How do South-South and North-South FDI affect energy intensity in developing countries?

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Abstract

This study is the first to examine the impact of both FDI from developed to developing countries (North-South FDI) and FDI from developing to other developing countries (South-South FDI) on energy intensity in developing countries. It is also the first in the FDI-energy intensity literature to carefully control for the endogeneity of FDI using several IV techniques, as well as the first in this literature to use a panel Granger causality approach. Applying these methods to an unbalanced panel of up to 57 economies over the period 2009 to 2019, we find that South-South FDI contributes to reductions in energy intensity in developing countries. This finding holds even when we use panel cointegration methods. In contrast, we find across all our estimation methods no evidence that North-South FDI reduces energy intensity in developing countries. The obvious policy implication of these findings is that policy makers in developing countries should focus on attracting South-South FDI, rather than on attracting North-South FDI.

KEYWORDS

Energy intensity; developing countries; South-South FDI; North-South FDI

JEL CLASSIFICATION

F21; F23; Q43; O13

1. Introduction

There is a small but growing number of studies on the impact of foreign direct investment (FDI) on economy-wide energy intensity — the ratio of energy use to GDP — in developing countries. The idea behind these studies is that (holding constant the shares of agriculture, manufacturing, and services in GDP) an estimated negative effect of FDI on economy-wide energy intensity can be interpreted as evidence of transfer of energy-saving technology from multinational enterprises (MNEs) to their affiliates and local firms in the host country.[1] If such a transfer exists, then developing countries can achieve energy savings per unit of output and thus economic growth without a proportional growth in energy use and the associated environmental problems — such as air and water pollution, noise due to wind turbines and other energy projects, radioactive waste from nuclear energy production, and greenhouse gas emissions from fossil-fuel fired power plants. Therefore, and also because the UN Sustainable Development Goals (SDGs) use energy intensity as the measure to track progress on SDG 7.3 (energy efficiency), which aims to double the global rate of improvement in energy efficiency by 2030,[2] the effect of FDI on energy intensity in developing countries is not only of academic interest but also of relevance to policy makers concerned with both economic development and sustainable development. The available evidence, however, is inconclusive. While the results of some studies suggest that FDI reduces energy intensity in developing countries (see e.g. Mielnik and Goldemberg, 2002; Herzer and Schmelmer, 2022),[3] others find insignificant effects (see e.g. Hübler and Keller, 2010; Kretschmer et al., 2013).

However, one potential problem with estimating the effect of FDI on energy intensity is the likely endogeneity of FDI. A lower energy intensity ceteris paribus means lower production costs. Low-energy intensity countries may therefore, ceteris paribus, attract more FDI than high-energy

[1] Such a transfer is typically referred to as a "technique effect". The technique effect is closely related to the so-called "pollution halo effect", which occurs if multinational firms transfer environmentally friendly technology to developing countries and this technology diffuses to local firms.
[2] Details on the SDGs are available at https://sdgs.un.org/goals.
[3] Herzer and Schmelmer (2022) distinguish between greenfield FDI and cross-border M&As. They find that while the effect of cross-border M&As on energy intensity is insignificant in upper-middle-income countries, greenfield FDI exerts a negative and significant impact on energy intensity in these countries. They also find that both greenfield FDI and cross-border M&As have an insignificant impact on energy intensity in low- and lower-middle-income countries.

intensity countries. If this is the case, the estimated coefficients may overstate the negative causal effect of FDI on energy intensity in developing countries. If, in contrast, high energy intensity reflects a less stringent energy policy that allows a greater use of energy and thereby attracts more FDI, the estimated coefficients may understate the negative effect of FDI on energy intensity in developing countries.

Herzer and Schmelmer (2022) account for these biases using system generalized methods of moments (GMM), but most studies ignore the likely endogeneity of FDI (see e.g. Mielnik and Goldemberg, 2002; Kretschmer et al., 2013), and some studies use a one-year lag of their FDI variable to account for endogeneity problems (see e.g. Hübler and Keller, 2010; Mimouni and Temimi, 2018; Herzer and Schmelmer, 2022). However, as shown by Bellemare et al. (2017), this strategy to identify the causal effect of an independent variable X_{it} on the dependent variable Y_{it} requires in the presence of a contemporaneous causal effect from the dependent variable to the independent variable that, while X_{it} depends on $X_{it\text{-}1}$, Y_{it} does not depend on $Y_{it\text{-}1}$. If this condition does not hold, contemporaneous reverse causality may bias the results in regressions with lagged independent variables (but no lagged dependent variable). In addition, it is well known that while a correlation between the current value of a variable Y_{it} and the past value of a variable X_{it} can be interpreted as a Granger causal effect of X_{it} on Y_{it}, the absence of such a correlation does not necessarily imply the absence of a contemporaneous effect of X_{it} on Y_{it}.

Another potential problem with estimating the effect of FDI on energy intensity in developing countries is that the energy-saving effect of FDI from developed to developing countries (North-South FDI) may differ from the energy-saving effect of FDI from developing to other developing countries (South-South FDI). If this is the case, then using total FDI may conflate these effects and thus lead to misleading conclusions.

To see why North-South FDI and South-South FDI may have different effects on energy intensity, consider the reasonable assumption that the technological gap between MNEs from developed countries and local firms in developing host countries is larger than the technological gap between developing country MNEs and their domestic counterparts. On the one hand, a larger technology gap implies a greater potential for the transfer of energy-saving technology. It may therefore be that the contribution of North-South FDI to reductions in energy intensity is greater than that of South-South FDI. On the other hand, a larger technology gap also implies a lower level of absorptive capacity, which may mean that domestic firms in many developing countries are unable to absorb energy-saving technology through North-South FDI. The reverse implication is that, if a smaller technology gap between foreign and local firms facilitates the absorption of new technologies, energy-saving technology is predominantly absorbed through South-South FDI. In addition, developing-country MNEs have a greater propensity to establish linkages with local firms than do their counterparts from developed countries (see e.g. UNCTAD, 2006), which in turn enables them to more deeply integrate into the host economies, and this deeper integration could be particularly beneficial in terms of technology spillovers to local firms. Thus, it may also be that South-South FDI has a greater negative effect on energy intensity than North-South FDI.

Another relevant point here is that there is evidence that foreign affiliates of MNEs from developing countries tend to be less energy intensive than North affiliates of North firms (see e.g. Lipsey and Sjöholm, 2011). This could be interpreted as support for the pollution haven hypothesis, which predicts that MNEs from developed countries will relocate their energy-intensive operations to developing countries where environmental policy is relatively weak. Under this hypothesis, it is possible that North-South FDI, via an increase in the relative size of energy-intensive industrial sectors, even leads to an increase in energy intensity.

Overall, it is therefore likely that the impact on energy intensity differs between North-South and South-South FDI. However, this has not been investigated to date, despite the obvious policy relevance: If there are differences in the effects of FDI on energy intensity between North-South and South-South FDI, then knowledge of these differences would be of value to policy makers in developing countries who face the practical problem of identifying those potential foreign investors that are more likely to transfer energy-saving technology.

Given these considerations, the objective of this study is to examine the impact of South-South and North-South FDI on energy intensity in developing countries using econometric methods that account for the likely endogeneity of FDI. More specifically, we make two main contributions to the literature. First, we do not focus on total FDI, but consider South-South and North-South FDI, using an unbalanced panel of 57 economies over the period 2009 to 2019. Second, we employ three estimation methods that allow estimation of causal effects in the presence of endogeneity: the system GMM estimator of Blundell and Bond (1998), the difference GMM estimator of Arellano and Bond (1991), and Lewbel's (2012) instrumental variable method. In addition, as a robustness check we examine the Granger causal relationship between North-South FDI and energy intensity, and between South-South FDI and energy intensity using the panel Granger causality approach recently developed by Juodis et al. (2021).

Since these methods do not account for non-stationary data, there is, however, a potential risk of spurious regressions — if the data are non-stationary. Although even if the data are non-stationary, this risk should be small if the number of observations per country is small and the number of countries is large, as in the present study, we address this risk by applying panel unit root and cointegration techniques to a subsample of (40) countries with sufficiently long time series ($T_i \geq 10$).

Cointegration implies the existence of a (non-spurious) long-run relationship between two or more non-stationary variables. The advantage of cointegration estimators is that they are consistent under cointegration even if the regressors are endogenous. However, a problem with panel unit root and cointegration methods in the present case is that these methods may produce biased results when the number of time-series observations is small relative to the number of cross-sectional units. Therefore, panel unit root and cointegration methods are used here as a robustness check rather than as the main analytic tool.

To preview our main results, we find across all our estimation methods that South-South FDI contributes to reductions in energy intensity. The estimated effect of North-South FDI on energy intensity, in contrast, is statistically insignificant in all specifications but one (where it is weakly significantly positive).

The remainder of this study is organized as follows. In Section 2 we present our basic empirical model and outline our data sources and definitions. Our results are discussed in Section 3. Section 4 concludes and provides some policy implications.

2. Model and data

Our basic empirical model is

$$\log ENERGY_{it} = \alpha \log ENERGY_{it\text{-}1} + \beta \log FDI_{it} + \gamma \log X_{it} + \mu_i + f_t + \varepsilon_{it} \tag{1}$$

where i and t are country and time indices; log denotes the natural logarithm; $ENERGY_{it}$ represents economy-wide energy intensity, measured as the ratio of primary energy use (in megajoules) to real GDP (in PPP terms); and FDI_{it} denotes two FDI variables. The first is the ratio of the stock of FDI from developed countries to GDP of developing country i, $NorthSouthFDI_{it}$; the second is the stock of FDI from developing countries relative to GDP, $SouthSouthFDI_{it}$. To avoid collinearity between $NorthSouthFDI_{it}$ and $SouthSouthFDI_{it}$, we include these variables separately.

X_{it} is a vector of control variables including real GDP per capita, $GDPPC_{it}$, imports as a percentage of GDP, IMP_{it}, the consumer price index (used as a proxy for the energy price), CPI_{it}, gross fixed capital formation as a percentage of GDP, $GFCF_{it}$, and industrial value added as a percentage of GDP, IND_{it}. We also control for country fixed effects, μ_i, and common time effects, f_t.

Data on the control variables are taken from the World Development Indicators (WDI) (available at https://databank.worldbank.org/source/world-development-indicators). The (nominal) data used to construct our FDI variables are from the coordinated direct investment survey database of the IMF (available at https://data.imf.org/?sk=40313609-F037-48C1-84B1-E1F1CE54D6D5), which reports bilateral FDI data.[4] Both FDI variables are ratios to (nominal) GDP. The (nominal) GDP data to construct these ratios are also from the WDI, like our data on energy intensity.

Combining the data from both sources, and excluding tax havens and countries with less than one million people,[5] yields an unbalanced panel dataset of 57 developing countries with data between 2009 and 2019.[6] The minimum number of observations per country is 2, while the maximum is 11; the average number of observations per country is 9.5.

3. Results

We estimate equation (1) using system and difference GMM. Both techniques (which are designed for small-*T* large-*N* panels such as the one used here) are dynamic panel methods that account for endogeneity while avoiding the well-known "Nickell bias" (that arises from applying a fixed effects estimator to a lagged dependent variable model in a panel with small *T*). In addition, we use the Lewbel (2012) instrumental variable estimator, which, however, is not designed for dynamic panels. Therefore, we do not include $\log ENERGY_{it-1}$ in the Lewbel regressions.

All three estimators use internal instruments. While the system and difference GMM estimators construct instruments using lagged observations, the Lewbel estimator exploits heteroskedasticity to construct instrumental variables.

The estimation results along with diagnostic tests are presented in Table 1. The Arellano and Bond (1991) tests for second-order serial correlation (AR2) indicate that the GMM residuals exhibit

[4] We aggregate the bilateral FDI data to South-South FDI and North-South FDI. To construct our measure of South-South FDI [North-South FDI], we classify a country as developing [developed] country if it is officially listed as a low- or middle-income [high-income] country by the World Bank in its World Development Reports (available at https://www.worldbank.org/en/publication/wdr/wdr-archive) in more than half of the years between 2009 and 2019.

[5] We exclude tax havens because most FDI into tax havens does not generate value adding activity. There is therefore no reason to assume that FDI into tax havens generates significant effects on energy intensity. The reason for excluding countries with less than one million people is that their FDI to GDP ratio is highly volatile due to single large transactions, including large profit repatriations. Their FDI to GDP ratio is therefore not a meaningful measure of the foreign value-adding activities of MNEs.

[6] The countries in our sample are Albania, Algeria, Armenia, Azerbaijan, Bangladesh, Belarus, Benin, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Cambodia, China, Cote d'Ivoire, El Salvador, Georgia, Ghana, Guatemala, Honduras, India, Indonesia, Kazakhstan, Kyrgyz Republic, Lebanon, North Macedonia, Malaysia, Mali, Mexico, Moldova, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nepal, Niger, Nigeria, Pakistan, Paraguay, Peru, Philippines, Romania, Russia, Rwanda, Senegal, Serbia, South Africa, Sri Lanka, Tanzania, Thailand, Togo, Turkey, Uganda, Ukraine, and Zambia.

no second-order serial correlation, and the Hansen tests of overidentifying restrictions (HANSEN) fail to reject the validity of the instruments in the GMM models. Moreover, the number of instruments is always smaller than the number of countries. We therefore conclude that the GMM models presented in columns (1) – (4) are correctly specified, like the Lewbel models presented in columns (5) and (6), which pass the Hansen test of overidentifying restrictions, the Kleibergen-Paap rk *LM* test of underidentification, and the Kleibergen-Paap rk Wald *F* test of weak identification.

Turning to the estimated coefficients on the FDI variables, we see that coefficient on $\log NorthSouthFDI_{it}$ is insignificant in all three specifications, whereas $\log SouthSouthFDI_{it}$ has a negative and significant coefficient in all three specifications.

For brevity, we do not discuss the results for the control variables in detail here, but note that the coefficients on the control variables are largely consistent with the literature on the determinants of energy intensity in developing countries. The only exception is the coefficient on $\log IMP_{it}$, which, in contrast to previous estimates in the literature, is positive and significant in most specifications. The most likely explanation for the positive coefficient is that while many imported goods and services are not a channel for technology spillovers, increased imports imply that transport-related energy use increases.

As is well known, the presence or absence of Granger causal or lagged effects says nothing about the presence or absence of contemporaneous effects. Since, however, the diffusion of spillovers of energy-saving technology may take some time, we also examine the Granger causal effects of North-South and South-South FDI on energy intensity (while controlling for the lagged dependent variable). To this end, we use the method recently developed by Juodis et al. (2021), which has superior size and power compared to traditional tests. It should perhaps be noted that this method corrects for Nickell bias using the split-panel jackknife method. Unfortunately, however, the Juodis et al. (2021) test requires a balanced panel. Therefore, we apply it to a subsample that only includes countries with complete data between 2010 and 2019 (38 countries).[7] Using the same control variables as above and a lag length of one year (as suggested by the BIC) yields the results presented in Table 2.

The results suggest that while there is no Granger causality from North-South FDI to energy intensity, South-South FDI Granger-causes energy intensity with a negative sign. For completeness, we also report the results of the "reverse" Granger causality tests, with log$NorthSouthFDI_{it}$ and log$SouthSouthFDI_{it}$ as the endogenous variables, and log$ENERGY_{it}$ as the exogenous variable. From these results, there is evidence (at the 10% level) of a positive Granger causal relationship from energy intensity to North-South FDI, whereas energy intensity has no Granger-causal effect on South-South FDI. It is needless to say that the latter does not imply absence of contemporaneous effects of energy intensity on South-South FDI.

Since, however, the above methods do not account for potential non-stationary data, the question arises whether our results change if we use non-stationary panel techniques. To assess whether this is the case, we restrict our sample to countries with at least 10 time series observations, yielding a subsample of 40 countries.[8] The reason for using this subsample is that panel unit root and cointegration methods are not feasible in our full sample given the relatively small number of observations for some countries. Moreover, because the existence of cointegration between two (or more) non-stationary variables is known to be robust to the addition of further variables, we focus on the main variables of interest: log$NorthSouthFDI_{it}$ and log$SouthSouthFDI_{it}$. Thus, we examine two bivariate relationships: (1) the relationship between log$NorthSouthFDI_{it}$ and log$ENERGY_{it}$, and (2) the relationship between log$SouthSouthFDI_{it}$ and log$ENERGY_{it}$.

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[7] The countries in this sample are Armenia, Azerbaijan, Bangladesh, Belarus, Bolivia, Bosnia and Herzegovina, Brazil, Bulgaria, Cambodia, China, El Salvador, Georgia, Guatemala, Honduras, India, Indonesia, Kazakhstan, Kyrgyz Republic, North Macedonia, Malaysia, Mexico, Moldova, Mongolia, Morocco, Mozambique, Nepal, Nigeria, Pakistan, Paraguay, Philippines, Romania, Russia, Serbia, South Africa, Thailand, Turkey, Ukraine, and Zambia.

[8] The countries in this sample are Armenia, Azerbaijan, Bangladesh, Belarus, Bolivia, Bosnia and Herzegovina, Brazil, Bulgaria, Cambodia, China, El Salvador, Georgia, Ghana, Guatemala, Honduras, India, Indonesia, Kazakhstan, Kyrgyz Republic, North Macedonia, Malaysia, Mexico, Moldova, Mongolia, Morocco, Mozambique, Nepal, Nigeria, Pakistan, Paraguay, Philippines, Romania, Russia, Serbia, South Africa, Thailand, Turkey, Uganda, Ukraine, and Zambia.

The first step in this examination is to pre-test the variables for unit roots. We use the panel unit root tests of Levin et al. (2002) and Pesaran (2007) for this purpose. As is well known, the Levin et al. (2003) test assumes cross-sectionally independent residuals and may suffer from size distortions in the presence of error cross-sectional dependence. To account for cross-sectional dependence due to common time effects, we demean the data by subtracting the cross-sectional means from the data and use the demeaned data in place of the original data to perform the Levin et al. (2002) test.[9] Since the Pesaran (2007) test accounts for error cross-sectional dependence via the use of weighted cross-sectional averages, we apply this test to the raw data. Both tests are performed both with country-specific intercepts (*c*) and country-specific intercepts and time trends (*c, t*). The results are presented in Table 3.

The Levin et al. (2003) tests reject the unit-root null for all three variables, regardless of whether country-specific intercepts or country-specific intercepts and country-specific time trends are included. The Pesaran (2007) tests do not reject the null hypothesis of unit root for all three variables only when country-specific intercepts and country-specific time trends are included. Thus, the results of these tests are ambiguous regarding whether $\log ENERGY_{it}$, $\log NorthSouthFDI_{it}$, and $\log SouthSouthFDI_{it}$ are stationary or non-stationary (in the sense that they have a unit root). If the variables are stationary, then there is no reason to be concerned that the results in Table 1 and 2 are spurious. If the variables are non-stationary, there is a risk of spurious regressions. Although it is reasonable to assume that this risk is small in short panels such as the one used here, it is not zero. Given the results in Column (4), we therefore assume that $\log ENERGY_{it}$, $\log NorthSouthFDI_{it}$, and $\log SouthSouthFDI_{it}$ have unit roots.

Under this assumption, the next step is to test for cointegration between $\log NorthSouthFDI_{it}$ and $\log ENERGY_{it}$ and between $\log SouthSouthFDI_{it}$ and $\log ENERGY_{it}$. Table 4 reports results of cointegration tests based on models with country-specific trends (and fixed effects).[10] Since the

[9] Using demeaned data is equivalent to using the residuals from regressions of each variable on time dummies.
[10] The trends are statistically significant in the majority of countries, and the evidence in favor of cointegration is weaker when using models without time trends. Thus, it is important to include country-specific time trends.

Pedroni (1999) tests assume error cross-sectional independence, we use the demeaned data for these tests. For the Gengenbach et al. (2016) and Banerjee and Carrion-i-Silvestre (2017) tests, which account for error cross-sectional dependence (via the use of weighted cross-sectional averages), we use the raw data. Since all these tests indicate that cointegration exists between log$NorthSouthFDI_{it}$ and log$ENERGY_{it}$ and between log$SouthSouthFDI_{it}$ and log$ENERGY_{it}$, we proceed to estimate these relationships using two panel cointegration estimators: the panel FMOLS (PFMOLS) and panel DOLS (PDOLS) estimators of Kao and Chiang (2001).

To control for cross-sectional dependence due to omitted common factors, we again use the demeaned data. Moreover, we include country-specific trends to control explicitly for the country-specific effects of any omitted factors that evolve relatively smoothly over time. In addition, to ensure that our results do not suffer from error cross-sectional dependence due to common factors, we test for cross-sectional dependence in the residuals from our regressions using the cross-sectional dependence test of Juodis and Reese (JR) (2022).[11]

The PFMOLS and PDOLS estimates of the relationships between log$NorthSouthFDI_{it}$ and log$ENERGY_{it}$ and between log$SouthSouthFDI_{it}$ and log$ENERGY_{it}$ are presented in Table 5. As can be seen from the table, the Juodis and Reese (2022) test indicates that the there is no common factor-induced cross-sectional dependence in the residuals, and the estimated coefficient on log$SouthSouthFDI_{it}$ is negative and statistically significant in both regressions, whereas the coefficient on log$NorthSouthFDI_{it}$ is positive and weakly significant in the PFMOLS regression and positive but insignificant in the PDOLS regression.

Finally, we evaluate the magnitude of the estimated effects of South-South FDI on energy intensity. The estimated elasticities of energy intensity with respect to South-South FDI in Table 1 and 5 range between -0.068 and -0.024. Multiplying these values by the ratio of the average growth rate of $SouthSouthFDI_{it}$ (5.875%) to the average growth rate of $ENERGY_{it}$ (-1.357%) in our 57-

[11] We use the Juodis and Reese (2022) test rather than the standard Pesaran (2004) test because the latter has no power to detect error cross-sectional dependence when the estimated models include time dummies (or cross-sectional averages) or are based on demeaned data. The Juodis and Reese (2022) test is a modified version of the Pesaran (2004) test that does not suffer from this problem.

country sample yields 0.104 and 0.294, respectively. These values imply a predicted average reduction in energy intensity due South-South FDI that accounts for between about 10% and 30% of the actual average reduction in energy intensity in our sample during the period 2009 to 2019. Thus, our estimates imply a substantial (but not implausibly large) effect of South-South FDI on energy intensity.

4. Conclusion and policy implications

A transfer of energy-saving technologies to developing countries through FDI would mean that FDI allows these countries to achieve economic growth without a proportional growth in energy use and the associated environmental problems. Since the implementation of energy-saving technologies manifests in energy savings per unit of output and thus reductions in energy intensity (the indicator used by the SDGs for monitoring energy efficiency), an estimated negative effect of FDI on economy-wide energy intensity can be interpreted as evidence for a transfer of such technologies from MNEs to their affiliates and local firms.

However, the effect of North-South FDI on economy-wide energy intensity may, theoretically, differ from the effect of South-South FDI. It is therefore important for policy makers to know which of these two forms of FDI contributes more to reductions in economy-wide energy intensity, and hence which of these two should be preferred in times of climate change and other environmental problems.

This study was the first to empirically examine the impact of North-South and South-South FDI on economy-wide energy intensity in developing countries. It was also the first in the FDI-energy intensity literature to carefully control for the endogeneity of FDI using several IV techniques, as well as the first in this literature to use a panel Granger causality approach.

Using an unbalanced panel of 57 economies over the period 2009 to 2019, we found, based on stationary panel methods, that South-South FDI has a negative effect on energy intensity in developing countries, a finding that is robust to the use of non-stationary panel methods. The estimated effect of North-South FDI on energy intensity, in contrast, is statistically insignificant in all but one regression, where it is marginally significant and positive. Thus our overall conclusion is that while North-South FDI does not contribute to reductions in energy intensity in developing countries, South-South FDI reduces energy intensity in developing countries.

The obvious policy implication of our study is that policy makers in developing countries should focus on attracting South-South FDI, rather than on attracting North-South FDI. Another policy implication is that South-South FDI can contribute to achieving SDG 7.3 ("By 2030, double the global rate of improvement in energy efficiency"). Finally, to the extent that improvements in global energy intensity contribute to reducing worldwide environmental problems, the results of this study imply that source countries of South-South FDI may benefit as well from reductions in energy intensity in host countries of South-South FDI.

References

Arellano, M., and O. Bover. 1995. "Another Look at the Instrumental Variable Estimation of Error-components Models." *Journal of Econometrics* 68 (1): 29-51.

Arellano, M., and S. Bond. 1991. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *Review of Economic Studies* 58 (2): 277-297.

Banerjee, A., and J.L. Carrion-i-Silvestre. 2011. "Testing for Panel Cointegration Using Common Correlated Effects Estimators." Department of Economics Discussion Paper 11–16 (Birmingham: University of Birmingham).

Banerjee, A., and J.L. Carrion-i-Silvestre. 2017. "Testing for Panel Cointegration Using Common Correlated Effects." *Journal of Time Series Analysis* 38 (4): 610-636.

Bellemare, M.F., Masaki, T., and T.B. Pepinsky. 2017. "Lagged Explanatory Variables and the Estimation of Causal Effect." *Journal of Politics* 79 (3): 949-963.

Blundell, R., and S. Bond. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics* 87 (1): 115-143.

Gengenbach, C., J.-P. Urbain, and J. Westerlund. 2016. Error Correction Testing in Panels with Common Stochastic Trends. *Journal of Applied Econometrics* 31 (6): 982-1004.

Herzer, D., and N. Schmelmer. 2022. "The Effects of Greenfield Foreign Direct Investment and Cross-Border Mergers and Acquisitions on Energy Intensity in Upper-Middle Income Countries and Low- and Lower-Middle Income Countries." *Applied Economics* 54 (41): 4732-4750.

Hübler, M., and A. Keller. 2009. "Energy Savings via FDI? Empirical Evidence from Developing Countries." *Environment and Development Economics* 15 (1): 59-80.

Juodis, A., Y. Karavias, and V. Sarafidis. 2021. "A Homogeneous Approach to Testing for Granger Non-Causality in Heterogeneous Panels. *Empirical Economics* 60 (4): 93-112.

Juodis, A., and S. Reese. 2022. "The Incidental Parameters Problem in Testing for Remaining Cross-Section Correlation." *Journal of Business & Economic Statistics* 40 (2): 1191-1203.

Kao, C., and M.-H. Chiang. (2001), "On the Estimation and Inference of a Cointegrated Regression in Panel Data", in Baltagi, B.H., Fomby, T.B. and Carter Hill, R. (Ed.) Nonstationary Panels, Panel Cointegration, and Dynamic Panels (Advances in Econometrics, Vol. 15), Emerald Group Publishing Limited, Bingley, 179-222.

Kretschmer, B., Hübler, M., and P. Nunnenkamp. 2013. "Does Foreign Aid Reduce Energy and Carbon Intensities of Developing Economies?" *Journal of International Development* 91 (May 2011): 67-91.

Levin, A., Lin, C.-F., and C.S. James Chu. 2002. "Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties." *Journal of Econometrics* 108 (1): 1-24.

Lewbel, A. 2012. "Using Heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models." *Journal of Business and Economic Statistics* 30 (1): 67-80.

Lipsey, R.E., and F. Sjöholm. 2011. "South-South FDI and Development in East Asia." *Asian Development Review* 28 (2): 11-31.

Mielnik, O., and J. Goldemberg. 2002. "Foreign Direct Investment and Decoupling between Energy and Gross Domestic Product in Developing Countries." *Energy Policy* 30 (2): 87-89.

Mimouni, K., and A. Temimi. 2018. "What drives Energy Efficiency? New evidence from Financial Crises." *Energy Policy* 122 (November): 332-348.

Pedroni, P. 1999. "Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors." *Oxford Bulletin of Economics and Statistics*, 61 (S1): 653-670.

Pesaran, M.H. 2004. "General Diagnostic Tests for Cross Section Dependence in Panels." CESifo Working Paper Series no. 1229, Munich: CESifo Group.

Pesaran, M.H. 2007. "A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence." *Journal of Applied Econometrics* 22 (2): 265-312.

UNCTAD. 2006. "World Investment Report 2006 - FDI from Developing and Transition Economies: Implications for Development." Geneva: United Nations Conference on Trade and Development.

Windmeijer, F. 2005. "A finite Sample Correction for the Variance of Linear Efficient two-step GMM Estimators." *Journal of Econometrics* 126 (1): 25-51.

Table 1. System GMM, difference GMM, and Lewbel IV results

	System GMM		Difference GMM		Lewbel IV	
	(1)	(2)	(3)	(4)	(5)	(6)
log$ENERGY_{it-1}$	0.965***	0.982***	0.878***	0.682***		
	(0.050)	(0.048)	(0.136)	(0.172)		
log$NorthSouthFDI_{it}$	-0.020		-0.024		0.094	
	(0.016)		(0.026)		(0.095)	
log$SouthSouthFDI_{it}$		-0.024**		-0.068**		-0.034***
		(0.010)		(0.030)		(0.010)
log$GDPPC_{it}$	0.003	-0.047***	-0.214	-0.052	-0.168***	-0.183***
	(0.013)	(0.017)	(0.228)	(0.236)	(0.022)	(0.031)
logIMP_{it}	0.093**	0.070**	0.173***	0.196*	0.020	0.141**
	(0.042)	(0.030)	(0.062)	(0.105)	(0.038)	(0.050)
logCPI_{it}	0.061	0.068*	0.036	0.026	0.481***	0.474***
	(0.054)	(0.037)	(0.075)	(0.111)	(0.067)	(0.070)
log$GFCF_{it}$	-0.038	-0.030	-0.036	-0.024	0.043**	0.038**
	(0.032)	(0.021)	(0.036)	(0.049)	(0.021)	(0.018)
logIND_{it}	0.027	0.047*	0.096*	0.123	-0.102	0.037
	(0.023)	(0.027)	(0.049)	(0.079)	(0.073)	(0.053)
AR2 (p-value)	0.440	0.431	0.459	0.327		
No. of instruments	42	42	37	37		
HANSEN (p-value)	0.248	0.519	0.411	0.321	0.111	0.554
Kleibergen-Paap rk *LM* statistic (p-value)					0.000	0.005
Kleibergen-Paap rkWald *F* statistic					15.312	22.238
No. of countries	57	57	57	57	57	57
No. of observations	511	511	454	454	550	550

Notes: The dependent variable is log$ENERGY_{it}$. The lagged dependent variable was treated as predetermined; the time dummies, logIND_{it}, and log$GFCF_{it}$ were treated as exogenous; and log$NorthSouthFDI_{it}$, log$SouthSouthFDI_{it}$, log$GDPPC_{it}$, logIMP_{it}, logCPI_{it}, and were treated as endogenous in the GMM procedures. We used the orthogonal deviations transformation of Arellano and Bover (1995) rather than the first-difference transformation because the former has the advantage of preserving sample size in panels with gaps (as in our panel). To reduce the risk of instrument proliferation (which can overfit endogenous variables), the number of lags was restricted to up to five lags and the instrument matrix was collapsed. As a rule of thumb, GMM can exhibit the problem of too many instruments when the number of instruments is greater than the number of cross-sectional units. We used the two-step estimator with Windmeijer's (2005) standard errors for the GMM procedures. Only the FDI variables were instrumented in the Lewbel regressions. When country dummies are included in the Lewbel regressions, a warning message is displayed that the estimated covariance matrix of moment conditions is not of full rank and standard errors and model tests should be interpreted with caution. We therefore approximated the fixed effects using the country means of the variables. AR2 is the Arellano-Bond test for second-order autocorrelation. HANSEN is the Hansen test of overidentifying restrictions. The Kleibergen-Paap rk *LM* and Wald *F* statistics correspond to tests of underidentification and weak identification. The critical values of the Kleibergen-Paap rk Wald *F* statistic for a maximal IV relative bias of 5, 10, 20, and 30 percent are 21.23, 11.51, 6.42, and 4.63, respectively. Numbers in parentheses are heteroskedasticity-consistent standard errors. *** (**) [*] indicates significance at the 1% (5%) [10%] level.

Table 2. Panel causality tests

Null Hypothesis	Wald	Coefficient on the lagged explanatory variable
log$NorthSouthFDI_{it}$ does not cause log$ENERGY_{it}$	0.110	-0.028
log$SouthSouthFDI_{it}$ does not cause log$ENERGY_{it}$	0.023	-0.014**
log$ENERGY_{it}$ does not cause log$NorthSouthFDI_{it}$	0.069	0.390*
log$ENERGY_{it}$ does not cause log$SouthSouthFDI_{it}$	0.228	-0.410

Notes: Since the test requires a balanced panel, we constructed a subsample that only includes countries with complete data between 2010 and 2019 (38 countries). All tests include country fixed effects, and we used demeaned data to account for common time effects. All tests are based on one lag, as suggested by the BIC, and include control variables (lagged one period). The column headed Wald reports the p-value of the Wald test of the null hypothesis that the lagged explanatory variable is significantly different from zero. This p-value is equal to the p-value of the z-statistic of the coefficient on the lagged explanatory variable. For all tests, we used heteroskedasticity-consistent standard errors. ** (*) indicates significance at the 5% (10%) level.

Table 3. Panel unit root tests

	Levin et al. (2002)		Pesaran (2007)	
	(1)	(2)	(3)	(4)
	c	*c, t*	*c*	*c, t*
log$ENERGY_{it}$	0.004	0.000	0.010	0.191
log$NorthSouthFDI_{it}$	0.000	0.000	0.009	0.638
log$SouthSouthFDI_{it}$	0.000	0.000	0.462	0.997

Notes: c (t) indicates that the tests include country-specific intercepts (and time trends). Given the small number of time-series observations, only one lag was used in the tests. The Levin et al. (2002) tests are based on demeaned data to account for error cross-sectional dependence due to unobserved common factors; the Pesaran (2007) tests account for error cross-sectional dependence due to unobserved common factors via the use of (weighted) cross-sectional averages (and are therefore based on the original data). Reported values are p-values.

Table 4. Panel cointegration tests

	Pedroni (1999)		Gengenbach et al. (2016)	Banerjee and Carrion-i-Silvestre (2017)
Panel A: Tests for cointegration between log$NorthSouthFDI_{it}$ and log$ENERGY_{it}$				
	Panel statistics	Group mean statistics		
PP t-statistics	-4.770***	-7.660***		
ADF t-statistics	-4.079***	-7.687***		
ECM t-statistic			-12.308***	
CIPS statistic				3.382*
Panel B: Tests for cointegration between log$SouthSouthFDI_{it}$ and log$ENERGY_{it}$				
	Panel statistics	Group mean statistics		
PP t-statistics	-5.480***	-5.747***		
ADF t-statistics	-6.032***	-7.099***		
ECM t-statistic			-6.590***	
CIPS statistic				3.491*

Notes: The dependent variable in the Pedroni (1999) and Banerjee and Carrion-i-Silvestre (2015) tests is log$ENERGY_{it}$; the dependent variable in the test of Gengenbach et al. (2016) is Δlog$ENERGY_{it}$. All tests include trends and intercepts. The Pedroni (1999) tests are based on one lag, and we employed the Newey-West bandwidth selection using the Bartlett kernel. Given the limited number of time-series observations available here, no lags of the first differences of the variables (and lo lags of the first differences of the cross-sectional averages) were included in the Gengenbach et al. (2016) tests. The results from the Banerjee and Carrion-i-Silvestre (2017) tests are based on unit root test specifications that include no lags of the first differences. Since the Banerjee and Carrion-i-Silvestre (2017) test requires a balanced panel, we used a subsample of 38 countries with complete data between 2010 and 2019 for this test. All tests reject for large negative values. The Pedroni (1999) statistics are distributed as standard normal. The critical value for the Gengenbach et al. (2016) t-test (for N = 50) at the 1% significance level is -3.067. The 5% [10%] critical value for the Banerjee and Carrion-i-Silvestre (2017) statistic is -3.52 [-3.37] (for T = 10 and N = 50). Since Banerjee and Carrion-i-Silvestre (2017) do not report critical values for T < 30, we use the critical values from the working paper version of their article (Banerjee and Carrion-i-Silvestre, 2011). *** [*] indicates rejection of the null hypothesis of no cointegration at the the 1% [10%] level.

Table 5. Estimates of the long-run relationship between log*NorthSouthFDI*$_{it}$ and log*ENERGY*$_{it}$ and the long-run relationship between log*SouthSouthFDI*$_{it}$ and log*ENERGY*$_{it}$

	PFMOLS		PDOLS	
	(1)	(2)	(3)	(4)
Long-run coefficient on log*NorthSouthFDI*$_{it}$	0.029*		0.053	
	(0.015)		(0.038)	
Long-run coefficient on log*SouthSouthFDI*$_{it}$		-0.024**		-0.062***
		(0.010)		(0.021)
JR (*p*-value)	0.149	0.156	0.176	0.221
No. of countries	40	40	40	40
No. of obs.	395	395	315	315

Notes: PFMOLS = panel FMOLS estimator of Kao and Chiang (2001); PDOLS = panel DOLS of estimator of Kao and Chiang (2001). The dependent variable in the PFMOLS and PDOLS regressions is log*ENERGY*$_{it}$; the dependent variable in the PMG regression is Δlog*ENERGY*$_{it}$. All regressions include country fixed effects and individual time trends. The PDOLS regressions were estimated with one lead and one lag of the first-differenced regressor. All regressions were performed using demeaned data to account for error cross-sectional dependence due to unobserved common factors. JR is the cross-sectional dependence test of Juodis and Reese (2022) applied to the residuals from the regressions. Numbers in parentheses are heteroscedasticity- and autocorrelation-consistent standard errors. *** (**) [*] indicates significance at the 1% (5%) [10%] level