \alpha_0 + \sum_{j=1}^{m} \alpha_j y_{it-j} + \sum_{j=1}^{m} \beta_j x_{it-j} + f_i + \varepsilon_{it}, i = 1, 2, ..., N, \tag{1}$$

where y_{it} and x_{it} are the dependent variable and the causal variable at time t for country i respectively, f_i is the fixed effect, the lag length m is sufficiently large to ensure that ε_{it} is a white noise error term and the α's and β's are the coefficients of the linear projection of y_{it} on a constant, past values of y_{it} and x_{it} and the individual effect f_i.

[2] See Baltagi (2001) for a useful overview of this issue.

Taking differences in equation (1) to eliminate the fixed effects leads to the model:

$$\Delta y_{it} = \sum_{j=1}^{m} \alpha_j \Delta y_{it-j} + \sum_{j=1}^{m} \beta_j \Delta x_{it-j} + u_{it}, i = 1, 2, ..., N, \tag{2}$$

where $\Delta y_{it-j} = y_{it-j} - y_{it-j-1}\, for\, j = 0, 1, .., m, \Delta x_{it-j} = x_{it-j} - x_{it-j-1}\, for\, j = 1, 2, , ..., m$ and $u_{it} = \varepsilon_{it} - \varepsilon_{it-1}$. Because Δy_{it-1} is correlated with the first difference error term, $u_{it}(= \varepsilon_{it} - \varepsilon_{it-1})$, it is necessary to use instrumental variable procedures. Following Holtz-Eakin *et al.* (1988, 1989), we can estimate the equation (2) by using 2SLS with a time-varying set of instruments. Holtz-Eakin *et al.* suggest that the vector of instrumental variables, Z_{it}, that is available to identify the parameters of equation (2), is

$$Z_{it} = [1, y_{it-2}, y_{it-3}, ..., y_{i1}, x_{it-2}, ..., x_{i1}].$$

The authors address the question of whether x Granger causes y or not by testing the joint hypothesis:

$$\beta_1 = \beta_2 = ... = \beta_m = 0. \tag{3}$$

In our study, we start with this procedure to address the question of whether public investment in T&C Granger causes economic growth.

However, there might be some potential problems for this instrumental approach. First of all, in practice it is often difficult to find good instruments for the first-differenced lagged dependent variable, which can itself create problems for the estimation. Kiviet (1995) shows that panel data models that use instrumental variable estimation often lead to poor finite sample efficiency and bias. Secondly, this approach imposes the assumption, widespread in the panel causality literature, that the coefficients on the explanatory variables are equal across units in the panel. Weinhold (1999) and Nair-Reichert and Weinhold (2001) point out that this restriction of a single coefficient on the causal variable for all the units saves the most degrees of freedom, but at the cost of the unlikely assumption that either causality occurs everywhere or it occurs nowhere in the panel and thus there might be potential bias induced by heterogeneity of the cross section units.

To avoid biased parameter estimates resulting from cross-sectional heterogeneity, they propose a mixed fixed and random coefficients model (MFR) in which the intercepts and the coefficients on the lagged dependent variables are specific to the cross section units, while the coefficients on the exogenous variables are assumed to be normally distributed across the cross section. Thus, the MFR model allows for greater heterogeneity in the parameters than do the traditional models. This model is originally developed by Hsiao *et al.* (1989) in a non-dynamic, non-fixed-effects panel data model of regional electricity demand and adapted in Weinhold (1996, 1999) as an alternative specification for panel data causality testing and of estimating panel data models with heterogeneous dynamics. Weinhold (1999) shows that the MFR model performs very well compared to instrumental variable approaches and her Monte Carlo experiments show the bias on the exogenous variable's parameter estimate when T is between 10 and 25 and N is between 20 and 40 is relatively small[3]. Following Weinhold (1999) and Nair-Reichert and Weinhold (2001), we consider an alternative specification for dynamic panel data model:

$$y_{it} = \alpha_i + \sum_{j=1}^{m} \gamma_{ij} y_{it-j} + \sum_{j=1}^{m} \beta_{ij} x_{it-j} + \varepsilon_{it}, \tag{4}$$

where the coefficients on the lagged dependent variables, γ_{ij}, are country-specific, the coefficient on the exogenous explanatory variable x, β_{ij}, is drawn from a random distribution with mean $\overline{\beta}_j, \beta_{ij} = \overline{\beta}_j + v_i$ and v_i is a random disturbance. In essence, this approach uses information on the distribution of the estimates on the lagged exogenous variable to extract the required information and to address the question of the direction of causality or possible joint determination between economic variables in a panel data

[3]The bias ranges from 0.002 to 0.003 when the true value of the coefficient is 0.2. For further details on the MFR model, see Weinhold (1999).

set. Weinhold (1999) suggests that the estimated variance of the random coefficients can be used as a diagnostic tool to determine the extent of heterogeneity in the relationship in question and thus, if the estimated variance is quite large relative to the coefficient estimates, this is a signal of significant heterogeneity in the panel. In our study, we employ this approach for further investigation of the causality between public investment in T&C and growth.

3 Estimation results

3.1 Data

Existing studies aiming at evaluating growth effects of public investment at a disaggregated level frequently suffer from the 'sparseness of data' problem.[4] For us, however, this problem poses a greater challenge due to the fact that a formal test for causality requires usage of lags and leads of the variables in question and such an analysis needs to be based on data sets containing relatively large number of observations per country. To overcome these shortcomings, we aimed at collecting a large and balanced data set on central government investment expenditure in the T&C sector for developing countries by consulting a large collection of World Bank Country Economic Reports and Public Expenditure Reviews.[5] But we ended up with a panel of 15 developing countries with annual data from 1970 to 1987 without any missing observations[6]. Our data for the growth rate of GDP is taken from World Bank CDROM. Our study uses the bivariate estimation and thus avoids any implausible results from using various control variables in the growth study.

[4] Due to shortage of data, Easterly and Rebelo (1993) have based their analysis on the decade averages implying only two data points per country.

[5] Our data set is available upon request. We wish to thank the World Bank for allowing us to use their archive at Washington D.C.

[6] Countries in our sample, are Bahamas, Congo, Ethiopia, Guatemala, Indonesia, Kenya, Malaysia, Morocco, Pakistan, Rwanda, Sierra Leone, Sri Lanka, Tanzania, Thailand, and Zambia.

Even though the time period is only 18 years, the ADF test (Augmented Dickey-Fuller test) for a unit root in public investment in T&C indicates that all countries have such a unit root. To avoid a specification with non-stationary explanatory variables leading to spurious results in a panel, we take the growth rate of our variables as adopted in Nair-Reichert and Weinhold (2001). Thus, we ask whether an increase in the growth rate of public investment in T&C helps forecast an increase in economic growth. In other words, we try to address the question whether a relatively high growth rate of public investment in T&C will lead to relatively high GDP growth rate.

3.2 Causality from public investment in T&C to economic growth

As outlined in section 2, we start with a traditional panel causality test proposed by Holtz-Eakin *et al.* (1988) for dynamic panel models. From the equations (1) and (2), we have:

$$\Delta GY_{it} = \sum_{j=1}^{m} \alpha_j \Delta GY_{it-j} + \sum_{j=1}^{m} \beta_j \Delta GTCI_{it-j} + u_{it}, i = 1, 2, ..., N, \tag{5}$$

where GY_{it} and $GTCI_{it}$ are the growth rates of GDP and public investment in T&C for the country i at time t and ΔGY_{it} and $\Delta GTCI_{it}$ are the first differences. How can we choose the correct lag length, m? Holtz-Eakin *et al.* (1988, 1989) discuss how to find the "best" value of m. First of all, we choose a relatively large value of m to be sure to avoid truncating the lag structure inappropriately. Denote by $\widetilde{m}$ the relatively large value of m used for initial estimation of the model. Re-estimate the system (5) with $m = \widetilde{m} - 1$. If the increase in the sum of squared residuals is "large", then $m = \widetilde{m}$ is accepted. If the increase is "small", then try $m = \widetilde{m} - 2$. Continue testing successively smaller lag lengths until one is rejected by the data, or $m = 0$. This procedure is consistent with the "general to specific" methodology. Following this procedure, we estimate equation (5) with $m = 3$ and different instrument sets and the procedure is summarized in the

Table 1. The procedure indicates that we cannot reject the null of $m = 2$ at the 1% and 10% levels for different instrument sets, while we can reject the null of $m = 3$ at the 5% level for both instrument sets. Thus, the procedure for the choice of lag length suggests that the lag length, $m = 2$ is appropriate.

Table 2 presents the results from 2SLS estimation of equation (5). While the estimated coefficient on $\Delta GTCI_{it-1}$ is statistically significant at the 10% level, that on $\Delta GTCI_{it-2}$ is not statistically significant. In contrast to Easterly and Rebelo (1993), in which the effect of public investment in T&C on growth is robustly significant with instrumental variables but the size of the coefficients is disturbingly high, the values of the estimated coefficients in our case are -0.004 and 0.004 and thus somewhat lower. The *p-value* in the Wald test of the null hypothesis that $\beta_1 = \beta_2 = 0$ is 0.025, implying that we reject the null at the 5% level. Thus, the Holtz-Eakin *et al.* dynamic panel causality test indicates that growth in public investment in T&C Granger causes GDP growth.

However, while the value of the estimated coefficient on $\Delta GTCI_{it-2}$ is positive, that of $\Delta GTCI_{it-1}$ is negative. As previous literature has reported contradictory results, our result based on the dynamic panel instrumental variable estimation might not indicate clearly that infrastructure has a positive impact on economic growth. One possible reason might be attributed to heterogeneity in the relationship between two variables. The econometric analysis presented in table 2 is based on underlying assumptions about the homogeneity of the relationships in question across countries in the panel. However, it is reasonable to expect quite a bit of heterogeneity both in the dynamic structure as well as in the relationship between economic growth and public investment in T&C, especially, in a panel of developing countries. Pesaran and Smith (1995) and Weinhold (1999) point out that the presence of such heterogeneity can result in serious mis-specification biases in the subsequent estimation that imposes homogenous parameter values.

To investigate whether this result can be attributed to heterogeneity in the cross-country units, we employ the MFR model described in Section 2. Following Nair-Reichert and Weinhold (2001), we use orthogonalization which is necessary to ensure that the coefficients are independent which in turn allows their estimated variances to be appropriately interpreted. That is, we have:

$$GY_{it} = \alpha_i + \sum_{j=1}^{m} \gamma_{ij} GY_{it-j} + \sum_{j=1}^{m} \beta_{ij} GTCI^{o}_{it-j} + \varepsilon_{it}, \tag{6}$$

where $GTCI^{o}_{it-j}$ denotes the orthogonalized growth rate of public investment in T&C after the linear influences of the other right-hand side variables have been removed (including any other lags of this variable if multiple lag lengths are used). As in the 2SLS estimation, we chose the lag length, $m = 2$. The estimated mean and variance of the indicated causal variables over countries are reported in table 3, as are the standard errors of the estimated means.

As pointed out in Weinhold (1999) and Nair-Reichert and Weinhold (2001), if the estimated variance of the coefficients on $GTCI^{o}_{it-j}$ is quite large relative to the mean of the estimated coefficients, this is a signal of significant heterogeneity in the panel. The estimated variances of the random coefficients are not large, implying that there might not be a great deal of the heterogeneity across this panel. In contrast to 2SLS estimation, the estimated means of the coefficients on $GTCI_{it-1}$ and $GTCI_{it-2}$ are positive but the value of the estimated coefficient on $GTCI_{it-1}$ is not statistically significant. The positive value and the statistical significance on $GTCI_{it-2}$ imply that public investment in T&C has a positive impact on economic growth and seem to support that there is a dynamic effect of public investment in T&C on growth.

For further investigation of the degree and shape of the heterogeneity in the relationship between GY_{it} and $GTCI_{it-2}$, Figure 1 plots the distribution of the estimated individual coefficients on $GTCI_{it-2}$. Even though the distribution is a little skewed to the right, it would seem that the distribution is approximately bell-shaped, implying that the coefficients are not completely idiosyncratic across countries. Overall, there is not a great deal of heterogeneity in this relationship. Nevertheless, the MFR model seems to be an appropriate methodology for explaining previous controversial results and taking heterogeneous behaviour in developing countries into account. In addition, the magnitudes of the values on the estimated coefficients of both estimations, Holtz-Eakin *et al.*'s instrumental estimation and the MFR model, are quite similar.

In sum, Holtz-Eakin *et al.*'s instrumental estimation and the MFR model for the dynamic panel suggest that public investment in T&C Granger causes economic growth. In particular, the values of the estimated coefficients on public investment in T&C are considerably lower in contrast to previous literature as in Aschauer (1989), and Easterly and Rebelo (1993). Our results support that infrastructure such as transportation and communication matters for economic growth in developing countries.

3.3 Reverse causality

In terms of the accelerating effect of output on investment, as in Clark (1979) and Wagner's law in Abizadeh and Gray (1985) and Ram (1987), there might be reverse causality, which means that public investments in T&C follow growth and thus rapid growth leads to higher investments in this sector. To investigate this issue, we employ the same methodology. First of all, we consider Holtz-Eakin *et. al.*'s (1988) instrumental variable estimation for the dynamic panel as follows:

$$\Delta GTCI_{it} = \sum_{j=1}^{m} \alpha_j \Delta GTCI_{it-j} + \sum_{j=1}^{m} \beta_j \Delta GY_{it-j} + u_{it}, i = 1, 2, ..., N. \tag{7}$$

Table 4 shows the 2SLS estimation results of equation (7). As in the causality test of equation (5), we choose the lag length at $m = 2$. The estimated coefficients on ΔGY_{it-1} and ΔGY_{it-2} are positive but not statistically significant and high, suggesting that there might be a great deal of heterogeneity in the reverse relationship. The Wald test for the null hypothesis that $\beta_1 = \beta_2 = 0$, indicates that we can not reject the null at the conventional level. This result implies that the reverse causality does not apply and thus economic growth does not Granger cause public investment in transportation and communication.

To examine this reverse causality taking heterogeneity in cross-country units into account, following Weinhold (1999) and Nair-Reichert and Weinhold (2001), we also estimate the MFR model:

$$GTCI_{it} = \alpha_i + \sum_{j=1}^{m} \gamma_{ij} GTCI_{it-j} + \sum_{j=1}^{m} \beta_{ij} GY^o_{it-j} + \varepsilon_{it}, \tag{8}$$

where we choose $m = 2$. The estimated mean and variance of the indicated causal variables are reported in table 5 as are the standard errors of the estimated means. The estimated means of estimated coefficients on GY_{it-1} and GY_{it-2} are positive and much lower than in Holtz-Eakin *et. al.*'s (1988) instrumental variable estimation. However, none of the estimated coefficients is statistically significant. In particular, the variances of the estimated mean on the random coefficients are much larger relative to the mean, implying that there are a great deal of heterogeneity across this panel in the reverse causal relationship. Overall, the estimation results in the MFR model are similar with Holtz-Eakin *et. al.*'s instrumental variable estimation for the dynamic panel causality test. Thus, we do not find significant evidence that there is a reverse causal relationship between growth and public investment in T&C and our empirical study does not support that the investment acceleration hypothesis works in the case of public investment in transportation and communication and economic growth for developing countries.

4 Concluding remarks

Empirical literature on the relationship between public investment in transportation and communication and economic growth has reported a mixed picture; sometimes significant and positive, sometimes significant and negative, and sometimes not significant. In addition, the size of the estimated coefficient on public investment in T&C is disturbingly high, implying a result which naturally casts doubt on the validity of the procedure.

This paper re-examined this issue by considering the dynamic effect of public investment in T&C on growth over time and allowing for heterogeneity in developing countries. For this end, we started with Holtz-Eakin *et. al.*'s (1988) instrumental estimation which is a benchmark model for a dynamic panel causality test. Our results in the instrumental variable estimation show that public investment in T&C matters for economic growth and the values of the estimated coefficients on lagged public investments in T&C are substantially lower than in previous literature. However, these values are a mixture of negative and positive ones as reported in previous literature, indicating that it is not clear that public investment in T&C has a positive impact on economic growth.

To investigate further whether these results are attributed to heterogeneity in developing countries, we employ the mixed fixed and random coefficient model (MFR) of Weinhold (1999) and Nair-Reichert and Weinhold (2001). The estimation results indicate that there is not a great deal of heterogeneity but the MFR model is more appropriate one to examine the relationship. From the MFR estimation, we confirm earlier findings that public investment in T&C has a positive impact on economic growth. Overall, both estimations suggest that public investment in T&C takes time to affect growth and thus a dynamic panel model is more desirable than a static one for studying the relationship between infrastructure such as transportation and communication and economic growth.

However, from both approaches, we do not find an evidence on the reverse causality which is suggested by the acceleration effect of output on investment and Wagner's law. In particular, the MFR model estimation suggests that there is a great deal of heterogeneity across developing countries in the reverse causal relationship. Hence, we feel that the effect of public investment in transportation and communication on economic growth is generally significant and considerable, while the other way around is questionable for developing countries.

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Table 1. The choice of lag length, m

H_0	χ^2	$p-value$	Instruments
$m=2$	2.226	0.329	constant, $GY_{it-j}, GTCI_{it-j}, j=2,..,5$
$m=2$	5.260	0.072	constant, $\Delta GY_{it-j}, \Delta GTCI_{it-j}, j=2,3,4$
$m=1$	8.014	0.091	constant, $GY_{it-j}, GTCI_{it-j}, j=2,..,5$
$m=1$	16.375	0.003	constant, $\Delta GY_{it-j}, \Delta GTCI_{it-j}, j=2,3,4$

Table 2 Holtz-Eakin *et al.* (1988) dynamic panel data Causality test

$$\Delta GY_{it} = \alpha_1 \Delta GY_{it-1} + \alpha_2 \Delta GY_{it-2} + \beta_1 \Delta GTCI_{it-1} + \beta_2 \Delta GTCI_{it-2} + u_{it}$$

coefficient	$\widehat{\alpha}_1$	$\widehat{\alpha}_2$	$\widehat{\beta}_1$	$\widehat{\beta}_2$
	-0.232^{***} (0.084)	-0.142^{*} (0.073)	-0.0044^{*} (0.0024)	0.0042 (0.0031)
$H_0 : \beta_1 = \beta_2 = 0, \chi^2 = 7.385, p-value = 0.025$				

Note: a. Instruments are constant, $GY_{it-j}, GTCI_{it-j}, j = 2, .., 5$.

b. *** and * denote the statistical significance at the 1% level and 10% level in a two-tail test respectively.

Table 3 MFR model causality test

$$GY_{it} = \alpha_i + \gamma_{i1} GY_{it-1} + \gamma_{i2} GY_{it-2} + \beta_{i1} GTCI_{it-1} + \beta_{i2} GTCI_{it-2} + \varepsilon_{it}$$

variable	Est. coeff.	Std. error	Coeff. variance
$GTCI_{t-1}$	0.0015	0.0033	0.0007
$GTCI_{t-2}$	0.0047***	0.0004	0.0008

Note: a. *** denotes a statistical significance at the 1% level.

b. Est. coeff., Std. error, and Coeff. variance denote the estimated mean of random coefficient, the standard error of the estimated mean and the estimated variance of the random coefficients respectively.

Table 4. Holtz-Eakin *et al.* (1988) Reverse causality test

$$\Delta GTCI_{it} = \alpha_1 \Delta GTCI_{it-1} + \alpha_2 \Delta GTCI_{it-2} + \beta_1 \Delta GY_{it-1} + \beta_2 \Delta GY_{it-2} + u_{it}$$

coefficient	$\widehat{\alpha}_1$	$\widehat{\alpha}_2$	$\widehat{\beta}_1$	$\widehat{\beta}_2$
	-0.701^{***} (0.102)	-0.315^{**} (0.134)	3.283 (3.663)	4.057 (3.196)
$H_0 : \beta_1 = \beta_2 = 0, \chi^2 = 1.836, p - value = 0.399$				

Note: a. Instruments are constant, $GY_{it-j}, GTCI_{it-j}, j = 2, .., 5$.

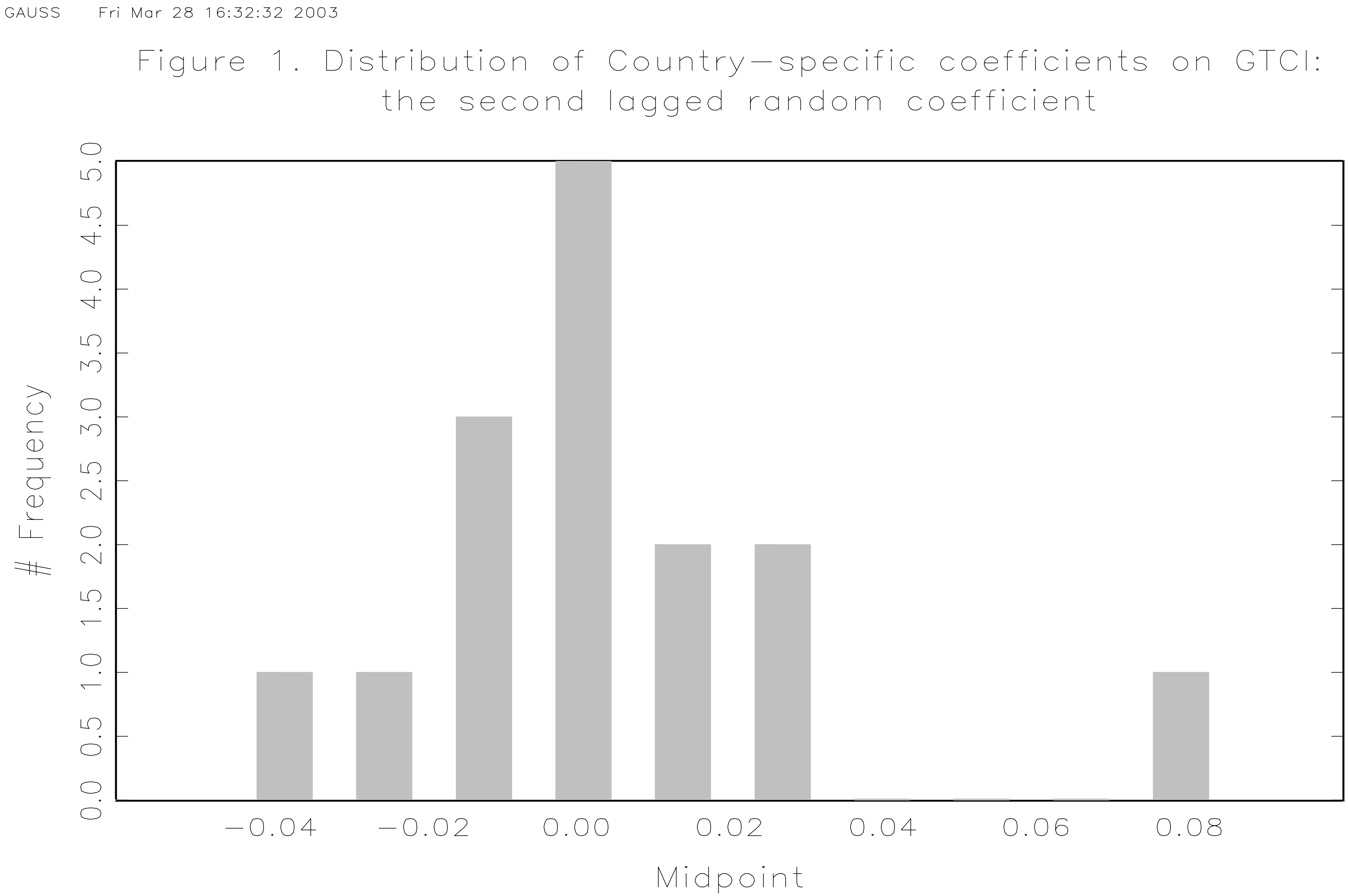
b. *** and ** denote the statistical significance at the 1% level and 5% level respectively.

Table 5. MFR Reverse causality test

$$GTCI_{it} = \alpha_i + \gamma_{i1} GTCI_{it-1} + \gamma_{i2} GTCI_{it-2} + \beta_{i1} GY_{it-1} + \beta_{i2} GY_{it-2} + \varepsilon_{it}$$

variable	Est. coeff.	Std. error	Coeff. variance
GY_{t-1}	0.886	2.892	80.802
GY_{t-2}	1.367	3.278	63.021

Note: Est. coeff., Std. error, and Coeff. variance denote the estimated mean of random coefficient, the standard error of the estimated mean and the estimated variance of the random coefficient respectively.


GAUSS Fri Mar 28 16:32:32 2003
Figure 1. Distribution of Country–specific coefficients on GTCI:
the second lagged random coefficient
Frequency
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
–0.04
–0.02
0.00
0.02
0.04
0.06
0.08
Midpoint