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Technology Transfer and External Shocks: Developing Country Growth from 1960 to 1990

By N. Gemmell and R. Kneller

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Abstract

The post-war growth experience of developing countries is characterised by three main features. Firstly, enormous divergence between the best and worst performers. Secondly, low persistence in growth rates across time, and finally a general decline in the average growth rate across all countries. Our evidence suggests that these patterns in the data are consistent with a technological growth model that is subject to random shocks. External shocks explain the variability of LDCs productivity growth rates, but only over the short-run: within 5 years; whereas faster growth of the technical frontier in innovating countries is associated with faster productivity growth in LDCs on average over the long-run. There are good reasons for believing that this reflects technology spillovers, and not simply demand effects.

Outline

Non-Technical Summary

The post-war growth experience of developing countries is characterised by three main features. Firstly, in any one period there was enormous divergence between the best and worst performers. Secondly, the countries that performed well one period did not necessarily do so again the next period and finally, there has been a general decline in the average growth rate across all countries.

Taken together these observations can be thought of as broadly consistent with a technology growth model that is subject to random economic shocks. In modern growth theory economic growth is generated through investment in knowledge-generating activities such as R&D. This technical knowledge might be expected to disperse across countries via some process such as international trade or FDI. In the long-run all countries grow at an identical rate to the technical frontier, but will vary at a given point in time because temporary factors, such as economic shocks, speed up or slow down technology transfer. Economic shocks may create dispersion in growth rates across countries and low correlation of growth rates across time but technological transfer prevents countries from drifting too far apart over long periods.

Using data for 59 developing countries over the period 1960 to 1990 we find that the patterns in the data are consistent with the growth model presented. Economic shocks explain the variability of productivity growth rates, but only over the short-run: within 5 years; whereas faster growth of the technical frontier in innovating countries is associated with faster productivity growth in less developed countries on average over the long-run. We also find that the effect of economic shocks on productivity growth is greater in countries in which domestic institutions are weak or the country is divided along ethnic lines. Divisions between different social groups lead to distributional conflicts and poor management of the consequences of shocks, which in turn magnify their effect on the economy.

These results are found to be robust to a barrage of statistical tests and alternative hypothesis. Among these we include tests of whether the measure of technology transfer used in the paper in fact measures demand effects, increases in the demand for imports in one country that lead to faster growth (through exports) in another country. We find evidence that countries within the same continent display this property but less so for the technical frontier is weaker. Finally, when we search closely whether less developed countries have managed to catch-up in their technology to the technical frontier we find that the poorest countries appear to have caught up slightly, but the richest developing countries have in fact fallen behind over the period. We suggest this is because the recent technological breakthroughs in developed countries require high skill levels to implement and operate.

1. Introduction

The post-war growth experience of developing countries is characterised by three main features. Firstly, in any one period there was enormous divergence between the best and worst performers. Secondly, the countries that performed well one period did not necessarily do so again the next period and finally, there has been a general decline in the average growth rate across all countries, at least since the 1970s. In this paper we consider whether these patterns in the data are consistent with a technological growth model that is subject to random shocks.

A number of results in the present empirical literature lead us to focus on this class of models. Easterly, Kremer, Pritchett & Summers (1993) and Rodrik (1999) find that the wide dispersion in growth rates and their low persistence across time can be explained by external shocks combined with low quality domestic institutions. Divisions between different social groups lead to distributional conflicts and poor management of the consequences of shocks, which in turn magnify their effect on the economy (Rodrik, 1999).

Studying cross-time persistence in economic data leads Easterly et al. (1993) to conclude that these external shocks are associated with a decline in the rate of productivity growth, rather than investment declines. The correlation between the average rate of TFP growth for the 1960s with that of the 1970s is below 10 per cent, and rises to just over 20 per cent for the 1970s with the 1980s. In contrast, the correlation between the share of investment in GDP over the same time periods remains between 80 and 90 per cent.

Terms of trade shocks, however, cannot explain the general deterioration of GDP growth across developing countries. The mean rate of growth among developing countries has declined despite a reduction in external volatility from the 1980s onwards and despite improvements in underlying policy variables (Easterly, 2001). Instead Easterly (2001) puts forward the idea that the slowdown in OECD country growth explains this feature of the data. The role of developed countries in determining developing country growth is also consistent with the evidence on technological transfer reviewed in Keller (2001b).

Taken together these observations can be seen to be broadly consistent with a model of technological growth that is subject to random shocks. In modern growth theory economic growth is generated through investment in knowledge-generating activities such as R&D. This technical knowledge is non-rival and infinitely expandable in character and disperses across countries via some process such as international trade or FDI. In the long-run all countries grow at an identical rate to the technical frontier, but will vary at a given point in time because temporary factors, such as economic shocks, speed up or slow down technology transfer. Economic shocks may create dispersion and low persistence in any one period but technological transfer prevents countries from drifting too far apart over the long-run. (Hall and Jones, 1999).

In this paper we explore the empirical basis for this type of 'technology transfer' model. The rest of the paper is organised as follows. Section 2 presents a simple model of growth that includes economic shocks and technology transfer. This section also reviews the data and empirical approach to be used in the paper. The results from the empirical exercise are then presented in Section 3, while Section 4 considers their robustness to a range of measurement and estimation issues. Conclusions are reached in Section 5.

2. Data and empirical methodology

In order to motivate the empirical section of the paper we briefly outline a simple technology gap model (Krugman, 1985) to which we add external shocks. Consider an economy, i, in which output at time t is produced using the following production technology, where L is labour, K is capital and A is technical efficiency or total factor productivity (TFP).

$$Y_{it} = A_{it} f_i (L_{it} K_{it}) \tag{1}$$

Advances in technology are a product of investments made in knowledge generating activities such as R&D. Only the most technologically advanced country, F, makes these investments. To focus on aspects of interest and to simplify the analysis we do not attempt to explain how country F advances technology, assuming instead that the stock of knowledge available to country i grows at the constant exogenous rate, γ_F:

$$A_{F,t} = \exp(\gamma_F t) \tag{2}$$

Given the focus of the paper on developing countries the assumption that advances in technology are exogenous to country *i* would appear reasonable. Even for many OECD countries the major sources of technological change are found to be external rather than internal to the country (Eaton and Kortum, 1999; Keller, 2001a).[1]

Technical knowledge is assumed to be non-rival and infinitely expandable in character, but does not disperse instantaneously across space. Instead countries are exposed to these new ideas as they undertake international trade, receive foreign direct investment, through personal contact or some other such mechanism. The lag in the acquisition of new technology results in a level of total factor productivity in the non-innovating country, *i*, that is below that of the frontier country. The size of this gap is captured by the size of the lag with which new knowledge is acquired, λ_t in equation (3) below. However, productivity in country *i* may also lie below the frontier because of differences in the efficiency with which a given foreign technique is applied domestically. Countries may differ in this respect because the application of new technologies does not provide identical yields in all countries, the technology may be 'inappropriate', because of innate differences in the ability to utilise new technology, or differences in the absorptive capacity of individuals.[2] To capture both these influences, technological efficiency in country *i* at time *t* may be defined as:

$$A_{i,t} = g_i(A_F) = \exp[\gamma_F(t - \lambda_i) - \sigma_i] \qquad \lambda_i \geq 0\,; \quad \sigma_i \geq 0 \qquad (3)$$

where the degree of domestic *inefficiency* is measured by σ_t, such that productivity is lower the larger is σ_t. Equation (3) collapses to equation (2) when the time lag between the innovation and acquisition of new technologies, λ_i, is zero (as it may be for advanced economies), and there is no loss of efficiency associated with domestic applications ($\sigma_t = 0$).

[1] Alternative models that allow endogenous technology growth can be found in Stadler (1990), Saint-Paul (1993), Martin & Rogers (1997) and Blackburn (1999).
[2] For example, Acemoglu and Zilibotti (2001, p.601) argue, and find some evidence, that 'technologies developed in the North may be inappropriate not only to the skills, but to a range of other conditions prevailing in the South. Climate, tastes, cultures and institutions affect the relative productivities of different technologies.' Policy environments, for example, have been shown to have important effects on productivity of per capita GDP growth. On macroeconomic policy, see Easterly et al (1993) and Fischer (1993); on fiscal policy, see Kneller et al (2000).

In the steady state the growth of technical progress in country *i* will be equal to the rate of technical progress of the frontier economy, $\gamma_i = \gamma_F$, the lag in the acquisition of knowledge and the efficiency with which new technology is used is constant. In the transition to this steady state, technical progress will depend on: (i) changes in the technical frontier that period; (ii) changes in the rate of technological transfer λ_t; and (iii) changes in domestic efficiency, σ_i. Differentiating (3) with respect to time yields an expression for the growth rate of TFP in country *i*, $\frac{\dot{A}_i}{A_i} = \gamma_i$, at a given point in time.

$$\frac{\dot{A}_i}{A_i} = \gamma_i = \gamma_F(1 - \dot{\lambda}_i) - \dot{\sigma}_i \tag{4}$$

where γ_F is the growth rate of the frontier, $\dot{\lambda}_i$ is the change in the lag parameter, and $\dot{\sigma}_i$ is the change in domestic efficiency.

We hypothesise that external volatility, $\varepsilon_{i,t}$, affects both the speed with which foreign technology is acquired, and the economy's ability to apply a given technology. While we do not formalise the mechanisms through volatility affects technological transfer or efficiency a number might be considered relevant. For example, volatility may discourage foreign firms from undertaking investment in country *i* reducing the direct transfer of knowledge through FDI. Alternatively, volatility may affect the decisions of domestic firms to import new technologies from abroad, and may encourage investment and employment decisions that are 'wasteful' (including rent-seeking by individuals). All of these will divert resources away from the productive sectors of the economy slowing the rate of technological transfer. The impact of this on the economy may be magnified, as Rodrik (1999) argues, where there is a high likelihood of conflict between different social groups within society. However, exogenous technical progress ensures that all of these effects of external shocks on technological progress are not permanent. Summarising the effects of exogenous volatility by:

$$\dot{\lambda}_i = h_i(\varepsilon_{i,t}), \text{ and} \tag{5.1}$$

$$\dot{\sigma}_i = g_i(\varepsilon_{i,t}), \tag{5.2}$$

and substituting into equation (4) gives:

$$\frac{\dot{A}_i}{A_i} = \gamma_i = \gamma_F (1 - h_i(\varepsilon_{i,t})) - g_i(\varepsilon_{i,t}) \,. \qquad (6)$$

This simple model provides us with a set of testable predictions. Firstly, TFP growth in developing country *i* depends on the rate of growth of the technical frontier. Secondly, external shocks may temporarily slow the rate of TFP growth in developing countries either directly via reduced domestic efficiency, or indirectly through the technological transfer term, or both.

A functional form through which the predictions of this model can readily be tested is given by equation (7.1), where changes in domestic efficiency and technological transfer are assumed to be a linear function of external volatility, V_i:

$$\begin{aligned}\gamma_{it} &= \alpha_{0i} + \alpha_1 \gamma_{i,t-1} + \alpha_2 \gamma_{F,t} + \alpha_3 \gamma_{F,t-1} + \alpha_4 V_{i,t} + \alpha_5 V_{i,t-1} \\ &\quad + \alpha_6 (\gamma_F V_i)_t + \alpha_7 (\gamma_F V_i)_{t-1} + u_{it}\end{aligned} \qquad (7.1)$$

Alternatively, the error-correction form in equation (7.2) may be estimated where both the short- and long-run effects of external shocks are separately identified:

$$\begin{aligned}\Delta\gamma_{Ait} &= \beta_{0i} - \beta_1 \gamma_{i,t-1} + \beta_2 \gamma_{F,t-1} + \beta_3 V_{i,t-1} + \beta_4 (\gamma_F V_i)_{t-1} \\ &\quad + \beta_5 \Delta\gamma_{F,t} + \beta_6 \Delta V_{i,t} + \beta_7 \Delta(\gamma_F V_i)_t + u_{it}\end{aligned} \qquad (7.2)$$

$$\beta_1 = (1-\alpha_1); \quad \beta_2 = (\alpha_2 + \alpha_3); \quad \beta_3 = (\alpha_4 + \alpha_5); \quad \beta_4 = (\alpha_6 + \alpha_7)$$

where γ_i = rate of TFP growth in country *i*; γ_F = rate of growth of the technical frontier; V_i = external volatility; and u_{it} is the usual classical error term. (7.2) is similar to the regression estimated by Rodrik (1999) in which the change in GDP growth is a linear function of external shocks. Following Bleaney, Gemmell & Kneller (2001) we allow lagged values of the independent variable to affect growth, even though the regression is estimated using 5-year period averages.

The coefficient β_1 in (7.2) measures the rate at which countries adjust to the long-run, while β_2 and β_5 respectively capture the long-run and short-run effects of growth in the technical frontier on domestic growth.[3] Similarly, β_3 and β_6 provide information on the direct

[3] The magnitude of this long-run effect is, of course, measured by β_2/β_1.

(domestic) effects of external shocks in the long and short-run respectively; while β_4 and β_7 are the equivalent indirect effects via technological transfer.

While we would expect TFP to grow at the same rate in all countries in the steady state (i.e. $\beta_2 = -\beta_1$), it is likely that the data period available to us is too short to capture these long-run effects fully. Therefore in regressions using the form in (7.2), the parameters β_1 and β_2 will provide information on whether the developing countries in the sample are converging towards, or diverging from, the technological frontier over the period. The condition: $|\beta_1| < \beta_2$ implies convergence of country *i* toward country *F* (from below); $\beta_2 = -\beta_1$ suggests that, ceteris paribus, the distribution of productivity across countries remains constant across time; and $|\beta_1| > \beta_2$ indicates divergence.

In the above model if volatility has a significant short-run effect on technology we expect $\beta_6 < 0$ and/or $\beta_7 < 0$, but $\beta_3 = \beta_4 = 0$ if there are no significant long-run effects from volatility. However both Easterly et al. (1993) and Rodrik (1999) appear to find long-run effects of volatility on GDP growth. If this is also reflected in TFP growth rates then we might expect β_3 and/or β_4 significantly less than zero. Following Temple (1999) we allow β_0 to vary across groups of continents rather than countries, where $\beta_0 \neq 0$ implies long-run differences in the level of TFP across continental groupings.

2.1. Data

Technological change is approximated in this study using total factor productivity growth. Benchmark estimates of TFP growth are made in this section using the Solow residual from a Cobb-Douglas production function of the form:

$$\Delta TFP = \Delta Y - \alpha \Delta K - (1-\alpha)\Delta L \tag{8}$$

A value of α equal to $1/3^{rd}$ and constant returns to scale are imposed on the equation. The limitations of such a measure of technology are well known (Hulten, 2000). In section 4 we test the robustness of the results to alternatives that adjust for changes in the quality of the labour input, remove restrictions regarding the functional form of equation (8), and the value of the imposed factor shares.

The GDP and capital stock data needed to estimate total factor productivity are taken from the World Bank databank (Nehru and Dhareshwar, 1993). Complete data are available for 59 developing countries over the period 1960 to 1989. This data set has been used previously by Duffy and Papageorgiou (2000) amongst others and is preferred to alternatives such as the Penn World Tables for reasons of data coverage. The data is available in 1987 constant local prices. In order to make international comparisons this is converted to US$ using the 1987 $/local currency exchange rate.[4] Finally, data on labour force size are taken from the Penn World Tables.

As is well documented, growth accounting measures of TFP tend to produce productivity estimates that are pro-cyclical in nature (Fernald and Basu, 1999). This may reflect, for example, unmeasured changes in the intensity with which factor inputs are used, so reducing the strength of the correlation between measured TFP and 'true' technological change, the variable of interest. One approach to deal with this would be some form of smoothing technique on the data. However, balanced against this are findings from the growth literature suggesting that the strength of the correlation between GDP growth and volatility is dependent on the time dimension of the volatility variable (Kneller and Young, 2001). This is found to be important both with respect to the period over which estimation is made, but also with respect to the length of the period over which volatility is measured. Volatility appears to have a stronger effect on GDP growth when the former is constructed from data for a shorter period. Thus, 'smoothing' of TFP over longer periods may well remove some of the short-tun effects on technology that we are seeking to identify. As a compromise we average the data across 5 year periods, which also makes for easier comparisons with earlier studies.

To approximate the technical frontier we use the level of TFP in the most technically advanced country, the US. In Section 4 we construct an alternative measure of the technical frontier using data for the G7 countries. Given that very little R&D is conducted outside of OECD countries endogeneity between TFP growth in developing countries and the frontier is unlikely to be of concern. Easterly (2001) provides further evidence is support of this. Finally, as in Rodrik (1999), external volatility is approximated using the log standard deviation in the (growth of the) terms of trade over 5-year periods.

[4] Large currency revaluations in Brazil, Mexico and Uruguay meant that the decision was made to omit these

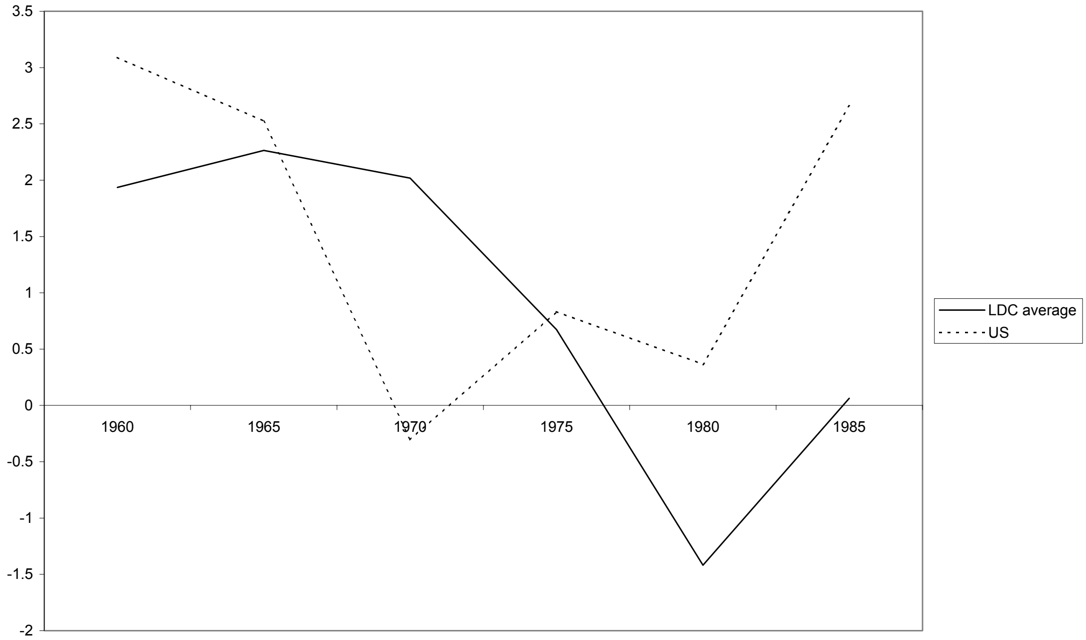
An initial glance at the data is suggestive of some support for the arguments put forward in the paper and match the main characteristics of developing country growth discussed above. Figure 1 plots average external volatility (across all countries) and the standard deviation in the growth rate of TFP (across all countries) over time. As suggested by Easterly et al. (1993) the cross-country variation in growth rates does appear to coincide with the periods in which external shocks were more prevalent

Figure 1: TFP Growth and External Volatility in Developing Countries (LDCs), 1960-1989

Figure 2 plots the average rate of growth of TFP for all developing countries over each 5-year period against the average rate of growth of the frontier, the US. There is evidence of co-movement here, except for 1975 when TFP growth in the developing countries did not experience the recovery observed in the US. An overall decline in the average rate of TFP growth for developing countries across time (at least until the late-1980s) is also evident in the data.

countries from the sample.

Figure 2: TFP Growth in the US and Developing Countries (LDCs), 1960-1989



3. Empirical results

The model of section 2 suggested two mechanisms by which volatility might affect a country's TFP growth – an 'indirect effect' via technology transfer from the frontier country, and by directly affecting domestic efficiency in the application of a given technology. Using equation (7.2), we begin by including both the direct and indirect effects separately in regressions 1 and 2 respectively in Table 1. Regression 3 includes both volatility effects simultaneously. Continent dummies for Sub-Saharan Africa (SSA) and Latin American countries (LAC) are also included in the regression, although we do not report the coefficients on these variables to conserve space.[5] Limitations on the time dimension of the panel mean we restrict the regression equation to include a single lag of the dependent and independent variables.

Productivity Persistence

The coefficient on lagged TFP growth in country *i*, β_1, is within expected bounds (−1, 0) in both regressions 1 and 2, and is very close to –1. An F-test on the restriction β_1 = -1 cannot be rejected at the 5 per cent level.[6] A similar result is found by Rodrik (1999) and would

[5] The estimated parameters on these dummies are consistently found to be significantly negative.

[6] The test statistic is 0.13 and 0.15 in regressions 1 and 2 respectively against a critical value of $F(1, 285) \cong 3.9$ at the 5 per cent level.

appear to confirm the evidence of Easterly et al. (1993) that TFP growth displays little persistence across time. More precisely, productivity growth in country *i* in one 5-year period is essentially unrelated to that country's productivity growth during the previous five years. The acceptance of this restriction would allow us to estimate equation (7) in a form typical of that estimated in the growth literature, where the growth rate (of TFP in this case) is used as the dependent variable and lagged growth does not appear among the independent variables. The result (that $\alpha_1 = 0$; $\beta_1 = -1$) also suggests that any bias generated by the inclusion of a lagged dependent variable in the estimated regression is not serious.[7]

Technology transfer

In both regressions 1 and 2 the coefficient on long-run growth of the frontier, β_2, is both positive and significant, supporting the finding of Easterly (2001) that changes in the rate of growth of developed countries help to explain changes in the rate of growth of developing countries over time. Notice also that the (contemporaneous) short-run parameter estimate (α_2) is negligible and insignificant, indicating that it is the 5-year lagged effect of US productivity growth that dominates the long-run impact on LDCs. This result raises two questions. Firstly, to what extent does this evidence suggest convergence or divergence of developing countries TFP levels towards those of the US? Secondly, our model hypothesises that β_2 captures the impact of US technology transfers, but can we be confident that our estimates are not merely picking up co-movements in productivity across the world economy in response, for example, to global demand or supply shocks? We consider the initial evidence from Table 1 regarding the first of these issues, but leave further analysis and the second issue to later in this section.

As noted earlier the magnitude of the long-run parameter on changes in the frontier, given by $-\beta_2/\beta_1$, provides information as to whether technology transfer enables LDCs' productivity levels to converge towards those of the US. In both regressions 1 and 2: the point estimate is around 0.8 (and is robust to the changes in specification in Table 2). This suggests that, ceteris paribus, the gap between technology in developing countries on average and the technological frontier has increased over the period. However, an F-test of

[7] Since the work of Arellano and Bond (1991) it has been recognised that estimates of the parameter on the lagged dependent variables in OLS or fixed-effects models may be biased away from zero. In the present context this implies a bias in favour of finding $\alpha_1 \neq 0$, or equivalently $\beta_1 \neq -1$. By contrast our estimates suggest β_1 is very close to -1.

the restriction that $-\beta_2/\beta_1 = 1$ (i.e. the technological gap has remained static over the period) cannot be rejected.[8] The evidence is therefore also consistent with the view that, over the long-run, LDCs' technical know-how has neither caught-up with nor fallen behind that of the US. Certainly there is no evidence here of productivity convergence in the average.

Volatility

Regression 1 also reports the direct effects of external volatility, both short-run (α_4 and α_5) and long-run (β_3). Regression 2 reports the indirect equivalent where volatility affects productivity only via technological transfer. Both cases support the model presented in Section 2 in which the long-run effect of external volatility on TFP growth is both small and statistically insignificantly different from zero. Secondly, as expected, the initial direct effect of external volatility is to lower TFP growth significantly ($\alpha_4 = -0.27$). The indirect effect, however, is much smaller and insignificantly different from zero ($\alpha_5 = -0.07$). Thus, external volatility appears to affect short-run technology growth but has no effect on the long-run and does not appear to operate via technological catch-up. Results for the nested case in regression 3, when we allow both direct and indirect effects of volatility, reinforce this conclusion. Short-run effects (i.e. up to five years) of volatility on productivity growth continue to show up strongly ($\alpha_4 = -0.303$) but indirect effects cannot be identified.[9]

Finding no long-run effect from volatility contrasts with evidence presented in Easterly et al. (1993), but also the empirical literature on volatility and GDP growth. Fischer (1993), in one of the few studies to have considered the effect of macroeconomic factors on TFP growth, finds that the black-market exchange rate premium (which Rodrik and Rodriguez, 2001, argue can be used as a measure of general macroeconomic volatility) is negatively correlated with TFP growth. Ramey and Ramey (1995), Grier and Tullock (1989) and Kormendi and Meguire (1985) all find an alternative measure of volatility (the standard deviation of GDP growth over a given period) has a negative effect on GDP growth.

[8] The test statistics for regressions 1 and 2 are 0.57 and 0.36 respectively against a critical value of $F(1, 285) \cong 3.9$ at the 5 per cent level.

[9] It may be that our failure to identify indirect effects simply arises because the data are not sufficiently refined to allow both individual and interactive terms to be separately identified. It would appear not to be due to collinearity among the frontier and volatility variables. The correlation between the measure of indirect volatility and the frontier is only 0.32.

Given that many of those papers also use 5- or 10-year period averages but without lag structures, the suggestion is that differences between those results and ours probably follow from the dynamic specification used in the estimation of equation (7). As a result previous papers have not been able to identify whether the effects of volatility on growth occur contemporaneously or with a lag. Evidence in support for this claim is found when equation 7.1 is estimated without dynamic adjustment terms. Then, and in accordance with the previous literature, external shocks enter the regression with a significant negative coefficient.[10] The results from Rodrik (1999) are also consistent with the above findings. Like Rodrik the estimated coefficients for volatility in regressions 1 and 2 imply that the change in the rate of growth between two time periods is negatively correlated with external volatility. The initial effect from an external shock is to lower the growth rate.

Further supportive evidence for the results found here can also be inferred from Kneller and Young (2001). As we noted earlier, in that paper the effect of volatility on growth is found to depend on the length of the time period over which the measure of volatility is constructed. A weaker correlation between volatility and GDP growth is found the longer the period average used. One interpretation of this evidence is that the effects of volatility on growth are not permanent.

Table 1: Regression Results

			1	2	3
Long-Run	*Frontier*	β_2	0.780* (0.24)	0.810* (0.25)	0.726* (0.26)
(direct)	*Volatility*	β_3	-0.053 (0.13)	-	-0.104 (0.18)
(indirect)	*Frontier* Volatility*	β_4	-	-0.007 (0.10)	0.061 (0.12)
	Adjustmen	β_1	-0.973* (0.07)	-0.970* (0.07)	-0.973* (0.07)
Short-Run	*Frontier$_t$*	α_2	0.069 (0.18)	0.175 (0.21)	0.014 (0.21)

[10] The results from this regression are not reported to conserve space, but are available from the authors on request.

	Frontier$_{t-1}$	α_3	0.711* (0.17)	0.635* (0.18)	0.712* (0.19)
direct)	*Volatility$_t$*	α_4	-0.266* (0.15)	-	-0.303** (0.18)
direct)	*Volatility$_{t-}$*	α_5	0.213* (0.08)	-	0.199** (0.11)
indirect)	*Frontier * Volatility$_t$*	α_6	-	-0.072 (0.12)	0.057 (0.11)
indirect)	*Frontier* Volatility$_{t-}$*	α_7	-	0.066* (0.03)	0.003 (0.04)
	Countries		59	59	59
	Obs.		293	293	293
	R^2		0.53	0.52	0.53

Note: standard errors in parenthesis; * (**) = significance at the 5% (10%) level.

3.1.Further Results

Positive versus negative shocks

By definition volatility involves both positive and negative shocks, and the above methodology assumes that both types of external volatility are identically bad for productivity growth. It is possible however that volatility in the terms of trade could have more adverse effects on TFP growth when the terms of trade are declining compared to situations of improvement. That is, uncertainty may be more adverse in an already difficult macroeconomic environment. In the above results, if the effects of positive and negative shocks are broadly offsetting this may also explain why no long-run effects from volatility are found.

To investigate this possibility volatility is separated into periods in which the terms of trade were increasing and periods in which the terms of trade were decreasing. In Appendix Table A1 we report regressions which add one of the following expressions:

$$\delta(\beta_3 V_{i,t-1} + \beta_6 \Delta V_{i,t}) \qquad \text{(regression A1)}$$

$$\delta[\beta_3(\gamma_F V_i)_{t-1} + \beta_6 \Delta(\gamma_F V_t)_t] \qquad \text{(regression A2)}$$

where *δ=1* when the terms of trade have fallen over the 5-year period and *δ=0* when the terms of trade rose over the period. Results suggest, however, that there is no additional adverse effect of volatility when this is associated with terms of trade declines. We conclude that it is volatility in the terms of trade *per se* which lowers TFP growth in the short-run.

Social conflict

Rodrik (1999) argues strongly that the effects of external shocks on GDP growth can be expected to be lower in countries with little social conflict and strong domestic institutions, because such conditions reduce the incentives to indulge in rent-seeking behaviour. We explore this possibility by adding the following direct and interaction terms to equation (7), capturing the impact of 'social institutions' (*SI*).[11]

$$\alpha_3 \Delta V_{i,t} * SI + \alpha_6 SI_{i,t}$$

or

$$\alpha_3 \Delta(\gamma_F V_i)_t * SI + \alpha_6 SI_{i,t}$$

To measure *SI* we use (i) an index of ethnic diversity (ETH) from the World Bank databank, and (ii) an index of corruption (COR) from Knack & Keefer (1997).[12] We prefer this latter variable to similar measures found elsewhere in the literature for reasons of data coverage.[13]

The results from these regressions are displayed as regressions 4 to 8 in Table 2. In regression 4, external volatility interacted with the ethnic mix is significant and negative. That is, the greater the degree of ethnic diversity within a country the greater (more negative) is the effect of external shocks on TFP growth. This result is the same as that found by Rodrik for GDP growth. Regression 4 also suggests a negative direct effect from the ethnic heterogeneity variable (although the coefficient on this variable lies just outside of the 10 per cent level of significance). The short-run effect of external volatility on TFP growth is now insignificantly different from zero at conventional levels of significance, and indeed is now positive.

When the indicator of corruption within society (*COR*) is used as an alternative test of heterogeneity in the estimated parameters (regression 5) a significant negative interaction

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[11] We allow social institutions to affect the short-run behaviour of volatility on TFP growth only. The results regarding the effect of volatility on long-run productivity growth and the effect of social institutions through short-run volatility are unaffected by including an interaction term with long-run volatility.

[12] Corruption is measured as the inverse of the Knack & Keefer (1997) index so that the interaction term is expected to be negative.

[13] The Mauro (1995) data is available for only 35 of the 59 countries used in the sample. The missing observations from this data set are concentrated in Sub-Saharan Africa and Latin America, which is also where the worst economic performers are concentrated. Within our dataset, data are unavailable for China and Bangladesh for ETH, and for Algeria, Mauritius, Rwanda, S. Africa, Sri Lanka and Taiwan using COR.

term is again found. TFP growth in countries in which social institutions are strong tend to be less affected by external volatility than countries in which social institutions are weak. In addition this regression finds evidence of direct negative effects on TFP growth from both external volatility and social institutions.

In regressions 6 and 7 we consider whether social institutions might affect TFP growth by inhibiting the acquisition of foreign technology (α_7). There is some evidence that the effect of volatility on technological catch-up is larger in countries in which the population is more heterogeneous. However, these 'indirect' effects appear to be less strong than the 'direct' effects captured in regressions 4 and 5. Whether this reflects a genuinely stronger direct effect or simply the difficulties of identifying, within the dataset, effects transmitted via the indirect route of our technological catch-up variable remains unclear.

Table 2 The Impact of Social Institutions

			4	5	6	7	8
			Social institutions variable:				
			ETH	*COR*	*ETH*	*COR*	*ETH*
Long Run	*Frontier*	β_2	0.824* (0.24)	0.803* (0.25)	0.824* (0.24)	0.823* (0.25)	0.812* (0.24)
	SI (ETH)		-0.015 (0.01)	-	-0.015 (0.01)	-	-0.014 (0.01)
	SI (COR)		-	-0.404* (0.15)	-	-0.403* (0.15)	-
	Adjustment	β_1	-0.977* (0.07)	-0.958* (0.07)	-0.969* (0.08)	-0.960* (0.08)	-0.972* (0.07)
Short Run	*ΔFrontier$_t$*	α_2	0.062 (0.19)	0.068 (0.19)	0.167 (0.20)	0.188 (0.21)	0.124 (0.21)
	ΔFrontier$_{t-1}$	α_3	0.762* (0.18)	0.734* (0.19)	0.657* (0.19)	0.635* (0.20)	0.687* (0.19)
	ΔVolatility$_t$	α_4	0.396 (0.30)	-0.388* (0.14)	-	-	0.491 (0.45)
	ΔVolatility$_t$ SI*	α_5	-0.008* (0.004)	-0.054** (0.03)	-	-	0.024 (0.17)
	Δ(Frontier Volatility)$_t$*	α_6	-	-	0.184 (0.13)	-0.157 (0.14)	-0.009** (0.005
	Δ(Frontier Volatility)$_t$**	α_7	-	-	-0.005** (0.003)	-0.022 (0.03)	-0.002 (0.003)

	I						
	Countries		57	53	57	53	57
	Obs.		283	263	283	263	283
	R^2		0.53	0.53	0.53	0.52	0.54

Convergence or divergence?

The evidence presented thus far suggests little evidence for convergence between US and LDC TFP levels over the sample period. We can explore this convergence issue further by restricting the sample by the level of TFP. In regressions 9 and 10 (Table 3) we replicate regression 1 but use only those observations from the bottom and top quartiles respectively of the distribution of TFP. The coefficient on long-run changes in the frontier is now substantially greater than one (1.38) when countries with very low TFP levels are used, but below one (0.56) for countries with the highest level of TFP.[14] As previously however, F-tests of the restriction that $-\beta_2/\beta_1 = 1$ cannot be rejected, suggesting that these point estimates must be treated with caution. Nevertheless, with such different estimates for the two sub-samples, we are inclined to interpret these results as evidence of convergence towards the middle for the sample of developing countries. Other things equal, countries with the poorest technology levels would appear to be reducing the size of the lag between domestic technology and US technology, whilst the lag for LDCs with initially better technologies is, if anything, increasing.

How does this compare with existing evidence in the literature? Our approach is closest in spirit to Acemoglu and Zilibotti (2001) who seek to explain productivity differences across both developed and developing countries.[15] They argue that, even with unrestricted access to best-practice US technology, LDC productivity levels are likely to remain below those of the US because technological developments in the latter are increasingly skill-biased,

[14] Running the same regressions using the specification in regression 2 does not alter this conclusion. We have also investigated how far these results might be influenced by the presence of outliers in the dataset and find that the parameter estimates on our technology frontier variable remain consistently above and below one respectively for the bottom and top quartile regressions. Results are available from the authors on request.

[15] Other evidence on technology transfer includes Keller (2001a) who finds, that the benefits from foreign R&D expenditure (approximating the growth of technical knowledge), declines with distance across OECD countries. See Venables (2001) for a more general review of this literature, which typically finds that a country's TFP is affected less the greater the economic and/or geographic distances involved. This finding contrasts with that of Easterly (2001). Using a different sample of countries and the growth rate of GDP, he finds a coefficient on the growth rate of OECD trading partners' GDP is substantially greater than one, implying conditional convergence.

creating a mis-match with the skill-scarce environments in most LDCs. While their evidence does not have a time-series dimension, and focuses on relatively high-income LDCs, it suggests significant LDC-US technology differences in the 1990s are due to the inappropriateness of new US technologies to LDC environments.

This may help to explain the apparent divergence of LDCs with higher TFP from the US in our results. To examine this further, in regressions 11 to 13 we substitute an ‘LDC frontier country’ (the LDC with the highest TFP in each period) for the US. Regression 11, which uses the full dataset, shows that there is indeed convergence of LDCs as a whole on what might be termed ‘best practice LDC technology’; and an F-test accepts $-\beta_2/\beta_1 > 1$. Similarly, when only the top and bottom quartiles are considered (regressions 12 &13), now both groups exhibit evidence of convergence. This suggests a plausible scenario: technology transfer in earlier decades from the US to the richer LDCs is now trickling down to the poorer LDCs causing their TFP to grow sufficiently rapidly to converge both towards those richer LDCs and the US. However, more recent, skill-biased technology emanating from the US is now less readily applied in LDCs such that TFP growth in the richer LDCs (the obvious first destination for such technology) is incapable of keeping up with US productivity growth.

Table 3 Testing for convergence

			)	10	11	12	13	14
			3ottom 25% TFP ample	Top 25% TFP ample	Using LDC frontier: Full ample	3ottom 25% TFP ample	Top 25% TFP ample	Full ample
Long-run	*Frontier*	β_2	.377* (0.42)	).563 (0.48)	.557*).244)	.327* (0.481)	.510* (0.441)	).467** (0.252)
	'Local Frontier'							).212* (0.083)
Short run	*Frontier$_t$*	α_2	).482 (0.32)	).137 (0.38)	).807	).677	).501	0.016 (0.125)
	Frontier$_{t-1}$	α_3	).896* (0.30)	).426 (0.32)	).751* (0.130)	).680*).250	.009* (0.24)	).484* (0.207)
	'Local Frontier$_t$'							).235* (0.068)
	'Local Frontier$_{t-1}$'							0.023 (0.064)
	Adjust-ment	β_1	0.888* (0.12)	0.972* (0.20)	1.017* (0.069)	0.989* (0.124)	1.013* (0.170)	0.984* (0.071)

	Countries		23	19	59	23	19	54
	Obs.		84	83	293	84	83	263
	R^2		0.62	0.52	0.55	0.57	0.56	0.56

Note: These regressions follow the specification in Table 1, regression 1. Other parameters are omitted to conserve space. Standard errors in parenthesis; * (**) = significance at the 5% (10%) level.

Technology transfer or common shocks?

In equation (7.2) β_2 measures the long-run (up to 10 years) impact of US TFP growth on TFP growth in developing countries. We have interpreted this as a measure of technology transfer from the US. But could it simply reflect the fact that demand and supply shocks tend to be transmitted around the world, so that both per capita income and TFP growth rates in the US, LDCs (and, for that matter, other OECD countries) tend to move together? Distinguishing between these hypotheses is likely to be difficult with the data available to us. However two aspects of our results suggest that technology transfer is at least a part of the story.

Firstly, all of our results show that the effect of US TFP growth on LDCs is not contemporaneous, but occurs with a (5-year) lag. If common shocks or trends, or even the transmission of US demand shocks around the globe, were the driving forces behind this evidence we might expect this to occur substantively within a 5-year period. Secondly, since demand and supply shocks tend to affect countries in the same region similarly, we re-estimated regression 1, adding a 'local frontier' term (the country in the local continental group with the highest TFP). This is shown in regression 14. It can be seen that though the coefficient on the US frontier is now lower, it continues to be significantly positive, while the positive long-run effects from the 'local frontier' are almost entirely contemporaneous. This latter evidence would suggest that while a 'common shocks' interpretation may be more appropriate for the observed local effects, technological spillovers are a more likely explanation for the US case.[16]

[16] When we substitute the *least* productive local LDC for the 'local leader', results are similar – strong positive contemporaneous effects on LDC TFP growth – suggesting further that local spillovers of TFP reflect common shocks rather than any transfer of best practice local technology. By contrast, when we treat the highest TFP LDC (globally) as the 'frontier country' (instead of the US) and include a 'local leader' in the regression, substantial lagged spillover effects from the LDC frontier are observed, while local spillovers remain entirely contemporaneous.

4. Robustness tests

To test whether the above results are a product of the methods used to estimate TFP or the frontier growth rate we consider three alternative measures of TFP growth, all generated using the same growth accounting framework, and two alternative measures of the rate of growth of the technical frontier. Overall the results are robust to changes in methodology. All of the reported regressions use an equivalent specification to regression 1 in Table 1 and are presented in Table 4 below.

Imposed Factor Shares

Growth accounting estimates of TFP are known to be sensitive to the choice of factor shares imposed in equations such (7) above (McGrattan and Schmitz, 1998). The exponent on capital in the Cobb-Douglas production function that underlies the calculation of the Solow residual used so far is set to 1/3rd. We begin by testing the robustness of the results to an alternative value set to 0.4.

The regression results presented in regression 15 are very similar to those from regression 1. Developing country TFP growth is positively correlated with movements in US TFP growth, while there is no evidence of convergence. The point estimates on the long-run frontier variable and the adjustment parameter are statistically equal and of opposite sign. External shocks have a negative contemporaneous effect on TFP growth, but there is no evidence of a permanent effect on the growth rate.

Table 4 Robustness Tests

			15	16	17	18	19
			Factor Share	Human Capital	CES	Technical Frontier	
						G7	Trade weighted
Long-run	*Frontier*	β_2	0.918* (0.26)	0.477* (0.24)	0.748* (0.24)	1.131* (0.19)	1.207* (0.21)
direct)	*Volatility*	β_3	-0.066 (0.14)	-0.124 (0.11)	-0.102 (0.08)	-0.047 (0.13)	-0.044 (0.12)
Short run	*Frontier$_t$*	α_2	0.191 (0.19)	-0.468* (0.20)	0.007 (0.20)	0.466* (0.19)	0.856* (0.26)
	Frontier$_{t-1}$	α_3	0.727* (0.20)	0.945* (0.19)	0.740* (0.18)	0.665* (0.18)	0.351 (0.24)
direct)	*Volatility$_t$*	α_4	-0.297** (0.17)	-0.344* (0.11)	0.208* (0.10)	-0.256** (0.15)	-0.251* (0.14)
direct)	*Volatility$_{t-1}$*	α_5	0.231* (0.09)	0.221* (0.06)	0.106* (0.05)	0.209* (0.08)	0.207* (0.08)

	djust-nent	β_1	-0.976* (0.07)	-0.968* (0.10)	1.011* (0.005)	-0.994* (0.07)	-0.950* (0.08)
	Countries						
	Obs.		293	250	293	293	282
	R^2		0.52	0.49	0.97	0.55	0.52

Human Capital

The benchmark estimates of TFP also do not allow for changes in the quality of labour over time. Here we augment the production function that underlies equation (7) above to include human capital.

$$Y = AK^{\alpha}H^{1-\alpha} \qquad (8)$$

Human capital is measured using the returns to schooling and takes the form used in Hall and Jones (1999).[17] Human capital depends on some function $\phi(.)$ of years of schooling, s. Years of schooling is measured as the average years of schooling in the total population over age 25 from Barro and Lee (2000). Following McGrattan and Schmitz (1998) we set $\phi(s_i) = 0.095s_i$ so that.

$$H_i = (e^{\phi(s_i)})L_i \qquad (9)$$

The use of this human capital adjusted measure of TFP has some interesting effects on the estimated parameters. The estimated relationship between changes in US TFP growth and LDC TFP growth is weaker than in regression 1. The long-run point estimate is 0.477 in regression 16 compared to 0.810 in regression 1. The contemporaneous and lagged effect of US technology from this regression also contrast with those estimated elsewhere in the paper. The contemporaneous correlation between US technology and growth in LDCs is negative, although the lagged effect remains strongly positive. That is, increases in US technology now appear to increase the productivity gap in the first time period but in the second time period LDCs imitate new technologies and close the technology gap.

The coefficient on the adjustment term again suggests low persistence in TFP growth rates, such that overall regression 16 suggests divergence in productivity levels between the US and LDCs over the time period. Formal statistical test are inconclusive on this point

[17] The form of the production function in (8) assumes that output growth is affected by the growth, but not the level, of human capital, though Gemmell (1996) and Krueger and Lindahl (2001) find some evidence for both effects.

however, though an F-test that $-\beta_2 = \beta_1$ is rejected at the 10 per cent level.[18] The effect of external volatility on TFP in developing countries is unchanged in regression 16.

CES Production Technology

To test whether assuming Cobb-Douglas technology is crucial for the results we generate alternatives using a more flexible functional form and allow the data to determine the imposed parameter values. A CES production function of the form in equation (10) below is chosen, which we parameterise using the estimated coefficients found in Table 1, regression 3 of Duffy and Papageorgiou (2000).[19] They estimate a CES production function using the same data set as that used here, where:

$$Y = A[\delta K^{-\rho} + (1-\delta)L^{-\rho}]^{-\nu/\rho} \qquad (10)$$

The parameters are set as follows:

$\rho = 0.19074;$ $\delta = 0.08629;$ $\nu = 1$

The results appear robust to this alternative measure of TFP growth. The main results from regression 1 are again apparent in regression 17. TFP growth in LDCs is found to be positively correlated with TFP growth in the US and external volatility has a contemporaneous negative effect of TFP growth and no long-run effect.

Technical Frontier

As a final test of the robustness of the results we consider whether the assumption that movements in US TFP solely define the technical frontier is crucial. Two alternatives are considered. Firstly observations for the G7 countries are used. The G7 countries account for around 90 per cent of R&D expenditure in the world economy. To control for differences in the size of the various G7 economies the growth rate of the frontier is calculated by aggregating outputs and inputs. Production technology is once again assumed to be Cobb-Douglas and a capital share of 1/3rd and constant returns to scale are imposed. The size of the US relative to the other economies means that the path of technical change over time for the G7 countries is similar to that for the US alone. Perhaps unsurprisingly the average rate of growth over the period is higher and the standard deviation lower for this larger number of countries.

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[18] The test statistic with $F(1,242)$ degrees of freedom is 2.95 which has a p-value of 0.087.

[19] The results are robust to the use of the parameter estimates found in Table 1, regression 1 of the same paper.

Secondly we use the GDP growth of OECD countries weighted by the trade share of each developing country with the OECD. The rate of growth of OECD countries and the frontier therefore varies across developing countries according to their exposure to OECD economies. This variable may capture openness to ideas but is also more likely to include the global demand/supply effects discussed earlier. This same measure is used by Easterly (2001) and is taken from the World Bank databank. The results are presented as regressions 18 and 19 in Table 4.

In both regressions 18 and 19 the long-run effect of movements in the frontier are greater than one (though an F-test accepts $-\beta_2/\beta_1 = 1$). One notable difference in the results is in regression 19, where the contemporaneous effect of the frontier on LDC is stronger than the lagged effect. This differs from the results for regression 1 where the lagged parameter was larger. While we might expect the trade weighted frontier measure to more accurately capture the interaction between OECD 'frontier countries' and LDCs, the results from regression 19 suggests that any demand effects may be stronger in these results.[20] Finally, as previously, the effect of external volatility on TFP growth is unchanged: a significant effect in the short-run but not in the long-run.

5. Conclusions

This paper has considered the question of whether developing counties benefit from technology transfers. To answer this question, a number of complementary approaches are possible. Acemoglu and Zilibotti (2001), for example, focus on industry-level TFP indices, categorised by skill intensity and consider whether lower LDC productivity (compared to developed countries) can be explained by the difficulties of absorbing skill-intensive US technology. We have followed the more aggregative approach of Rodrik (1999) and Easterly (2001), constructing a panel of economy-wide TFP indices for around 60 LDCs. Taking Krugman's (1985) analysis of 'technology gaps' as a starting point, we constructed a regression model which integrates (a) a process of technology transfer from innovating countries such as the US, to LDCs and; (b) the effects of external volatility on TFP growth in LDCs.

The growth literature has long recognised that the technology used in LDCs falls some way short of the best practice available in the OECD or the US, though whether this is best treated as associated with capital deficiencies (including human capital) or differences in technology has remained in doubt. By constructing TFP measures, recent studies have sought to remove capital shortage aspects, and consider how far remaining productivity differences can be explained by technology gaps. However, observing these technology gaps in the past has undoubtedly been hampered by the lack of persistence in TFP growth rates for individual countries from one 5- or 10-year period to another.

Recognising that this phenomenon arises, at least in part, from exogenous volatility in LDCs' terms of trade has, however, allowed us to explore the ceteris paribus effects of technology transfer from the US. Our evidence suggests that external shocks can indeed explain a great deal of the variability of LDCs productivity growth rates, but only over the short-run: within 5 years. That is, as might be expected, shocks do not have strong persistence effects on TFP. We have found evidence however that faster US productivity growth is associated with faster productivity growth in LDCs on average over the long-run. There is a good case for believing that this reflects technology spillovers, and not simply demand effects. In addition, these spillovers have been strongest for developing countries with the lowest productivity levels enabling their technologies to converge (in the absence of shocks) towards those in richer LDCs and in the US, albeit from a long way below. Technology in initially more productive LDCs, on the other hand, appears to be struggling to keep up with improving US levels, consistent with the evidence of Acemoglu and Zilibotti (2001).

Finally, we have subjected our results to a number of robustness tests related to the measurement of TFP and the definition of 'frontier technology'. They appear to stand up well to these tests.

[20] Easterly (2001) also finds a surprisingly large parameter on this variable when using GDP per capita growth as his dependent variable.

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Appendix Table A1 Negative and positive shocks

			A1	A2
Long-Run	*Frontier*	β_2	0.814* (0.23)	0.810* (0.25)
	Volatility	β_3	-0.188 (0.15)	-
	Frontier∗ Volatility	β_4	-	0.020 (0.14)
	Negative Volatility		0.456 (0.38)	-
	Negative Volatility∗ Frontier		-	-0.035 (0.24)
	Adjustment	β_1	-0.983* (0.07)	-0.972* (0.08)
Short-Run	*Frontier$_t$*	α_2	0.081 (0.19)	0.199 (0.22)
	Frontier$_{t-1}$	α_3	0.733* (0.17)	0.611* (0.19)
	Volatility$_t$	α_4	-0.343* (0.15)	-
	Volatility$_{t-1}$	α_5	0.156** (0.09)	-
	Frontier∗ Volatility$_t$	α_6	-	-0.050 (0.14)
	Frontier∗ Volatility$_{t-1}$	α_7	-	0.070* (0.03)
	Negative Volatility$_t$		0.119 (0.24)	
	Negative Volatility$_{t-1}$		0.338 (0.27)	
	Negative Volatility∗ Frontier$_t$		-	-0.086 (0.18)
	Negative Volatility∗ Frontier$_{t-1}$		-	0.052 (0.11)
	Countries		59	59
	Obs.		293	293
	R^2		0.53	0.52