Causality Tests for Cross-Country Panels: New Look at FDI and Economic Growth in Developing Countries

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Abstract

The remarkable increase in FDI flows to developing countries over the last decade has focused attention on whether this source of financing enhances overall economic growth. We use a mixed fixed and random (MFR) panel data estimation method to allow for cross country heterogeneity in the causal relationship between FDI and growth and contrast our findings with those from traditional approaches. We find that the relationship between investment, both foreign and domestic, and economic growth in developing countries is highly heterogeneous and that estimation methods which assume homogeneity across countries can yield misleading results. Our results suggest there is some evidence that the efficacy of FDI in raising future growth rates, although heterogeneous across countries, is higher in more open economies.

key words: panel data, causality testing, FDI, growth, openness
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1. Introduction

There is an ongoing debate about the economic impact of multinationals on host countries, especially developing economies. This debate assumes special importance in view of recent changes in the composition and direction of foreign direct investment (FDI), and liberalization of government policies towards FDI in developing economies. After a decline of about 4% each year during 1980-1985, the volume and share of FDI to developing economies has risen significantly. During the later part of the 1980s, FDI in developing economies increased by 17% each year. In 1993, total FDI to developing countries was $70 billion, and the value of inflows of FDI increased by 125% in the first three years of the decade (Lal (1998)).

There is, however, conflicting evidence in the literature regarding the impact of multinational enterprises (MNEs) and FDI on both transitional and long-term economic growth. While some studies, both theoretical and empirical, indicate that FDI may have a strong positive effect on growth rates in developing countries, others suggest that these positive effects may not be unconditional and point to the lack of technological spillovers and the possibility of enclave economies developing. Given that the relationship between FDI and growth may be complex and heterogeneous across countries, this paper highlights the potential for serious errors in the analysis of the relationship if unrealistic homogeneity assumptions are imposed in the econometric modeling.

We examine the possibility that the effect of FDI on growth could display quite heterogeneous behavior in a panel of 24 developing countries over 25 years, and find that heterogeneity may be a serious issue. Thus we propose the use of a mixed fixed and random (MFR) coefficient approach as an alternative estimation method that allows for heterogeneity in the causal relationship between FDI and growth. The key results of this econometric analysis indicate that there is indeed considerable heterogeneity across developing countries regarding the impact of FDI and other conditioning variables on economic growth. The paper also highlights the fact that allowing for heterogeneity in the MFR model produces substantially different results from the traditional panel estimators, and suggests that results from models that assume homogeneity across countries should be treated with some caution.

The rest of the paper proceeds as follows. Section 2 reviews selected literature on the relationship between FDI and growth, and Section 3 describes both the traditional and MFR framework for causality testing. We discuss the data in Sections 4 and present the main results in Section 5. Section 6 summarizes the key conclusions and policy implications.

2. FDI and Growth: A Discussion of the Empirical Evidence

The theoretical foundation for empirical studies on FDI and growth derives from either the neo-classical models of growth or the endogenous growth models. In neoclassical models of growth, FDI increases the volume of investment and / or its efficiency, and leads to long-term level effects and medium-term, transitional increases in growth. The new endogenous growth models consider long run growth as a function of technological progress, and provide a framework in which FDI can permanently increase the rate of growth in the host economy through technology transfer, diffusion, and spillover effects. Evidence in the existing empirical literature on the causal relationship between FDI and economic growth is rather inconclusive. Most of these studies conduct traditional causality tests, using single time series or panel data. In the latter case, the relationship between FDI and growth is assumed to be homogeneous across countries. In this section, we briefly review select papers that have investigated the causal relationship between FDI and growth and note several drawbacks of these traditional approaches.

Micro studies at the firm level suggest that the impact of FDI on growth may depend on many factors. Atkins and Harrison's (1999) study using panel data from Venezuelan plants uncovers considerable heterogeneity at the micro level. They find that foreign equity participation is positively correlated with plant productivity, but that this relationship is robust only for small enterprises. Harrison (1994) cites case study evidence in Morocco and Venezuela, which indicate that firms with foreign equity participation are more productive than domestic firms and have higher productivity growth. However, she finds that in Venezuela the productivity of domestic competitors was hurt because the presence of multinational enterprises (MNEs) decreased their market share. Weinhold (1991) also finds few technological spillovers to domestic companies from Japanese firms operating in Mexico, due mostly to a lack of local sourcing.

Macro-empirical analysis of the effects of FDI on growth is largely based on the single equation time averaged cross-section estimation approach, with or without instrumental variables. For example, Balasubramanyam et. al. (1999, 1996) use cross-sectional annual data averaged over the period 1970-85 for a sample of 46 developing countries and find that that the size of the domestic market, the competitive climate in relation to local producers and interactions between FDI and human capital exert an important influence upon growth performance. Their analysis indicates that FDI is more productive in countries that have pursued export promotion rather than import-substitution policies.

Borensztein, De Gregorio and Lee (1995) develop an endogenous growth model in which FDI increases long run growth through its effect on the rate of technological diffusion from the industrialized world to the host country. They use seemingly unrelated regression (SUR) with instrumental variables (IV) estimation to conduct cross-country analysis of 69 developing countries with panel data averaged over two separate time-periods 1970-79 and 1980-89, where the dependent variables are per-capita GDP growth rates over each decade. They conclude that FDI, by itself, has a positive but insignificant effect on economic growth. Only when a country has a minimum threshold stock of human capital is FDI an important determinant of economic growth; in that case, it actually contributes to growth more than domestic investment does. In addition, the authors find that FDI has the effect of increasing total investment in the economy more than one for one.

There are several potential drawbacks to the approach adopted by most of the papers we have reviewed. First, models estimated with time-averaged data lose dynamic information and, due to both the lack of dynamics and degrees of freedom, run increased risk of serious omitted variable bias. Second, contemporaneous correlation across the cross-section does not imply causation, and thus these models may suffer from endogeneity biases. In addition, as some of the authors have themselves acknowledged, these problems are difficult to address satisfactorily since suitable instruments are often not available. Thus a cross section analysis without good instrumentation will be unable to distinguish between the hypothesis that increased FDI has led to increased growth, versus the hypothesis that good growth has attracted additional FDI.

One possible solution to the problems regarding the analysis of FDI and growth discussed above is the use of time-series, cross-section panel data estimation. This allows the researchers to control for country-specific, time-invariant "fixed effects," and include dynamic, lagged dependent variables which can also help to control for omitted variable bias. The ability to lag explanatory variables may also help control for endogeneity bias[1]. Along these lines, a dynamic specification of the model can be used to test for Granger causality or joint determination of the variables. For example, De Mello (1999) estimates the impact of foreign direct investment on capital accumulation, and output and total factor productivity (TFP) growth in a sample of OECD and non-OECD countries during 1970-90. His time series and panel data analysis indicate that that the extent to which FDI is growth enhancing depends on the degree of complementarity and substitution between FDI and domestic investment.

In terms of causality testing however, the dynamic estimators do not solve all these issues raised with cross section analysis. Although these estimators allow for *testing* whether increased growth has attracted more FDI (rather than simply assuming this is not the case), these methods still cannot rule out the possibility that it is the (correct) *expectation* of future high growth rates that has "caused" the increased FDI. In the case of developing countries, however, we do not think this will be a major source of error. Growth rates in developing countries are extremely difficult to predict in advance (for a discussion of this see Easterly et.al (1993), and much of the literature surveying the 1997 Asian crisis has pointed at "herding," backward-looking behavior of international investors (see, for example, Griffith-Jones (1998)).

[1] With the usual caveat that in the case where the relationship in question is driven by forward-looking expectations, then these expectations should be modelled within the framework of the analysis. If not done, the resulting misspecified model may give the illusion of Granger causality.

Another potentially much more serious problem with the traditional panel data fixed effects estimators (FEE) is the imposition of homogeneity assumptions on the coefficients of lagged dependent variables when in fact the dynamics are heterogeneous across the panel. Pearson (1995) argues that this mis-specification can lead to serious biases that cannot be remedied with instrumental variable estimation. De Mello (1999) briefly discusses this issue and provides parameter estimates using the mean group estimator (MGE) for heterogeneous panels. In the case of non-OECD countries, he finds that aggregate estimates differ from the average of individual country coefficients, while they are similar in the case of the OECD sample, suggesting the need to further explore the panel heterogeniety issue. One drawback of the MGE, however, is that it produces interpretable estimates even if the relationship is completely idiosyncratic across countries. In section 3.1, we discuss an estimation method that falls somewhere in between the two extremes of FEE and MGE in terms of allowing for heterogeneity. Our estimation method imposes more structure on the coefficient values of the exogenous variables than the MGE (after all, if the relationship is completely idiosyncratic across countries then it is difficult to meaningfully interpret the results from an economic or policy perspective). However we allow for country-specific dynamics and significantly more heterogeneity than do traditional dynamic panel data estimators.

3. Causality in Panel Data

In this section, we examine some potential problems in testing causality using traditional models, and present an alternate approach, the Mixed Fixed and Random Model for causality testing in panel data. A representative example of traditional panel data causality testing is Holtz-Eakin et.al (1988). The Holtz-Eakin et. al. model is

$$y_{it} = a_0 + \sum_{j=1}^{m} a_j y_{it-1} + \sum_{j=1}^{m} d_j x_{it-1} + f_i + u_{it}$$

where $i = 1 \ldots N$. In order to eliminate the fixed effects, f_i, the authors difference the data leading to the model:

$$y_{it} - y_{it-1} = \sum_{j=1}^{m} a_j (y_{it-j} - y_{it-j-1}) + \sum_{j=1}^{m} d_j (x_{it-j} - x_{it-j-1}) + (u_{it} - u_{it-1})$$

This specification introduces a problem of simultaneity because the error term is correlated with the regressor $y_{it-j} - y_{it-j-1}$. Therefore, a 2SLS instrumental variables procedure with a time-varying set of instruments is used to estimate the model. The authors then equate the question of whether or not *x* causes *y* with a test of the joint hypothesis:

$$d_1 = d_2 = \ldots = d_m = 0$$

This approach is representative of the assumption widespread in the panel causality literature in that the coefficients on the explanatory variables are equal across units in the panel. 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. However, given the cross-sectional heterogeneity present in many panel data sets, even with a correctly specified model, it could be expected that one variable could help predict another for most but not all of the cross-section units. In addition, in a heterogeneous data set it is possible that the mean coefficient could take statistically significant values of either sign, or even be insignificantly different from zero, without reflecting much of the underlying economics[2].

The issue of actual causality versus joint determination should use more flexible criteria to allow for the additional cross section dimension in the panel data. We wish to be able to estimate a distribution of causality across the panel and suggest an alternative causality test for panel data models that does just this.

3.1 A Causality Testing Framework for Panel Data

We consider a variation of the Mixed Fixed and Random (MFR) model first suggested by Hsiao (1989) in a non-dynamic model and later explored in Weinhold (1996, 1999) as an alternative specification for panel data causality testing and of estimating panel data models with heterogeneous dynamics. In particular we have:

$$y_{it} = a_i + g_i y_{it-1} + b_{1i} x^{O}_{1it-1} + b_2 x_{2it-1} + e_{it}$$

[2] The "degree" of causality is sometimes casually interpreted to be related to how significant the test statistic of the null hypothesis is, but this is not (nor should it be) formally exposited.

where $b_{1i} = \overline{b}_1 + h_i$ and x^{O}_{1it-1} denotes the orthogonalized candidate causal variable 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). Orthogonalization is necessary to ensure that the coefficients are independent which in turn allows their estimated variances to be appropriately interpreted.

The MFR estimator imposes more structure on the distribution of the coefficients than a seemingly unrelated regressions (SURE) or MGE estimator and is thus more efficient when the distribution of the coefficients is approximately normal. In addition, the estimate of the mean will be less sensitive to large outliers. Weinhold (1999) shows that the MFR model performs very well compared to the traditional instrumental variables approaches. In particular, Monte Carlo experiments show the bias on the exogenous variable's parameter estimate (even when the coefficients are simulated to be uniformly distributed) when T is between 10 and 25 and N is between 20 and 40 ranges from 0.002 to 0.003, which is well within the range reported in the literature for popular Anderson-Hsiao and GMM estimators.

Unlike FEE and other traditional dynamic panel estimators, the MFR estimation method allows for heterogeneous dynamics and thus avoids the serious Pesaran-type biases (see Pesaran 1992, 1995) induced by imposing unrealistic homogeneity conditions on coefficients of the lagged dependent variable(s).

In addition, the model has other features which make it ideally suited to the task of testing for causality in heterogeneous panel data sets. In particular, we allow for a *distribution* of causality across the panel, rather than imposing an assumption that causality occur everywhere, or nowhere, in the panel. Weinhold (1996) proposes a general “rule of thumb” method for determining the extent of causality. However, as this method is quite inexact, in this paper we rather use the distributional information to gain a *general* idea of the degree of heterogeneity. The combination of a less-biased mean estimate and an idea of the degree of heterogeneity will give a researcher more information about the underlying process than traditional panel causality tests.

Finally, it is important to point out that the MFR approach can first be used as a diagnostic tool. If the estimated variance is quite large relative to the coefficient estimates, this is a signal of significant heterogeneity in the panel. Rather than continuing with the panel data analysis it would be prudent at that point to investigate the heterogeneity in greater detail to assess the appropriateness of the specification and/or the pooling of the data.

We now turn to an analysis of FDI and economic growth in a panel of developing countries to illustrate how these theoretical benefits can be used in practice to yeild more insight into the underlying economic processes in a cross country panel data set.

4. Data

Section 4 describes the data. In this paper we use a panels of 24 developing countries from 1971 to 1995 to analyze the dynamic relationship between FDI and economic growth. We examine the contemporaneous correlation of FDI and growth, and check for evidence of Granger causality between the FDI and GDP growth. We also consider the role of gross domestic investment (GDI) and control for openness to trade (as proxied by the ratio of exports to GDP) as well as the rate of inflation[3]. Except for the human capital variables, the data is from World Development Indicators (1997). Data on human capital is taken from Nehru et al (1994) and is the average years of schooling of adults. It is useful to note that the data on schooling is available on average only every 5 years, and evolves very slowly in a fairly predictable fashion. Thus, it may not a suitable control variable per se for our analysis[4]. A full list of variables and their definitions can be found in Appendix A, while Appendix B lists the countries in the data set.

We take the growth rate of all of our variables (except inflation, which is itself a growth rate) for the analysis and justify this in several ways. First, we are primarily interested in the relationship between the variables over time in a particular country. Thus we ask whether an increase in FDI will lead to an increase in the growth rate, controlling for time-invariant country-specific characteristics and for other dynamic

[3] Other analyses have also controlled for proportion of government spending in GDP, population growth, foreign aid, and human capital, the results of which are all available from the authors upon request. However due to data availability problems the time series and number of countries was limited by the inclusion of these variables. The fundamental results of the paper do not change with the different samples and sets of control variables.
[4] The growth of human capital was not statistically significant when included in the analysis.

control variables. Modeling growth as a function of the growth of FDI (and the control variables) provides a more rigorous method of assuring that the results from a panel of countries applies as much as possible to individual countries. With this approach, the question being answered is, if FDI grew relatively quickly compared to other countries will GDP also grow relatively quickly? A second advantage of using growth rates of the explanatory variables is that the variables are much more likely to be stationary, which is a nontrivial advantage with a panel of these dimensions. Weinhold (1996) shows that investment shares in developing countries could be non-stationary, so this precaution seems warranted.

5. Results

Section 5 presents the main results of this analysis. We begin by considering some simple contemporaneous correlation using a non-dynamic fixed effects panel. Table 1, regression (1) presents the results from estimation of the model:

$$GGDP_{it} = a_i + b_1 GGDI_{it} + b_2 GFDI_{it} + b_3 GEXP_{it} + b_4 INFL_{it} + e_{it} \qquad (1)$$

As we can see, GFDI is not statistically significant. However, given the findings in the literature this is perhaps not surprising. Borensztein, De Gregorio, and Lee (1995) find that FDI is productive only in countries that have reached a particular threshold level of human capital. Balasubramanyam, Salisu, and Sapsford (1996) present results indicating that FDI is correlated with growth mainly in export-oriented countries, and not in import-substituting countries. We then test, again using contemporaneous correlation, whether the coefficients on GFDI and GGDI depend on either the level of openness to trade or the level of human capital so that we have:

$$b_k = b_{k0} + b_{k1} OPEN_{it} \qquad (2)$$

$$b_k = b_{k0} + b_{k1} HUMCAP_{it} \qquad (3)$$

where k =1, 2. By substituting either (2) or (3) into equation (1) we derive the model:

$$GGDP_{it} = a_i + b_1 GGDI_{it} + b_2 GFDI_{it} + b_3 GEXP_{it} + b_4 INFL_{it} + b_5 INTER_{it} + e_{it} \qquad (4)$$

where $b_5 = b_{k1}$ and *INTER* is the interaction term (multiplication) of either *GFDI* or *GGDI* with either *OPEN* or *HUMCAP*. These interaction variables are denoted by *FDIOP*, *FDIHK*, *GDIOP*, and *GDIHK*, respectively.

Table 1, regressions (2) - (5) present the results from checking for each of these possible relationships in turn. We observe that allowing for the effect of GFDI to vary with the level of openness we indeed find statistically significant coefficient estimates that start negative at very low levels of openness and become positive at higher levels of openness. However we find no such statistically significant effect of interacting human capital with GFDI. The results for GGDI are quite surprising. Interacting this variable with level of openness indicates that the economic growth returns of extra GDI actually *decline* with increased openness. GFDI is significant in this regression. Clearly there is something going on, but we hesitate to interpret these simple regressions. Finally, as with GFDI, there is no significant effect of human capital with GGDI.

In order to provide a sense of whether there is a causal relationship between GFDI and GGDP we turn to dynamic panel models in which GDP growth is modeled as a function only of lags of itself and other explanatory variables, as outlined in section 3. Thus the basic model becomes:

$$GGDP_{it} = a_i + gGGDP_{it-1} + b_1 GGDI_{it-1} + b_2 GFDI_{it-1} + b_3 GEXP_{it-1} + b_4 INFL_{it-1} + e_{it} \quad (5)$$

By including lagged dependent variables we can not only take into account the dynamic process of growth, but the lagged dependent variable provides an excellent proxy variable for many omitted variables. A lag length of one was selected due to the large number of explanatory variables and relatively short time series for each country[5]. As discussed in section 3, we consider both a traditional panel causality test first proposed by Holtz-Eakin et al. (1988), and the MFR panel causality test suggested here.

Table 2 presents the results from a first-differenced, instrumented Holtz-Eakin (1988) estimation of model (5). As can be observed, the results are completely contrary to those from the simple contemporaneous correlations. The Holtz-Eakin causality tests indicate that GFDI has a strong positive causal impact on growth of GDP, while GGDI is not statistically significant. The growth of exports is not statistically significant either, despite consistently strong positive contemporaneous correlation. It may surprise some that inflation seems to have a positive causal impact on growth. However, care must be taken in interpreting this as it is quite common for growth to increase sharply after

[5] Similar analysis with a lag length of two (2) did not fundamentally change the results.

successful stabilization programs that are almost exclusively implemented to curb high inflation. Thus high inflation may precede high growth rates in a few countries, although in no way would any economist suggest that it was the inflation, rather than the stabilization program, that caused the higher growth. This result is a good example of how imposing homogenous parameters on heterogeneous data may result in a few outlying observations having a large impact that is erroneously interpreted as a characteristic of the entire panel, and is discussed at length in the subsequent paragraphs.

Regressions (2) – (5) from table 2 present the results from four Holtz-Eakin causality tests for the relationships implied by equations (2) and (3). As with the contemporaneous correlations, we find no statistically significant effects of interactions with human capital. However, the results reported in regression (2) in table 2 on the interaction between GFDI and OPEN are exactly the opposite of what both the theoretical literature and the preliminary contemporaneous analyses predict. The coefficient estimate of FDIOP is both negative and statistically significant, seemly indicating that the more open a country is, the *lower* the causal impact an increase in FDI will have on the growth rate of GDP.

The entire econometric analysis presented in tables 1 and 2 are 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 the relationships between growth, FDI, and domestic investment, especially in a panel of developing countries. As discussed in section 3, the presence of such heterogeneity can result in serious mis-specification biases in the subsequent estimation that imposes homogenous parameter values. In particular, if the dynamics are heterogeneous across countries but are assumed to be equal, Pesaran (1995) shows that estimates will be biased and inconsistent. Monte Carlo studies (i.e. see Weinhold (1999)) show that not only are estimates on the other RHS variables biased in this case, but that this bias actually increases as T and N grow larger.

We then estimate MFR causality models as outlined in section 3, which allow for heterogeneous dynamics across countries and for a distribution over the coefficients on the explanatory variables. The estimated mean and variance of the indicated causal variables are reported in tables 3 and 4, as are the standard error of the estimated means.

Table 3 presents the results from an MFR estimation of the basic model (1) in which the coefficient on the lagged dependent variable is country-specific and the coefficients on the other RHS variables are allowed to have a normal distribution (these models are reiterated for convenience by each table). In addition to reporting the mean and variance estimate for each of the RHS variables (except the lagged dependent variable, whose country-specific estimates are not reported) in table 3, figure 1 illustrates the distribution of the coefficients on lagged FDI. It is immediately apparent from the estimated variances of the coefficients and the histogram presented in figure 1 that there is a great deal of heterogeneity across this panel. Unlike the traditional analyses, however, the MFR results alert us to this problem. Fortunately, the degree and shape of the heterogeneity in the relationship between GFDI and growth does not seem to imply that the coefficients are completely idiosynchratic across countries.

Interestingly, we see that while the Holtz-Eakin causality results indicated that inflation had a statistically significant positive causal impact on growth, the MFR results correctly identify this relationship as highly heterogeneous across countries, with a negative mean effect that is not statistically significantly different from zero. Thus, by allowing for some heterogeneity, the MFR estimates are less biased and less susceptible to a few outliers. At the same time, the MFR results give us relatively more confidence in the positive causal impact of GFDI on growth. Not only is the mean estimate positive and significant, as in the Holtz-Eakin test, but the variance, while large, is much smaller relative to the mean than the variances of the other coefficients and has an approximately bell-shaped distribution.

In table 4, we explore the alternative specifications implied by equations (2) and (3) to see if the impact of GFDI and GGDI is effected by either the level of openness or the level of human capital. Again, we find quite different results from those yielded by the Holtz-Eakin technique. In particular the mean coefficient estimate of FDIOP is positive rather than negative, more in line with economic theory and our own expectations. However, the variance is extremely large indicating that this relationship is certainly not universal across the panel.[6]

The mean estimates on the remaining interaction variables are not statistically different from zero, and there are enormous variance estimates. Thus we cannot draw any general conclusions from these results that would apply to all, or even most, of the countries in the panel. It is important to clarify that although we find no statistically significant role for human capital in our analysis, this does not necessarily imply that human capital is unimportant. Educational attainment is a very slowly evolving variable, and a country's relative educational level vis-à-vis other countries is approximately controlled for by time-invariant fixed "effects" and the lagged dependent variable. Also, it is often assumed that human capital accumulation leads to growth, but the reverse could also be true; such a relationship is likely to be quite complex and may not be adequately captured in our simple linear models.

6. Conclusion

A review of the theoretical and empirical literature on the causal relationship between FDI and growth suggests this relationship may be fairly heterogeneous in developing countries. However, traditional panel estimators have often imposed homogeneity assumptions across countries, even when the characteristics of the data warrant allowing for heterogeneity. This study concludes that the results from the MFR estimation of the causal relationship between FDI and growth in our panel of developing countries differ substantially from traditional panel data causality results. The MFR test for panel data causality allows the strength of causality to vary from country to country and permits heterogeneity of dynamics that is characteristic of developing country panels. Thus, by avoiding some of the homogeneity assumptions imposed by existing panel causality tests (and the accompanying biases that result when these assumptions are violated in the data), the mean estimate of the MFR is also less biased. In addition, the estimated variance of the coefficients can be a useful diagnostic tool for investigating the appropriateness of pooling in any given situation.

[6] In fact, it is most likely this large heterogeneity and a few countries with negative relationships led to the

One important finding of this study is that the relationship between investment, both foreign and domestic, and economic growth in developing countries is highly heterogeneous. Second, despite the large amount of variation across the countries in our panel, we can draw some policy relevant inferences from this analysis. While domestic investment seems be strongly correlated contemporaneously with growth, it is not as strong a causal determinant of future growth as foreign direct investment. There is some evidence that the efficacy of FDI in raising future growth rates is higher in more open economies. This relationship is also highly heterogeneous across countries.

In conclusion, the key results of this econometric analysis indicate that there is indeed considerable heterogeneity across developing countries regarding the impact of FDI and other conditioning variables on economic growth. We show that the results from the MFR model, that allows for heterogeneity, differ considerably from the results of traditional panel estimators. This suggests that results from models that assume homogeneity across countries should be treated with some caution. The MFR results point to a need for additional research to further understand the factors that lead to such heterogeneity across countries and to build better models to accommodate these factors.

Holtz-Eakin negative estimates for this coefficient.

7. Tables

Table 1: Contemporaneous OLS "Fixed Effects" panel regressions: Dependent Variable = *GGDP* (N = 600, Fixed effects not shown, Heteroskedasticity-consistent t-statistics in parentheses)

Variable	**1**	**2**	**3**	**4**	**5**
GGDI	1.717 (5.268***)	1.722 (5.174***)	1.723 (5.333***)	12.831 (9.808***)	2.643 (1.647*)
GFDI	0.034 (0.797)	-0.369 (2.953***)	0.022 (0.151)	0.053 (2.617***)	0.029 (0.689)
GEXPORT	7.269 (8.216***)	7.235 (8.321***)	7.187 (8.188***)	6.418 (7.431***)	7.252 (8.300***)
INFL	-5.406 (8.015***)	-5.557 (8.420***)	-5.412 (8.055***)	-4.927 (8.006***)	-5.342 (7.949***)
FDIOP		1.799 (3.363***)			
FDIHK			0.002 (0.062)		
GDIOP				-28.346 (9.429***)	
GDIHK					-0.186 (0.575)
R-square	0.2780	0.2897	0.2783	0.3736	0.2786
Adj. R-square	0.2440	0.2549	0.2429	0.3429	0.2432

Table 2: Holtz-Eakin et al. Causality tests

(N=504, heteroskedasticity-consistent t-statistics reported)

Variable	**1**	**2**	**3**	**4**	**5**
DDIVL1	-0.217 (1.953**)	-0.236 (2.162**)	-0.221 (2.006**)	-0.218 (1.972**)	-0.230295 (2.051**)
DDFDIL1	0.142 (6.208***)	0.455 (4.142***)	0.209 (1.268)	0.140 (5.822***)	0.140329 (6.257***)
DDGDIL1	-0.527 (0.820)	-0.403 (0.635)	-0.502 (0.764)	-1.059 (0.595)	-1.419056 (0.736)
DDINFL1	3.269 (2.453**)	3.402 (2.572***)	3.270 (2.469**)	3.211 (2.367**)	3.318596 (2.469**)
DDEXPL1	0.509 (0.508)	0.407 (0.442)	0.632 (0.621)	0.646 (0.655)	0.581014 (0.593)
DDFDIOPL1		-1.461 (2.949***)			
DDFDIHKL1			-0.010 (0.367)		
DDGDIOPL1				2.068 (0.367)	
DDGDIHKL1					0.146529 (0.505)
R-square	0.0644	0.0707	0.0649	0.0644	0.0646
Adj. R-square	0.0550	0.0595	0.0536	0.0531	0.0533

Table 3: MFR Causality Tests

Model:

$$GGDP_{it} = a_i + g_i GGDP_{it-1} + b_{1i} GGDI_{it-1} + b_{2i} GFDI_{it-1} + b_{3i} GEXP_{it-1} + b_{4i} INFL_{it-1} + e_{it}$$

Variable	Est. coeff.	Std. error	Coeff. variance	Est. prob. of causality
GFDI	0.159	0.067	0.573	0.396564
GGDI	0.947	1.061	32.142	0.070553
GEXP	4.680	1.508	41.633	0.060191
INFL	-0.925	0.763	492.193	0.736483

Table 4: MFR Causality Tests

$$GGDP_{it} = a_i + g_i GGDP_{it-1} + b_{1i} GGDI_{it-1} + b_{2i} GFDI_{it-1} + b_{3i} GEXP_{it-1} + b_{4i} INFL_{it-1} + b_{5i} CAUS_{it-1} + e_{it}$$

Causal Var. (*CAUS*)	Est. coeff.	Std. error	Coeff. variance	Est. prob. of causality
FDIOP	3.384	1.931	886.937	0.528
FDIHK	0.226	0.1960	2.553	0.234
GDIOP	-19.802	17.523	18010.148	0.206
GDIHK	-1.027	1.830	91.376	0.062

Figures

Figure 1: Distribution of Country-specific Coefficients on *GFDI* from Table 3

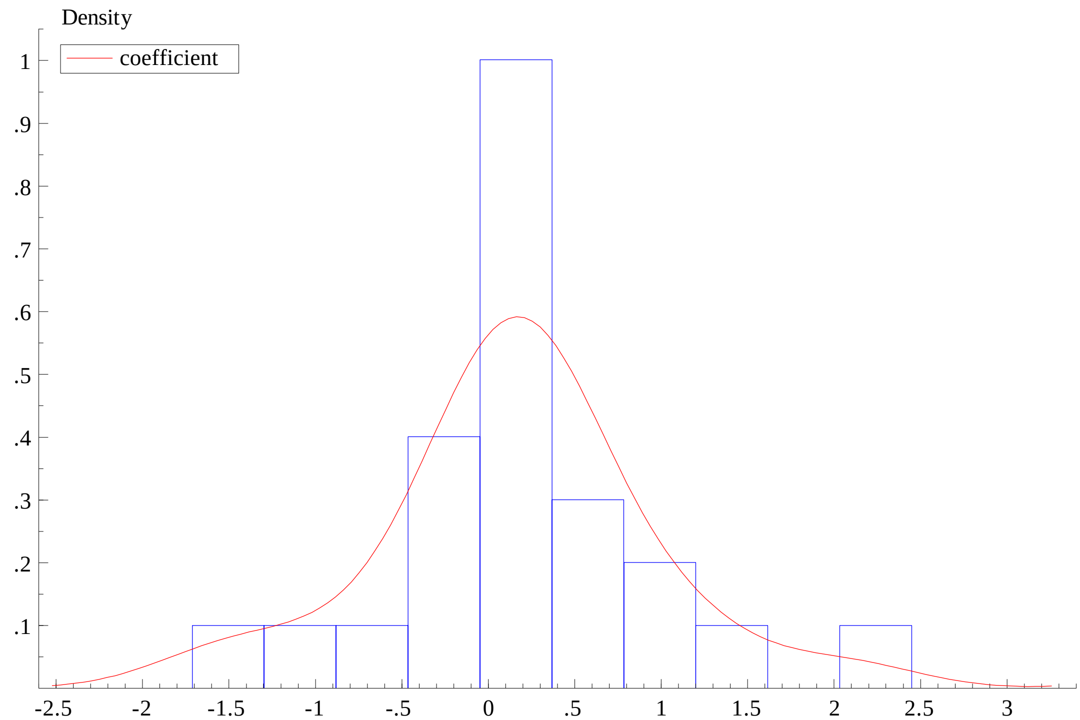
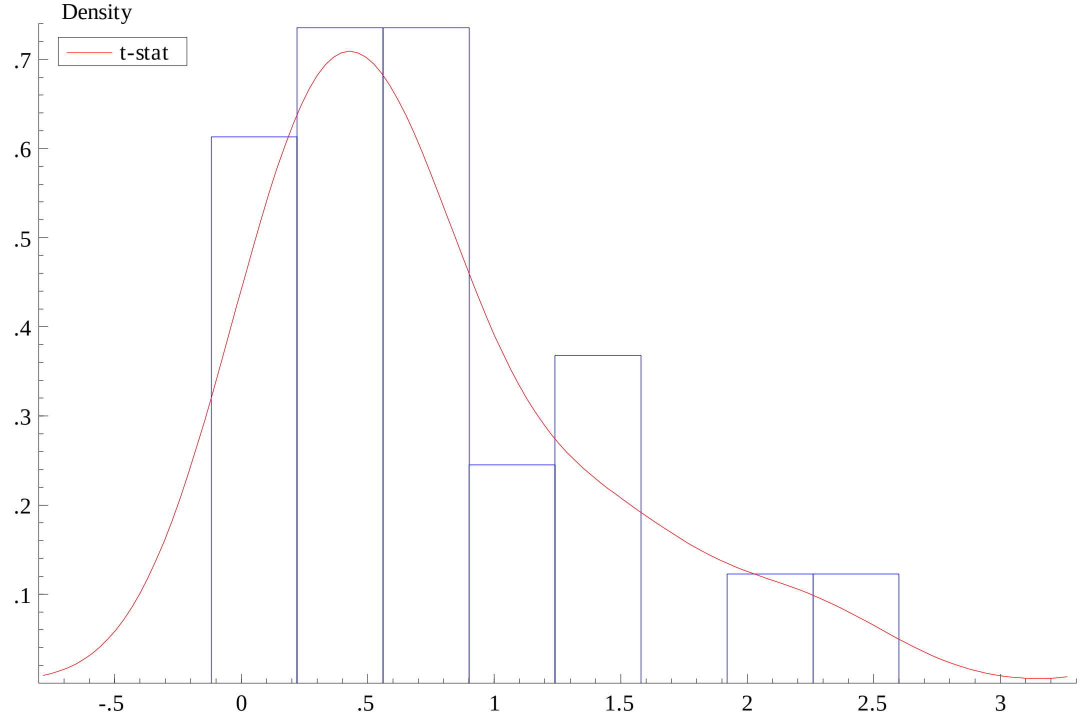


Figure 2

Distribution of T-statistics of Country-specific Coefficients on *GFDI* from Table 3



Appendix A

List of Variables

Variable[7]	Definition
GEXP	Growth rate of exports of goods and services (% of GDP)
GFDI	Growth rate of foreign direct investment, net inflows (% of GDP)
GGDP	Growth rate of GDP at market prices (constant 1987 US)
GGDI	Growth rate of gross domestic investment (% of GDP)
GINFL	Inflation, consumer prices (annual %)
HUMCAP	Human Capital (as proxied by average years of schooling of adults)
OPEN	Exports of goods and services (% of GDP)
FDIOP	GFDI * OPEN
FDIHK	GFDI * HUMCAP
GDIOP	GGDI * OPEN
GDIHK	GGDI * HUMCAP

Appendix B

List of Countries

Brazil	Mexico
Chile	Malaysia
Cote d’Ivoire	NGA
CMR	Pakistan
Colombia	Peru
Costa Rica	Philippines
Ecuador	Sierra Leon
Ghana	El Salvador
Honduras	Thailand
Indonesia	Tunisia
India	Turkey
Jamaica	Venezuela

[7] L1 indicate one period lagged variables
DD indicates first differences

References

Aitken Brian J. and Ann E Harrison. 1999. “Do domestic firms benefit from direct foreign investment? Evidence from Venezuela” *American Economic Review* 89:3 605-618.

Anderson, T.W. and Cheng Hsiao, 1982. “Formulation and Estimation of Dynamic Models Using Panel Data”, *Journal of Econometrics,* vol. 18.

Balasubramanyam, V.N., M. Salisu, and D. Sapsford, 1999. “Foreign direct investment as an engine of growth” *The Journal of International Trade and Economic Development* 8:1 27-40.

______, 1996. “Foreign direct investment and growth in EP and IS countries” *The Economic Journal* vol. 106, January.

Baldwin, R. and E. Seghezza 1996. “Testing for trade-induced investment-led growth” NBER Working paper # 5416, January.

Baltagi, Badi H. 1995. Econometric Analysis of Panel Data, John Wiley & Sons Ltd. West Sussex, England

Borensztein, E., J.D. Gregorio and J.W. Lee 1995. “How does foreign direct investment affect economic growth?” NBER Working paper # 5057, March.

Connolly, M. P. 1997. “Technological diffusion through trade and imitation” Federal Reserve Bank of New York Staff Report # 20, February.

De Mello, Luiz R. 1999, “Foreign direct investment led growth: evidence from time series and panel data” *Oxford Economic Papers* 51 133-151.

Easterly, William, M. Kremer, L. Pritchett, and L. Summers 1993, "Good Policy or Good Luck? Country Growth Performance and Temporary Shocks," *Journal of Monetary Economics*, Vol. 32, December, 459-483.

Griffith-Jones, Stephany, 1998 Global capital flows: Should they be regulated? New York: St. Martin's Press; London: Macmillan Press

Harrison, Ann, 1994. “The role of multinationals in economic development” *The Columbia Journal of World Business*, Winter.

Holtz-Eakin, D., W. Newey and H. Rosen, 1988. “Estimating Vector Autoregressions with Panel Data”, *Econometrica* vol. 56, no. 6.

Hsiao, Cheng, Analysis of Panel Data, 1986. Cambridge University Press, Cambridge, England.

Hsiao, Cheng., “Modeling Ontario Regional Electricity System Demand Using a Mixed Fixed and Random Coefficients Approach,” *Regional Science and Urban Economics*, vol. 19, 1989

Kiviet, Jan F. 1995. “On bias, inconsistency, and efficiency of various estimators in dynamic panel data models” *Journal of Econometrics* vol. 68.

Lach, S. and M. Schankerman, “Dynamics of R& D and Investment in the Scientific Sector”, *Journal of Political Economy* vol. 97, no. 4, 1989

Nickell, Stephen 1981. “Biases in Dynamic Models with Fixed Effects,” *Econometrica*, vol. 49, no. 6.

Pesaran, Hashem M. and R. Smith, 1995. “Estimating Long-Run Relationships From Dynamic Heterogeneous Panels”, *Journal of Econometrics* vol. 68.

Pesaran, Hashem M., “Estimating Long-Run Relationships From Dynamic Heterogeneous Panels”, paper prepared for presentation at the Fourth Conference on Panel Data, Budapest, June, 1992

Rodriguez-Clare, A. 1996. “Multinationals, linkages and economic development” *American Economic Review* vol. 86, no. 4.

Tsai, P. 1994. “Determinants of foreign direct investment and its impact on economic growth” *Journal of Economic Development* vol. 19, no. 1 June.

Weinhold, D and M. Klasen 1991. "Supplier Networks, Multinationals, and Development" (with M. Klasen) in *Manufacturing Across Borders and Oceans: Japan, the United States, and Mexico*, Gabriel Szekely, Editor, Center for U.S.-Mexican Studies Monograph Series, 36. University of California, San Diego.

Weinhold, D. 1996. "Investment, Growth and Causality Testing in Panels" *Economie et Prevision*, no. 126-5.

Weinhold, D. 1999 “A dynamic “fixed effects” model for heterogeneous panel data” unpublished manuscript, London School of Economics 1999.