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The long-run effect of foreign direct investment on total factor productivity in developing countries: A panel cointegration analysis

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Abstract. This paper examines the long-run effect of the level of foreign direct investment (FDI) on the level of total factor productivity (TFP) for 70 developing countries for the period 1981-2011 using panel cointegration techniques. It is found that (i) FDI has, on average, a negative long-run effect on TFP in developing countries; (ii) causality runs in only one direction, from FDI to TFP, and (iii) the long-run effect of FDI on TFP differs between selected groups of countries: while the estimated long-run FDI-TFP coefficients are significantly negative for subsamples of countries with lower levels of human capital, financial development, and trade openness, the coefficients are insignificant or significantly positive for subgroups of countries with higher levels of human capital, financial development, and trade openness.

Keywords: FDI; TFP; panel cointegration

JELClassification: F21; O47; C23

1. Introduction

Many developing countries offer generous tax and financial incentives to attract foreign direct investment (FDI) in the belief that FDI promotes growth. In principle, FDI can affect economic growth via two channels: the capital accumulation channel and the total factor productivity (TFP) channel (see, e.g., Wang and Wong, 2009). The simple logic behind the capital accumulation channel is that FDI brings a net addition to domestic investment and thus increases total investment in the host economy (provided that FDI does not crowd out equal amounts of investment from domestic sources). The TFP channel assumes that multinationals bring with them some sort of superior technology and that this will “spill over” to domestic firms, thus assisting them in improving their productivity.

A large body of evidence suggests that it is TFP rather than capital accumulation that accounts for the bulk of cross-country differences in the level and growth of GDP per capita (see, e.g., Klenow and Rodríguez-Clare, 1997; Prescott, 1998; Easterly and Levine, 2001). However, firm-level studies generally do not support the view that FDI increases TFP in developing countries. Contrary to the literature for developed countries, most firm-level studies of developing countries find that productivity spillovers from FDI to domestic firms are insignificant or even negative (for a survey of this literature, see, e.g., Görg and Greenaway, 2004; Harrison and Rodríguez-Clare, 2010).

One explanation for the negative productivity effects of FDI is that multinationals have lower marginal costs due to some firm-specific advantage, which allows them to attract demand away from domestic firms, thus forcing the domestic firms to reduce production (see, e.g., Görg and Greenaway, 2004). Another, related, explanation is that multinationals displace national firms and source fewer inputs locally than the domestic firms they displace, leading to a decrease in local demand for inputs and thus to a reduction in domestic input variety and productivity (see, e.g., Rodríguez-Clare, 1996).

Possible explanations for the insignificant results are that domestic firms using very backward production technology and low-skilled workers are unable to learn from multinationals or that multinationals are able to effectively protect their firm-specific knowledge (see, e.g., Görg and Greenaway, 2004).

An alternative explanation for the insignificant results is that spillovers may occur not horizontally but vertically through relationships that are missed in conventional spillover studies (see, e.g., Görg and Greenaway, 2004). In fact, there is some evidence of positive vertical spillovers in developing countries (see, e.g., Bwalya, 2006). However, if multinationals generate positive vertical linkages, then this should benefit domestic firms that use inputs similar to those used by

multinationals. One would then expect to see positive horizontal spillovers in developing countries, but this is not what the literature generally finds (see, e.g., Harrison and Rodríguez-Clare, 2010).

Firm-level studies on FDI productivity spillovers provide valuable insights into the effects of the presence of multinationals on domestic firms operating in the same or vertically related sectors, but they are, by definition, unable to capture the effect of total FDI on aggregate TFP for the economy as a whole. Moreover, since firm-level studies typically focus on only one country, it is difficult to draw conclusions regarding the average effect of FDI on TFP in developing countries.

Surprisingly, multi-country macroeconomic studies on the FDI-TFP nexus are few, and most do not focus exclusively on developing countries. In one of these studies, Alfaro et al. (2009) estimate cross-sectional regressions using a sample of 19 developed and 43 developing countries. They find that FDI itself has no effect on TFP growth, although when interacted with financial development there is a conditional effect; FDI stimulates TFP growth only in countries with well-developed financial markets. The explanation is that to take advantage of knowledge spillovers from FDI, local firms need to reorganize their structure, buy new machines, and hire new managers and skilled labor. In countries without developed financial markets, local firms are unable to make such investments (see also Alfaro et al., 2004).

Baltabaev (2014), using panel data for 21 developed and 28 developing countries, finds that FDI has a positive effect on TFP growth, but this effect is statistically significant only for those countries in which GDP per worker relative to the United States is below a certain threshold. He argues that the opportunities for countries to improve their productivity through FDI are greater the larger the technological gap. The implication is that FDI is a more important source of productivity gains for developing than for developed countries.

Woo (2009) estimates cross-sectional, pooled, and fixed effects regressions for a sample of 22 developed and 70 developing countries and finds that FDI has an unconditional positive effect on TFP growth. Interestingly, there is no substantial difference in the results between the total sample and a sample restricted to developing economies.

de Melo (1999) uses pooled, fixed-effects, and pooled mean-group regressions. He finds for a sample of 16 developed and 17 developing countries that the effects of FDI on TFP growth are negative but mostly insignificant for the total sample, positive and significant for developed countries, and insignificant (with different signs) for developing countries.

To our knowledge, there is only one macroeconomic study examining the effect of FDI on TFP growth exclusively for developing countries. In this study, Wang and Wong (2009) apply panel seemingly unrelated regressions (without fixed effects) to a sample of 69 developing countries. They find that FDI has a negative effect on TFP growth in developing countries with low

levels of human capital, but the negative effect becomes smaller in absolute value and ultimately turns positive as the level of human capital increases. The obvious interpretation of this result is that a minimum threshold stock of human capital is necessary to absorb foreign technologies efficiently (see also Borensztein et al., 1998). 38 out of the 69 countries in their sample have human capital levels above the threshold, implying that FDI has a positive and statistically significant effect on TFP growth in the majority of the countries considered. Another finding is that there is no robust evidence that the effect of FDI on TFP growth in developing countries varies with the level of financial development. A summary of these studies is presented in Table A1 in Appendix A.

Given the limited evidence on the macroeconomic impact of FDI on TFP in developing countries, we revisit this issue. Our study differs from previous studies in several ways.

First, while previous studies employ the growth rate of TFP as the dependent variable, we use the (log) level of TFP. The reason for this change in the specification of the dependent variable is that TFP growth rates tend to follow a mean-reverting process, whereas measures of FDI such as the ratio of FDI flows or stocks to GDP exhibit stochastic trends (unit roots). In other words, while TFP growth rates tend to be stationary, FDI levels tend to be non-stationary. The empirical implication is that there cannot be a long-run relationship between the growth rate of TFP and the level of FDI over time.

Second, we use panel cointegration methods to examine the long-run relationship between the level of TFP and the level of FDI. It is well known that most macroeconomic time series in levels are non-stationary. What is less known is that conventional panel regressions involving non-stationary variables are spurious in the absence of panel cointegration. Therefore, it is important to test for panel cointegration. The cointegration property not only allows one to obtain meaningful, non-spurious results, but it is also invariant to the inclusion of additional variables. Another advantage of the cointegration approach is that it allows us to estimate long-run coefficients in a manner that is free of endogeneity bias. Moreover, panel cointegration analysis, like conventional panel analysis, allows us to control for time-invariant omitted-variable bias by including fixed effects. We discuss these issues in more detail in Section 2.

Third, we use a panel vector error correction model (PVECM) to identify the direction of causality in the long-run relationship between FDI and TFP. As it is well known that wages are lower in countries where productivity is lower, it could be that higher TFP leads to less FDI motivated by the search for low labor costs. Alternatively, to the extent that FDI is motivated by knowledge and technology acquisition considerations, it could be that higher TFP leads to more FDI. Thus, regardless of whether the long-run relationship between FDI and TFP is positive or negative, causality could operate in the opposite direction or in both directions simultaneously.

Finally, we address the issue of parameter heterogeneity by presenting estimates of the long-run FDI-TFP coefficients for certain groups of countries with similar characteristics such as high or low levels of human capital, financial development, and trade openness. In a widely cited study, Borensztein et al. (1998) find that FDI is positively associated with economic growth only in countries with sufficiently high levels of human capital. The widely cited study of Alfaro et al. (2004) suggests strong growth effects from FDI only for those countries with well-developed financial markets. Balasubramanyam et al. (1996), also widely cited, find that the effects of FDI on growth are stronger in countries that are more open to trade. A possible explanation for this finding is that local firms in more open economies have more contact with firms from abroad than their counterparts in relatively closed economies, which allows them to acquire the necessary knowledge and skills to be able to learn from foreign investors. In addition, firms exposed to international competition are better able to compete with or supply multinationals (see, e.g., Iršová and Havránek, 2013). The point is that if the effect of FDI on economic growth differs across countries, as Herzer (2012) explicitly demonstrates, then it is very likely that the effect of FDI on TFP also differs across countries. This conclusion is supported by the studies of Alfaro et al. (2009) and Wang and Wong (2009). As discussed above, the former find that FDI promotes TFP growth only in countries with well-developed financial markets, and the latter find that FDI stimulates TFP growth only in countries with sufficiently high levels of human capital. The potential role of trade openness in the aggregate relationship between FDI and TFP, however, has been ignored in previous studies.

To preview the main results, we find for a sample of 70 developing countries for the period 1981-2011 that FDI has, on average, a negative long-run effect on TFP in developing countries and that causality is unidirectional from FDI to TFP. Subsample results, however, show that the long-run effect of FDI on TFP differs between selected groups of countries: while the long-run effect of FDI on TFP is negative and significant for subsamples of countries with lower levels of human capital, financial development, and trade openness, we find for a subsample of countries with higher levels of human capital that the estimated long-run FDI-TFP coefficient is negative but insignificant; for a subsample of countries with higher levels of financial development, the coefficient is positive but insignificant; for a subsample of countries that are more open to trade, the coefficient is positive and weakly significant; and for the overlapping group of countries with higher levels of human capital, financial development, and trade openness, the coefficient is positive and highly significant.

The organization of the rest of the paper is as follows. In Section 2 we present the basic empirical model, discuss some econometric issues, and lay out the empirical strategy. Section 3 presents the results. Section 4 contains our conclusions.

2. Model specification, data, and empirical strategy

2.1. Basic model

The basic empirical model used to analyze the long-run effect of FDI on TFP is as follows:

$$\log(TFP_{it}) = c_i + \delta_i t + \beta(FDI_{it} / GDP_{it}) + \varepsilon_{it} \quad (1)$$

where $\log(TFP_{it})$ is the log of TFP of country i in period t and FDI_{it} represents our measure of FDI for country i at time t . Following most of the recent literature (see, e.g., Ford et al., 2008; de Sousa and Lochard, 2011; Chintrakarn et al., 2012, Baltabaev, 2014), we measure FDI by FDI stocks rather than FDI flows. Stocks may more effectively capture long-run effects due to the accumulation of flows (see, e.g., Chintrakarn et al., 2012). More specifically, the use of FDI stocks ensures that the effects of FDI are not limited to the period in which the investment is made and thus that the effects of both new and established foreign firms are fully accounted for (see, e.g., Ford et al., 2008). Moreover, TFP is typically interpreted as a measure of the stock of knowledge or technology in an economy. It is therefore reasonable to assume a relationship between TFP and the stock, rather than the flow, of FDI. In addition, stock data are considered more reliable than flow data, which are more volatile and more often negative (due to disinvestment) than stock data (see, e.g., de Sousa and Lochard, 2011).

As is common practice, the FDI variable is expressed as a percentage of GDP to account for economic size. Also following common practice, the variable (FDI_{it}/GDP_{it}) is not logged because the FDI stock is negative for some countries in some years (as just mentioned).

Given the definition of the variables, the coefficient β represents the long-run semi-elasticity of TFP with respect to the FDI stock/GDP ratio. The c_i are country fixed effects controlling for omitted country-specific factors that are relatively stable over longer periods of time, such as geography (including country size, location and natural resource endowments), culture, and basic institutions (such as the protection of property rights and the rule of law); the $\delta_i t$ are country-specific deterministic time trends capturing omitted time-varying country-specific factors that change smoothly over time, such as deterministic technological progress; the error term is denoted by ε_{it} .

We now briefly describe the data used to estimate the long-run relationship given by equation (1). Unfortunately, there is no database that provides data on the level of TFP.¹ Therefore, we compute TFP in the usual way by defining

$$TFP_{it} = \frac{Y}{K^{(1-\alpha)} L^{\alpha}}, \quad (2)$$

where Y is aggregate output, K is capital input, L is labor input, $(1-\alpha)$ is the capital share of income, and α is the labor share of income. We set the labor share parameter to $\alpha = 2/3$ for all countries and time periods, which can be justified as follows: First, it is common practice to assume a constant labor share of 2/3. Second, a widely cited study by Gollin (2002) suggests that the labor share is approximately constant across time and space with a value of about 2/3. It should be noted that recent studies show that labor's share has declined since the 1980s in many (but not all) countries (see, e.g., Karabarbounis and Neiman, 2013). However, and third, reliable labor share data are not available for many countries and years. Thus, we are forced to rely on the standard assumption of $\alpha = 0.6667$ to maximize the number of countries in our sample. In the robustness section, we present results for a smaller sample based on country-specific time-varying labor shares, α_{it} . Moreover, we measure TFP using an alternative, homogeneous value for labor's share ($\alpha = 0.7$). In addition, we calculate TFP as the residual from country-specific OLS regressions of the log of aggregate output per employed person on the log of capital per employed person to allow for time-constant country-specific estimated values of the labor share, $\hat{\alpha}_i$.

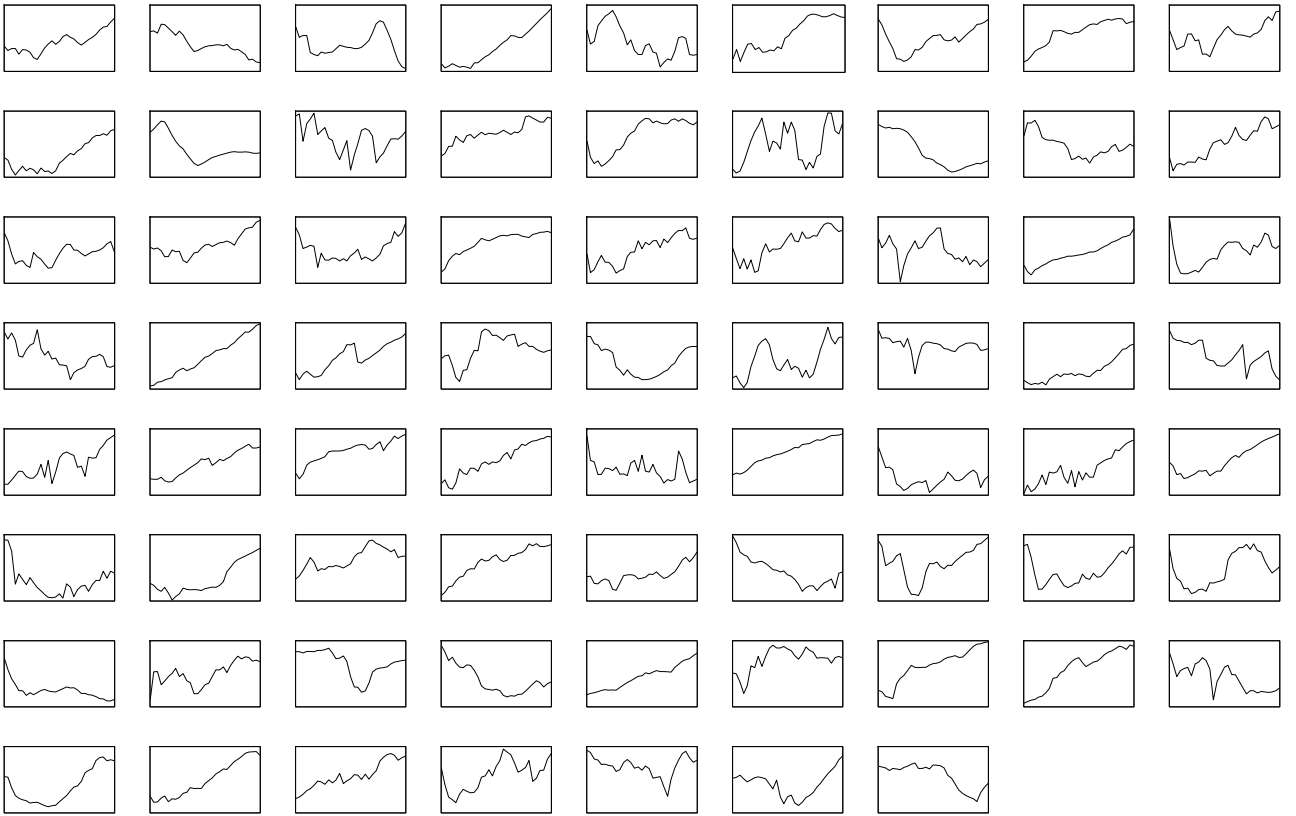
All data used to calculate TFP are from the Penn World Tables (PWT) version 8.0 (Feenstra et al., 2013). Aggregate output is measured by real GDP in constant (2005) dollars; capital input is measured by the constant dollar value (in 2005) of the stock of real capital (which has been constructed by the perpetual inventory method); and L is measured by the number of persons employed. Of course, a better measure of labor input would be employment times average hours, but reliable data on employment and hours worked are not available for most developing countries. Nevertheless, we use this alternative measure of labor input as a robustness check for a smaller sample of countries.

The data on FDI stocks as shares of GDP are from various issues of the World Investment Report of the United Nations Conference on Trade and Development (UNCTAD) and the accompanying UNCTAD World Investment Report Database.

¹ Although the Penn World Tables (version 8.0) report TFP growth rates and relative TFP levels (relative to the US), this database contains no data on the (absolute) level of TFP.

The data sets for $\log(TFP_{it})$ and (FDI_{it}/GDP_{it}) are unbalanced in the sense that the length of the available time series varies across countries. Since the techniques employed in this paper require a balanced panel, we construct a balanced panel of data from 70 developing countries over the period 1981-2011. This 31-year period is long enough to capture the long-run effect of FDI on TFP and thus to conduct a meaningful panel cointegration analysis. The classification of developing countries follows that of the IMF, for the years 1992-2011 (IMF, 2000, 2014)—more than half of the sample period. The countries in our main sample along with the average values for $\log(TFP_{it})$ and (FDI_{it}/GDP_{it}) over the sample period are listed in Table A2 in Appendix B. In the following, we discuss some methodological issues regarding the estimation of β in equation (1).

Figure 1. Log of total factor productivity by country over the period 1981-2011, $\log(TFP_{it})$



Notes: The countries from left to right are: Argentina, Bahamas, Bahrain, Bangladesh, Barbados, Benin, Bolivia, Botswana, Brazil, Burkina Faso, Cameroon, Central African Republic, Chad, Chile, Colombia, Dem. Rep. of Congo, Rep. of Congo, Costa Rica, Cote d'Ivoire, Dominican Republic, Ecuador, Egypt, El Salvador, Fiji, Gabon, Ghana, Guatemala, Honduras, India, Indonesia, Jamaica, Jordan, Kenya, Kuwait, Lesotho, Madagascar, Malawi, Malaysia, Maldives, Mali, Mauritania, Mauritius, Mexico, Morocco, Mozambique, Niger, Nigeria, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Qatar, Saudi Arabia, Senegal, Sierra Leone, South Africa, Sri Lanka, Sudan, Swaziland, Thailand, Togo, Trinidad & Tobago, Tunisia, Turkey, Uruguay, Venezuela, Zambia, and Zimbabwe.

2.2. Non-stationarity and cointegration

Figures 1 and 2 show that the individual time series of the FDI/GDP ratio and the log of TFP exhibit trends and are thus non-stationary. Since it is well known that most economic time series are

characterized by a stochastic rather than deterministic non-stationarity, it is reasonable to assume that the trends in $\log(TFP_{it})$ and (FDI_{it}/GDP_{it}) are also stochastic, through the presence of a unit root, rather than deterministic, through the presence of polynomial time trends. This assumption is confirmed by panel unit root tests (available upon request), which indicate that the variables are integrated of order one, or $I(1)$.²

Figure 2. FDI stock as a percentage of GDP by country over the period 1981-2011, (FDI_{it}/GDP_{it})



Notes: The countries from left to right are: Argentina, Bahamas, Bahrain, Bangladesh, Barbados, Benin, Bolivia, Botswana, Brazil, Burkina Faso, Cameroon, Central African Republic, Chad, Chile, Colombia, Dem. Rep. of Congo, Rep. of Congo, Costa Rica, Cote d'Ivoire, Dominican Republic, Ecuador, Egypt, El Salvador, Fiji, Gabon, Ghana, Guatemala, Honduras, India, Indonesia, Jamaica, Jordan, Kenya, Kuwait, Lesotho, Madagascar, Malawi, Malaysia, Maldives, Mali, Mauritania, Mauritius, Mexico, Morocco, Mozambique, Niger, Nigeria, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Qatar, Saudi Arabia, Senegal, Sierra Leone, South Africa, Sri Lanka, Sudan, Swaziland, Thailand, Togo, Trinidad & Tobago, Tunisia, Turkey, Uruguay, Venezuela, Zambia, and Zimbabwe.

If $\log(TFP_{it})$ and (FDI_{it}/GDP_{it}) are driven by *separate* stochastic $I(1)$ trends, then any linear combination of these variables will also be $I(1)$. In this case, equation (1) is a spurious regression, and there is no long-run relationship between (FDI_{it}/GDP_{it}) and $\log(TFP_{it})$. Entorf (1997) and Kao (1999) demonstrate that the tendency for spuriously indicating a relationship between variables may even be stronger in panel data regressions than in the pure time series case.

² The order of integration is the number of times a time series must be differenced to make it stationary. An $I(1)$ variable

If $\log(TFP_{it})$ and (FDI_{it}/GDP_{it}) share a *common* stochastic trend (and no irrelevant non-stationary variables are included), then a linear combination of these variables will be stationary, or $I(0)$. In this case, $\log(TFP_{it})$ and (FDI_{it}/GDP_{it}) are said to be cointegrated, and there exists a long-run relationship between (FDI_{it}/GDP_{it}) and $\log(TFP_{it})$. Thus, cointegration of the two variables is the condition required for regression (1) not to be spurious—a condition that must be tested.

2.3. Omitted variables

As should be clear from the above, a regression containing all the variables of a cointegrating relationship has a stationary error term. An important implication is that if a relevant non-stationary variable is omitted from the cointegrating regression, then this variable would enter the error term, thereby inducing residual non-stationarity and thus failure to detect cointegration (see, e.g., Everaert, 2011). Another important implication is that the finding of a particular cointegrating relationship in a small set of non-stationary variables will also hold in an extended variable set. To put it differently, the cointegration property is invariant to model extensions (see also Lütkepohl, 2007), which is in stark contrast to regression analysis where one new variable can alter the existing estimates dramatically (Juselius, 2006, p. 11). From this it follows that estimates from cointegrating regressions are robust to the omission of variables that do not form part of the cointegrating relationship and that no additional variables are required in a correctly-specified cointegrating regression (in our case equation (1)).

Although these considerations justify a parsimonious model such as equation (1) (if cointegrated), we nevertheless check the robustness of our results to the inclusion of additional variables, such as population (in logs), $\log(POP_{it})$, human capital (in logs), $\log(HC_{it})$, domestic credit to the private sector as a share of GDP as a measure of financial development, $Credit_{it}$, and trade as a share of GDP as a measure of trade openness, $Openness_{it}$. The data on population and human capital (measured based on years of schooling weighted by an efficiency parameter) are from the PWT8.0. The data on private credit and trade openness are obtained from the World Development Indicators (WDI) 2015 online database.

2.4. Endogeneity and causality

It is well known that coefficient estimates of cointegrating parameters are superconsistent (even in the presence of omitted stationary variables). The superconsistency property means that any endogeneity between the dependent and independent variables does not affect the estimated long-run coefficients. However, although even the standard OLS fixed effects estimator is

must be differenced one time to make it stationary, or $I(0)$.

superconsistent under panel cointegration (see, e.g., Mark and Sul, 2003), it suffers from a second-order asymptotic bias arising from serial correlation and endogeneity. The implication is that the OLS t -ratio is not asymptotically standard normal and thus useless for inference. The solution of this problem requires the use of an estimator that is superconsistent, asymptotically unbiased and normally distributed, even in the presence of endogenous regressors. Examples of such estimators are panel versions of the dynamic OLS (DOLS) and fully modified ordinary least squares (FMOLS) procedures. As shown by Wagner and Hlouskova (2010), the panel DOLS estimator of Kao and Chiang (2000) outperforms other asymptotically efficient panel cointegration estimators.³ Therefore, this estimator is preferred here, but in the robustness section we also present results based on alternative estimation procedures. Section 3 describes these estimation methods in more detail.

A related problem is that, although the existence of cointegration implies long-run Granger causality in at least one direction (see, e.g., Granger, 1988), cointegration says nothing about the direction of causality. A statistically significant cointegrating relationship between $\log(TFP_{it})$ and (FDI_{it}/GDP_{it}) does therefore not necessarily imply that, in the long run, changes in FDI cause changes in aggregate productivity. Causality could operate in the opposite direction or in both directions simultaneously, as discussed in the Introduction. An important point in this context is that the cointegration estimate of the coefficient on (FDI_{it}/GDP_{it}) , β , can be strictly interpreted as the long-run effect of FDI on TFP only if (FDI_{it}/GDP_{it}) is not Granger caused by $\log(TFP_{it})$, neither in the short nor in the long run. The empirical implication is that it is important not only to employ an asymptotically efficient cointegration estimator (to account for serial correlation and the potential endogeneity of FDI), but also to conduct tests of causality or exogeneity. Following the common practice in the literature, we employ a PVECM for this purpose (described in more detail in Subsection 3.4).

2.5. Heterogeneity

As discussed in the Introduction, there is evidence to suggest that the effect of FDI on TFP is not the same for all countries. If the effect of FDI on TFP is heterogeneous across countries, we are, however, faced with a dilemma. On the one hand, efficiency gains from pooling of observations over the cross-sectional units can be achieved when the individual slope coefficients are the same. On the other hand, pooled estimators may yield biased estimates of the sample mean of the

³ An extension of the panel DOLS estimator is the dynamic seemingly unrelated regression (DSUR) estimator proposed by Mark et al. (2005), which was not included in the simulation study by Wagner and Hlouskova (2010). Unfortunately,

individual coefficients when the true slope coefficients are heterogeneous. Comparative studies, however, suggest that the efficiency gains from pooling more than offset the biases due to individual country heterogeneity (see, e.g., Baltagi and Griffin, 1997; Baltagi et al., 2008). Therefore, our preferred estimator is the homogeneous, pooled DOLS estimator of Kao and Chiang (2000). In the robustness section, we also use the heterogeneous, group-mean DOLS estimator of Pedroni (2001).

In addition, and more importantly, we address the issue of heterogeneity by estimating the long-run effect of FDI on TFP for certain groups of countries with similar characteristics. More specifically, inspired by the literature discussed in the Introduction, we estimate the long-run FDI-TFP coefficients (using the pooled DOLS estimator) (i) for the 20 countries with highest and lowest levels of human capital, (ii) for the 20 countries with the highest and lowest levels of financial development, (iii) for the 20 countries with the highest and lowest levels of trade openness, and (iv) for the overlapping subsamples of 6 and 4 countries with the highest and lowest levels, respectively, of human capital, financial development, and trade openness.

Thus, the empirical strategy involves the following steps. The first step is to test whether $\log(TFP_{it})$ and (FDI_{it}/GDP_{it}) are cointegrated with a country-specific trend and intercept in the cointegrating equation, as assumed by equation (1). In the second step, we estimate the cointegrating relationship by panel DOLS and test the robustness of the estimates. The third step involves testing the direction of causality. Finally, we provide estimates of the cointegrating relationship between FDI and TFP for the subsamples described above.

3. Empirical analysis

3.1. Cointegration

We first test for cointegration using the standard panel cointegration approach of Pedroni (1999, 2004), which involves two steps. In the first step, the cointegrating regression (given by equation (1)) is estimated separately for each country. In the second step, the estimated residuals ($\hat{\varepsilon}_{it}$) are tested for stationarity using seven test statistics. Four of these seven pool the autoregressive coefficients across different countries during the unit-root test and thus restrict the first-order autoregressive coefficients to be the same for all countries. Pedroni refers to these statistics as panel cointegration statistics. The other three test statistics are based on estimators that simply average the individually estimated autoregressive coefficients for each country, thus

the DSUR estimator is seriously biased or not applicable when, as in this study, the number of time periods is small relative to the number of cross-sectional units (Mark et al. 2005, Di Iorio and Fachin, 2012).

allowing the autoregressive coefficient to vary across countries. Pedroni refers to these statistics as group mean panel cointegration statistics.

However, residual-based (panel) cointegration tests, such as the Pedroni (1999, 2004) procedure, impose the assumption that the short- and long-run elasticities are equal. If this assumption is violated, then residual-based tests suffer from low power (see, e.g., Westerlund, 2007). In addition, residual-based cointegration tests are generally not invariant to the normalisation of the cointegrating regression. Therefore, we also use the Larsson et al. (2001) procedure, which is based on Johansen's (1988) maximum likelihood approach. Like the Johansen time-series cointegration test, the Larsson et al. panel test treats all variables as potentially endogenous, thus avoiding the normalisation problems inherent to residual-based cointegration tests. Furthermore, the Larsson et al. procedure allows the long-run elasticities to differ from the short-run elasticities and hence does not impose a possibly invalid common factor restriction on the dynamics of the relationship between the variables involved.

The Larsson et al. panel cointegration test involves estimating the Johansen vector error-correction model for each country separately and then computing the individual trace statistics $LR_{iT}\{H(r)|H(p)\}$. However, the Johansen trace statistics are biased toward rejecting the null hypothesis in small samples. To avoid the Larsson et al. test, as a consequence of this bias, also overestimating the cointegrating rank, we also compute the standardized panel trace statistics based on small-sample corrected country-specific trace statistics. Specifically, we follow Herzer et al. (2012) and use the small-sample correction factor suggested by Reinsel and Ahn (1992) to adjust the individual trace statistics as follows:

$$LR_{iT}\{H(r)|H(p)\} \times \left[\frac{T - k_i \times p}{T} \right], \quad (3)$$

where k_i is the lag length of the models used in the test.

The above-outlined tests are applied to both the raw data and to data that have been demeaned over the cross-sectional dimension; that is, in place of $\log(TFP_{it})$ and (FDI_{it}/GDP_{it}) , we also use

$$\begin{aligned} \log(TFP_{it})' &= \log(TFP_{it}) - \overline{\log(TFP_t)} \text{ and} \\ (FDI_{it}/GDP_{it})' &= (FDI_{it}/GDP_{it}) - \overline{(FDI_t/GDP_t)}, \text{ where} \\ \overline{\log(TFP_t)} &= N^{-1} \sum_{i=1}^N \log(TFP_{it}) \text{ and} \\ \overline{(FDI_t/GDP_t)} &= N^{-1} \sum_{i=1}^N (FDI_{it}/GDP_{it}), \end{aligned} \quad (4)$$

to account for cross-sectional dependence due to common shocks or spillovers among countries at the same time.

Table 1 reports the test results. As can be seen, four of the seven Pedroni statistics reject the null hypothesis of no cointegration at the 1 % level both for the raw and the demeaned data. Specifically, the ADF-type tests reject the null hypothesis. Given that these tests have been shown to have the highest power in small T samples such as $T = 31$ (see, e.g., Pedroni 2004), the ADF test results, in particular, provide strong evidence of cointegration (with a trend). This conclusion is supported by the panel trace statistics which, regardless of whether the unadjusted or demeaned data are used, show that there is cointegration between $\log(TFP_{it})$, (FDI_{it}/GDP_{it}) , and a linear trend.

Table 1. Panel cointegration tests

	Cointegration rank			
	$r = 0$		$r = 1$	
	Raw data	Demeaned data	Raw data	Demeaned data
Larsson et al. (2001)				
Panel trace statistics	4.774***	4.612***	-2.800	-2.141
Pedroni (1999, 2004)	Panel statistics		Group mean statistics	
	Raw data	Demeaned data	Raw data	Demeaned data
Variance ratio statistics	0.989	0.257516		
PP ρ -statistics	0.047	0.479367	1.737	1.783
PP t -statistics	-3.372***	-2.592***	-4.520***	-3.249***
ADF t -statistics	-5.133***	-3.647***	-5.825***	-4.760***

Notes: For the Pedroni (1999, 2004) tests, the number of lags was determined by the Schwarz criterion with a maximum of three lags. Given the short sample period, only one lag was included in the Larsson et al. (2001) test to avoid overparametrization. The test statistics are asymptotically normally distributed. The panel trace test is right-sided, while the other tests are left-sided. To construct the standardized panel trace statistics, we used the mean and variance of the asymptotic trace statistic tabulated by Breitung (2005). *** indicate a rejection of the null hypothesis of no cointegration / r cointegrating relations at the 1% level.

3.2. Long-run relationship

In order to estimate the long-run relationship between FDI and TFP, we use the panel DOLS estimator suggested by Kao and Chiang (2000). The idea behind the DOLS estimator is to account for possible serial correlation and endogeneity of the regressors by augmenting the cointegrating regression with lead, lag, and current values of the first differences of the $I(1)$ regressors. Thus, the specification of the DOLS regression used in this study is as follows:

$$\log(TFP_{it}) = c_i + \delta_i t + \beta(FDI_{it} / GDP_{it}) + \sum_{j=-k}^k \theta_{ij} \Delta(FDI_{it} / GDP_{it}) + \mu_{it} . \quad (5)$$

We estimate equation (5) using both the unadjusted data and demeaned data to account for potential cross-sectional dependence. However, a problem with the demeaning approach is that, on the one hand, it may be ineffective in eliminating cross-sectional dependence when the individual responses to the common shocks differ across countries. On the other hand, the demeaning

approach may introduce cross-sectional correlation among the error terms when it is not already present (see, e.g., Carporale and Cerrato, 2006). Therefore, we explicitly test for cross-sectional dependence (CD) in the residuals of the estimated models using the CD test of Pesaran (2004).

The results of the panel DOLS estimation for the raw and demeaned data, including the CD statistics, are presented in Rows 1 and 2 of Table 2. Both the results for the raw and demeaned data show a negative and statistically significant relationship between FDI and TFP. However, the CD test rejects the null hypothesis of no cross sectional dependence for the raw data, while the null of no cross sectional dependence is not rejected for the demeaned data. Thus, the estimated coefficient in row 1 is likely to be biased due to cross-sectional dependence. Therefore we focus on the long-run effect implied by the coefficient in row 2.

Table 2. Estimates of the long-run relationship between FDI and TFP

Estimation method	Coefficient on (FDI_{it}/GDP_{it})	CD statistic	Demeaned data	No. of countries	No. of obs.
(1) Pooled panel DOLS estimator (Kao and Chiang, 2000)	-0.00088** (-2.43)	13.80***	No	70	2065
(2) Pooled panel DOLS estimator (Kao and Chiang, 2000)	-0.00136*** (-3.78)	-1.46	Yes	70	2063
(3) Pooled panel DOLS estimator (Kao and Chiang, 2000)	-0.00152*** (-3.65)	-0.89	Yes	67	1972
(4) Group-mean panel DOLS estimator (Pedroni, 2001)	-0.00147** (-2.42)	1.28	Yes	70	2063
(5) Pooled panel FMOLS estimator (Kao and Chiang, 2000)	-0.00124*** (-3.79)	-1.61	Yes	70	2100
(6) Group-mean panel FMOLS estimator (Pedroni, 2001)	-0.00149** (-2.55)	1.01	Yes	70	2100

Notes: The dependent variable is $\log(TFP_{it})$. The optimal number of leads and lags in the DOLS regressions was determined by the Schwarz criterion with an observation-based maximum number of leads and lags of one. In row (3), 3 countries with extreme observations for $\log(FDI_{it})$ and FDI_{it} (identified by the Hadi (1992) procedure) were excluded from the sample: Bahamas, Republic of Congo, and Zambia. The CD test statistic is normally distributed under the null hypothesis of no cross-sectional dependence. *t*-statistics in parenthesis. *** (**) indicate significance at the 1% (5%) level.

The coefficient implies, if viewed causally, that, in the long run, a one percentage point increase in the FDI/GDP ratio leads, on average, to a decrease in total factor productivity by 0.00136 percent (holding all else constant).

To evaluate the magnitude of this effect, consider the average annual change in the FDI/GDP ratio, $\overline{\Delta(FDI / GDP)} = 0.86823$, and the average annual change in the log of TFP in the sample, $\overline{\Delta \log(TFP)} = 0.00399$. Multiplying the coefficient of (FDI_{it}/GDP_{it}) with the average annual change in the FDI/GDP ratio yields a value of -0.00118 , implying that the increase in the FDI/GDP ratio between 1981 and 2011 has led to a decrease in the log of TFP by 0.00118 units for the average country in the sample. With an average increase in the log of TFP of 0.00399 units, this

means that the log of TFP would have increased by 0.00517 units if there had been no change in the FDI/GDP ratio. From this it follows that TFP would have been about 23 percent higher without the increase in the FDI/GDP ratio. Thus, FDI has a relatively large (but not implausibly large) negative effect on TFP.

3.3. Robustness

To verify that the negative effect of FDI on TFP is not due to potential outliers, the DOLS regression (with demeaned data to account cross-sectional dependence)⁴ is re-estimated excluding countries with extreme observations for the log of TFP and the FDI/GDP ratio identified by the Hadi (1992) procedure. As can be seen from the third row of Table 2, the resulting coefficient on (FDI_{it}/GDP_{it}) is still negative and highly significant, suggesting that the negative productivity effect is not the result of outliers.

We also examine whether the negative relationship between FDI and TFP is robust to alternative estimation techniques. As discussed above, a potential problem with panel DOLS is the assumption of homogeneous slope coefficients. To allow the slope coefficients to vary between countries, we use the group-mean DOLS estimator suggested by Pedroni (2001). This estimator involves estimating separate country-specific DOLS regressions and averaging the individual coefficients. In addition, we use the panel FMOLS estimator of Pedroni (2000). Like the time-series FMOLS estimator, the panel FMOLS estimator incorporates a semi-parametric correction to the OLS estimator, which eliminates the second order bias induced by the endogeneity of the regressors. For completeness, we also apply the group-mean FMOLS estimator of Pedroni (2000), which (like the group-mean DOLS estimator) is based on individual country time-series regressions.

We report the results of these estimation methods in rows 4-6 of Table 2. The estimated coefficients on the FDI variable are negative, statistically significant, and have similar magnitudes, implying that the estimated effect is robust to alternative estimation methods.

It should be noted that given that all CD statistics in Table 2 suggest that the empirical results based on the demeaned data do not suffer from cross-sectional dependence, the CD statistics for the other models are not reported for the sake of brevity.

Next, we examine whether the results are robust to alternative measures of total factor productivity. In the first row of Table 3 we present results using a common labor share of 0.7 in calculating TFP. In the second row, TFP is measured based on country-specific estimated labor shares, by using the residuals from country-specific OLS regressions of the log of output per

employed person on the log of capital per employed person. The third row reports results using country-specific, time-varying labor shares in the calculation of TFP. Finally, in the fourth row of Table 3, we use country-specific, time-varying labor shares and total employment multiplied by average hours worked (as a measure of labor input) to calculate TFP. Regardless of which measure is used, the coefficient on (FDI_{it}/GDP_{it}) is negative and highly significant.

Table 3. DOLS estimates using different measures of total factor productivity

TFP measure	Coefficient on (FDI_{it}/GDP_{it})	No. of countries	No. of obs.
(1) TFP based on $(1 - \alpha) = 0.3$	-0.00133*** (-3.66)	70	2065
(2) TFP measured as the residual from individual country regressions of the log of output per worker on the log of capital per worker	-0.00172*** (-4.92)	70	2063
(3) TFP based on country-specific, time-varying labor shares, $(1 - \alpha_{it})$	-0.00432*** (-4.04)	58	1708
(4) TFP based on country-specific, time-varying labor shares, $(1 - \alpha_{it})$, and total employment multiplied by average hours worked	-0.00632*** (-2.87)	8	236

Notes: The optimal number of leads and lags in the DOLS regressions was determined by the Schwarz criterion with an observation-based maximum number of leads and lags of one. The results are based on demeaned data. *t*-statistics in parenthesis. *** indicate significance at the 1% level.

As discussed in Section 2, the finding of cointegration between $\log(TFP_{it})$ and (FDI_{it}/GDP_{it}) implies that there are no omitted variables. Nevertheless, we check the robustness of the results to the inclusion of population (in logs), human capital (in logs), domestic credit to the private sector as a percentage of GDP, and trade openness.

Table 4. DOLS estimates with additional control variables

Independent variables	(1)	(2)	(3)	(4)
(FDI_{it}/GDP_{it})	-0.00140*** (-4.11)	-0.00103*** (-2.70)	-0.00116** (-2.49)	-0.00128*** (-3.45)
$\log(POP_{it})$	0.04789 (0.41)	0.75178*** (6.28)	0.17864 (1.31)	-0.08227 (-0.45)
$\log(HC_{it})$		0.48865*** (2.66)	-0.08451 (-0.42)	-0.40041** (-2.20)
$Credit_{it}$			0.00153*** (3.29)	0.00195*** (5.33)
$Openness_{it}$				0.00024 (0.92)
No. of countries	70	64	55	52
No. of obs.	2033	1858	1577	1476

Notes: The dependent variable is $\log(TFP_{it})$. The optimal number of leads and lags was determined by the Schwarz criterion with an observation-based maximum number of leads and lags of one. The results are based on demeaned data. *t*-statistics in parenthesis. *** (**) indicate significance at the 1% (5%) level.

As can be seen from Table 4, the coefficients of the additional variables are insignificant or change sign, with the exception of the coefficient on private credit/GDP. Because of potential

⁴ In the following, we use the demeaned data to account for dependence.

multicollinearity problems, these estimates should not be taken too seriously, however. Most importantly, the effect of FDI remains negative and significant even after including $\log(POP_{it})$, $\log(HC_{it})$, $Credit_{it}$, and $Openness_{it}$.

3.4. Causality

To test for causality, we use a two-step approach, as is common practice in panel cointegration studies (see, e.g., Canning and Pedroni, 2008; Herzer et al., 2012; Eberhardt and Teal, 2013). In the first step, the estimated coefficients of the long-run relationship are used to construct the error correction term ec_{it} , defined here as

$$ec_{it} = \log(TFP_{it}) - [c_i + \delta_i t - 0.00136(FDI_{it} / GDP_{it})] \quad (6)$$

In the second step, the lagged error correction term is entered into a PVECM, given here by

$$\begin{aligned} \Delta \log(TFP_{it})_{it} &= c_{1i} + a_1 ec_{it-1} + \sum_{j=1}^k \phi_{11j} \Delta \log(TFP_{it-j}) + \sum_{j=1}^k \phi_{12j} \Delta (FDI_{it-j} / GDP_{it-j}) + e_{it}^{TFP} \\ \Delta (FDI_{it} / GDP_{it}) &= c_{2i} + a_2 ec_{it-1} + \sum_{j=1}^k \phi_{21j} \Delta \log(TFP_{it-j}) + \sum_{j=1}^k \phi_{22j} \Delta (FDI_{it-j} / GDP_{it-j}) + e_{it}^{FDI} \end{aligned} \quad (7)$$

where the lagged differences capture the short-run dynamics, while the error correction term captures the long-run relationship. More specifically, the error correction term represents the error in, or deviation from, the long-run relationship, and the adjustment coefficients a_1 and a_2 capture how $\log(TFP_{it})$ and (FDI_{it}/GDP_{it}) respond to deviations from the long run relationship. From the Granger Representation Theorem (according to which cointegration implies the existence of an error correction model), it follows that if there is cointegration then at least one of the adjustment coefficients will be nonzero. Failure to include the error correction term in the relevant equation will therefore result in a misspecified model (in differences).

If the adjustment coefficient in the $\Delta(FDI_{it}/GDP_{it})$ equation is zero, then (FDI_{it}/GDP_{it}) is said to be weakly exogenous for β . Hall and Milne (1994) show that weak exogeneity in a cointegrated system is equivalent to the notion of long-run non-causality. Thus, non-rejection of the null hypothesis of weak exogeneity of (FDI_{it}/GDP_{it}) , $H_0 : a_2 = 0$, implies that TFP has no causal effect, in the long run, on FDI; the long-run causality runs from FDI to TFP. If the null hypothesis of weak exogeneity of $\log(TFP_{it})$, $H_0 : a_1 = 0$, is not rejected, then $\log(TFP_{it})$ is weakly exogenous, implying that FDI has no long-run effect on TFP; the long-run causality runs from TFP to FDI. If both a_1 and a_2 are nonzero, then long-run Granger causality runs in both directions (see also Eberhardt and Teal, 2013).

An obvious and intuitive point is that there are two possible sources of causation in the PVECM, through the error correction term, as just discussed, and/or through the lagged dynamic terms (see, e.g., Granger, 1988); the latter is often referred to as short-run Granger causality. Given the two different sources of causality, three types of causality tests can be performed: weak exogeneity, short-run Granger causality, and strong (or strict) exogeneity.

As just discussed, the test of weak exogeneity is a test of zero restrictions on the adjustment coefficients. The short-run Granger causality can be tested by the joint significance of the lagged differences of the explanatory variables (here only one, $k = 1$, according to the Schwarz criterion). Finally, one can also perform the strong exogeneity test by testing the joint significance of both the lagged differenced explanatory variables and the error correction term. Strong exogeneity of one variable in a system of two cointegrated variables implies that this variable is not Granger caused by the other variable, neither in the short nor in the long run. Given that all variables in the model, including ec_{it-1} , are stationary (because the level variables are $I(1)$ and cointegrated), a conventional likelihood ratio chi-square test can be used to conduct these tests.

Table 5. Causality tests between $\log(TFP_{it})$ and (FDI_{it}/GDP_{it})

	Chi-square statistics
$H_0: (FDI_{it}/GDP_{it})$ does not Granger-cause $\log(TFP_{it})$	
Weak exogeneity test: $a_1 = 0$	263.335*** (0.000)
Short-run Granger non-causality test: $\phi_{12j} = 0$	1.373 (0.241)
Strong exogeneity test: $\phi_{12j} = a_1 = 0$	264.337*** (0.000)
$H_0: \log(TFP_{it})$ does not Granger-cause (FDI_{it}/GDP_{it})	
Weak exogeneity test: $a_2 = 0$	0.750 (0.387)
Short-run Granger non-causality test: $\phi_{21j} = 0$	1.641 (0.200)
Strong exogeneity test: $\phi_{21j} = a_2 = 0$	3.207 (0.201)

Note: The PVECM was estimated with one lag, $k = 1$, as suggested by the Schwarz criterion. The results are based on demeaned data. p -values in parentheses. *** indicate significance at the 1% level.

The results are reported in Table 5. They show that the null hypothesis of weak exogeneity is rejected for $\log(TFP_{it})$, implying that there is long-run causality from FDI to TFP. The short-run causality test from (FDI_{it}/GDP_{it}) to $\log(TFP_{it})$ suggests that FDI does not cause TFP in the short run. The strong-exogeneity test, which does not distinguish between short-run and long-run causality, shows that FDI has a causal impact on TFP.

In contrast, both the null hypothesis of weak exogeneity of (FDI_{it}/GDP_{it}) and the null of no short-run Granger causality from TFP to FDI cannot be rejected. From this, it can be concluded that there are no significant causal effects of TFP on FDI, neither in the long nor short run, which is also supported by the strong exogeneity test of (FDI_{it}/GDP_{it}) . Thus, we find for the sample as a whole that an increase in the FDI stock (relative to GDP) leads causally to a long-run decline in productivity, while TFP is strongly exogenous over the sample period.

Table 6. DOLS estimates for subsamples

	Coefficient on (FDI_{it}/GDP_{it})	No. of countries	No. of obs.
1. Countries with the highest human capital level	-0.00095 (-1.57)	20	589
Countries with the lowest human capital level	-0.00363*** (-3.51)	20	586
2. Countries with the highest level of financial development	0.00022 (0.35)	20	591
Countries with lowest level of financial development	-0.00240*** (-3.78)	20	589
3. Countries with the highest share of trade in GDP	0.00094* (1.71)	20	587
Countries with the lowest share of trade in GDP	-0.00260*** (-3.28)	20	588
4. Countries belonging to the group of countries with the highest human capital level, the highest level of financial development, and the highest share of trade in GDP	0.00396*** (4.95)	6	175
Countries belonging to the group of countries with the lowest human capital level, the lowest level of financial development, and the lowest share of trade in GDP	-0.00867*** (-2.67)	4	118

Notes: The dependent variable is $\log(TFP_{it})$. The optimal number of leads and lags in the DOLS regressions was determined by the Schwarz criterion with an observation-based maximum number of leads and lags of one. The results are based on demeaned data. *t*-statistics in parenthesis. *** [*] indicate significance at the 1% [10%] level.

3.5. Heterogeneity

To address the issue of heterogeneity, we estimate the long-run FDI-TFP coefficients for the subsamples discussed in Section 2. The results are reported in Table 6. As can be seen from panel 1, the estimated effect of FDI on TFP, although still negative, is not significant for the 20 countries with the highest levels of human capital (listed in Appendix B).⁵ For the 20 countries with the lowest levels of human capital, in contrast, we find a strong, negative, and statistically significant relationship between FDI and TFP.

The results in panel 2 show that the coefficient on the FDI variable for the 20 countries with the highest levels of financial market development is positive, although insignificant. The estimated coefficient for the 20 countries with the lowest levels of financial market development, in contrast, is negative, large, and significant.

According to the results in panel 3, the estimated effect of FDI on TFP is positive and significant at the ten percent level in the group of the 20 countries with the highest levels of openness. In the group of the 20 countries with the lowest levels of trade openness, FDI has a large and statistically significant negative impact on TFP.

⁵ The data used to rank the countries according to their human capital, financial market development, and trade openness levels are averaged over the period 1981-2011.

Finally, in panel 4, we see that FDI has a positive and highly significant effect on TFP in the 6 countries belonging to the groups of high human capital countries, high financial development countries, and high openness countries. For the 4 countries with low levels of human capital, poorly developed financial markets, and low openness levels, we find a strong and significant negative effect of FDI on TFP.

4. Conclusion

In this paper, we used panel cointegration techniques to explore a relationship that has received surprisingly little attention in the FDI literature—the long-run relationship between the level of FDI and the level of TFP in developing countries. The panel cointegration approach was chosen not only to obtain non-spurious results, but also to account for omitted variables and the possible endogeneity of FDI.

Employing data for 70 developing for the period 1981-2011, we found that an increase in the stock FDI (relative to GDP) has, on average, a robust negative long-run effect on TFP in developing countries. While the finding of a negative productivity effect of FDI is consistent with many firm-level studies, it contradicts previous macro-level studies that suggest that FDI has (on average) a positive or insignificant effect on TFP growth in developing countries.

Another result of this study is that FDI does not affect TFP in the short run. In addition, we found no causality from TFP to FDI (neither in the short nor in the long run); causality runs in only one direction, from FDI to TFP.

While the long-run effect of FDI on TFP is significantly negative on average in developing countries, subsample results show that FDI does not have a significant negative long-run effect on TFP in all countries. The estimated effect is negative but insignificant in a subsample of countries with higher levels of human capital; the effect is positive, although insignificant in a subsample of countries with higher levels of financial development; the effect is positive and weakly significant in a subsample of countries with higher levels of trade openness; it is positive and highly significant for the overlapping group of countries with higher levels of human capital, financial development, and trade openness. In contrast, we found significant negative effects of FDI on TFP in subsamples with lower levels of human capital, financial development, and trade openness.

From this it can be concluded that human capital, financial development, and trade openness are parameters that determine the impact of FDI on TFP on average across countries (though not necessarily in each country). Of these parameters, the most important is trade openness. However, these parameters alone have relatively little effect on the impact of FDI on TFP; it appears that it is the combination of these parameters that strongly determines the impact of FDI.

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Appendix A. Macro-studies on the impact of FDI on TFP

Table A1. *Summary of multi-country macroeconomic studies on the impact of FDI on total factor productivity*

Study	TFP measure	FDI variable	No. of countries	Period	Estimation method	Main findings
Baltabaev (2014)	TFP growth rates	FDI stocks/GDP	49 [21 developed and 28 developing countries, including transition economies]	1974-2008	Dynamic panel GMM regressions	FDI has a positive effect on TFP growth, but this effect is statistically significant only for those countries in which GDP per worker relative to the United States is below a certain threshold.
Alfaro et al. (2009)	TFP growth rates	Net FDI inflows/GDP	62 [19 developed and 43 developing countries]	1975-95	Cross-country OLS regressions	FDI stimulates TFP growth only in countries with well-developed financial markets.
Woo (2009)	TFP growth rates	Net FDI inflows/GDP, sum of inward and outward FDI/GDP, net FDI inflows from OECD countries/GDP	92 [22 developed and 70 developing countries]	1970-2000	Cross-country OLS, pooled OLS, and fixed effects panel regressions	FDI has a statistically significant positive effect on TFP growth. There is no substantial difference in the results between the total sample and a sample restricted to developing economies.
Wang and Wong (2009)	TFP growth rates	Net FDI inflows/GDP	69 [69 developing countries]	1970-1989	SUR panel regressions and panel instrumental variables regressions (without fixed effects)	FDI stimulates TFP growth only in countries that are well endowed with human capital. The effect does not vary with the level of financial development.
de Melo (1999)	TFP growth rates	Mix of net and gross FDI inflows	33 [16 developed and 17 developing countries]	1970-1990	Pooled, fixed-effects, and pooled mean-group regressions (without time effects)	The estimated effects of FDI on TFP growth are negative but mostly insignificant for the total sample, positive and significant for developed countries, and insignificant (with different signs) for developing countries.

Appendix B. Countries in the Sample, 1981-2011

Table A2. *Countries and summary statistics*

	Average of $\log(TFP_{it})$	Average of (FDI_{it}/GDP_{it})		Average of $\log(TFP_{it})$	Average of (FDI_{it}/GDP_{it})
Argentina	6.24	15.57	Madagascar	4.65	9.99
Bahamas	7.05	59.78	Malawi	4.29	15.24
Bahrain	6.72	43.70	Malaysia	6.18	33.05
Bangladesh	5.05	3.45	Maldives	6.40	18.49
Barbados	7.34	18.55	Mali	4.92	13.66
Benin	4.93	-3.25	Mauritania	5.41	23.51
Bolivia	5.69	33.38	Mauritius	5.98	10.99
Botswana	5.90	38.58	Mexico	6.58	15.76
Brazil	5.96	15.01	Morocco	5.55	23.99
Burkina Faso	4.59	2.48	Mozambique	4.24	19.91
Cameroon	5.34	12.92	Niger	4.41	13.33
Central African Republic	4.42	20.66	Nigeria	5.19	35.84
Chad	5.21	33.48	Oman	6.98	15.62
Chile	6.38	54.43	Pakistan	5.55	7.80
Colombia	6.08	14.20	Panama	6.64	55.61
Congo, Dem. Rep.	4.07	14.69	Paraguay	5.86	11.69
Congo, Republic of	5.69	54.08	Peru	5.95	13.63
Costa Rica	6.35	21.09	Philippines	5.58	12.17
Cote d'Ivoire	5.28	17.29	Qatar	7.58	9.07
Dominican Republic	6.15	7.29	Saudi Arabia	7.09	16.27
Ecuador	5.95	18.42	Senegal	6.24	6.90
Egypt	6.09	25.57	Sierra Leone	7.05	22.56
El Salvador	4.15	13.07	South Africa	6.72	22.04
Fiji	5.74	34.00	Sri Lanka	5.05	9.82
Gabon	6.49	12.46	Sudan	7.34	9.33
Ghana	5.05	15.15	Swaziland	4.93	35.59
Guatemala	6.07	17.03	Thailand	5.69	19.16
Honduras	5.70	16.99	Togo	5.90	23.24
India	5.38	3.56	Trinidad & Tobago	5.96	64.13
Indonesia	5.49	11.01	Tunisia	4.59	59.19
Jamaica	5.88	49.35	Turkey	6.65	10.67
Jordan	5.93	44.88	Uruguay	6.23	12.64
Kenya	5.12	6.37	Venezuela	6.42	16.68
Kuwait	7.45	1.70	Zambia	4.87	83.99
Lesotho	4.76	24.46	Zimbabwe	6.67	14.82

Appendix C. Countries in the subsamples

Table A3. *List of countries and their classification*

Argentina	1	4	6	Madagascar		4		
Bahamas		3	5	Malawi	2	4		
Bahrain	1	3	5	7	Malaysia	1	3	5
Bangladesh	2		6	Maldives	2		5	
Barbados	1	3	5	7	Mali	2	4	
Benin	2			Mauritania	2		5	
Bolivia	1	3		Mauritius		3	5	
Botswana	1	4	5	Mexico	1		6	
Brazil		3	6	Morocco	2	3		
Burkina Faso		4	6	Mozambique	2	4		
Cameroon		4	6	Niger	2	4	6	8
Central African Republic	2	4	6	8	Nigeria		4	
Chad		4		Oman				
Chile	1			Pakistan	2		6	
Colombia			6	Panama	1	3	5	7
Congo, Dem. Rep.		4	6	Paraguay			5	
Congo, Republic of		4	5	Peru	1		6	
Costa Rica	1			Philippines	1			
Cote d'Ivoire	2			Qatar		3		
Dominican Republic				Saudi Arabia				
Ecuador	1		6	Senegal	2			
Egypt		3		Sierra Leone	2	4	6	8
El Salvador				South Africa	1	3		
Fiji	1	3	5	7	Sri Lanka	1		
Gabon		4	5	Sudan	2	4	6	8
Ghana		4		Swaziland			5	
Guatemala	2		6	Thailand		3	5	
Honduras			5	Togo	2			
India	2		6	Trinidad & Tobago	1	3		
Indonesia	2			Tunisia		3		
Jamaica	1		5	Turkey			6	
Jordan	1	3	5	7	Uruguay	1	3	6
Kenya				Venezuela			6	
Kuwait		3	5	Zambia		4		
Lesotho		4	5	Zimbabwe				

Notes: The number 1 [2] indicates that the country was included in the subsample of 20 countries with the highest [lowest] highest human capital level. The human capital index is not available for Bahamas, Burkina Faso, Chad, Madagascar, Nigeria, and Oman. The number 3 [4] indicates that the country was included in the subsample of 20 countries with the highest [lowest] level of financial development. The number 5 [6] indicates that the country was included in the subsample of 20 countries with the highest [lowest] share of trade in GDP. The number 7 [8] indicates that the country was included in the overlapping subsample of countries with the highest [lowest] human capital level, the highest [lowest] level of financial development, and the highest [lowest] share of trade in GDP.