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The impact of domestic R&D and North–South R&D spillovers on energy intensity in developing countries

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Abstract

This study utilizes panel data between 1995 and 2015 for a cross section of 33 developing (low- and middle-income) countries to investigate the impact on domestic energy intensity both of domestic R&D and of possible spillovers from foreign R&D conducted in developed (high-income) countries. More specifically, it examines R&D spillovers from developed countries (North) to domestic energy intensity in developing countries (South) through disembodied channels, total goods imports, and imports of machinery and equipment. Our main findings, based on panel cointegration techniques, are as follows: First, domestic R&D in the long run does not contribute to reductions in energy intensity in developing countries; second, there is no evidence to suggest that disembodied North–South R&D spillovers affect the long-run level of domestic energy intensity; third, there are nevertheless significant spillovers from R&D conducted in industrial countries that reduce energy intensity in developing countries; and fourth, while many imported goods are not a channel for North–South R&D spillovers, such spillovers are transmitted through imports of machinery and equipment.

Keywords Energy intensity · Domestic R&D · North–South R&D spillovers · Developing countries · Panel cointegration methods

JEL Classification Q43 · Q55 · F18

1 Introduction

Several studies find positive effects of domestic research and development (R&D) performed in developing countries and foreign R&D performed in industrial countries on total factor productivity (TFP) in developing countries (see, e.g., Coe et al.

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1997; Madsen et al. 2010; Herzer 2022a, b). An increase in TFP implies that a given output can be produced with fewer standard factors of production, such as labor and physical capital, as well as human capital, or that more output can be produced with the same quantity of factors of production. Thus, an increase in TFP can be interpreted as factor-saving technical change. Consequently, the available R&D-TFP literature suggests that both domestic R&D and foreign R&D conducted in developed countries generate new technologies that are factor saving in developing economies. Given this implication, and given that energy is necessary for the production of all kinds of goods, including energy itself, it is natural to ask: *Do domestic and foreign R&D also generate energy savings per unit of output and thus reduce energy intensity (i.e., the ratio of energy use to GDP) in developing economies?* The answer to this question is the subject of this study.

A reduction in energy intensity in developing countries means that they can raise their living standards without a proportional increase in energy use, thereby reducing the growth of the environmental problems associated with increasing energy demand—such as air and water pollution, land disturbance, radioactive waste from nuclear energy production, and global climate change due to greenhouse gas emissions from fossil-fuel fired power plants. According to data from the World Development Indicators, the ratio of energy use to real GDP in the group of low- and middle-income countries (defined here as developing countries) exceeded that in the group of high-income countries by more than factor 1.4 in 2014 (the last year with available data for these country groups). Therefore, the answer to the above question is not only of academic interest but also directly relevant to policymakers concerned with both economic and sustainable development.

However, the answer is theoretically unclear (as discussed in Sect. 2), and the empirical evidence is scarce. There are only six studies on the impact of domestic R&D on energy intensity in developing countries (Yu 2012; Wang and Han 2017; Dong et al. 2018; Huang et al. 2018, 2020; Huang and Chen 2020), and only three on the impact of both domestic and foreign R&D on energy intensity in developing countries (Huang et al. 2018, 2020; Wang and Han 2017). All these studies are single-country studies for China, based on province-level panel data.[1]

The evidence from all of these studies suggests that *domestic* R&D has an energy intensity reducing effect.[2] With respect to the effect of *foreign* R&D on domestic energy intensity, two studies find evidence of a negative (reducing) effect of both import-related and foreign direct investment (FDI)-related spillovers from R&D

[1] A related study is that of Godil et al. (2021), who examine, among other things, the effect of R&D intensity (i.e., the ratio of R&D expenditures to GDP) on energy consumption per capita (not measured in logs) using time-series data for India. Their results suggest that R&D intensity has a negative effect on energy consumption per capita. However, their empirical model has the counterfactual implication that a doubling of R&D can reduce energy consumption per capita in an economy with only one dollar of R&D to the same extent as in an economy where R&D expenditures amount to one billion dollars. In addition, R&D intensity suffers from endogeneity because higher energy use may result in higher GDP (the denominator of R&D intensity).

[2] Huang and Chen (2020) also consider different types of R&D and find that while industrial R&D contributes to reductions in energy intensity, independent R&D and higher education R&D have no significant effect on energy intensity. They also find that experimental R&D has a negative effect on energy intensity, whereas the effect of both basic R&D and applied R&D is insignificant.

performed in high-income countries on domestic energy intensity (Wang and Han 2017; Huang et al. 2018); one study finds, somewhat surprisingly, that while the effect of foreign R&D spillovers through imports is insignificant, and while the effect of foreign R&D spillovers through FDI is negative, foreign R&D spillovers through exports increase domestic energy intensity (Huang et al. 2020).

However, the majority of these studies (Wang and Han 2017; Huang et al. 2018, 2020; Huang and Chen 2020) do not control for (strong) error cross-sectional dependence due to unobserved common factors. Consequently, the results of the majority of studies may be biased in the presence of omitted common factors that are correlated with the included explanatory variables and the dependent variable.[3] In addition, some studies (Yu 2012; Huang and Chen 2020; Huang et al. 2020) use methods that assume stationary data and thus can produce misleading results when the data are non-stationary. Moreover, most studies (Yu 2012; Wang and Han 2017; Huang and Chen 2020; Dong et al. 2018) utilize estimators that require strict exogeneity of the regressors, thus yielding potentially misleading results when the regressors are not strictly exogenous.[4] Since all these studies suffer from at least one of these shortcomings, their results should be viewed with some caution. In addition, it is well known that findings from single-country studies cannot necessarily be generalized. Even if the findings of these studies are valid, it may therefore be that they apply only to China.

Given the lack of general cross-country studies on the impact of domestic and foreign R&D on energy intensity in developing countries, this study aims to fill this gap. More specifically, we conduct a cross-country panel analysis using data from 33 developing countries (including China) spanning the years 1995 to 2015. It is worth noting that our study is the first to use panel data for a cross section of developing countries.

In addition, this study differs from previous research by examining disembodied, non-trade-related R&D spillovers from developed to developing countries, as well as R&D spillovers through imports of all goods and imports of machinery and equipment. Furthermore, this study takes into account all the methodological problems addressed above.[5] More specifically, we use panel cointegration methods to

[3] Cross-sectional dependence may be due to common factors that affect all panel units and/or spatial spillover effects across subsets of panel units. Cross-sectional dependence due to common factors is also known as strong cross-sectional dependence; cross-sectional dependence due to spatial spillovers is also known as weak cross-sectional dependence. The presence of weak cross-sectional dependence does not affect the consistency of conventional panel data estimators, but the standard errors may be biased. In contrast, strong cross-sectional dependence, if not controlled, can lead to biased coefficient estimates (Chudik and Pesaran 2015).

[4] If reductions in energy intensity imply GDP growth due to energy-saving technical change, and if firms respond to growth-induced increases in demand for variety by engaging in horizontal R&D to develop new varieties of existing products, then it is possible that reductions in energy intensity contribute to increased R&D activities via increases in GDP, at least in the short run. The implication is that domestic R&D is likely not strictly exogenous.

[5] We note two things here. First, it is not possible to measure R&D spillovers through FDI over our sample period because complete time series data on bilateral FDI flows from developed source countries are not available for developing host countries over the period 1995–2015. It is perhaps interesting to

address the non-stationary nature of the data and analyze the long-run relationships between our variables of interest. As discussed in more detail in Sect. 4.3, and as noted by Coe et al. (2009, p. 724), "[u]nder cointegration, parameter estimates are super consistent, and hence are robust to problems such as omitted variables, simultaneity, and endogeneity." While we are not aware of theoretical reasons to suggest that foreign R&D is endogenous to domestic energy intensity, we thus account for the likely endogeneity of domestic R&D. In addition, we control and test for error cross-sectional dependence in the residuals of our models.

It should be explicitly noted here that we use the World Bank classification of developing countries according to which low- and middle-income countries are classified as "developing countries" (World Bank 2007, 2012). Thus, the term "developing countries" includes post-communist countries. All countries in our sample (listed in Table 2) that fall under the category of developing countries according to the World Bank classification are classified by the IMF as "emerging market and developing economies," which also include post-communist countries. As a robustness check, we also use a sample of "developing economies" as classified by UNCTAD that does not include post-communist countries. We come back to this point in Sect. 4.2. Here, we note for completeness that, following common practice, we use the term "North" as shorthand for developed or industrial economies and "South" as shorthand for developing countries.

An important point is that our study also differs from previous work in that it also examines the impact of domestic R&D conducted in developed source countries of foreign R&D spillovers to developing countries on energy intensity within these source countries. If foreign R&D conducted in industrialized countries contributes to reductions in energy intensity in developing countries (through international R&D spillovers), it can be plausibly concluded that R&D conducted by industrialized countries tends to result in energy-saving technologies. If this conclusion is correct, then one should expect to find a negative effect of domestic R&D (conducted in developed countries) on energy intensity in developed countries. To our knowledge, there is only one cross-country panel study on the impact of R&D on energy intensity in developed countries: Alam et al. (2019). The authors analyze firm-level data for the G-6 countries (which include Canada, France, Germany, Japan, the UK, and the US) and find that R&D reduces energy intensity in these nations. Our study is the first both to examine the impact of foreign R&D conducted in industrial countries on energy intensity in developing countries and to conduct a plausibility check

Footnote 5 (continued)
note in this context that there are several studies on the impact of FDI on energy intensity in developing countries, which, however, do not explicitly examine the effect of FDI-related foreign R&D spillovers on energy intensity in developing countries, but focus on the broader impact of FDI. The evidence from these studies is mixed, with some indicating that FDI reduces energy intensity in developing countries, while others find no significant effect. For a review of this literature see Herzer and Schmelmer (2022). Second, we also examined R&D spillovers through exports of total goods and R&D spillovers through exports of machinery and equipment, but found little or no evidence of long-run spillovers from foreign R&D conducted in developed to domestic energy intensity in developing countries through exports of total goods and exports of machinery and equipment (from developing to developed countries).

for our main results by investigating the impact of domestic R&D on energy intensity in 15 developed source countries of foreign R&D spillovers.

To preview our main results, we find that while domestic R&D, in the long run, does not contribute to reductions in energy intensity in developing countries, foreign R&D performed in industrial countries reduces energy intensity in developing countries in the long run. Specifically, our results suggest that North–South spillovers occur mainly through imports of machinery and equipment rather than through imports of other goods and that the impact of foreign R&D varies with the share of machinery and equipment imports in GDP. However, we find no evidence of disembodied spillover effects. An additional result of this study is that there is evidence that domestic R&D performed in industrial source countries of R&D spillovers reduces energy intensity in these countries as well.

The remainder of this paper is organized as follows. In Sect. 2, we discuss the theoretical background. Section 3 presents the empirical model and defines the variables. Section 4 describes the data, including the sample, and discusses some econometric issues and the empirical methodology. Section 5 reports our results, and Sect. 6 concludes and provides some policy implications.

2 Theoretical background

We begin with a general energy-augmented aggregate production function of the form $Y = Af(AK, AL, AE)$. In this equation, Y represents aggregate output, K stands for capital, L for labor, and E for energy. The multiplier A denotes the level of technology, which is the focus of our discussion here. In the terms AK, AL, and AE, A indicates that the technology augments capital, labor, and energy, respectively. If A appears in front of the function f, the technology is factor neutral. Technical change, $\dot{A}$, improves the productivity of K, L, and E, respectively. In the case of purely labor- or capital-augmenting technical change, without energy-saving advances, technical change thus reduces the labor- or capital-output ratio. It has no effect on energy intensity, the ratio of E to Y, provided both that there are no substitution effects between energy and labor or capital and that the growth of income due to technical change does not induce a shift in consumption patterns toward energy-intensive goods. Since labor- or capital-saving technical change reduces the effective price of labor or capital, labor or capital will, however, be induced to substitute for energy. In addition, the reduction in the effective price of labor or capital should lead to lower prices for labor or capital-intensive products. The pattern of demand may therefore shift away from energy-intensive goods, so that less energy-intensive sectors expand relative to energy-intensive sectors. Thus, even purely labor or capital-augmenting technical change may, in the long-run, contribute to reductions in energy intensity. If, however, irrespective of relative prices, increases in income during industrialization are associated with a shift in consumption patterns toward energy-intensive goods and services (such as private vehicles, air conditioners, and flights), as argued and demonstrated by Hart (2018), then the increases in real income from rising productivity may result in increases in the relative size of energy-intensive sectors. It is therefore also possible, and likely, that labor or capital-augmenting technical change leads to an increase in energy intensity in the long run, even if there is substitutability between energy and labor or capital.

Analogously, purely energy-augmenting technical change implies that the same output can be produced with less energy and thus that the effective price of energy declines. The decline in the effective price of energy induces a substitution in favor of energy versus labor or capital, which offsets to some degree the initial reduction in energy intensity. The lower the elasticity of substitution between labor or capital and energy, the smaller the offsetting effect.[6] In addition, the decline in the effective price of energy implies an increase in real income. If this extra income is spend on energy-intensive goods, the relative size of energy-intensive sectors increases. Thus, even energy-saving technical change does, in the long run, not necessarily lead to reductions in energy intensity.

Finally, the concept of factor-neutral technical change implies that the ratio of L to Y, the ratio of K to Y, and the ratio of E to Y decrease, at least initially. Like above, increases in income as a result of factor-neutral technical change may, however, induce an increase in the relative size of energy-intensive sectors, and thus an increase in energy intensity in the long run.

Thus, it can be assumed that energy intensity, EI, depends on the level of technology (which can be more or less energy-augmenting) using a function of the form $\mathrm{EI}=A^{\beta}$. Although the sign of the elasticity β is theoretically indeterminate, it is reasonable to assume that the more energy saving technical change is, the greater the likelihood will be that technical change will contribute to reductions in energy intensity in the long run. Assuming further a long-run relationship between R&D effort and the level of technology of the form $A=\mathrm{R\&D}^{\varphi}$, energy intensity can be expressed as

$$\mathrm{EI} = \mathrm{R\&D}^{\alpha} \tag{1}$$

where $\alpha \equiv \varphi \times \beta$ is the elasticity of energy intensity with respect to R&D.[7] Based on this equation and on the above theoretical considerations, it can be hypothesized

6 If the elasticity of substitution of energy is less than one, then improvements in energy productivity will lead to reductions in energy intensity (holding income effects constant). If the elasticity of substitution is greater than one, then energy-augmenting technical change will induce increases in energy intensity. Koetse et al. (2008) find in a meta-analysis that the elasticity of substitution between capital and energy is less than one. Stern and Kander (2012), using historical data for Sweden, find that the elasticity of substitution between a capital-labor aggregate and energy ranges between 0.64 and 0.69.

7 The relationship between R&D effort and the level of technology of the form $A=\mathrm{R\&D}^{\varphi}$ can be derived as follows. As discussed, for example, in Herzer (2022), semi-endogenous growth models assume a knowledge production of the form $\dot{A}=\delta A^{\phi}\mathrm{R\&D}^{\lambda}$, where $\dot{A}$ is the flow of new knowledge or technical change; δ is a constant of proportionality; A represents the stock of existing knowledge or the level of technology; ϕ is a parameter that describes the nature of the returns to the stock of knowledge, R&D stands for R&D effort; and λ, where $0<\lambda\leq 1$, is a parameter that captures the possibility of duplication in research (i.e., the possibility that a doubling of research effort less than doubles the production of new knowledge because of duplication). Assuming that the stock of knowledge grows in the long run at a constant rate g, the above equation can be solved for the stock of knowledge, yielding $A=\left(\frac{\delta}{g_A}\right)^{\frac{1}{1-\phi}}\mathrm{R\&D}^{\frac{\lambda}{1-\phi}}$. This equation predicts that, provided the growth rate of knowledge is constant over the long run, changes in R&D effort are positively associated with changes in the level of technology. For simplicity, setting the term $\left(\frac{\delta}{g_A}\right)^{\frac{1}{1-\phi}}$, which is constant, equal to 1, the above equation corresponds to the equation $A=\mathrm{R\&D}^{\varphi}$, where $\varphi\equiv\frac{\lambda}{1-\phi}$.

that if more R&D is oriented more toward energy-saving technologies than toward labor- or capital-saving technologies, it is more likely that R&D will contribute to long-term reductions in energy intensity.

Unfortunately, data that allow the construction of proxies for R&D in labor- or capital-saving technologies and/or R&D in energy-saving technologies are not available for a large number of countries, particularly developing countries.[8] It is therefore not possible to quantify the relative amounts of R&D in energy-saving technologies and R&D in labor- or capital-saving technologies in developing countries, and hence to assess a priori whether R&D in developing countries, in general, is oriented more toward energy-saving technologies than toward labor- or capital-saving technologies. What can be said, however, is that the vast majority of worldwide R&D activity takes place in industrial nations.[9] If R&D by industrial countries generates technologies that save more energy than those generated by R&D in developing countries, then it is possible that foreign R&D performed in industrial countries contributes more to reductions in energy intensity in developing countries through international R&D spillovers than domestic R&D. However, to the extent that R&D performed in industrial countries generates technologies that cannot be adapted to local conditions in developing countries, it may contribute less to reductions in domestic energy intensity than domestically performed R&D. Thus, the effects of domestic and foreign R&D on domestic energy intensity in developing countries are an empirical question.

3 Empirical model and variable definitions

We begin by taking natural logarithms of both sides of Eq. 1. Then, we introduce country and time subscripts i and t, and add an error term ε_{it}. Additionally, we include country fixed effects c_i to control for any unobserved time-invariant country characteristics. We also control for effects of unobserved time-varying common factors ρF_t, which, if left uncontrolled, can induce cross-sectional dependence in the

[8] OECD data (available at https://stats.oecd.org/Index.aspx?DataSetCode=GERD_TORD) on total public and private energy R&D expenditures are available for only 25 countries, and all these countries have short and/or incomplete time series. The International Energy Agency reports data on government spending on energy R&D for 32 countries (available at https://www.iea.org/data-and-statistics/data-product/energy-technology-rd-and-d-budget-database-2), but data on total public and private energy R&D expenditures are reported for only three countries.

[9] According to data from the UNESCO Institute for Statistics (available at available at http://data.uis.unesco.org/Index.aspx?DataSetCode=SCN_DS), high-income countries accounted for about 68% of the total worldwide R&D in 2015 (the last year of our sample period), whereas middle- and low-income countries were responsible for about 32% of worldwide R&D expenditures.

regression error and lead to inconsistent estimates. Our basic empirical model is thus given by

$$\log \mathrm{EI}_{it} = \alpha \log \mathrm{R\&D}_{it} + c_i + \rho F_t + \varepsilon_{it} \tag{2}$$

where $\log \mathrm{EI}_{it}$ is the log of energy intensity in developing country i in year t, and $\log \mathrm{R\&D}_{it}$ represents the log of R&D effort. We estimate one specification with (the log of) domestic R&D effort in developing countries, $\log \mathrm{R\&D}^d_{it}$, and five other specifications with foreign R&D, which takes place in developed countries.

The first of these five specifications is used to examine whether R&D spillovers from developed to developing countries occur through disembodied channels such as scientific journals, international conferences, and the internet. Following, among others, Coe et al. (1997) and Herzer (2022), we define the measure of foreign R&D spillovers in this specification as the log of the sum of the R&D efforts of N developed countries, $\log \mathrm{R\&D}^f_t$,

$$\log \mathrm{R\&D}^f_t \equiv \log \sum_{j=1}^{N} \mathrm{R\&D}^d_{jt} \tag{3}$$

where $\mathrm{R\&D}^d_{jt}$ is the R&D effort of industrial country j. It is perhaps needless to say that the two country groups do not overlap.

To estimate the impact of import-related R&D spillovers from North to South on energy intensity, we use four other specifications with further spillover variables. One of these spillover variables is $\log \mathrm{R\&D}^{f-T}_{it}$, which, following the weighting scheme of Coe and Helpman (1995),[10] is the log of the weighted average of the domestic R&D efforts of the N developed countries, with bilateral shares of (total) imports as weights,

$$\log \mathrm{R\&D}^{f-T}_{it} \equiv \log \sum_{j=1}^{N} \frac{\mathrm{IM}^T_{ijt}}{\mathrm{IM}^T_{it}} \mathrm{R\&D}^d_{jt} \tag{4}$$

where IM^T_{ijt} stands for imports of total goods of developing country i from developed country j and IM^T_{it} denotes imports of total goods of country i from all N industrial countries, $\mathrm{IM}^T_{it} = \sum_{j=1}^{N} \mathrm{IM}^T_{ijt}$.

Coe and Helpman (1995) use total imports as their weighting factor and find evidence of spillovers from foreign R&D to domestic TFP in a sample of OECD countries.

[10] Lichtenberg and van Pottelsberghe de la Potterie (1998) argue that the weighting scheme of Coe and Helpman (1995) is sensitive to a potential merger between countries, and suggest an alternative weighting scheme that is less sensitive to the level of aggregation. While Lichtenberg and van Pottelsberghe de la Potterie (1998) find that their weighting scheme yields somewhat better empirical results than the Coe and Helpman (1995) weighting scheme, Coe et al. (2009) find that the weighting scheme of Coe and Helpman (1995) performs somewhat better than the Lichtenberg and van Pottelsberghe de la Potterie (1998) scheme. We repeated the analysis using the latter scheme and found qualitatively similar results (available on request).

Coe et al. (1997) and Herzer (2022) measure R&D spillovers from developed to developing countries based on total imports and imports of machinery and equipment and find evidence of such spillovers only in the machinery and equipment imports specification. Following these two studies, we use both imports of total goods and machinery and equipment imports as weighting factors. The third spillover (and fourth R&D) variable is thus

$$\log \mathrm{R\&D}_{it}^{f\_M} \equiv \log \sum_{j=1}^{N} \frac{\mathrm{IM}_{ijt}^{M}}{\mathrm{IM}_{it}^{M}} \mathrm{R\&D}_{jt}^{d} \tag{5}$$

where IM_{ijt}^{M} represents imports of machinery and equipment of developing country i from developed country j and IM_{it}^{M} is machinery and equipment imports of country i from all N developed countries, $\mathrm{IM}_{it}^{M} = \sum_{j=1}^{N} \mathrm{IM}_{ijt}^{M}$.

Following the R&D-TFP literature (see, e.g., Coe and Helpman 1995; Coe et al. 1997; Herzer 2022), we also interact the import-weighted foreign R&D variables with the share of imports of total goods (machinery and equipment imports) from the N developed countries in GDP in each developing country i, mi_{it}^{T} (mi_{it}^{M}),

$$\mathrm{mi}_{it}^{T} \times \log \mathrm{R\&D}_{it}^{f\_T} \equiv \mathrm{mi}_{it}^{T} \times \log \sum_{j=1}^{N} \frac{\mathrm{IM}_{ijt}^{T}}{\mathrm{IM}_{it}^{T}} \mathrm{R\&D}_{jt}^{d} \tag{6}$$

$$\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M} \equiv \mathrm{mi}_{it}^{M} \times \log \sum_{j=1}^{N} \frac{\mathrm{IM}_{ijt}^{M}}{\mathrm{IM}_{it}^{M}} \mathrm{R\&D}_{jt}^{d} \tag{7}$$

Thus, we estimate six separate specifications with the following R&D variables: $\log \mathrm{R\&D}_{it}^{d}$, $\log \mathrm{R\&D}_{t}^{f}$, $\log \mathrm{R\&D}_{it}^{f\_T}$, $\log \mathrm{R\&D}_{it}^{f\_M}$, $\mathrm{mi}_{it}^{T} \times \log \mathrm{R\&D}_{it}^{f\_T}$, and $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$. It should perhaps be mentioned here that we also estimate specifications that include more than one R&D variable, in the robustness checks.

4 Data, sample, and empirical methodology

4.1 Data on domestic energy intensity, domestic R&D, and measures of foreign R&D spillovers

Energy intensity is the ratio of energy use to real GDP. Energy use data are from the World Development Indicators (WDI) (calculated as the product of population and energy use in kg of oil equivalent per capita); real GDP data (at constant 2017 national prices in millions of 2017 US dollars) are from the Penn World Table (PWT) version 10.01.

Domestic R&D effort is measured by real domestic R&D expenditures. To construct real R&D expenditures (at constant 2017 national prices in millions of 2017

US dollars), we use gross expenditures on R&D as a percentage of GDP from the UNESCO Institute for Statistics database and the OECD Main Science and Technology Indicators database and multiply these percentages by real GDP from the PWT.

It should perhaps be noted that many studies in the R&D-TFP literature use as their R&D variable the perpetual inventory stock of R&D capital, constructed based on cumulative R&D expenditures. The idea behind this is that the R&D capital stock, just like TFP, is "a proxy for a stock of knowledge" (Coe and Helpman 1995, p. 860). Here, however, we follow, among others, Herzer (2022) and use R&D expenditures because on the one hand there is no theoretical reason to prefer R&D capital stocks to R&D expenditures,[11] but on the other hand data availability prevents us from constructing internationally comparable R&D capital stocks for a sufficiently large number of developing countries.[12]

The bilateral trade data used to construct our import-weighted foreign R&D variables are from the UNCTADstat database[13]; these data are in nominal terms. To construct the share of imports of total goods (machinery and equipment imports) from the N developed countries in GDP in each developing country, mi_{it}^{T} (mi_{it}^{M}), we use nominal GDP data from the WDI.

The following developed countries are included in the calculation of the spillover measures: Australia, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, Norway, Spain, Sweden, the United Kingdom, and the United States. These are the 15 high-income countries with the highest R&D expenditures. They accounted for 81% of the R&D expenditures of this country group in 2015. In the empirical analyses, we also examine whether R&D conducted by these countries reduces R&D intensity in these countries (as noted in the Introduction).

Since the bilateral trade data from the UNCTADstat database begin in 1995 and the energy use data from the WDI currently (i.e., as of March 2023) end in 2015, our analysis covers the period 1995–2015. We include all developing countries with at least ten consecutive time-series observations in this period. This allows us to examine the long-run relationship between the variables and to conduct a panel cointegration analysis, which we discuss in more detail in Sect. 4.3. All data sources are listed in Table 1.

[11] Semi-endogenous growth models predict a long-run relationship between the log-level of R&D expenditures (rather than R&D stocks) and the log-level of technology (or TFP), as Footnote 8 implies.

[12] The construction of internationally comparable R&D capital stocks requires the availability of sufficiently long and uninterrupted R&D expenditure series of approximately equal length.

[13] We note here that because of missing observations for some countries, the bilateral imports are measured from the country of origin (i.e., as bilateral exports from the developed to the developing countries). We also note that for some [developing] (developed) countries, [uninterrupted time-series data on bilateral trade flows between these countries and all their 15 major developed country trading partners] (uninterrupted time-series data on R&D) are not available over the period 1995–2015. To construct our import-weighted foreign R&D variables, we therefore filled small data gaps of no more than two consecutive years by linear interpolation.

4.2 Samples and summary statistics

Regarding our classification of developing countries, it is important to note that there is no uniform, generally accepted classification or definition of developing countries. The IMF, for example, divides countries into "advanced economies" and "emerging market and developing economies" in its World Economic Outlook reports (available at https://www.imf.org/en/Publications/WEO) since 2004. Before 2004, the World Economic Outlook reports distinguished between "advanced economies," "countries in transition," and "developing countries." However, the IMF does not provide a definition of what constitutes a "developing country" or which criteria are used to classify countries as "emerging market and developing economies." UNCTAD notes on its website that its "categorization is based on a distinction between developing and developed regions that was commonly used in the past" (UNCTAD 2023). Unfortunately, UNCTAD does not define what is meant by "commonly used in the past" or which criteria classify countries as "developing economies." Finally, the World Bank distinguishes between low-income, middle-income, and high-income countries and traditionally classifies low- and middle-income countries as "developing countries." For example, the World Bank (2007) notes in its 2007 World Development Report (on page xvii) that "[t]he term developing countries includes low- and middle-income economies and thus may include economies in transition from central planning, as a matter of convenience." Although the income-based classification by the World Bank can be criticized for being too narrow, this classification is understandable, in contrast to the classifications of the IMF and UNCTAD. It is therefore not surprising that the World Bank classification is a commonly used classification, if not the most commonly used classification, in empirical studies (see, among others, Boubakri and Cosset 1998; Harding and Javorcik 2011; Sadorsky 2013; Baccini and Urpelainen 2014; Cortina et al. 2018; Brandi et al. 2020; Herzer 2022).

Consistent with common practice, we classify a country as a developing country if it is officially listed as a low- or middle-income country by the World Bank in its "historical classification by income" (available at https://datahelpdesk.worldbank.org/knowledgebase/articles/906519) in more than half of the years between 1995 and 2015, our sample period. The countries we classify as developing countries according to the World Bank's definition are classified as "emerging market and developing economies" by the IMF in its World Economic Outlook reports (available at https://www.imf.org/en/Publications/WEO).

In addition, we use a sample of developing countries as classified by UNCTAD as a robustness check. This sample is a subsample of our main sample of developing countries according to the World Bank classification (and emerging market and developing economies according to the IMF classification). It includes only those countries that are classified as "developing economies" by UNCTAD, which does not classify transition or post-communist countries as "developing economies," as already noted in the Introduction. Table 2 displays the countries in our samples and their respective classifications by the World Bank, the IMF, and UNCTAD.

Our main sample, composed of developing countries according to the World Bank definition, includes 33 countries. The number of countries in the sample

Table 1 Data sources for the variables

Variable	Component	Source
Energy intensity, EI_{it}: ratio of energy use to real GDP	Energy use (product of population and energy use in kg of oil equivalent per capita) Real GDP (at constant 2017 national prices in millions of 2017 US dollars)	World Development Indicators (available at https://databank.worldbank.org/source/world-development-indicators) Penn World Table version 10.01 (available at https://www.rug.nl/ggdc/productivity/pwt/?lang=en)
Domestic R&D effort of developing country *i* (industrial country *j*), $R\&D^d_{it}$ ($R\&D^d_{jt}$), measured by real domestic R&D expenditures of country *i* (*j*) (at constant 2017 national prices in millions of 2017 US dollars), calculated as the product of real GDP and gross expenditures on R&D as a share of GDP	Gross expenditures on R&D as a percentage of GDP Real GDP (at constant 2017 national prices in millions of 2017 US dollars)	UNESCO Institute for Statistics database (available at http://data.uis.unesco.org/Index.aspx?DataSetCode=SCN_DS), OECD Main Science and Technology Indicators database (available at https://stats.oecd.org/Index.aspx?DataSetCode=MSTI_PUB#) Penn World Table version 10.01
Imports of total goods (imports of machinery and equipment) of developing country *i* from developed country *j*, IM^T_{ijt} (IM^M_{ijt}) (in current prices)		UNCTADstat database (available at https://unctadstat.unctad.org/wds)
Share of (nominal) imports of total goods (machinery and equipment imports) from the *N* developed countries in (nominal) GDP in each developing country, mi^T_{it} (mi^M_{it})	Imports of total goods (machinery and equipment imports) from the *N* developed countries Nominal GDP	UNCTADstat database World Development Indicators
Real GDP per capita (real GDP divided by population), $GDPPC_{it}$	Real GDP (at constant 2017 national prices in millions of 2017 US dollars) Population	Penn World Table version 10.01 World Development Indicators
Capital-to-labor ratio (ratio of the capital stock to employment), KL_{it}	Capital stock Employment	Penn World Table version 10.01
Ratio of industrial value added to GDP, IND_{it},		World Development Indicators
Foreign direct investment inflows as a share of GDP, FDI_{it}		World Development Indicators
Consumer price index, CPI_{it}		World Development Indicators

of developing countries according to the UNCTAD definition is 21. Since the countries in our samples have time-series of unequal length, our panels are unbalanced during the period 1995–2015. While the minimum number of observations per country in both samples is 13, the maximum number of observations per country in both samples is 21. The average number of observations per country in our main sample is 18.3, and it is 17.6 in our second sample.

Table 3, Panel A, shows the correlation matrix and summary statistics for the main variables in our analysis for our main sample of 33 developing countries. For comparison, we also present in Table 3, Panel B, the correlation matrix and summary statistics for $\log \mathrm{EI}_{it}$ and $\log \mathrm{R\&D}^{d}_{it}$ for the 15 industrial source countries of R&D spillovers. Since the exponent of the mean of the natural logarithm of a variable is not its (arithmetic) mean, we present in parentheses the means of energy intensity and R&D expenditures for the two samples. While average energy intensity in the sample of developing countries (155,407.5) is higher than average energy intensity in the sample of developed countries (118,977.4) by factor 1.31, average R&D expenditures in the sample of developed countries (52,937.06) are higher than average R&D expenditures in the sample of developing countries (8899.64) by factor 5.95.

4.3 Econometric issues and empirical methodology

In panels with a relatively large time-series dimension, such as the panels used here, regressions involving non-stationary or integrated variables may produce spurious results when the integrated variables are not cointegrated. Spurious regressions, indicating a relationship between non-stationary variables when there is none, are well-known in time series literature, but are often ignored in the panel studies. Entorf (1997) and Kao (1999), however, find in Monte Carlo simulations that there is a high risk of spurious regressions in conventional panel regressions even when N and T are not very large.[14] Indeed, panel unit root tests (reported in the Appendix) indicate that all variables in Eq. (1) are integrated of order one, $I(1)$, and thus have stochastic trends or "unit roots." Since the presence of cointegration is required to avoid spurious regressions with non-stationary variables, conducting cointegration tests and analysis is essential.

Cointegration analysis has several advantages over conventional panel methods. First, cointegration tests allow one to determine whether or not a non-spurious long-run relationship exists between two or more non-stationary variables, and hence to rule out spurious regressions. Second, the existence of cointegration between two or more variables implies the absence of relevant omitted variables in the relationship

[14] Entorf (1997) finds in simulations that the mean of the t-statistics in bivariate fixed-effects regressions of independent random walks with drift is 2.2 [2.3] (12.0) in samples with $N=T=10$ [$N=T=20$] ($N=T=30$). Kao's (1999) simulations show that in the case where $N=T=10$ [$N=T=20$] ($N=T=30$), the probability of rejecting the null hypothesis of a zero coefficient in bivariate fixed-effects regressions of independent random walks at the 5% level is 0.3150 [0.4889] (0.5723).

between these variables. The reason is that omitted non-stationary variables that are part of the cointegrating relationship would become part of the error term, producing non-stationary residuals and preventing the detection of cointegration.[15] However, if there is cointegration between two or more variables, this stationary relationship also exists in an extended variable space. In contrast to regression analysis, where the addition of one new variable can dramatically alter existing estimates, cointegration is thus invariant to model extensions (see, e.g., Juselius 2006).

Of course, many factors can affect domestic energy intensity. However, if these factors also influence domestic R&D and/or foreign R&D spillovers, their inclusion can lead to cointegration among the regressors. The problem is that cointegration estimators are, in general, inconsistent when the regressors are cointegrated (see, e.g., Kao and Chiang 2001). In contrast, if a non-stationary variable that is not cointegrated with the other variables is added to the cointegrating regression, the error term will no longer be stationary. Consequently, the coefficient of the added variable will not converge to zero, as one would expect in a standard regression when dealing with an irrelevant variable. In other words, adding further non-stationary variables to a regression consisting of cointegrated variables may produce spurious results, at least for the added variables (see, e.g., Davidson 1998). Moreover, since any irrelevant non-stationary variable that is not part of a cointegrating relationship tends to generate non-stationary residuals, the addition of irrelevant non-stationary variables induces a tendency toward the rejection of cointegration. This, together with the invariance of cointegration to model extensions, justifies the use of bivariate models—if the variables are cointegrated—and explains why it is common practice in (panel) cointegration studies to estimate parsimonious specifications (see, among others, Coe and Helpman 1995; Pedroni 2007; Coe et al. 2009; Francois and Keinsley 2019; Herzer 2020). Following common practice, we examine bivariate relationships in our main analysis, in our case between energy intensity and our R&D variables, but in the robustness checks, we also provide results based on different specifications that include more than one R&D variable.

In addition, we check whether our significant, non-spurious results are robust to the inclusion of numerous control variables. Inspired by the literature on the determinants of energy intensity (Metcalf 2008; Mimouni and Temimi 2018; Herzer and Schmelmer 2022), and by previous studies on the impact of R&D on energy intensity (discussed in the Introduction), we control for the log of real GDP per capita, $\log \text{GDPPC}_{it}$, the log of the capital-to-labor ratio, $\log \text{KL}_{it}$, the ratio of industrial value added to GDP, IND_{it}, the ratio of gross fixed capital formation to GDP, GFCF_{it}, foreign direct investment inflows as a share of GDP, FDI_{it}, and the log of the consumer price index (used as a proxy for the overall energy price level), $\log \text{CPI}_{it}$. The sources of the data for the control variables are also listed in Table 1.

[15] To illustrate this, consider a situation where x, y and z are $I(1)$ and cointegrated. This means that the residuals ε from the regression $x = c + \beta_1 y + \beta_2 z + \varepsilon$ are $I(0)$, $\varepsilon \sim I(0)$. Now, suppose that we inadvertently omit z and run $x = c + \beta_1 y + \mu$. Since $\mu = (\beta_2 z + \varepsilon) \sim I(1)$, we would mistakenly conclude that there is no cointegrating relationship between x and y.

Table 2 Sample countries and their classification during the period 1995–2015

	World Bank classification	IMF classification	UNTAD classification
Argentina	Middle-income country	Emerging market or developing economy	Developing economy
Armenia	Middle-income country	Emerging market or developing economy	Developing economy
Brazil	Middle-income country	Emerging market or developing economy	Developing economy
Bulgaria	Middle-income country	Emerging market or developing economy	
China	Middle-income country	Emerging market or developing economy	Developing economy
Colombia	Middle-income country	Emerging market or developing economy	Developing economy
Costa Rica	Middle-income country	Emerging market or developing economy	Developing economy
Croatia	Middle-income country	Emerging market or developing economy	
Czech Republic	Middle-income country	Emerging market or developing economy	
Ecuador	Middle-income country	Emerging market or developing economy	Developing economy
Egypt, Arab Rep	Middle-income country	Emerging market or developing economy	Developing economy
Estonia	Middle-income country	Emerging market or developing economy	
Hungary	Middle-income country	Emerging market or developing economy	
India	Low-income country	Emerging market or developing economy	Developing economy
Iran, Islamic Rep	Middle-income country	Emerging market or developing economy	Developing economy
Kazakhstan	Middle-income country	Emerging market or developing economy	Developing economy
Latvia	Middle-income country	Emerging market or developing economy	
Lithuania	Middle-income country	Emerging market or developing economy	
Mexico	Middle-income country	Emerging market or developing economy	Developing economy
Mongolia	Low-income country	Emerging market or developing economy	Developing economy
Panama	Middle-income country	Emerging market or developing economy	Developing economy
Poland	Middle-income country	Emerging market or developing economy	
Romania	Middle-income country	Emerging market or developing economy	
Russian Federation	Middle-income country	Emerging market or developing economy	
Slovak Republic	Middle-income country	Emerging market or developing economy	
South Africa	Middle-income country	Emerging market or developing economy	Developing economy
Tajikistan	Low-income country	Emerging market or developing economy	Developing economy
Thailand	Middle-income country	Emerging market or developing economy	Developing economy

Table 2 (continued)

	World Bank classification	IMF classification	UNTAD classification
Trinidad and Tobago	Middle-income country	Emerging market or developing economy	Developing economy
Tunisia	Middle-income country	Emerging market or developing economy	Developing economy
Türkiye	Middle-income country	Emerging market or developing economy	Developing economy
Ukraine	Middle-income country	Emerging market or developing economy	Developing economy
Uruguay	Middle-income country	Emerging market or developing economy	Developing economy

A country is classified as a "middle-income country" ["low-income country"] if it is officially categorized as such by the World Bank in its "historical classification by income" (available at https://datahelpdesk.worldbank.org/knowledgebase/articles/906519) for more than half of the calendar years between 1995 and 2015. The World Bank classifies low- and middle-income countries as "developing countries" (World Bank 2007). A country is classified as an "emerging market or developing economy" if it is listed in the category "emerging market and developing economies" by the IMF in its World Economic Outlook reports (available at https://www.imf.org/en/Publications/WEO) for the years 2004 onwards. All countries classified as emerging markets or developing economies were previously categorized as either "developing countries" or "countries in transition" in the World Economic Outlook reports. A country is classified here as a "developing economy" if it is listed by UNCTAD as such in its classification (available at https://unctadstat.unctad.org/en/classifications.html)

A third advantage associated with cointegration is that it implies long-run Granger causality in at least one direction (Granger 1988).[16] Here we assume—and test the assumption—that long-run causality runs from log R&D$_{it}$ to log EI$_{it}$. Finally, a fourth advantage is that endogeneity does not lead to inconsistency in the regression coefficients in the presence of cointegration.

However, although even the standard fixed-effects estimator is (super) consistent under panel cointegration even when the regressors are endogenous, it suffers from a second-order asymptotic bias due to endogeneity and serial correlation, and, as a consequence, its usual standard errors are not correct. Therefore, we use the panel DOLS of estimator of Kao and Chiang (2001), which allows for endogenous regressors and which has been shown to perform well in samples like the one used here (see, e.g., Kao and Chiang 2001; Wagner and Hlouskova 2009).[17]

[16] The concept of long-run (Granger) causality is to be distinguished from the more familiar notion of "Granger causality," which refers to short-run forecastability and does not account for long-run causality through the error correction term in a cointegrated error-correction model.

[17] The DOLS method employs a parametric correction for endogeneity and serial correlation, based on lead, lag, and current values of the differenced regressors. An alternative estimation method for estimating cointegrating relationships is the (panel) FMOLS estimator, which uses a semi-parametric correction for endogeneity and serial correlation (based on the OLS residuals and the first differences of the regressors). Simulation evidence suggests that the DOLS estimator performs better than the FMOLS estimator in small samples (see, e.g., Kao and Chiang 2001; Wagner and Hlouskova 2009). Therefore, we prefer the DOLS estimator. The results (available on request) do not change qualitatively when the FMOLS estimator is used.

Table 3 Correlation matrix and summary statistics

	Log EI_{it} (EI_{it})	$\log R\&D_{it}^{d}$($R\&D_{it}^{d}$)	$\log R\&D_{t}^{f}$	$\log R\&D_{it}^{f\_T}$	$\log R\&D_{it}^{f\_M}$	$mi_{it}^{T} \times \log R\&D_{it}^{f\_T}$	$mi_{it}^{M} \times \log R\&D_{it}^{f\_M}$
A. Sample of 33 developing countries (according to World Bank classification)							
$\log EI_{it}$	1.000						
$\log R\&D_{it}^{d}$	0.183	1.000					
$\log R\&D_{t}^{f}$	−0.256	−0.028	1.000				
$\log R\&D_{it}^{f\_T}$	−0.412	0.024	0.293	1.000			
$\log R\&D_{it}^{f\_M}$	−0.365	0.024	0.292	0.986	1.000		
$mi_{it}^{T} \times \log R\&D_{it}^{f\_T}$	−0.202	−0.491	0.003	−0.122	−0.149	1.000	
$mi_{it}^{M} \times \log R\&D_{it}^{f\_M}$	−0.049	−0.386	0.412	−0.192	−0.193	0.578	1.000
Mean	11.810 (155,407.5)	7.669 (8899.64)	22.828	20.791	20.807	3.631	0.546
Maximum	13.113	12.740	23.002	22.101	22.093	19.136	3.807
Minimum	10.895	2.555	22.456	19.666	19.865	0.309	0.013
Std. Dev	0.468	1.818	0.134	0.594	0.545	2.969	0.554
B. Sample of the 15 developing countries that were used as sources of R&D spillovers							
Log EI_{it}	1						
$\log R\&D_{it}^{d}$	0.254	1					
Mean	11.631 (118,977.4)	9.931 (52,937.06)					
Maximum	12.402	13.05					
Minimum	10.656	7.140					
Std. Dev	0.332	1.308					

It should, however, be noted that the panel DOLS estimator is based on the assumption of error cross-sectional independence.[18] To account for weak cross-sectional dependence in the residuals of the DOLS models, we follow Bordo et al. (2017) and use Driscoll and Kraay (1998) standard errors; these standard errors are robust to heteroskedasticity, autocorrelation, and spatial correlation. To account for strong cross-sectional error dependence, we demean the data by subtracting the cross-sectional averages from the data and then use the demeaned data in place of the original data (which is equivalent to using the residuals from regressions of each variable on time dummies). In addition, to ensure that our results do not suffer from error cross-sectional dependence due to common factors, we test for strong cross-sectional dependence in the residuals from our DOLS regressions using the cross-sectional dependence (CD) test of Juodis and Reese (2022).[19]

5 Results

5.1 Main results

Panel A of Table 4 shows the panel DOLS results for the relationship in our sample between each of the R&D variables and the log of energy intensity. In Panel A, we also present the results of the Juodis–Reese test for strong cross-sectional dependence in the residuals of the DOLS regressions. The results of several panel cointegration tests are shown in Panel B.

Regarding the results in Panel B, two things should be noted. First, for the Pedroni (1999, 2004) panel cointegration tests, which assume error cross-sectional independence, we report test statistics based on the demeaned data to control for error cross-sectional dependence. For the Gengenbach et al. (2016) test, which explicitly accounts for cross-sectional dependence via the use of cross-sectional averages of the variables, we report test statistics based on the raw data.

Second, error-correction-based cointegration tests such as the Gengenbach et al. (2016) test incorporate in the alternative hypothesis the assumption that the dependent variable is not weakly exogenous with respect to the independent variables. Rejection of the null of no cointegration using an error-correction model with $\Delta \log \mathrm{EI}_{it}$ as the dependent variable can therefore be interpreted as evidence that $\log \mathrm{EI}_{it}$ is not weakly exogenous to the independent variables and thus that the independent variables "cause" $\log \mathrm{EI}_{it}$ (provided that they are significant).

[18] We also experimented with the pooled common correlated effects (PCCE) estimator and the common correlated effects mean group (CCEMG) of Pesaran (2006). Both these estimators are specifically designed to account for error cross-sectional dependence. While the results from the PCCE estimator are significant (and negative) only for $\log \mathrm{R\&D}^f_t$, the results from the CCEMG estimator are significant (and negative) only for $\log \mathrm{R\&D}^d_{it}$. Given, however, that these estimators are designed for large N and large T and that they require strictly exogenous regressors, the PCCE and CCEMG estimates are not reliable here due to the possibility of endogenous or weakly exogenous regressors and/or the relatively small number of countries and years in our sample.

[19] We use the Juodis and Reese (2022) test rather than the standard Pesaran (2021) 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 (2021) test that does not suffer from this problem.

Turning to the results in column (1) of Table 4, we find a weakly significant positive effect of domestic R&D on energy intensity. This effect appears not to be due to the presence of strong cross-sectional dependence in the residuals, as suggested by the Juodis–Reese test. Since, however, two of the cointegration tests do not reject the null of no cointegration, it cannot be ruled out with certainty that the observed effect is the result of spurious regression. We come back to this point when we discuss the results in column (1) of Table 6.

In column (2) of Table 4, we see that while four of the five tests indicate cointegration, the coefficient on the log of the unweighted sum of the R&D expenditures of industrial countries is positive and statistically insignificant. However, the Juodis–Reese test indicates the presence of strong cross-sectional dependence in the DOLS residuals, and thus the estimation results should be viewed with caution.

In column (3), the coefficient on $\log \mathrm{R\&D}_{it}^{f\_T}$ is positive but insignificant, and only one test rejects the null hypothesis of no cointegration. We thus find no long-run evidence of uninteracted spillover effects of import-weighted foreign R&D expenditures using total imports as weights. For completeness, however, it should be said that we cannot rule out the possibility that the insignificant coefficient is the result of unobserved common factors in the DOLS residuals (as suggested by the Juodis–Reese test).

Our evidence also does not support the existence of an uninteracted effect of capital goods import-weighted foreign R&D expenditures on the long-run level of domestic energy intensity. Column (4) shows that $\log \mathrm{R\&D}_{it}^{f\_M}$ has a significant negative coefficient and that the Juodis–Reese test is insignificant, as in columns (1), (5), (6), and (7). However, none of the tests rejects the null hypothesis of no cointegration, suggesting that the regression result is spurious.

Similarly, the coefficient in column (5) for the variable $\mathrm{mi}_{it}^{T} \times \log \mathrm{R\&D}_{it}^{f\_T}$ is negative and significant, but only two tests provide clear evidence (at the conventional 5% level or better) of cointegration. Thus, there is also no clear support for an interacted spillover effect of total import-weighted foreign R&D expenditures on the long-run level of domestic energy intensity.

In contrast, the results in column (6) show clear evidence that R&D performed in industrial countries weighted by the bilateral share of machinery and equipment imports from the industrial countries reduces energy intensity in developing countries through its interaction with the machinery and equipment import share in developing countries' GDP. All tests indicate cointegration between $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$ and $\log \mathrm{EI}_{it}$ at least at the 5% level; the Gengenbach et al. (2016) test suggests that $\log \mathrm{EI}_{it}$ is „caused" in the long run by $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$[20]; and the coefficient on $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$ is negative and statistically significant with a value of -0.025.

[20] We also computed the Gengenbach et al. (2016) t test statistic using the reverse regression with $\Delta \mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$ on the left-hand side. The value of the test statistic is -1.813, implying that the null of weak exogeneity cannot be rejected for $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$. Weak exogeneity implies long-run Granger non-causality (see, e.g., Hall and Milne 1994). Thus, the evidence that $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$ is weakly exogenous and $\log \mathrm{EI}_{it}$ is not weakly exogenous means that $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$ has a long-run (causal) effect on $\log \mathrm{EI}_{it}$, whereas $\log \mathrm{EI}_{it}$ has no long-run effect on $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$.

Table 4 Main results

	(1)	(2)	(3)	(4)	(5)	(6)
A. DOLS estimates						
$\log \mathrm{R\&D}_{it}^{d}$	0.030* (0.016)					
$\log \mathrm{R\&D}_{t}^{f}$		0.017 (0.029)				
$\log \mathrm{R\&D}_{it}^{f\_T}$			0.028 (0.080)			
$\log \mathrm{R\&D}_{it}^{f\_M}$				− 0.312*** (0.073)		
$\mathrm{mi}_{it}^{T} \times \log \mathrm{R\&D}_{it}^{f\_T}$					− 0.027** (0.008)	
$\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$						− 0.025*** (0.008)
Juodis–Reese (*p* value)	0.234	0.000	0.050	0.338	0.776	0.866
No. of countries	33	33	33	33	33	33
No. of obs	531	532	532	532	532	532
Adjusted R^2	0.951	0.951	0.951	0.954	0.951	0.951
B. Panel cointegration tests						
Pedroni (1999, 2004)						
Panel PP *t*-statistic	− 1.045	− 5.496***	− 1.125	0.073	− 1.385*	− 2.159**
Panel ADF *t*-statistic	− 1.270	− 6.540***	− 0.214	− 0.000	− 1.460*	− 1.671**
Group PP *t*-statistic	− 1.955**	− 5.360***	− 1.120	0.411	− 3.645***	− 2.312**
Group ADF *t*-statistic	− 4.058***	− 7.755***	− 0.988	− 0.686	− 3.197***	− 2.806***
Gengenbach et al. (2016)						
ECM *t*-statistic	− 4.107***	− 1.764	− 4.202***	− 2.105	− 2.428	− 3.558***

Table 4 (continued)

The dependent variable in the DOLS regressions and the Pedroni (1999, 2004) tests is $\log \mathrm{EI}_{it}$. The dependent variable in the Gengenbach et al. (2016) tests is $\Delta\log \mathrm{EI}_{it}$. All regressions (and tests) include country fixed effects. The DOLS regressions were estimated with one lead and one lag of the first-differenced regressors. The data on $\log \mathrm{EI}_{it}$, $\log \mathrm{R\&D}^{d}_{it}$, $\log \mathrm{R\&D}^{f\_T}_{it}$, $\mathrm{mi}^{T}_{it} \times \log \mathrm{R\&D}^{f\_T}_{it}$, $\log \mathrm{R\&D}^{f\_M}_{it}$, and $\mathrm{mi}^{M}_{it} \times \log \mathrm{R\&D}^{f\_M}_{it}$ for the DOLS regressions and the Pedroni (1999, 2004) tests were demeaned to account for (strong) error cross-sectional dependence due to unobserved common factors; $\log \mathrm{R\&D}^{f}_{t}$ is the same for each country and can be considered as an observed common factor (that cannot be demeaned). The Gengenbach et al. (2016) test accounts for strong error cross-sectional dependence via the use of cross-sectional averages. Juodis–Reese is the test for strong cross-sectional dependence of Juodis and Reese (2022) applied to the residuals from the DOLS regressions. The number of lags in the Pedroni (1999, 2004) (PP and ADF) and Gengenbach et al. (2016) tests was determined using the general-to-specific approach with a maximum of two lags. Two lags of the cross-sectional averages were included in the Gengenbach et al. (2016) tests. All tests reject for large negative values. The Pedroni (1999) test statistics are distributed as standard normal. The Gengenbach et al. (2016) critical value for one regressor at the 1% (5%) [10%] significance level is −2.735 (−2.601) [−2.530] for $N=30$. Numbers in parentheses are Driscoll and Kraay (1998) heteroskedasticity autocorrelation spatial correlation robust standard errors. *** (**) [*] indicate significance at the 1% (5%) [10%] level

To provide a sense of the magnitude of the effect implied by this coefficient, consider that a one standard deviation increase in $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$ is associated with a decrease of 10.12 percent of a standard deviation in the energy intensity variable ($-0.025 \times 1.977/0.4885$), an effect that is economically significant.

5.2 Robustness checks

In columns (1)–(6) of Table 5, we check the robustness of our results with respect to the use of the sample of developing countries classified by UNCTAD. The results are very similar to those in Table 4. The only worth mentioning differences are that the coefficients on $\log \mathrm{R\&D}_{it}^{d}$ and $\log \mathrm{R\&D}_{it}^{f\_M}$ are now insignificant, and that the coefficient on $\mathrm{mi}_{it}^{T} \times \log \mathrm{R\&D}_{it}^{f\_T}$ is significant only at the 10% level. Thus, the results in columns (1)–(6) of Table 5 once again suggest that domestic R&D does not contribute to reductions in energy intensity in developing countries. Furthermore, foreign R&D does not appear to affect domestic energy intensity through disembodied channels. Instead, we again find that foreign R&D conducted in developed countries reduces energy intensity in developing countries through imports, particularly imports of machinery and equipment, and that this effect depends on the share of machinery and equipment imports in developing countries' GDP.

In column (7) of Table 5, we present results for the relationship between domestic R&D conducted in the 15 industrial source countries of R&D spillovers and energy intensity in those countries, as a plausibility check. Four of the five cointegration tests suggest that there is a long-run relationship between $\log \mathrm{R\&D}_{it}^{d}$ and $\log \mathrm{EI}_{it}$, and the DOLS coefficient on $\log \mathrm{R\&D}_{it}^{d}$ is negative and highly significant. Thus, we find evidence that domestic R&D contributes to reductions in energy intensity in developed source countries of foreign R&D spillovers, which supports the plausibility of our finding that there are significant spillovers from R&D conducted in industrial countries that reduce energy intensity in developing countries.

In Table 6, we once again use the sample of 33 developing countries, classified according to the World Bank, and assess the robustness of our results to various specifications involving multiple R&D variables in columns (1)–(6). In column (1), we report DOLS results of a regression that includes both $\log \mathrm{R\&D}_{it}^{d}$ and $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$. The coefficient on $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$ remains negative and statistically significant, and the coefficient on $\log \mathrm{R\&D}_{it}^{d}$ is positive and significant at the 10% level, like in column (1) of Table 4. However, the evidence for cointegration between $\log \mathrm{R\&D}_{it}^{d}$, $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$, and $\log \mathrm{EI}_{it}$ in column (1) of Table 6 is weaker than the evidence for cointegration between $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$ and $\log \mathrm{EI}_{it}$ in column (6) of Table 4. If (as discussed in Sect. 4.3) there is an integrated regressor that is not cointegrated with other cointegrated variables in an equation, the residuals of such an equation will tend to be non-stationary, and the evidence of cointegration may therefore be weak (or even absent). Thus, the results of the cointegration tests in column (1) of Table 6 together with those in column (6) of Table 4 can be interpreted as an indication that while there is a long-run relationship between $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$ and $\log \mathrm{EI}_{it}$, there is no long-run relationship between

Table 5 Results based on the subsample of developing countries classified by UNCTAD (columns (1) – (6)) and results using the source countries of R&D spillovers as the sample (column (7))

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. DOLS estimates							
$\log \mathrm{R\&D}_{it}^{d}$	0.010 (0.012)						−0.136*** (0.033)
$\log \mathrm{R\&D}_{t}^{f}$		0.016 (0.033)					
$\log \mathrm{R\&D}_{it}^{f\_T}$			0.027 (0.073)				
$\log \mathrm{R\&D}_{it}^{f\_M}$				−0.042 (0.059)			
$\mathrm{mi}_{it}^{T} \times \log \mathrm{R\&D}_{it}^{f\_T}$					−0.022* (0.012)		
$\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$						−0.023*** (0.007)	
Juodis–Reese (*p* value)	0.199	0.312	0.002	0.153	0.456	0.766	0.466
No. of countries	21	21	21	21	21	21	15
No. of obs	324	325	325	325	325	325	270
Adjusted R^2	0.950	0.950	0.950	0.950	0.951	0.951	0.977
B. Panel cointegration tests							
Pedroni (1999, 2004)							
Panel PP *t*-statistic	−1.574*	−4.261***	−0.896	−0.039	−0.671	−3.902***	−0.816
Panel ADF *t*-statistic	−1.772**	−4.823***	−1.237	−0.139	−1.450*	−2.505***	−2.447***
Group PP *t*-statistic	−1.099	−3.979***	−1.093	−1.041	−2.361***	−4.287***	−2.911***
Group ADF *t*-statistic	−2.463***	−5.375***	−0.375	−1.138	−1.943**	−2.808***	−6.153***
Gengenbach et al. (2016)							
ECM *t*-statistic	−1.869	−1.886	−1.745	0.320	−2.172	−3.394***	−2.805**

Table 5 (continued)

The dependent variable in the DOLS regressions and the Pedroni (1999, 2004) tests is $\log \mathrm{EI}_{it}$, The dependent variable in the Gengenbach et al. (2016) tests is $\Delta\log \mathrm{EI}_{it}$. All regressions (and tests) include country fixed effects. The DOLS regressions were estimated with one lead and one lag of the first-differenced regressors. The data on $\log \mathrm{EI}_{it}$, $\log \mathrm{R\&D}^{d}_{it}$, $\log \mathrm{R\&D}^{f\_T}_{it}$, $\mathrm{mi}^{T}_{it} \times \log \mathrm{R\&D}^{f\_T}_{it}$, $\log \mathrm{R\&D}^{f\_M}_{it}$, and $\mathrm{mi}^{M}_{it} \times \log \mathrm{R\&D}^{f\_M}_{it}$ for the DOLS regressions and the Pedroni (1999, 2004) tests were demeaned to account for (strong) error cross-sectional dependence due to unobserved common factors; $\log \mathrm{R\&D}^{f}_{t}$ is the same for each country and can be considered as an observed common factor (that cannot be demeaned). The Gengenbach et al. (2016) test accounts for strong error cross-sectional dependence via the use of cross-sectional averages. Juodis–Reese is the test for strong cross-sectional dependence of Juodis and Reese (2022) applied to the residuals from the DOLS regressions. The number of lags in the Pedroni (1999, 2004) (PP and ADF) and Gengenbach et al. (2016) tests was determined using the general-to-specific approach with a maximum of two lags. Two lags of the cross-sectional averages were included in the Gengenbach et al. (2016) tests. All tests reject for large negative values. The Pedroni (1999) test statistics are distributed as standard normal. The Gengenbach et al. (2016) critical value for one regressor at the 1% (5%) [10%] significance level is −2.796 (−2.653) [−2.530] for $N=20$. The Gengenbach et al. (2016) critical value for one regressor at the 5% significance level is −2.698 for $N=15$. Numbers in parentheses are Driscoll and Kraay (1998) heteroskedasticity autocorrelation spatial correlation robust standard errors. *** (**) [*] indicate significance at the 1% (5%) [10%] level

$\log \text{R\&D}^{d}_{it}$ and $\log \text{EI}_{it}$. It therefore seems likely that the estimated positive effect of domestic R&D on energy intensity is a spurious correlation, but this cannot be said with certainty on the basis of our cointegration tests.

In columns (2)–(6) of Table 6, we successively add $\log \text{R\&D}^{f}_{t}$, $\log \text{R\&D}^{f\_T}_{it}$, $\log \text{R\&D}^{f\_M}_{it}$, and $\text{mi}^{T}_{it} \times \log \text{R\&D}^{f\_T}_{it}$. To avoid collinearity problems due to the high correlation between $\log \text{R\&D}^{f\_T}_{it}$ and $\log \text{R\&D}^{f\_M}_{it}$ (with a correlation coefficient of 0.986 (see Table 3)), we include these variables separately in the regressions, presented in columns (3) and (4), and in columns (5) and (6). Before discussing the results in columns (2)–(6), it should be noted that, due to the limited number of time-series observations available for some countries, the Gengenbach et al. (2016) panel cointegration test cannot be applied to models involving more than four regressors, such as the ones used in columns (5) and (6). For completeness, we also note that the Juodis–Reese test indicates the presence of strong cross-sectional dependence in the residuals of the DOLS regression in column (6), implying that the results in column (6) must be interpreted with caution.

The results in columns (2)–(6) consistently indicate a significant negative long-run relationship between $\text{mi}^{M}_{it} \times \log \text{R\&D}^{f\_M}_{it}$ and $\log EI_{it}$. The coefficients on $\log \text{R\&D}^{f\_M}_{it}$ are also significant and negative. However, the evidence for cointegration between $\text{mi}^{M}_{it} \times \log \text{R\&D}^{f\_M}_{it}$ and $\log \text{EI}_{it}$ (in column (6) of Table 4) is stronger than the evidence for cointegration between $\log \text{R\&D}^{d}_{it}$, $\log \text{R\&D}^{f}_{t}$, $\text{mi}^{M}_{it} \times \log \text{R\&D}^{f\_M}_{it}$, and $\log \text{EI}_{it}$ (in column (4) of Table 6) and the evidence for cointegration between $\log \text{R\&D}^{d}_{it}$, $\log \text{R\&D}^{f}_{t}$, $\text{mi}^{T}_{it} \times \log \text{R\&D}^{f\_T}_{it}$, $\text{mi}^{M}_{it} \times \log \text{R\&D}^{f\_M}_{it}$, and $\log \text{EI}_{it}$ (in column (6) of Table 6). In addition, there is no evidence of cointegration between $\log \text{R\&D}^{f\_M}_{it}$ and $\log \text{EI}_{it}$ (in column (4) of Table 4). The implication is that the significant negative coefficients on $\log \text{R\&D}^{f\_M}_{it}$ in columns (4) and (6) are very likely spurious, similar to the significant positive coefficients on $\log \text{R\&D}^{d}_{it}$ in columns (2), (3), and (5). Finally, the coefficients on $\log \text{R\&D}^{d}_{it}$ in columns (4) and (6) are insignificant, like the coefficients on $\log \text{R\&D}^{f}_{t}$, $\log \text{R\&D}^{f\_T}_{it}$, and $\text{mi}^{T}_{it} \times \log \text{R\&D}^{f\_T}_{it}$.

In column (7) of Table 6, we finally check whether the coefficient on $\text{mi}^{M}_{it} \times \log \text{R\&D}^{f\_M}_{it}$ loses its significance when we estimate a specification with the control variables presented in Sect. 4.3. Before discussing the results in column (7), three things should be noted. First, due to missing data on the consumer price index for Argentina and the ratio of gross fixed capital formation to GDP for Trinidad and Tobago, we are forced to exclude these countries from the estimation. Second, due to the limited number of time-series observations available for some countries, and the large number of regressors, neither the Pedroni (1999, 2004) nor the Gengenbach et al. (2016) tests can be applied to test for cointegration among the variables in the estimated equation. Third, when we include the control variables, the number of time series observations for some countries becomes too small to apply the DOLS estimator (which involves adding lead, lag, and current values of the differenced regressors to the equation). We are therefore forced to use the OLS fixed-effects estimator (with heteroskedasticity autocorrelation spatial correlation robust standard errors), whose standard errors may be biased due to endogeneity. This, however should not be a serious problem since there is no plausible theoretical reason

Table 6 Results based on different specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Estimates	DOLS						OLS
$\log R\&D_{it}^{d}$	0.040* (0.022)	0.038* (0.021)	0.037* (0.018)	0.030 (0.022)	0.034* (0.018)	0.027 (0.019)	
$\log R\&D_{t}^{f}$		−0.026 (0.241)	−0.025 (0.022)	−0.015 (0.023)	−0.005 (0.016)	0.013 (0.020)	
$\log R\&D_{it}^{f\_T}$			0.024 (0.079)		0.040 (0.078)		
$\log R\&D_{it}^{f\_M}$				−0.332*** (0.067)		−0.377*** (0.072	
$mi_{it}^{T} \times \log R\&D_{it}^{f\_T}$					−0.042 (0.031)	−0.056 (0.021)	
$mi_{it}^{M} \times \log R\&D_{it}^{f\_M}$	−0.033*** (0.010)	−0.033*** (0.010)	−0.033*** (0.010)	−0.034*** (0.009)	−0.034*** (0.010)	−0.034*** (0.010)	−0.019*** (0.007)
$\log GDPPC_{it}$	0.866	0.895	0.113	0.161	0.505	0.000	−0.615*** (0.054)
$\log KL_{it}$							0.091*** (0.035)
IND_{it}							0.475** (0.195)
$GFCF_{it}$							0.209* (0.126)
FDI_{it}							0.168 (0.110)
$\log CPI_{it}$							−0.008 (0.014)
Juodis–Reese (p value)	0.866	0.895	0.113	0.161	0.505	0.000	0.201
No. of countries	33	33	33	33	33	33	31
No. of obs	531	531	531	531	531	531	554
Adjusted R^2	0.952	0.952	0.952	0.952	0.952	0.952	0.957
B. Panel cointegration tests							
Pedroni (1999, 2004)							
Panel PP t-statistic	−1.436*	−3.835***	−3.030***	−0.608	−1.284	−0.967	

Table 6 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel ADF *t*-statistic	−1.121	−4.721***	−3.631***	−3.693***	−2.012**	−2.029**	
Group PP *t*-statistic	−3.140***	−6.992***	−4.663***	−5.382***	−4.932***	−4.750***	
Group ADF *t*-statistic	−3.511***	−6.887***	−4.490***	−5.595***	−3.669***	−4.470**	
Gengenbach et al. (2016)							
ECM *t*-statistic	−3.031**	−3.502***	−2.524	−1.521			

The dependent variable in the regressions and the Pedroni (1999, 2004) tests is log EI_{it}. The dependent variable in the Gengenbach et al. (2016) tests is Δlog EI_{it}. All regressions (and tests) include country fixed effects. The DOLS regressions were estimated with one lead and one lag of the first-differenced regressors. The data on log EI_{it}, $\log R\&D^{d}_{it}$, $\log R\&D^{f\_T}_{it}$, $mi^{T}_{it} \times \log R\&D^{f\_T}_{it}$, $\log R\&D^{f\_M}_{it}$, and $mi^{M}_{it} \times \log R\&D^{f\_M}_{it}$ for the DOLS regressions and the Pedroni (1999, 2004) tests were demeaned to account for (strong) error cross-sectional dependence due to unobserved common factors; $\log R\&D^{f}_{t}$ is the same for each country and can be considered as an observed common factor (that cannot be demeaned). The Gengenbach et al. (2016) test accounts for strong error cross-sectional dependence via the use of cross-sectional averages. The OLS results are based on demeaned data. Juodis–Reese is the test for strong cross-sectional dependence of Juodis and Reese (2022) applied to the residuals from the DOLS and OLS regressions. The number of lags in the Pedroni (1999, 2004) (PP and ADF) tests was determined using the general-to-specific approach with a maximum of two lags. Given the limited number of time-series observations available for some countries here, it is not possible to include two lags of the first differences in the multivariate Gengenbach et al. (2016) tests. Therefore, no lags of the first differences were included in the multivariate Gengenbach et al. (2016) tests, and no lags of the cross-sectional averages were included in the Gengenbach et al. (2016) tests. Due to the limited number of time-series observations available for some countries, this test cannot be applied to models involving more than four regressors, such as the ones used in columns (5) and (6). Due to the limited number of time-series observations available for some countries, neither the Pedroni (1999, 2004) nor the Gengenbach et al. (2016) tests can be applied to the model in column (7). All tests reject for large negative values. The Pedroni (1999) test statistics are distributed as standard normal. The Gengenbach et al. (2016) critical value for one regressor/two regressors/three regressors/four regressors at the 1% (5%) [10%] significance level is −2.735/−3.120/−3.438/−3.746 (−2.601/−2.981/−3.305/−3.607) [−2.530/−2.909/−3.238/−3.538] (for $N=30$). Numbers in parentheses are Driscoll and Kraay (1998) heteroskedasticity autocorrelation spatial correlation robust standard errors. *** (**) [*] indicate significance at the 1% (5%) [10%] level to suggest that energy intensity in developing countries has a noticeable effect on (import-weighted) foreign R&D expenditures of developed countries. Turning to the estimated coefficients, we see that the coefficients on the control variables are consistent with previous findings (see, e.g., Metcalf 2008; Mimouni and Temimi 2018; Herzer and Schmelmer 2022), and that the coefficient on $\mathrm{mi}_{it}^{M} \times \log \mathrm{R\&D}_{it}^{f\_M}$ remains negative and statistically significant. All in all, the robustness checks in Table 6 support our main results in Table 4.

6 Conclusions and policy implications

Using data for 33 developing countries between 1995 and 2015, we found that domestic R&D has no or even a positive effect on the long-run level of energy intensity. This can be interpreted as evidence that R&D in these countries generates technologies that in general save little or no energy. In addition, we found no evidence of long-run spillovers from R&D in the North to energy intensity in the South through disembodied channels. Nevertheless, our results show that there are significant spillovers from R&D conducted in industrial countries that reduce energy intensity in developing countries. These spillovers occur mainly through imports of machinery and equipment rather than through imports of other goods, and they vary with openness to machinery and equipment imports from industrial countries. Overall, our results suggest that new technologies generated through R&D in developed countries are more energy saving than new technologies generated through R&D in developing countries. In addition, our results suggest that domestic R&D performed in industrial source countries of R&D spillovers reduces energy intensity in these countries as well.

These results have three obvious policy implications: First, governments in developing countries should develop strategies to encourage R&D in energy-saving technologies and thereby to ensure that overall R&D activity increases the likelihood of decreasing energy intensity. Second, governments in developed countries should provide funds and incentives to increase R&D activity in their countries, especially in the area of energy efficiency. If R&D in developed countries not only leads to a reduction in domestic energy intensity, as found by Alam et al. (2019) and confirmed in this study, but also decreases energy intensity in developing countries, as demonstrated here, R&D in developed countries can play a crucial role in reducing global energy intensity and, consequently, global environmental problems. And third, policy makers in developing countries can strengthen spillovers from foreign R&D to domestic energy intensity by increasing their openness to imports of machinery and equipment (i.e., by reducing import tariffs on machinery and equipment).

Appendix

See Table 7.

Table 7 Unit root tests

	CIPS panel unit root test of Pesaran (2007)	ADF time series unit root test of Dickey and Fuller (1981)
Levels (c, t)		
$\log \mathrm{EI}_{it}$	0.094	
$\log \mathrm{R\&D}^{d}_{it}$	0.187	
$\log \mathrm{R\&D}^{f}_{t}$		0.515
$\log \mathrm{R\&D}^{f\_T}_{it}$	0.484	
$\log \mathrm{R\&D}^{f\_M}_{it}$	0.362	
$\mathrm{mi}^{T}_{it} \times \log \mathrm{R\&D}^{f\_T}_{it}$	0.777	
$\mathrm{mi}^{M}_{it} \times \log \mathrm{R\&D}^{f\_M}_{it}$	0.442	
First differences (c)		
$\Delta\log \mathrm{EI}_{it}$	0.000	
$\Delta\log \mathrm{R\&D}^{d}_{it}$	0.000	
$\Delta\log \mathrm{R\&D}^{f}_{t}$		0.044
$\Delta\log \mathrm{R\&D}^{f\_T}_{it}$	0.000	
$\Delta\log \mathrm{R\&D}^{f\_M}_{it}$	0.000	
$\Delta\mathrm{mi}^{T}_{it} \times \log \mathrm{R\&D}^{f\_T}_{it}$	0.000	
$\Delta\mathrm{mi}^{M}_{it} \times \log \mathrm{R\&D}^{f\_M}_{it}$	0.000	

The reported values are p values. c (t) indicates that the tests include country-specific intercepts (and time trends). The Pesaran (2007) panel unit root tests account for error cross-sectional dependence via the use of (weighted) cross-sectional averages. One lag was used in the unit root tests. The results of the CIPS panel unit root tests suggest that $\log \mathrm{EI}_{it}$, $\log \mathrm{R\&D}^{d}_{it}$, $\log \mathrm{R\&D}^{f\_T}_{it}$, $\log \mathrm{R\&D}^{f\_M}_{it}$, $\mathrm{mi}^{T}_{it} \times \log \mathrm{R\&D}^{f\_T}_{it}$, and $\mathrm{mi}^{M}_{it} \times \log \mathrm{R\&D}^{f\_M}_{it}$ are $I(1)$, assuming the usual 5% significance level as the rejection criterion. Since the unweighted sum of the R&D expenditures of high-income countries is the same for all countries in the panel, we report the results of the ADF time series test for $\log \mathrm{R\&D}^{f}_{t}$

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Declarations

Conflict of interest The author declares that they have no conflict of interest.

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