World Development 151 (2022) 105754

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

The impact of domestic and foreign R&D on TFP in developing countries

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A R T I C L E   I N F O

Article history:
Accepted 12 November 2021
Available online 7 January 2022

JEL classification:
O30
O47
O11
F43

Keywords:
Semi-endogenous growth models
Schumpeterian growth models
Domestic R&D
International R&D spillovers
TFP
Developing countries

A B S T R A C T

There are few studies on the impact of domestic R&D on TFP in developing countries and even less on the impact of both domestic and foreign R&D on TFP in developing countries. Only one of these studies—a single-country study—also tests semi-endogenous and Schumpeterian R&D growth models against each other. All these studies focus on a relatively small number of developing countries, and none examines the extent to which there are differences in the effects of domestic R&D and international R&D spillovers on TFP between middle- and low-income countries. Using a large panel of countries, this study (*i*) tests the predictions of Schumpeterian theory against the predictions of semi-endogenous theory regarding the R&D-TFP relationship for developing economies, (*ii*) examines and compares the effects of domestic R&D and international R&D spillovers on TFP in developing countries, and (*iii*) investigates differences in the effects of domestic R&D and international R&D spillovers on TFP between middle- and low-income countries. It is found that an increase in the level (growth rate) of domestic R&D expenditures has a positive effect on the level (growth rate) of TFP, as semi-endogenous growth theory predicts, but this effect is greater in middle-income than in low-income countries. It is also found that domestic R&D has a much greater effect on TFP in developing countries than international R&D spillovers.

1. Introduction

A large body of evidence demonstrates that most of the cross-country variation in per capita income can be explained by differences in total factor productivity (TFP) rather than differences in inputs such as physical capital, human capital, and labor (e.g. Hall & Jones, 1999; Easterly & Levine, 2001; Hsieh & Klenow, 2010). It is therefore not surprising that TFP is a common, if not the most common, measure of the stock of knowledge or technology. Growth in the stock of knowledge, in turn, is driven in research and development (R&D)-based growth models, as the name implies, by R&D—an idea that is supported, at least for industrial countries, by numerous TFP studies (e.g. Ha & Howitt, 2007; Madsen, 2008, 2010). However, although developing countries tend to have low TFP and thus a high potential for productivity increases through R&D, it may be wrong to assume that domestic R&D performed in developing countries, whether aimed at discovering new knowledge or at transferring technology from industrial countries, exerts a major effect on TFP in these countries as well.

The reasons for this skepticism are several. One is that, given that the vast majority of worldwide R&D activity takes place in industrial nations,[1] R&D efforts in many developing countries, particularly low-income countries, may be too small to have a measurable impact on TFP (e.g. Coe et al., 1997). Another reason is that the low levels of R&D activity in many developing countries, particularly low-income countries, may be a symptom of low private returns to R&D, and may be caused by factors that may also cause a reduction in the effect of R&D on TFP, such as low levels of human capital, less developed financial markets, political and economic instability, and poor protection of physical and intellectual property rights—factors that may inhibit the creation, adaption, and diffusion of knowledge and technology (e.g. Goñi & Maloney, 2017). Finally, a third reason is that there are surprisingly few studies on the effect of domestic R&D on TFP in developing countries, and the results of these studies are contradictory.

Birdsall and Rhee (1993) find (controlling for capital and labor growth) no significant positive relationship between domestic R&D and GDP growth (and thus TFP growth) in a subsample of

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[1] 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 68% of the total worldwide R&D in 2015. Middle-income countries were responsible for 32% of worldwide R&D expenditures; and low-income countries had a share of 0.16%. R&D expenditures made up 2.3% of GDP in high-income countries; the ratio of R&D expenditures to GDP in middle-income countries was 1.1%, and that in low-income countries was 0.26%.

https://doi.org/10.1016/j.worlddev.2021.105754
0305-750X/

ten developing countries.[2] Madsen et al. (2010a) find for a subsample of 32 developing countries that domestic R&D has a significant and positive effect on TFP growth, at least when R&D activity is measured by the share of researchers in total employment, but this effect is conditional: developing countries that are far from the technology frontier experience a greater effect than developing countries that are closer to the technology frontier. The implication from this finding is that the effect of domestic R&D on TFP growth tends to be greater in low-income countries than in middle-income countries. However, using R&D expenditures as a percentage of GDP as a measure of R&D activity, they find no significant (unconditional or conditional) effect on TFP growth in developing countries.[3] Another relevant study is that of Goñi and Maloney (2017), who use a sample of 70 developed and developing countries (of which 45 are developing countries). Their results suggest that the effect of domestic R&D on TFP growth follows an inverted-U pattern with respect to the distance to the technology frontier: the effect first increases with increasing distance to the technology frontier, reaches a maximum at a certain distance, and then declines with further increases in distance. This finding implies that domestic R&D tends to have a greater effect in middle-income countries than in low-income (and high-income) countries.

In addition to the effect of *domestic* R&D on domestic TFP growth, other studies examine the effect of *foreign* R&D performed in industrial countries on domestic TFP growth in developing (or transition) countries and, specifically, whether imports act as a channel for the international transfer of technology. Before turning to these studies, it should be noted that a potentially important factor that determines the magnitude of this technology transfer effect is the technology gap between countries. On the one hand, a larger technology gap implies a greater potential for international knowledge spillovers. On the other hand, a larger technology gap also implies a lower level of absorptive capacity; it could therefore be that countries furthest from the technology frontier—specifically low-income countries—are unable to adopt new technologies from industrial countries. Thus, the effect of foreign R&D may be smaller than the effect of domestic R&D on TFP, particularly if domestically developed technologies suit local conditions better than technologies from abroad, but it is also possible that foreign R&D has larger impact on TFP than domestic R&D, given the reasons outlined above. Krammer (2010) finds insignificant effects of domestic R&D on TFP but significant international R&D spillovers through imports (and FDI) in a subsample of 27 transition countries.[4] Madsen et al. (2010b) find, in a study for India, that both domestic R&D and import-related R&D spillovers from industrial countries have a positive and significant effect on TFP growth and that foreign R&D has a larger impact on TFP growth than domestic R&D.[5]

What is important in the present context is that most recent R&D-based growth models can be divided into two categories. On the one hand, there are Schumpeterian growth models (e.g. Young, 1998; Peretto, 1998; Howitt, 1999), in which new knowledge is produced using resources devoted to R&D and the existing stock of knowledge that exhibits constant returns. As an economy grows, however, the associated proliferation of product varieties reduces the effectiveness of R&D because available R&D resources have to be spread more thinly over a larger number of varieties. Since the number of varieties, in the long run, is proportional to the scale of the economy, the growth rate of the stock of knowledge depends on R&D intensity, i.e., the ratio of the amount of R&D resources to the scale of the economy, typically measured by population size or GDP. On the other hand, there are semi-endogenous growth models (e.g. Jones, 1995a; Kortum, 1997; Segerstrom, 1998), which assume diminishing returns to the stock of knowledge and the absence of product proliferation effects. In these models, the growth rate of knowledge depends on the growth rate of R&D effort, so that if the growth rate of R&D effort is constant in the long run (as is the case in a balanced growth equilibrium), the log-level of R&D effort is positively related to the log-level of the knowledge stock. Thus, while Schumpeterian growth models imply a relationship between R&D intensity and the growth rate of TFP, semi-endogenous models imply a relationship between the log-level or the growth rate of R&D effort and the log-level or the growth rate of TFP. It follows that, when examining the effects of domestic and foreign R&D on TFP, it is important to test these theories against each other, not only because the results may depend critically on the specification of the estimating equation, but also because such tests are important for theory development as well as for economic policy. From an economic policy perspective, Schumpeterian growth models are more promising because they predict that a policy that increases R&D intensity will increase the long-run growth rate of TFP (and hence of per capita income), whereas such a policy has "only" a level effect on TFP in semi-endogenous growth models. Of the above studies, only Madsen et al. (2010b) test semi-endogenous growth models versus Schumpeterian growth models (for India) and find evidence for the latter.

Thus, there are only five studies that deal, explicitly or implicitly, with the effects of domestic R&D on the level or the growth rate of TFP in developing countries, two of which also examine the effect of foreign R&D on the level or the growth rate of TFP in developing countries,[6] and only one of which—the single-country study by Madsen et al. (2010b)—also tests Schumpeterian versus semi-endogenous growth models. All of the above studies focus on a relatively small number of countries, and none examines the extent to which there are differences in the effects of domestic R&D and international R&D spillovers on TFP between middle- and low-income countries.

The present study contributes to this literature in three main ways. First, we test Schumpeterian growth models versus semi-endogenous growth models for a panel of developing (i.e., low- and middle-income) countries. Second, we examine the impact of domestic R&D and international R&D spillovers on TFP using a large sample of developing countries, including 49 middle- and 33 low-income countries. Third, we study whether the TFP effects of domestic R&D and international R&D spillovers differ between middle- and low-income countries.

Given the above discussion, the purpose of this study can be divided into four objectives. The first is to examine the effectiveness of domestic R&D in generating domestic TFP growth for developing countries. The second objective is to compare the effect of domestic R&D with that of R&D performed in industrial countries on TFP or TFP growth in developing countries. The third objective is to examine whether there are differences in the TFP effects of

[2] Domestic R&D is weakly significant and negative in one of two specifications.

[3] Both the results of Birdsall and Rhee (1993) and those of Madsen et al. (2010a) suggest that domestic R&D affects TFP growth in industrial countries.

[4] Krammer (2010) finds significant effects of domestic and foreign R&D on TFP for industrial countries.

[5] There are also studies that focus exclusively on the effect of foreign R&D on domestic TFP in developing countries and ignore the effect of domestic R&D on domestic TFP. These studies include those of Coe et al. (1997), Engelbrecht (2002), Blyde (2004), Savvides and Zachariadis (2005), Falvey et al. (2007), and Seck (2012), who all find evidence of trade-related R&D spillovers in developing countries.

[6] Three other studies should be mentioned, although their focus is not specifically on developing countries. Ang and Madsen (2011) and Ang and Madsen (2013) report for a sample of six Asian countries (including four high-income countries) that both domestic R&D and foreign R&D spillovers significantly affect TFP growth. Their results also suggest that domestic R&D has a larger impact on TFP than foreign R&D. Bravo-Ortega and Marín (2011) find, using a sample of 65 developed and developing countries, that domestic R&D increases TFP, while foreign R&D has no statistically significant effect on TFP.

domestic and foreign R&D between middle- and low-income countries. For these objectives, it is necessary to identify the appropriate class of theoretical models, Schumpeterian or semi-endogenous growth models. Therefore, the fourth objective of this study is to test Schumpeterian versus semi-endogenous growth models for developing countries.

To preview our main results, we find that an increase in the level (growth rate) of domestic R&D expenditures has a positive effect on the level (growth rate) of TFP, as semi-endogenous growth theory, rather than Schumpeterian growth theory, predicts, but this effect is greater in middle-income than in low-income countries. We also find evidence that domestic R&D has a much greater effect on TFP in developing countries than foreign R&D. Specifically, our results suggest that knowledge gained from R&D in industrial countries in general does not spillover to low-income countries.

The remainder of the paper is organized as follows. Section 2 summarizes the main assumptions, predictions, and empirical implications of Schumpeterian and semi-endogenous growth theories. Section 3 defines our variables, outlines our empirical strategy, and describes the data sources and the sample. Section 4 presents our empirical results, and Section 5 concludes.

2. Theoretical predictions and empirical implications of Schumpeterian and semi-endogenous growth models

The central component of any R&D-based growth model is a knowledge production function. A general form of this function is

$$\dot{A}_{it} = \delta_i A_{it}^{\phi}\left(\frac{X_{it}}{Q_{it}}\right)^{\lambda} \quad (1)$$

where $\dot{A}_{it}$ is the flow of new knowledge in country i at time t; δ_i is a country-specific constant of proportionality; A_{it} represents the stock of existing knowledge; ϕ is a parameter that describes the nature of the returns to the stock of knowledge, X_{it} stands for R&D effort (or input); 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); Q_{it} represents a measure of the scale of the economy, and placement of Q_{it} in the denominator captures the idea that as the scale of the economy increases, the proliferation of product varieties reduces the effectiveness of R&D because a given amount of research effort has to be spread more thinly over a larger number of varieties; finally, β is a parameter that quantifies the extent of product proliferation effects associated with increasing economic scale.

Rewriting (1) in terms of the growth rate of the stock of knowledge gives

$$\frac{\dot{A}_{it}}{A_{it}} = \delta_i A_{it}^{\phi-1}\left(\frac{X_{it}}{Q_{it}}\right)^{\lambda} \quad (2)$$

Schumpeterian growth models, in which the number of product varieties is proportional to the scale of the economy, are based on the assumption that β = 1 and ϕ = 1. Under this assumption, Eq. (2) reduces to

$$\frac{\dot{A}_{it}}{A_{it}} = \delta_i\left(\frac{X_{it}}{Q_{it}}\right)^{\lambda} \quad (3)$$

where (X_{it}/Q_{it}) is commonly referred to as R&D intensity. Taking logs, approximating $\log(\dot{A}_{it}/A_{it}) \approx \Delta\log A_{it}$, and adding an error term gives

$$\Delta\log A_{it} = c_i + \lambda\log\left(\frac{X_{it}}{Q_{it}}\right) + \varepsilon_{it} \quad (4)$$

where $c_i \equiv \delta_i$. Here, and in the remainder of the paper, c_i denotes country fixed effects to control for any unobserved time-invariant country characteristics. In our empirical analysis, we also control for unobserved time-varying common factors (such as global crises), f_t. Thus, the error term is composed of idiosyncratic stochastic shocks μ_{it} and unobserved common factors that can induce cross-sectional error dependence and lead to inconsistent estimates if they are correlated with both the dependent and independent variables, $\varepsilon_{it} = \rho f_t + \mu_{it}$.

Eq. (4) predicts that changes in (the log of) R&D intensity are positively associated with changes in the growth rate of knowledge. One necessary condition for this prediction to hold is that if $\Delta\log A_{it}$ is stationary (or integrated of order zero, $I(0)$),[7] $\log(X_{it}/Q_{it})$ is also stationary (or $I(0)$).[8] Assuming that $\log X_{it}$ is $I(1)$, $\log(X_{it}/Q_{it})$ will be stationary if (and only if) $\log X_{it}$ and $\log Q_{it}$ are cointegrated with a cointegrating vector $(1, -1)$. Thus, another, related necessary condition for the validity of Schumpeterian hypotheses is that (if $\log A_{it}$ and $\log X_{it}$ are $I(1)$) $\log X_{it}$ cointegrates with $\log Q_{it}$ and that the coefficient β on $\log Q_{it}$ in the cointegrating equation $\log X_{it} = c_i + \beta\log Q_{it} + \varepsilon_{it}$ is (close to) unity. Finally, Schumpeterian theory implies that the coefficient on $\log(X_{it}/Q_{it})$ in Eq. (4) should be positive and statistically significant.

Semi-endogenous growth models, in contrast, are characterized by the absence of product proliferation effects and diminishing returns to the stock of knowledge. If β = 0 and ϕ < 1, then Eq. (2) reduces to

$$\frac{\dot{A}_{it}}{A_{it}} = \delta_i A_{it}{}^{\phi-1} X_{it}{}^{\lambda} \quad (5)$$

Assuming that the stock of knowledge grows in the long run at a constant rate g_{Ai}, the above equation can be solved for the stock of knowledge, yielding

$$A_{it} = \left(\frac{\delta_i}{g_{Ai}}\right)^{\frac{1}{1-\phi}} X_{it}{}^{\frac{\lambda}{1-\phi}} \quad (6)$$

Taking logs of Eq. (6) and adding an error term gives

$$\log A_{it} = c_i + \frac{\lambda}{1-\phi}\log X_{it} + \varepsilon_{it} \quad (7)$$

This equation predicts that, provided that the growth rate of knowledge is constant over the long run (or stationary), changes in R&D effort are positively associated with changes in the stock of knowledge. One necessary condition for this prediction to hold is that if $\log A_{it}$ and $\log X_{it}$ are $I(1)$, the two variables cointegrate. Cointegration implies a long run equilibrium relationship. If the variables are $I(1)$ and cointegrated, the term $\frac{\lambda}{1-\phi}$ can be interpreted as the long-run elasticity of knowledge with respect to research effort. Hence, another necessary condition or the validity of the above prediction is that the estimated coefficient on $\log X_{it}$ in the above regression is positive and statistically significant.

Eq. (7) also implies that the growth rate of A_{it} depends (in the long run) on the growth rate of X_{it}, as can be easily seen by differencing (7):

$$\Delta\log A_{it} = \frac{\lambda}{1-\phi}\Delta\log X_{it} + \Delta\varepsilon_{it} \quad (8)$$

Now, combining Eq. (8) with Eq. (4) yields the following empirical model that nests Schumpeterian and semi-endogenous growth (e.g. Madsen, 2008):

[7] The order of integration is the number of times a (stochastically) non-stationary variable must be differenced to make it stationary.

[8] Generally speaking, a permanent change in a variable x cannot produce a long-run change in a variable y when x is $I(1)$ and y is $I(0)$.

$$\Delta \log A_{it} = c_i + \rho_1 \log\left(\frac{X_{it}}{Q_{it}}\right) + \rho_2 \Delta \log X_{it} + \varepsilon_{it} \tag{9}$$

A positive estimate of ρ_2 ($\equiv \frac{\lambda}{1-\phi}$) and can be interpreted as evidence of semi-endogenous growth, whereas Schumpeterian growth models predict ρ_1 ($\equiv \lambda$) > 0.

Finally, for completeness, we note that Jones's (1999) hybrid semi-endogenous model considers the case where the number of varieties grows less than proportionally with the scale of the economy, $0 < \beta < 1$, and the stock of knowledge exhibits diminishing returns, $\phi < 1$. Assuming (again) a constant growth rate of the stock of knowledge, Eq. (2) can then be solved for A_{it} as follows:

$$A_{it} = \left(\frac{\delta_i}{g_{Ai}}\right)^{\frac{1}{1-\phi}} X_{it}^{\frac{\lambda}{1-\phi}} Q_{it}^{\frac{\lambda(-\beta)}{1-\phi}} \tag{10}$$

The log linear version of this equation (with the usual error term) is

$$\log A_{it} = c_i + \frac{\lambda}{1-\phi}\log X_{it} - \frac{\lambda\beta}{1-\phi}\log Q_{it} + \varepsilon_{it} \tag{11}$$

According to this equation, increases in research effort are associated with increases in the stock of knowledge, whereas the scale of the economy has a negative effect on the stock of knowledge (for a given level of research effort).

So far the discussion has ignored potential R&D spillovers from industrial countries to developing economies. Assuming that growth of domestic knowledge in developing countries depends not only on domestic R&D intensity, but also on growth in foreign knowledge from industrial countries, and assuming further that knowledge is embodied in imports and that countries that import more relative to their GDP benefit more from foreign knowledge, Eq. (4) from *Schumpeterian growth theory* can be extended as follows (e.g. Madsen et al., 2010b):

$$\Delta \log A_{it} = c_i + \gamma^d \log\left(\frac{X_{it}^d}{Q_{it}^d}\right) + \gamma^{fmi} mi_{it} \times \log\left(\frac{X_{it}}{Q_{it}}\right)^f + \varepsilon_{it} \tag{12}$$

where (X_{it}^d/Q_{it}^d) is domestic R&D intensity, mi_{it} is the share of imports from industrial countries in GDP (of country i in year t), and $(X_{it}/Q_{it})^f$ is an import-weighted average of R&D intensities of industrial countries. Eq. (12) postulates that international R&D spillovers are trade-related and that changes in import-weighted foreign R&D intensities affect the growth rate of knowledge only through their interaction with the import share. In the empirical analysis, we also estimate versions with uninteracted import-weighted foreign R&D intensities. In addition, we use the unweighted sum of the R&D intensities of industrial countries to examine disembodied R&D spillovers through non-trade channels, such as scientific journals, international conferences, and the sale of patent rights.

The corresponding equation implied by *semi-endogenous growth models* is

$$\log A_{it} = c_I + \gamma^d \log X_{it}^d + \gamma^{fmi} mi_{it} \times \log X_{it}^f + \varepsilon_{it} \tag{13}$$

where X_{it}^d is domestic research effort, X_{it}^f is an import-weighted average of foreign R&D efforts, and mi_{it} is, as before, the share of imports from industrial countries in GDP. In addition to the equation above, we also estimate specifications in which we replace $mi_{it} \times \log X_{it}^f$ with either $\log X_{it}^f$ or the unweighted sum of the R&D efforts of industrial countries.

3. Variable definitions, empirical strategy, and data

3.1. Variable definitions and empirical strategy

We now define our variables, describe our empirical strategy, and outline the organization of the empirical analysis that follows in Section 4.

Following common practice, we measure the stock of domestic knowledge by domestic TFP. Given that agriculture is an important part of the economy in many developing countries,[9] failure to account for the contribution of land to total output would result in an upward bias in the calculation of TFP for many countries. To account for land as a factor of production, we follow the works of Madsen (2010) and Ang and Madsen (2013) and calculate TFP as

$$TFP_{it} = \frac{Y_{it}}{K_{it}^{(1-\alpha_{it})(1-s_{it})} T_{it}^{(1-\alpha_{it})s_{it}} (L_{it}h_{it})^{\alpha_{it}}} \tag{14}$$

where Y_{it} is output, measured as real GDP; K_{it} denotes the stock of physical capital; T_{it} is agricultural land under cultivation; L_{it} is the number of employed persons; h_{it} represents human capital per worker; s_{it} is the share of agricultural value added in GDP; and $(1-\alpha_{it})(1-s_{it})$, $(1-\alpha_{it})s_{it}$, and a_{it} denote, respectively, the capital, land, and labor shares of income. Like the above studies, we measure the land share of income by the share of agriculture in GDP. Thus, factor shares are allowed to vary across countries (and through time), given large differences in the share of agriculture in GDP across countries. As a robustness check, we also use alternative measures of TFP, based on a production function without land (and varying factor shares) and based on a production function without land and human capital (and constant capital and labor shares of income). We present the results of this exercise in Section A5 of the online appendix, where we also present results from fixed effects regressions using the number of domestic patent applications (in logs) as an alternative dependent variable.

Also following common practice, we measure domestic R&D effort as real domestic R&D expenditures, denoted by R_{it}^d. It should be noted here that an alternative measure of R&D input is the number of scientists and engineers engaged in R&D. However, a disadvantage of this measure is that it does not include spending on equipment and that it does not account for the quality of researchers: if expanding research involves employing better-qualified researchers and more equipment, this will be more properly measured by R&D spending than by the mere number of researchers. In addition, R&D expenditure data are available for more countries and years than data on the number of researchers.[10] It should also be noted that some studies measure R&D input by the perpetual inventory stock of R&D capital, constructed from cumulative R&D expenditure data. The implicit and implausible assumption behind the use of the R&D stock as a measure of R&D input is that (current) R&D output is produced even if R&D expenditures in the current period are zero (i.e., even if no researchers are present in the current period). An additional, more technical problem is that 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, which prevents us from con-

[9] According to our data from the World Development Indicators, the average share of agricultural value added in GDP between 1990 and 2016 in our sample ranges from 1.34 percent in Trinidad and Tobago to 45.65 percent in Ethiopia, and the average share of agricultural value added in GDP between 1990 and 2016 is greater than 20 percent in about one-third of the countries in our sample. The implication is that estimates of TFP for developing countries that do not account for the contribution of land to total output tend to be biased.

[10] We also experimented with the number of scientists and engineers engaged in R&D but found no significant relationship between the number of researchers and TFP (in middle-income countries and in low-income countries).

structing R&D capital stocks for a sufficiently large number of developing countries.

While domestic R&D effort is measured by domestic R&D expenditures, we use real domestic GDP, GDP^d_{it}, as our measure of domestic economic scale. Consequently, the variable for domestic R&D intensity is the ratio of domestic R&D expenditures to domestic GDP, R^d_{it}/GDP^d_{it}, as is standard in the literature.

Based on these measures, *Schumpeterian growth theory* implies that if $\Delta\log TFP_{it}$ is stationary (or $\log TFP_{it}$ is $I(1)$), $\log(R^d_{it}/GDP^d_{it})$ should also be stationary. This is equivalent to the requirement that if $\log R^d_{it}$ is $I(1)$, then $\log R^d_{it}$ and $\log GDP^d_{it}$ should be cointegrated with a vector $(1, -1)$. In addition, the coefficient on $\log(R^d_{it}/GDP^d_{it})$ should be positive and significant in TFP *growth* regressions.

Semi-endogenous growth theory implies that if $\log TFP_{it}$ and $\log R^d_{it}$ are $I(1)$, these variables should be cointegrated. In addition, the coefficient on $\log R^d_{it}$ should be positive and significant in TFP *level* regressions. Finally, a significant and positive coefficient on $\Delta\log R^d_{it}$ in TFP *growth* regressions provides additional evidence of semi-endogenous growth. Conversely, however, an insignificant relationship between the growth rate of TFP and the growth rate of R&D expenditures does not imply that semi-endogenous growth models can be rejected, as shown in the online appendix (Section A6).

Hence, our empirical strategy, which we employ in Section 4.1, involves sequential, interconnected analyses where we first examine the time series properties of $\log TFP_{it}$, $\log R^d_{it}$, and $\log(R^d_{it}/GDP^d_{it})$, and then analyze (*i*) whether $\log R^d_{it}$ is cointegrated with $\log GDP^d_{it}$ and (*ii*) whether $\log R^d_{it}$ is cointegrated with $\log TFP_{it}$. This is the *first* step in evaluating the validity of Schumpeterian and semi-endogenous growth models. In this step, we also test whether the variables are driven by common factors, by testing the variables for cross-sectional dependence, and we also test whether domestic R&D expenditures are weakly exogenous or long-run forcing for domestic TFP.

If there is cointegration between $\log R^d_{it}$ and $\log GDP^d_{it}$, the *second* step in Section 4.1 is to estimate the cointegrating relationship between the two variables and to test whether the cointegrating coefficient on the log of GDP is equal to one. In this *second* step, we also estimate the relationships (*i*) between $\log(R^d_{it}/GDP^d_{it})$ and $\Delta\log TFP_{it}$, and (*ii*), provided that $\log R^d_{it}$ is cointegrated with $\log TFP_{it}$, between $\log R^d_{it}$ and $\log TFP_{it}$. In addition, we include $\Delta\log R^d_{it}$ in the regression of $\Delta\log TFP_{it}$ on $\log(R^d_{it}/GDP^d_{it})$.

Because panel unit root and cointegration methods require sufficiently long time series, the *first* step uses a subsample of 32 countries with at least 15 observations (listed in Table A1 in the online appendix). In the *second* step, we use the subsample of 32 countries with at least 15 observations, the remaining subsample of 50 countries with less than 15 time series observations, and the full sample of 82 developing countries to estimate our relationships of interest.

Section 4.1 focuses on the impact of domestic R&D on TFP. In Section 4.2, we consider the effects of both domestic and foreign R&D on domestic TFP. International R&D spillovers are measured in the "*Schumpeterian growth specification*" (Eq. (12)), following the weighting scheme of Coe and Helpman (1995), by

$$mi^T_{it} \times \log\left(\frac{R_{it}}{GDP_{it}}\right)^{f\_T\_CH} = mi^T_{it} \times \log \sum_{j=1=1}^{15} \frac{IM^T_{ijt}}{IM^T_{it}} \frac{R^d_{jt}}{GDP^d_{jt}} \quad (15.1)$$

$$mi^M_{it} \times \log\left(\frac{R_{it}}{GDP_{it}}\right)^{f\_M\_CH} = mi^M_{it} \times \log \sum_{j=1=1}^{15} \frac{IM^M_{ijt}}{IM^M_{it}} \frac{R^d_{jt}}{GDP^d_{jt}} \quad (15.2)$$

where mi^T_{it} (mi^M_{it}) is the share of imports of total goods and services (machinery and equipment imports) from the 15 industrial countries with the highest R&D expenditures in GDP in each developing country, IM^T_{ijt} (IM^M_{ijt}) are imports of total goods and services (machinery and equipment imports) of developing country *i* from developed country *j*, IM^T_{it} (IM^M_{it}) is total imports (machinery and equipment imports) of country *i* from all 15 industrial countries, R^d_{jt} denotes R&D expenditures of industrial country *j*, and GDP^d_{jt} is GDP of industrial country *j*; thus, R^d_{jt}/GDP^d_{jt} represents the R&D intensity of country *j*.[11]

Coe and Helpman (1995) use imports of total goods and services as their weighting factor, and find evidence of knowledge spillovers between OECD countries. Coe et al. (1997) measure knowledge spillovers from developed to developing countries based on imports of total goods and services, total imports of manufactures, and machinery and equipment imports, and find stronger (no) evidence of international R&D spillovers using machinery and equipment imports (total imports of goods and services). We use both machinery and equipment imports and total imports of goods and services as weighting factors to account for, and retest, the possibility that these two weighting factors produce different effects.

Coe et al. (1997) find, based on foreign R&D capital stocks, that foreign R&D has a positive and significant coefficient only interactively with the import share. Other studies, such as Krammer (2010) and Madsen et al. (2010b), do not interact their foreign R&D variables with the ratio of imports to GDP, but nevertheless find evidence of R&D spillovers from developed countries. Following these studies, we also use uninteracted R&D variables, given here by

$$\log\left(\frac{R_{it}}{GDP_{it}}\right)^{f\_T\_CH} = \log \sum_{j=1=1}^{15} \frac{IM^T_{ijt}}{IM^T_{it}} \frac{R^d_{jt}}{GDP^d_{jt}} \quad (15.3)$$

$$\log\left(\frac{R_{it}}{GDP_{it}}\right)^{f\_M\_C} = \log \sum_{j=1=1}^{15} \frac{IM^M_{ijt}}{IM^M_{it}} \frac{R^d_{jt}}{GDP^d_{jt}} \quad (15.4)$$

Lichtenberg and van Pottelsberghe de la Potterie (1998) argue that the weighting scheme of Coe and Helpman (1995), applied to foreign R&D capital stocks, 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. Although the weighting scheme of Coe and Helpman (1995) applied to foreign R&D intensities does not suffer from potential aggregation problems,[12] we also use the weighting scheme of Lichtenberg and van Pottelsberghe de la Potterie (1998) and define

[11] We include the following countries in our calculations: 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 industrial countries with the highest R&D expenditures. Within the group of high-income countries, they were responsible for 81% of R&D in 2015.

[12] Given that the weights of Coe and Helpman (1995) are fractions that add up to one, the weighting scheme of Coe and Helpman (1995), applied to foreign R&D capital stocks, implies that a merger between countries would always increase the import-weighted foreign R&D stock. This logic also applies to import-weighted foreign R&D expenditures, but it does not apply to import-weighted foreign R&D intensities (which do not necessarily increase as a result of mergers).

$$mi_{it}^{T}\times\log\left(\frac{R_{it}}{GDP_{it}}\right)^{f\_T\_LP}=mi_{it}^{T}\times\log\sum_{j=1=1}^{15}\frac{IM_{ijt}^{T}}{GDP_{jt}^{d}}\frac{R_{jt}^{d}}{GDP_{jt}^{d}} \tag{15.5}$$

$$mi_{it}^{M}\times\log\left(\frac{R_{it}}{GDP_{it}}\right)^{f\_M\_LP}=mi_{it}^{M}\times\log\sum_{j=1=1}^{15}\frac{IM_{ijt}^{M}}{GDP_{jt}^{d}}\frac{R_{jt}^{d}}{GDP_{jt}^{d}} \tag{15.6}$$

In addition, to allow for the possibility of disembodied, non-trade-related spillovers, we consider the unweighted sum of the foreign R&D intensities, motivated by the work of Xu and Wang (1999),

$$\left(\frac{R_{t}}{GDP_{t}}\right)^{f}=\sum_{j=1=1}^{15}\frac{R_{jt}^{d}}{GDP_{jt}^{d}} \tag{15.7}$$

In the "*semi-endogenous growth specification*" (Eq. (13)), in which the log level of TFP is the dependent variable, we measure international R&D spillovers using

$$mi_{it}^{T}\times\log R_{it}^{f\_T\_CH}=mi_{it}^{T}\times\log\sum_{j=1=1}^{15}\frac{IM_{ijt}^{T}}{IM_{it}^{T}}R_{jt}^{d} \tag{16.1}$$

$$mi_{it}^{M}\times\log R_{it}^{f\_M\_CH}=mi_{it}^{M}\times\log\sum_{j=1=1}^{15}\frac{IM_{ijt}^{M}}{IM_{it}^{M}}R_{jt}^{d} \tag{16.2}$$

$$\log R_{t}^{f}=\log\sum_{j=1=1}^{15}R_{jt}^{d} \tag{16.3}$$

where the right hand side variables are defined as above. Thus, as above, we consider import-related and disembodied, non-trade-related R&D spillovers.

Using definition 16.1 (16.2), we examine whether capital goods import-weighted (total import-weighted) foreign R&D expenditures affect domestic TFP through their interaction with the machinery and equipment import share (total import share). To examine the impact of foreign R&D on TFP when it does not interact with the share of imports in GDP, we also employ

$$\log R_{it}^{f\_T\_CH}=\log\sum_{j=1=1}^{15}\frac{IM_{ijt}^{T}}{IM_{it}^{T}}R_{jt}^{d} \tag{16.4}$$

$$\log R_{it}^{f\_M\_CH}=\log\sum_{j=1=1}^{15}\frac{IM_{ijt}^{M}}{IM_{it}^{M}}R_{jt}^{d} \tag{16.5}$$

In addition, as a robustness check, we use the weighting scheme of Pottelsberghe de la Potterie (1998) and define

$$mi_{it}^{T}\times\log R_{it}^{f\_T\_LP}=mi_{it}^{T}\times\log\sum_{j=1=1}^{15}\frac{IM_{ijt}^{T}}{GDP_{jt}^{d}}R_{jt}^{d} \tag{16.6}$$

$$mi_{it}^{M}\times\log R_{it}^{f\_M\_LP}=mi_{it}^{M}\times\log\sum_{j=1=1}^{15}\frac{IM_{ijt}^{M}}{GDP_{jt}^{d}}R_{jt}^{d} \tag{16.7}$$

Finally, in Section 4.2.2., we estimate separate TFP level regressions for middle- and low-income countries, without and with additional variables. The first of these variables is the log of real GDP, $\log GDP_{it}^{d}$. As discussed in Section 2, the hybrid semi-endogenous model implies that (holding aggregate R&D effort fixed) the scale of the economy, and thus real GDP, may have a negative effect on TFP because an increase in economic scale may lead to an increase in the number of varieties and thus to a reduction in R&D effort per variety. However, to the extent that increases in GDP lead to increases in expenditures for health and infrastructure, and these expenditures promote TFP, real GDP may also have a positive effect on TFP. Since real R&D expenditures and real GDP may be highly correlated, we control for real GDP to ensure that the estimated coefficient on $\log R_{it}^{d}$ does not reflect the effect of real GDP on TFP.

The second variable we include is tertiary education, proxied, following Krammer (2010), by the tertiary school enrolment rate (in percent) and denoted by $tertiary_{it}$.[13] It is widely recognized that human capital plays direct role in the production process, by increasing the physical and technical skills of the labor force. Tertiary education, in particular, may also indirectly affect production, through TFP, by broadening the base of engineering and scientific skills that facilitate the process of creating new technologies. Tertiary education may also improve the absorption of new technologies, and thus have an additional positive impact on TFP. Finally, it is quite plausible that increased tertiary education may lead to greater efficiency in both the choice and use of health inputs (including better nutrition and healthcare) and thus to increases in productivity through improvements in health. Contrary to these arguments, however, several studies find no evidence that education is an important positive determinant of TFP growth in developing countries (e.g. Falvey et al., 2007; Madsen et al., 2010b).

To the extent that institutions are stable over long periods of time, their effects will be absorbed by the country fixed effects. Nevertheless, to control for the possibility that the estimates on our variables of interest (partially) pick up the effect of time-varying institutional characteristics, we also include a measure of the rule of law, $RuleOfLaw_{it}$.

The fourth additional variable is the log of the stock of FDI (relative to GDP), $\log FDI_{it}$. While Savvides and Zachariadis (2005), Madsen et al. (2010a), and Madsen et al. (2010b) use total FDI (relative to GDP) as a control variable, Krammer (2010) and Seck (2012) use a measure of FDI-weighted foreign R&D stocks to examine explicitly whether FDI from developed countries is a source of technology transfer to developing countries. Savvides and Zachariadis (2005) and Madsen et al. (2010b) find significant positive effects of FDI on TFP growth in developing countries; the results of Madsen et al. (2010a), in contrast, suggest that FDI has an insignificant effect on TFP growth in developing countries; and Krammer (2010) and Seck (2012) find evidence of R&D spillovers through FDI. Unfortunately, it is not possible to construct a reasonably reliable measure of FDI-weighted foreign R&D expenditures for developing countries 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 1995–2016. Therefore, we use the stock of total FDI (as a percentage of GDP).

The final two variables are the log of the unweighted sum of the R&D expenditures of middle-income countries, $\log R_{it}^{f\_middle}$, and the log of the unweighted sum of the R&D expenditures of low-income countries, $\log R_{it}^{f\_low}$ (calculated without including the R&D expenditures of country i). We note here that due to the limited availability of bilateral trade data between developing countries, we are unable to construct import-weighted R&D expenditures of

[13] We are aware that measures of educational attainment of the adult population (such as the average years of primary/secondary/tertiary schooling in the labor force or the percentage of the population over 25 years with a bachelor's/master's/doctoral degree) are better measures of the education of the working population than school enrollment rates. However, the availability of data for these measures is limited (in the sense that data on the average years of schooling of the labor force from the Barro-Lee dataset are available only at 5-year intervals and that data on the percentage of the population over 25 years with a bachelor's/master's/doctoral degree from the World Development Indicators are available only sporadically), and when we include measures of educational attainment of the adult population, the sample size for middle-income countries (low-income countries) reduces dramatically to fewer than 100 (20) observations. Therefore, following Krammer (2010), we use the tertiary school enrolment rate in our analysis.

middle-income countries and import-weighted R&D expenditures of low-income countries for middle- and low-income countries.

3.2. Data sources, sample composition, and descriptive statistics

The data used to calculate TFP come from two sources: The first data source, from which Real GDP (at constant 2011 national prices in millions of US dollars), GDP^d_{it} ($\hat{=} Y_{it}$), the physical capital stock (at constant 2011 national prices in millions of US dollars), K_{it}, the number of employed persons, L_{it}, human capital per worker, h_{it}, and the labor share (the share of labor compensation in GDP), α_{it}, are drawn, is the Penn World Table (PWT) version 9.1 (available at https://www.rug.nl/ggdc/productivity/pwt/pwt-releases/pwt9.1?lang=en). Human capital (per worker) is measured as $h_{it}=e^{\theta(S_{it})}$, where S_{it} is the average years of schooling in country i at time t, the derivative $\theta'(S_{it})$ is the return to schooling estimated in a Mincerian wage regression, and θ is a piecewise linear function, with a zero intercept and a slope of 0.134 through the fourth year of education, 0.101 for the next four years, and 0.068 for education beyond the eighth year. The coefficient on the first four years is the return to schooling in sub-Saharan Africa (13.4%); the coefficient on the second four years is the world average return to schooling (10.1%); and the coefficient on schooling above eight years is the OECD return to schooling (6.8%). These coefficients are from Psacharopoulos (1994).

The second data source is the World Development Indicators (WDI) (available at https://databank.worldbank.org/source/-world-development-indicators), from which agricultural land, T_{it}, and the share of agricultural value added in GDP, s_{it}, are drawn. Because the land data end in 2016, our sample period (s) ends in this year.

As our measure of the ratio of R&D expenditures to GDP, R^d_{it}/GDP^d_{it} (R^d_{jt}/GDP^d_{jt}), we use gross expenditures on R&D as a percentage of GDP from the UNESCO Institute for Statistics database (available at http://data.uis.unesco.org/Index.aspx?DataSetCode=SCN_DS) and the OECD Main Science and Technology Indicators (MSTI) database (available at https://stats.oecd.org/Index.aspx?DataSetCode=MSTI_PUB#). To construct real R&D expenditures (at constant 2011 national prices in millions of US dollars), R^d_{it} (R^d_{jt}), we multiply the R^d_{it}/GDP^d_{it} (R^d_{jt}/GDP^d_{jt}) ratio by real GDP from the PWT.[14] Given that the earliest year for which data are available for developing countries (from the MSTI database) is 1990, our analysis in Section 4.1 is based on data between 1990 and 2016. We include all middle- and low-income countries with available data, resulting in an unbalanced panel with (a maximum of) 82 countries.

The (nominal) bilateral trade data used to construct our import-weighted foreign R&D variables are taken from the UNCTADstat database (available at https://unctadstat.unctad.org/wds). Given that these data start in 1995, the analysis in Section 4.2 covers the period 1995–2016.

Two things should be noted here. First, 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) instead of from the country of destination. Second, for some [developing] (developed) countries, [complete data on bilateral trade flows between these countries and all their 15 major developed country trading partners] (complete data on R&D) are not available over the period 1995–2016. 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.

To construct the share of total imports of goods and services (machinery and equipment imports) from the 15 industrial countries with the highest R&D expenditures in GDP in each developing country, mi^T_{it} (mi^M_{it}), as well as the ratio of total imports of goods and services (machinery and equipment imports) imports from industrial country j to the GDP of industrial country j, IM^T_{ijt}/GDP^d_{jt} (IM^M_{ijt}/GDP^d_{jt}), we use nominal GDP data from the WDI. The real GDP data are from the PWT, as noted above.

The data on the tertiary school enrolment rate, $tertiary_{it}$, are again from the WDI. The UNCTADstat database is also the source of the data on the stock of FDI as a percentage of GDP, FDI_{it}. Finally, the data on the rule of law measure, $RuleOfLaw_{it}$, are from the Worldwide Governance Indicators (available at https://info.worldbank.org/governance/wgi/) (and are measured on a −2.5 – +2.5 scale).

Table A1 in the online appendix lists the countries in our sample, including their classification. We classify a country as a middle-income country (low-income country) if it is officially listed as a middle-income country (low-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 1995 and 2016; this is the sample period used in Section 4.2, where we also split our sample of 82 developing countries into 49 middle- and 33 low-income countries.

In addition to the countries, Table A1 also shows the means of $\Delta\log TFP_t$, (R^d_t/GDP^d_t), TFP_t, and R^d_t for each country. Because the number of observations per country varies from 1 (for Angola, Cote d'Ivoire, Nigeria, and Rwanda) to 27 (for Turkey),[15] these means (with one exception) do not represent averages over the entire period 1990–2016. Nevertheless it is informative to note that the mean of TFP growth is lowest for Angola and Nigeria, and highest for Mongolia and Ecuador. Angola has the lowest mean of R&D intensity, followed by Honduras, while the average percentage ratio of R&D expenditures to GDP is highest in China and the Czech Republic. Croatia is the country with the highest average productivity, followed by Poland, while Zambia and Ghana rank at the bottom of the productivity scale. Finally, average R&D expenditures are highest in India and China, and lowest in Lesotho and Gambia.

In Fig. 1a, we plot the mean of $\Delta\log TFP_t$ (for country i) versus the log of the mean of (R^d_t/GDP^d_t) (for country i); and in Fig. 1b, we plot the log of the mean of TFP_t versus the log of the mean of R^d_t. Fig. 1a and Fig. 1b also show the regression lines and their equations. The slope of the regression line in Fig. 1a is very small (-0.0003) and statistically insignificant. Overall, the plot shows no systematic relationship between the log of the average ratio of R&D expenditures to GDP and the average growth rate of TFP. In contrast, the scatter plot in Fig. 1b reveals a significant positive relationship between the log of the mean of R&D expenditures

[14] Unfortunately, price deflators for R&D expenditures are not available for most countries, particularly developing countries, due to the lack of data on the prices of R&D labor and equipment. Therefore, to construct real R&D expenditures, we multiply the ratio of nominal R&D expenditures to nominal GDP by real GDP and thus implicitly use the GDP deflator to deflate nominal R&D expenditures, as is common practice. Admittedly, to the extent that the price of R&D changes relative to the price of GDP, changes in GDP deflator-based real R&D expenditures may in part reflect measurement error rather than real changes in R&D activity, and our measure of the R&D share in GDP may be subject to measurement error as well. If, however, there is serious measurement error in $\log R^d_{it}$ and hence in $\log(R^d_{it}/GDP^d_{it})$, then we would expect to find conclusive evidence neither for semi-endogenous growth models nor for Schumpeterian growth models.

[15] We retain all countries in our fixed effects models (estimated in Section 4), including those with a single observation because even though countries with only one observation will not contribute any information to the slope coefficients, they affect the estimated standard errors.

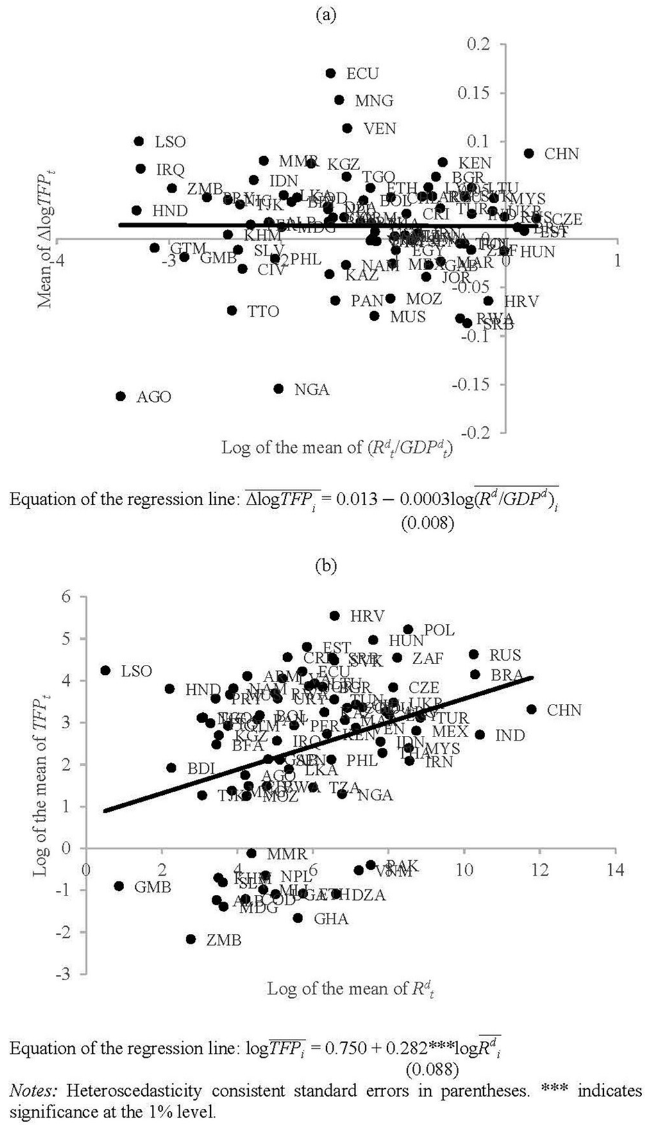

Fig. 1. Scatter plots of (a) the mean of $\Delta\log TFP_t$, $\overline{\Delta\log TFP_i}$, versus the log of the mean of (R^d_t/GDP^d_t), $\log\overline{(R^d/GDP^d)}_i$, and (b) the log of the mean of TFP_t, $\log\overline{TFP_i}$, versus the log of the mean of R^d_t, $\log\overline{R^d_i}$.

and the log of the mean of TFP. Thus, the scatter plots provide no support for Schumpeterian growth models but support for semi-endogenous growth models.

Fig. 2 plots the cross-country averages of $\Delta\log TFP_{it}$, $\log(R^d_{it}/GDP^d_{it})$, $\log TFP_{it}$, and $\log R^d_{it}$ for the subsample of 32 countries with at least 15 time series observations over periods for which complete data are available for all countries in the subsample. The average growth rate of TFP appears to fluctuate around a constant mean, whereas the average log of R&D intensity has an upward trend; this contradicts the implication of Schumpeterian growth models that TFP growth and R&D intensity data should exhibit similar time series behavior. In contrast, the data on both average TFP and average R&D expenditures show a positive trend, as semi-endogenous growth theory predicts.

Of course, these graphs are only suggestive. In the next section, we use more advanced econometric techniques to examine the relationships between R&D intensity and the growth rate of TFP, and between R&D expenditures and the level of TFP, and to compare the effects of domestic versus foreign R&D (for middle- and low-income countries).

4. Econometric results

4.1. Tests of Schumpeterian and semi-endogenous growth models

4.1.1. Panel unit root, cointegration, and weak exogeneity tests

We investigate the time series properties of $\log(TFP_{it})$, $\log R^d_{it}$, and $\log(R^d_{it}/GDP^d_{it})$ using a so-called second generation panel unit root test: the cross-sectionally augmented panel unit root test (CIPS) of Pesaran (2007). So-called first-generation panel unit root tests, which assume error cross sectional independence, can lead to spurious results if a significant degree of residual cross-sectional dependence exists. In fact, the p-values of Pesaran's (2015) test for strong cross-sectional dependence, reported in Table 1, indicate that both the levels and first differences of the series are strongly cross-sectionally dependent due to the presence of common factors.[16] The CIPS test, which is based on averaging individual ADF unit root statistics, is designed to filter out the strong cross-sectional dependence in the residuals by augmenting the individual ADF regressions with the cross-sectional averages of lagged levels and first differences of the individual series (as proxies for the unobserved common factors). In addition, as demonstrated by Baltagi et al. (2007) using Monte Carlo analysis, the CIPS test performs well in both the presence of spatial dependence and the absence of cross-sectional dependence.

Table 1 shows the results of the CIPS tests for the levels and first differences of the three series, based on our subsample of 32 countries with complete observations over 15 years between 1990 and 2016. The null hypothesis of a unit root cannot be rejected for all series in levels but can be rejected for all in their first differences. Thus, we have stationarity in first differences, and each of the three variables can be regarded as $I(1)$. This evidence that $\Delta\log TFP_{it}$ is $I(0)$ and $\log(R^d_{it}/GDP^d_{it})$ is $I(1)$ contradicts Schumpeterian growth theory.[17]

Table 2 presents the results of several first- and second-generation tests for panel cointegration between $\log R^d_{it}$ and $\log GDP^d_{it}$ and between $\log TFP_{it}$ and $\log R^d_{it}$. For the (first-generation) tests that assume error cross-sectional independence, such as the Pedroni (1999) tests, we report results based on demeaned data to control for strong error cross-sectional dependence.[18] For the (second-generation) tests that explicitly account

[16] Cross-sectional dependence may be due to common factors that affect all countries in the panel (but not necessarily with the same magnitude) and/or spatial spillover effects across subsets of countries. 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.

[17] Strictly speaking, of course, the stochastic process for R&D intensity cannot be a pure unit root process, at least when the sample size approaches infinity. The reason is that the ratio of R&D expenditures to GDP is bounded in the long run (with lower and upper limits), but we know that a unit root process will cross any finite bound with probability one. Nevertheless, as argued by Jones (1995b), it may be the case that in the relevant range such variables are well characterized by a unit root process. Specifically, if the determining factors of the ratio of R&D expenditures to GDP change over time, we may observe R&D intensity series with permanent movements that can be well approximated by a unit root process, at least in small samples. However, although panel unit root tests have higher power to distinguish between unit root and near-unit root processes than single time series unit root tests, panel unit root tests may still fail to reject the null hypothesis of a unit root when the true root is close to unity. It therefore cannot be completely ruled out that the ratio of R&D expenditures to GDP can be better approximated by a near-unit root process during the sample period than by a pure unit root process. But even if $\log(R^d_{it}/GDP^d_{it})$ is near-$I(1)$, and $\Delta\log TFP_{it}$ is $I(0)$, Schumpeterian growth theory does not hold.

[18] The use of demeaned data is equivalent to using the residuals from regressions of each variable on time dummies and serves to account for potential strong cross-sectional dependence.

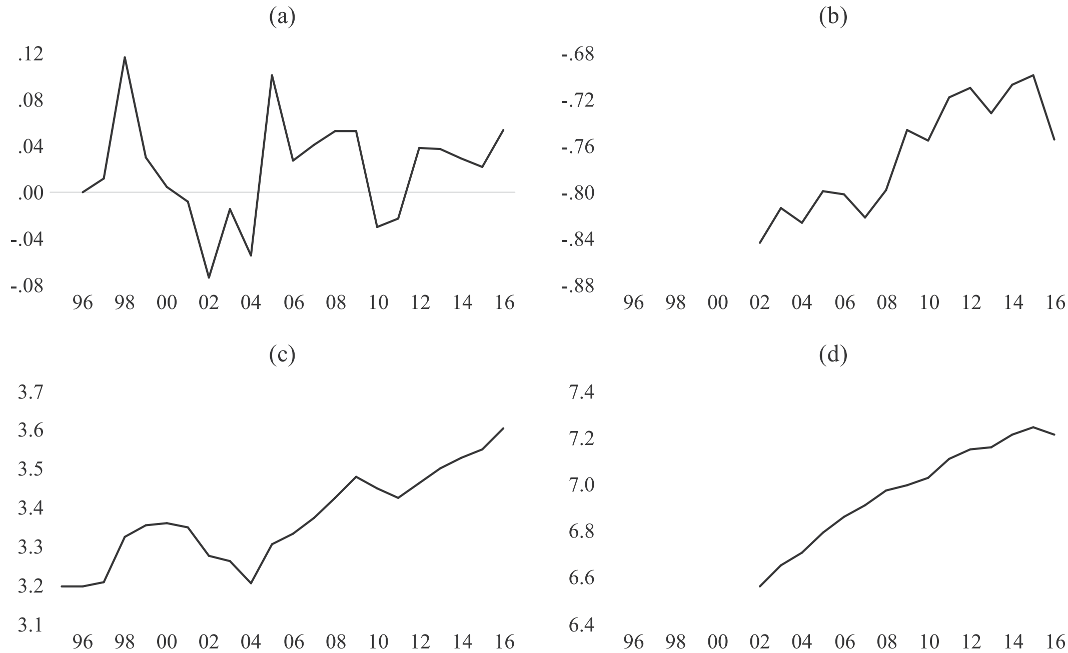

Fig. 2. Cross-country averages of (a) $\Delta\log TFP_{it}$, (b) $\log(R^d_{it}/GDP^d_{it})$, (c) $\log TFP_{it}$, and (d) $\log R^d_{it}$.

Table 1
Cross-sectional dependence and panel unit root tests for $\log TFP_{it}$, $\log R^d_{it}$, and $\log(R^d_{it}/GDP^d_{it})$.

	CD		Pesaran's (2007) CIPS panel unit root test	
	Levels	First differences	Levels	First differences
$\log TFP_{it}$	0.000***	0.000***	0.169	0.000***
$\log R^d_{it}$	0.000***	0.000***	0.169	0.000***
$\log(R^d_{it}/GDP^d_{it})$	0.000***	0.000***	0.474	0.018**

Notes: Reported values are *p*-values. CD is the cross-sectional dependence test of Pesaran (2015) (adjusted for unbalanced panel data); this test tests the (implicit) null hypothesis of weak cross-sectional dependence against the alternative hypothesis of strong cross-sectional dependence. Two lags were used in the Pesaran (2007) tests. All unit root tests include country-specific intercepts. *** (**) indicates significance at the 1% (5%) level.

Table 2
Panel cointegration tests.

	Tests for cointegration between $\log R^d_{it}$ and $\log GDP^d_{it}$ (Tests of Schumpeterian models)		Tests for cointegration between $\log TFP_{it}$ and $\log R^d_{it}$ (Tests of semi-endogenous models)	
Pedroni (1999)	Panel statistics	Group mean statistics	Panel statistics	Group mean statistics
Variance ratio statistic	0.193		2.954***	
PP *rho*-statistics	−1.443*	−1.025	−3.371***	−2.124**
PP *t*-statistics	−1.356*	−1.480*	−2.544***	−3.623***
ADF *t*-statistics	0.792	1.367	−1.180	−1.584*
Westerlund (2007)	Panel statistics	Group mean statistics	Panel statistics	Group mean statistics
τ-statistics (*z*-values) [Bootstrap *p*-values]	0.202	−1.251	−2.381	−2.332
	[0.478]	[0.068]*	[0.048]***	[0.008]***
α-statistics (*z*-values) [Bootstrap *p*-values]	−0.099	0.412	−1.443	−0.122
	[0.326]	[0.046]**	[0.066]*	[0.010]***
Gengenbach et al. (2016)				
ECM *t*-statistic	−2.424		−2.982***	

Notes: The dependent variable in the Pedroni (1999) tests for cointegration between $\log R^d_{it}$ and $\log GDP^d_{it}$ ($\log TFP_{it}$ and $\log R^d_{it}$) is $\log R^d_{it}$ ($\log TFP_{it}$); the dependent variable in the tests of Westerlund (2007) and Gengenbach et al. (2016) for cointegration between $\log R^d_{it}$ and $\log GDP^d_{it}$ ($\log TFP_{it}$ and $\log R^d_{it}$) is $\Delta\log R^d_{it}$ ($\Delta\log TFP_{it}$). Two lags were used in the Pedroni (1999) (PP and ADF) tests. Given the limited number of time series observations available (for some countries) here, no lags of the first differences were included in the Westerlund (2007) and Gengenbach et al. (2016) tests. The Pedroni (1999) test statistics are distributed as standard normal; the Westerlund (2007) statistics are distributed as standard normal in the case of no error cross-sectional dependence. The variance ratio test has a one-sided rejection region consisting of large positive values, whereas all other tests reject for large negative values. The critical value at the 1% [10%] significance level for the Gengenbach et al. (2016) *t*-test for $N = 30$ (and one regressor) is −2.735 [-2.530]. The results of the Pedroni (1999) tests are based on demeaned data to account for potential error cross-sectional dependence due to unobserved common factors. To account for error cross-sectional dependence in the Westerlund (2007) tests, we used the bootstrap approach of Westerlund (2007). Bootstrap *p*-values (based on 500 replications) are in brackets. The Gengenbach et al. (2016) test accounts for error cross-sectional dependence via the use of cross-sectional averages. *** (**) [*] indicates significance at the 1% (5%) [10%] level.

Table 3
Tests of weak exogeneity of $\log R\&D^d_{it}$.

Westerlund (2007)		Panel statistics	Group mean statistics
	τ-statistics (z-values)	2.818	2.424
	[Bootstrap p-values]	[0.914]	[0.900]
	α-statistics (z-values)	2.424	3.773
	[Bootstrap p-values]	[0.992]	[0.984]
Gengenbach et al. (2016)			
	ECM t-statistic	−2.099	

Notes: The dependent variable is $\Delta\log R^d_{it}$. Given the limited number of time series observations available (for some countries) here, no lags of the first differences were included in the tests. The Westerlund (2007) test statistics are distributed as standard normal in the case of no error cross-sectional dependence. Both tests reject for large negative values. The critical value at the 10% significance level for the Gengenbach et al. (2016) t-test for $N = 30$ is −2.530. To account for error cross-sectional dependence in the Westerlund (2007) tests, we used the bootstrap approach of Westerlund (2007). Bootstrap p-values (based on 500 replications) are in brackets. The Gengenbach et al. (2016) test accounts for error cross-sectional dependence via the use of cross-sectional averages.

for strong cross-sectional dependence (via the use of bootstrap p-values or weighted cross-sectional averages), such as the Westerlund (2007) and Gengenbach et al. (2016) tests, we report results based on the original data.

Of the twelve tests, only five reject the null hypothesis of no cointegration between $\log R^d_{it}$ and $\log GDP^d_{it}$ at the 10% level or better. In contrast, with one exception, all tests indicate cointegration between $\log TFP_{it}$ and $\log R^d_{it}$ at least at the 10% level. Thus, the cointegration tests provide weak evidence for Schumpeterian growth, and strong evidence for semi-endogenous growth.

Error-correction-based cointegration tests, such as the Westerlund (2007) and Gengenbach et al. (2016) tests, incorporate in the alternative hypothesis the assumption of weak exogeneity of the regressors included in the cointegrating equation. Rejection of the no cointegration null using an error-correction model (ECM) with $\Delta\log TFP_{it}$ as the dependent variable can therefore be interpreted as rejection of weak exogeneity of TFP. Thus, the results in the last two columns of Table 2 imply that the Westerlund (2007) and Gengenbach et al. (2016) tests reject the null hypothesis of weak exogeneity of $\log TFP_{it}$. To test whether $\log R^d_{it}$ is weakly exogenous, we perform the Westerlund (2007) and Gengenbach et al. (2016) tests using an ECM with $\Delta\log R^d_{it}$ as the dependent variable. The results are reported in Table 3. All tests are unable to reject the weak exogeneity hypothesis for $\log R^d_{it}$.

Weak exogeneity implies long-run Granger non-causality (e.g. Hall & Milne, 1994). Thus, the evidence that $\log R^d_{it}$ is weakly exogenous and $\log TFP_{it}$ is not weakly exogenous means that $\log R^d_{it}$ has a long-run (causal) effect on $\log TFP_{it}$ (if significant), while $\log TFP_{it}$ has no long-run effect on $\log R^d_{it}$.

4.1.2. Regression results on the productivity effect of domestic R&D

We first use our 32-country, 1990–2016 sample to estimate the relationships between (i) $\log GDP^d_{it}$ and $\log R^d_{it}$, (ii) $\log(R^d_{it}/GDP^d_{it})$ and $\Delta\log TFP_{it}$, and (iii) $\log R^d_{it}$ and $\log TFP_{it}$. Given that the countries in this subsample have continuous data of up to 27 years, we able to use methods that require continuous time series of sufficient length. Specifically, we employ the pooled DOLS (PDOLS) of estimator of Kao and Chiang (2001), which has been shown to perform well in samples like the one used here and which allows for endogenous regressors (e.g. Kao & Chiang, 2001; Wagner & Hlouskova, 2009). In Section A2 of the online appendix, we also present results using alternative estimation techniques (as a robustness check).

The PDOLS estimator (which is a first-generation estimator) is based on the assumption of error cross-sectional independence. We include time dummies in the PDOLS regressions to account for strong error cross-sectional dependence. To account for weak cross-sectional dependence in the residuals of the PDOLS 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 (HACSC).

Table 4 presents the results. In column 1, the coefficient on $\log GDP^d_{it}$ is positive, statistically significant, and greater than one. In column 1, we also report the p-values of a Wald test of the restriction that the coefficient on $\log GDP^d_{it}$ equals one. This restriction is rejected, implying that (even if $\log R^d_{it}$ and $\log GDP^d_{it}$ are cointegrated) the results in column 1 fail to support the predictions of Schumpeterian growth theory.

The results in column 2 are based on the implicit assumption that $\log(R^d_{it}/GDP^d_{it})$ and $\Delta\log TFP_{it}$ are $I(1)$ and cointegrated. However, the coefficient on $\log(R^d_{it}/GDP^d_{it})$ is insignificant, implying that even if these variables are $I(1)$ (which is not supported by results of our unit root tests), the potential cointegrating relationship between these variables is not significant. Hence, the regression results in column 2 do not support Schumpeterian theory either.

In contrast, the regression results in column 3 show a significant positive relationship between $\log R^d_{it}$ and $\log TFP_{it}$, and thus are consistent with semi-endogenous growth theory. In combination with the results of our tests for weak exogeneity, these results imply that domestic R&D expenditures have a long-run causal impact on TFP.

We next use both the remaining subsample of 50 countries with less than 15 time series observations and the full sample of 82 countries to estimate (i) the effect of $\log(R^d_{it}/GDP^d_{it})$ on $\Delta\log TFP_{it}$ and (ii) the effect of $\log R^d_{it}$ on $\log TFP_{it}$. Table 5 presents the results of fixed effects models with year dummies and HACSC robust standard errors.[19] The results again provide evidence for semi-endogenous growth models, and fail to provide evidence for Schumpeterian growth models. R&D intensity is not significant in the 50-country subsample (see column 1). It is significant in the full sample (column 3) but loses its significance when the growth rate of R&D expenditures is added to the regression (column 4). The growth rate of R&D expenditures, in contrast, is significant in this regression. Similarly, the coefficient on the current level of R&D expenditures is positive and statistically significant in all TFP level regressions (columns 2, 5, and 6).

While many studies reject semi-endogenous in favor of Schumpeterian growth models for developed countries (e.g. Ha & Howitt, 2007; Madsen, 2008), other (albeit fewer) studies for developed countries provide evidence in favor of semi-endogenous growth models and against Schumpeterian growth models (e.g. Venturini, 2012; Bloom et al., 2020). Thus, the above evidence of the validity of semi-endogenous growth models in developing countries is consistent with the findings of several studies for developed countries (including those that do not test the validity

[19] We use year dummies and HACSC robust standard errors in all regressions that follow.

Table 4
PDOLS results for the subsample of 32 countries with at least 15 time series observations over the period 1990–2016.

	(1) Dep. var.: $\log R^d_{it}$ (Schumpeterian theory)	(2) Dep. var.: $\Delta\log TFP_{it}$ (Schumpeterian theory)	(3) Dep. var.: $\log TFP_{it}$ (Semi-endogenous theory)
$\log GDP^d_{it}$	1.300***		
	(0.093)		
$\log(R^d_{it}/GDP^d_{it})$		0.034	
		(0.025)	
$\log R^d_{it}$			0.312***
			(0.034)
WALD (p-value)	0.081*		
No. of obs.	659	595	599

Notes: The regressions were estimated with one lead and one lag of the first-differenced regressors. All regressions include country and time fixed effects. WALD is a Wald test that the coefficient on $\log GDP^d_{it}$ equals one. Numbers in parentheses are Driscoll and Kraay (1998) heteroskedasticity autocorrelation spatial correlation robust standard errors. *** (*) indicates significance at the 1% (10%) level.

of Schumpeterian growth models (e.g. Abdih and Joutz, 2006; Bottazzi and Peri, 2007)). In addition, TFP growth has declined or remained relatively stable in developed countries in recent decades (e.g. Fernald & Inklaar, 2020), whereas R&D intensity has tended to increase in recent decades in developed countries (e.g. Jones, 2016), an observations which is also evident for developing countries (see Fig. 2) and which is inconsistent with the prediction of Schumpeterian growth models that R&D intensity drives TFP growth.[20] In this sense, the explanation for why we do not find evidence of an effect of R&D intensity on the growth rate of TFP is that the β = 1 and ϕ = 1 assumptions in Schumpeterian models do not hold. In contrast, we find that the level (growth rate) of TFP in developing countries depends on the level (growth rate) of R&D expenditures, as semi-endogenous growth models predict.

To address possible concerns about endogeneity and reverse causality in the relationship between R&D expenditures and TFP, we report the results of the Wooldridge (2010) test for strict exogeneity in column 6 of Table 5. This test involves adding leads and lags of $\log R^d_{it}$ to the regression of the relationship between $\log R^d_{it}$ and $\log TFP_{it}$. In this specification, only the coefficients on contemporaneous and lagged R&D expenditures should be significant, whereas $\log R^d_{it+1}$ should be insignificant. If the latter is not the case, there is evidence that R&D expenditures are endogenous. Thus, the results in column 6 indicate that R&D expenditures can be considered as strictly exogenous.

Finally, we note that the estimated coefficients on $\log R^d_{it}$ in columns 2 and 5 are smaller than that in column 3 Table 4. The most plausible explanation for the difference is that the sample in Table 4 includes relatively more middle-income and relatively fewer low-income countries than the samples in Table 5.[21] If domestic R&D has a greater effect on TFP in middle-income nations, it is obvious that the estimated effect sizes are larger in samples with relatively more middle-income countries than in samples with relatively few middle-income countries. We address this issue in the next section, where we examine the effects of domestic and foreign R&D on domestic TFP for developing countries both as a whole (Subsection 4.2.1) and subdivided into middle- and low-income countries (Subsection 4.2.1).

4.2. Domestic R&D and foreign R&D spillovers

4.2.1. Results for developing countries as a whole

In this section, we first estimate versions of Eq. (12) to examine the empirical relevance of Schumpeterian theory in explaining R&D spillovers from industrial to developing countries. Table 6 reports the results of fixed effects regression using the R&D spillover variables defined by Eqs. (15.1)–(15.7). In all these regressions, we include both domestic R&D intensity and the growth rate of domestic R&D expenditures. Only the latter is significant, implying no evidence of R&D spillovers from industrial to developing countries based on Schumpeterian TFP growth specifications. We therefore proceed to examine the effects of domestic and foreign R&D on domestic TFP from the perspective of semi-endogenous growth theory.

Tests for unit roots and cointegration, which are reported in Section A4 of the online appendix, suggest that $mi^T_{it} \times \log R^{f\_T\_CH}_{it}$, $mi^M_{it} \times \log R^{f\_M\_CH}_{it}$, and $\log R^f_t$ are non-stationary and that cointegration exists among the variables in Eq. (13). We now estimate Eq. (13) using $mi^T_{it} \times \log R^{f\_T\_CH}_{it}$, $mi^M_{it} \times \log R^{f\_M\_CH}_{it}$, and $\log R^f_t$ as our measures of foreign R&D spillovers.

Table 7 presents the results. In columns 1–3, we report PDOLS estimates based on the sample of countries with at least 15 observations. In columns 4–6, we report fixed effects estimates for the full sample. Finally, columns 7–10 present fixed effects results based on the full sample using our alternative measures of international R&D spillovers. The coefficient on $\log R^d_{it}$ is positive and significant in all regressions, and the estimates imply an elasticity of TFP with respect domestic R&D expenditures of 0.243–0.310 (quantitatively consistent with the fixed effects results in Table 5 and the PDOLS estimate in column 3 of Table 4. Similarly, the coefficients on $mi^M_{it} \times \log R^{f\_M\_CH}_{it}$ and $\log R^f_t$ are positive and significant in both samples. This provides evidence of international R&D spillovers through imports of machinery and equipment and also suggests the presence of disembodied foreign knowledge spillovers. However, as we show later (in Tables 8 and 9), when the control variables are included in the equation, $\log R^f_t$ is no longer significant. Similarly, the coefficient on $mi^T_{it} \times \log R^{f\_T\_CH}_{it}$ is insignificant in the full sample, suggesting that many imported goods and services are not a channel for R&D spillovers.

[20] It might be objected that our failure to find evidence of significant positive effects of R&D intensity on TFP growth in developing countries may be due to the use of the ratio of R&D expenditures to GDP as our measure of research intensity and that other measures might produce significant results. To address this objection, we also used four other measures of R&D intensity, but again found insignificant results (which are reported in Section A3 of the online appendix).

[21] About 16 (56) [40] percent in the sample in Table 4 (in column 2 of Table 5) [in column 5 of Table 5] are low-income countries.

Table 5
Fixed effects estimates of (*i*) the impact of R&D intensity on TFP growth and (*ii*) the impact of domestic R&D expenditures on TFP.

	Subsample of countries with less than 15 time series observations		Full sample			
	(1)	(2)	(3)	(4)	(5)	(6)
	(*i*)	(*ii*)	(*i*)	(*i*)	(*ii*)	(*ii*)
	Dep. var.: $\Delta \log TFP_{it}$	Dep. var.: $\log TFP_{it}$	Dep. var.: $\Delta \log TFP_{it}$	Dep. var.: $\Delta \log TFP_{it}$	Dep. var.: $\log TFP_{it}$	Dep. var.: $\log TFP_{it}$
$\log(R_{it}^d/GDP_{it}^d)$	0.008		0.027**	0.011		
	(0.010)		(0.010)	(0.012)		
$\Delta \log R_{it}^d$				0.078**		
				(0.029)		
$\log R_{it+1}^d$						−0.075
						(0.090)
$\log R_{it}^d$		0.257***			0.255***	0.185**
		(0.081)			(0.041)	(0.075)
$\log R_{it-1}^d$						0.179**
						(0.073)
No. of obs.	308	311	989	989	998	801
No. of countries	50	50	82	82	82	61
Within R^2	0.066	0.343	0.045	0.065	0.198	0.194

Notes: All regressions include country and time fixed effects. Numbers in parentheses are Driscoll and Kraay (1998) heteroskedasticity autocorrelation spatial correlation robust standard errors. *** (**) indicates significance at the 1% (5%) level.

Table 6
Fixed effects regression results of the effects of domestic and foreign ratios of R&D to GDP on TFP growth: tests of Schumpeterian models.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\log(R_{it}^d/GDP_{it}^d)$	0.014	0.010	0.013	0.013	0.010	0.007	0.011
	(0.014)	(0.013)	(0.013)	(0.013)	(0.015)	(0.014)	(0.013)
$\Delta \log R_{it}^d$	0.068**	0.065**	0.068**	0.063**	0.068**	0.067**	0.074**
	(0.029)	(0.028)	(0.028)	(0.029)	(0.029)	(0.028)	(0.030)
$mi_{it}^T \times \log(R_{it}/GDP_{it})^{f\_T\_CH}$	−0.003						
	(0.085)						
$mi_{it}^M \times \log(R_{it}/GDP_{it})^{f\_M\_CH}$		0.151					
		(0.107)					
$\log(R_{it}/GDP_{it})^{f\_T\_CH}$			−0.008				
			(0.199)				
$\log(R_{it}/GDP_{it})^{f\_M\_CH}$				0.069			
				(0.159)			
$mi_{it}^T \times \log(R_{it}/GDP_{it})^{f\_T\_LP}$					−0.016		
					(0.032)		
$mi_{it}^M \times \log(R_{it}/GDP_{it})^{f\_M\_LP}$						−0.046	
						(0.029)	
$\log(R_t/GDP_t)^f$							0.003
							(0.005)
No. of obs.	802	790	801	790	797	790	811
No. of countries	66	64	66	64	66	64	66
Within R^2	0.059	0.062	0.061	0.062	0.061	0.063	0.062

Notes: The dependent variable is $\Delta \log TFP_{it}$. All regressions include country and time fixed effects. Numbers in parentheses are Driscoll and Kraay (1998) heteroskedasticity autocorrelation spatial correlation robust standard errors. ** indicates significance at the 5% level.

To compare the TFP effects of foreign versus domestic R&D, we also present in Table 7 the elasticities of TFP with respect to $mi_{it}^T \times \log R_{it}^{f\_T\_CH}$, $mi_{it}^M \times \log R_{it}^{f\_M\_CH}$ and $\log R_t^f$ (and $\log R_{it}^{f\_T\_CH}$, $\log R_{it}^{f\_M\_CH}$, $mi_{it}^T \times \log R_{it}^{f\_T\_LP}$, and $mi_{it}^M \times \log R_{it}^{f\_M\_LP}$).[22] The estimated elasticities of TFP with respect to foreign R&D range between 0.007 (−0.215) and 0.061 and are thus much smaller than the estimated elasticities of TFP with respect to domestic R&D.

It should perhaps be mentioned here that the foreign R&D elasticity in column 5 is smaller than its counterpart in column 2, which can again be explained by the relatively large number of middle-income in the sample in column 2. If capital goods import-weighted foreign R&D has a greater effect on TFP in middle-income countries, then the estimated foreign R&D elasticity will be greater in samples with relatively more middle-income countries. We address this issue in the next subsection (where we present estimates of the effects of domestic and foreign R&D on domestic TFP for middle- and low-income countries separately).

In columns 7 and 8, we estimate Eq. (13) using $\log R_{it}^{f\_T\_CH}$ and $\log R_{it}^{f\_M\_CH}$, respectively, in place of $mi^T \times \log R\&D_{it}^{f\_T\_CH}$ and $mi^M \times \log R\&D_{it}^{f\_M\_CH}$. The coefficients of these variables are not significant, implying (together with the results in columns 2 and 5) that capital goods import-weighted foreign R&D expenditures affect developing countries' TFP only through their interaction with the capital goods import share in GDP.

Columns 9 and 10 report results when import-share interacted R&D expenditures are used based on the weighting scheme of Pottelsberghe de la Potterie (1998), with weights again based on both total imports and machinery and equipment imports. The coeffi-

[22] The foreign R&D elasticities were calculated in columns 1 and 4 [columns 2 and 5] {columns 7 and 8} by multiplying the estimated coefficients on $mi_{it}^T \times \log R_{it}^{f\_T\_CH}$ [$mi_{it}^M \times \log R_{it}^{f\_M\_CH}$] {$mi_{it}^T \log R_{it}^{f\_T\_LP}$ and [$mi_{it}^M \times \log R_{it}^{f\_M\_LP}$]} by the sample mean of mi_{it}^T [mi_{it}^M]. The elasticity of TFP with respect to foreign R&D in columns 3 and 6 [9 and 10] is the estimated coefficient on $\log R_t^f$ [$\log R_{it}^{f\_T\_CH}$ and $\log R_{it}^{f\_M\_CH}$].

Table 7
Regression results of the effects of domestic and foreign R&D on TFP.

	PDOLS (1)	PDOLS (2)	PDOLS (3)	FE (4)	FE (5)	FE (6)	FE (7)	FE (8)	FE (9)	FE (10)
$\log R_{it}^{d}$	0.280***	0.251***	0.310***	0.243***	0.243***	0.255***	0.244***	0.255***	0.247***	0.245***
	(0.043)	(0.040)	(0.042)	(0.038)	(0.037)	(0.042)	(0.039)	(0.039)	(0.038)	(0.037)
$mi_{it}^{T} \times \log R_{it}^{f\_T\_CH}$	0.081***			0.047						
	(0.027)			(0.029)						
$mi_{it}^{M} \times \log R_{it}^{f\_M\_CH}$		0.159***			0.100***					
		(0.022)			(0.022)					
$\log R_{t}^{f}$			0.061***			0.054***				
			(0.013)			(0.010)				
$\log R_{it}^{f\_T\_CH}$							−0.215			
							(0.199			
$\log R_{it}^{f\_M\_CH}$								0.052		
								(0.130		
$mi_{it}^{T} \times \log R_{it}^{f\_T\_LP}$									0.058	
									(0.038)	
$mi_{it}^{M} \times \log R_{it}^{f\_M\_LP}$										0.134***
										(0.033)
Foreign R&D elasticity	0.014	0.013	0.061	0.007	0.007	0.054	−0.215	0.052	0.009	0.009
No. of obs.	591	590	601	960	942	976	958	942	954	942
No. of countries	32	32	32	82	81	82	82	81	82	81
Within R^2	0.209	0.251	0.188	0.205	0.223	0.189	0.196	0.191	0.202	0.220

Notes: The dependent variable is $\log TFP_{it}$. PDOLS = panel DOLS of estimator of Kao and Chiang (2001); FE = fixed effects estimator. All regressions include country and time fixed effects. The DOLS regressions were estimated using one lead and one lag (and the current value) of the first differences of $\log R_{it}^{d}$, $mi_{it}^{T} \times \log R_{it}^{f\_T\_CH}$ and $mi_{it}^{M} \times \log R_{it}^{f\_M\_CH}$. Leads and lags of the first difference of $\log R_{t}^{f}$ were not included due to perfect collinearity with the time effects. Foreign R&D elasticity is the elasticity of TFP with respect to foreign R&D. The elasticity of TFP with respect to foreign R&D in columns 1, 2, 4, and 5 is the estimated coefficient on $mi_{it}^{T} \times \log R_{it}^{f\_T\_CH}$ ($mi_{it}^{M} \times \log R_{it}^{f\_M\_CH}$) multiplied by the sample mean of the share of imports of total goods and services (machinery and equipment imports) from industrial countries in GDP; the elasticity of TFP with respect to foreign R&D in columns 3 and 6 is the estimated coefficient on $\log R_{t}^{f}$; the elasticity of TFP with respect to foreign R&D in columns 7 and 8 is the estimated coefficient on $\log R_{it}^{f\_T\_CH}$ ($\log R_{it}^{f\_M\_CH}$); the elasticity of TFP with respect to foreign R&D in columns 9 and 10 is the estimated coefficient on $mi_{it}^{T} \times \log R_{it}^{f\_T\_LP}$ ($mi_{it}^{M} \times \log R_{it}^{f\_M\_LP}$) multiplied by the sample mean of the share of imports of total goods and services (machinery and equipment imports) from industrial countries in GDP. Numbers in parentheses are Driscoll and Kraay (1998) heteroskedasticity autocorrelation spatial correlation robust standard errors. *** (*) indicates significance at the 1% (10%) level.

Table 8
Fixed effects regression results of the effects of domestic and foreign R&D on TFP for middle-income countries.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\log R_{it}^{d}$	0.402***	0.400***	0.388***	0.402***	0.231***	0.294***	0.245***
	(0.046)	(0.042)	(0.042)	(0.046)	(0.048)	(0.051)	(0.053)
$mi_{it}^{T} \times \log R_{it}^{f\_T\_CH}$		0.056**			0.050		
		(0.026)			(0.031)		
$mi_{it}^{M} \times \log R_{it}^{f\_M\_CH}$			0.092***			0.105***	
			(0.022)			(0.034)	
$\log R_{t}^{f}$				0.032**			0.075
				(0.012)			(0.071)
$\log GDP_{it}^{d}$					0.274	0.443**	0.097
					(0.168)	(0.189)	(0.257)
$tertiary_{it}$					0.754**	0.624*	0.817**
					(0.319)	(0.343)	(0.326)
$RuleOfLaw_{it}$					0.264*	0.247	0.258*
					(0.142)	(0.149)	(0.140)
$\log FDI_{it}$					−0.224	−0.245	−0.198
					(0.166)	(0.164)	(0.174)
$\log R_{t}^{f\_low}$					−0.627	−0.941**	−0.354
					(0.415)	(0.454)	(0.538)
$\log R_{it}^{f\_middle}$					0.420	0.554*	0.231
					(0.304)	(0.318)	(0.383)
Foreign R&D elasticity		0.009	0.007	0.032	0.009	0.009	0.075
No. of obs.	753	746	744	753	496	494	496
No. of countries	49	49	49	49	46	46	46
Within R^2	0.199	0.231	0.244	0.199	0.229	0.263	0.211

Notes: The dependent variable is $\log TFP_{it}$. All regressions include country and time fixed effects. Foreign R&D elasticity is the elasticity of TFP with respect to R&D in developed countries. The elasticity of TFP with respect to foreign R&D in columns 2, 3, 5, and 6 is the estimated coefficient on $mi_{it}^{T} \times \log R_{it}^{f\_T\_CH}$ ($mi_{it}^{M} \times \log R_{it}^{f\_M\_CH}$) multiplied by the sample mean of the share of imports of total goods and services (machinery and equipment imports) from industrial countries in GDP; the elasticity of TFP with respect to foreign R&D in columns 4 and 7 is the estimated coefficient on $\log R_{t}^{f}$. Numbers in parentheses are Driscoll and Kraay (1998) heteroskedasticity autocorrelation spatial correlation robust standard errors. *** (**) indicates significance at the 1% (5%) level.

cient on $mi_{it}^{T} \times \log R_{it}^{f\_T\_LP}$ is insignificant, whereas the coefficient on $mi_{it}^{M} \times \log R_{it}^{f\_M\_LP}$ is significant, consistent with the results in columns 4 and 5.

4.2.2. Results for middle- and low-income countries.

Table 8 reports the regression results for *middle-income countries*, both without control variables and with control variables. The coefficient on $\log R_{it}^{d}$ is positive and significant in columns 1–4, and although the size of the coefficient decreases with the addi-

Table 9
Fixed effects regression results of the effects of domestic and foreign R&D on TFP for low-income countries.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log R^d_{it}$	0.099***	0.077***	0.080***	0.099***	0.112***	0.085**	0.125***	0.125***	0.125***
	(0.024)	(0.016)	(0.019)	(0.024)	(0.032)	(0.040)	(0.031)	(0.031)	(0.031)
$mi^T_{it} \times \log R^{f\_T\_CH}_{it}$		−0.005			−0.007				
		(0.041)			(0.043)				
$mi^M_{it} \times \log R^{f\_M\_CH}_{it}$			0.072			0.180			
			(0.231)			(0.133)			
$\log R^f_t$				0.018***			−0.219**	0.192	
				(0.005)			(0.090)	(0.135)	
$\log GDP^d_{it}$					−0.055	0.001	−0.288	−0.288	−0.288
					(0.255)	(0.290)	(0.288)	(0.288)	(0.288)
$tertiary_{it}$					1.637*	2.509***	2.205***	2.205***	2.205***
					(0.833)	(0.660)	(0.649)	(0.649)	(0.649)
$RuleOfLaw_{it}$					−0.143	−0.112	−0.069	−0.069	−0.069
					(0.219)	(0.204)	(0.249)	(0.249)	(0.249)
$\log FDI_{it}$					0.107**	0.079**	0.100***	0.100***	0.100***
					(0.045)	(0.038)	(0.047)	(0.047)	(0.047)
$\log R^{f\_low}_{it}$					0.00001	−0.001	−0.088	−0.088	−0.088
					(0.034)	(0.041)	(0.078)	(0.078)	(0.078)
$\log R^{f\_middle}_{t}$					0.046	−0.014	0.715***		0.328
					(0.216)	(0.240)	(0.215)		(0.262)
Foreign R&D elasticity		−0.0004	0.002	0.018	−0.0006	0.005	−0.219	0.192	
No. of obs.	223	214	198	223	157	150	162	162	162
No. of countries	33	33	32	33	29	28	29	29	29
Within R^2	0.440	0.418	0.421	0.440	0.550	0.574	0.591	0.591	0.591

Notes: The dependent variable is $\log TFP_{it}$. All regressions include country and time fixed effects. Foreign R&D elasticity is the elasticity of TFP with respect to R&D in developed countries. The elasticity of TFP with respect to foreign R&D in columns 2, 3, 5, and 6 is the estimated coefficient on $mi^T_{it} \times \log R^{f\_T\_CH}_{it}$ ($mi^M_{it} \times \log R^{f\_M\_CH}_{it}$) multiplied by the sample mean of the share of imports of total goods and services (machinery and equipment imports) from industrial countries in GDP; the elasticity of TFP with respect to foreign R&D in columns 4, 7, and 8 is the estimated coefficient on $\log R^f_t$. Numbers in parentheses are Driscoll and Kraay (1998) heteroskedasticity autocorrelation spatial correlation robust standard errors. *** (**) [10%] indicates significance at the 1% (5%) [10%] level.

tion of controls, it remains significant in columns 5–7. Similarly, the significance of the association between capital goods import-weighted foreign R&D expenditures (interacted with the capital goods import share) and TFP remains consistent in models with and without control variables for GDP, tertiary education, the rule of law, FDI, and disembodied R&D spillovers between middle- and low-income countries and between middle-income countries themselves (see columns 3 and 6). In contrast, $mi^T_{it} \times \log R^{f\_T\_CH}_{it}$ is significant when it is the only variable besides $\log R^d_{it}$ (column 2); however, it becomes insignificant when the control variables are included (column 5). The variable $\log R^f_t$ is also statistically significant in the model without control variables (column 4), but loses its significance in the multivariate model (column 7). Again, the estimated elasticities indicate that domestic R&D has a much stronger effect on domestic TFP than foreign R&D.

Turning to the control variables, the coefficient on $\log GDP^d_{it}$ is always positive although not significant in columns 5 and 7. In contrast, the coefficient for tertiary education is positive and significant (at least at the 10% level) in all specifications. While the rule of law measure has a positive and significant coefficient in two of three regressions, the coefficient on the FDI variable is always negative but insignificant. In column 6, the sign of the coefficient is negative for the sum of the R&D expenditures of low-income countries and positive for the sum of the R&D expenditures of middle-income countries, but this is likely due to collinearity between these variables and $mi^M_{it} \times \log R^{f\_M\_CH}_{it}$; both the coefficient on $\log R^{f\_low}_t$ and the coefficient on $\log R^{f\_middle}_{it}$ are not significant in columns 5 and 7.

In Table 9, we report the results for *low-income countries*. Again, domestic R&D is positive and significant in all specifications. However, the estimated coefficients on $\log R^d_{it}$ are always considerably smaller than those in Table 8, implying that the impact of domestic R&D on domestic productivity is greater in middle-income than in low-income countries. It is also interesting that in contrast to the results in Table 8 for middle-income countries, the relationship between $mi^M_{it} \times \log R^{f\_M\_CH}_{it}$ and $\log TFP_{it}$ is insignificant with and without the controls (see columns 3 and 6). Given the insignificant coefficients for $mi^M_{it} \times \log R^{f\_M\_CH}_{it}$, it is not surprising that the estimated coefficients on $mi^T_{it} \times \log R^{f\_T\_CH}_{it}$ are also insignificant in both models (see columns 2 and 5). Similar to the results in Table 8, the coefficient on $\log R^f_t$ is positive and significant without controls (see column 4). However, when the control variables are added to the regression, the coefficient becomes negative and significant (see column 7), a result that is due to collinearity between $\log R^f_t$ and $\log R^{f\_middle}_t$; in fact, the coefficient on $\log R^f_t$ becomes insignificant once we exclude $\log R^{f\_middle}_t$ from the regression (see column 8). Thus, the results in Table 9 suggest that knowledge gained from R&D in industrial countries does not significantly spillover to low-income countries.

Regarding the control variables, both tertiary education and FDI have a positive and significant coefficient, and the coefficients are robust across all specifications (in columns 5–9).[23] However, because developing countries have large FDI stocks from other developing countries (e.g. UNCTAD, 2017), it is unclear whether the positive coefficient on $\log FDI_{it}$ reflects FDI-related knowledge spillovers from developed to low-income countries or South-South spillovers. In addition, FDI may improve TFP through positive competition effects as domestic firms respond by seeking to become more productive and cost-efficient. Thus, it is also unclear whether (and to what extent) the positive relationship between FDI and TFP in low-income countries reflects knowledge spillovers or competition effects. Moreover, it may of course be that the positive coefficient on $\log FDI_{it}$ is picking up the potential effect of TFP on FDI.

[23] We also experimented with FDI inflows (as a percentage of GDP) and found insignificant FDI coefficients for both middle- and low-income countries. Using FDI flows in place of FDI stocks does not affect our main results (results not reported here).

The coefficient on $\log R_t^{f\_middle}$ is positive and significant in the regression with $\log R_t^f$, but becomes insignificant when $\log R_t^f$ is excluded (see column 9), again suggesting collinearity between these variables. The coefficients on all other control variables are also insignificant.

Lastly, a word of caution: although an advantage of the cointegration approach is that it allows one to estimate cointegration coefficients in a manner that is free of endogeneity bias (e.g. Stock, 1987), and although our exogeneity tests suggest that domestic R&D has a causal effect on TFP—as semi-endogenous growth theory predicts, the estimated coefficients represent correlations, and not causal effects of domestic and foreign R&D on TFP. Therefore, the possibility that the estimated coefficients reflect, to some degree, the potential effect of domestic TFP on domestic R&D and foreign R&D spillovers should not be excluded. However, we cannot think of any plausible reason why there should be a large direct causal effect from domestic TFP to domestic R&D and foreign R&D spillovers. We are therefore convinced that even if there is some reverse causality bias in the estimates of the effects of domestic R&D and foreign R&D spillovers on TFP, this bias is not large enough to overturn our conclusions.

5. Conclusions

This study was the first to use a large panel of countries to (*i*) test the predictions of Schumpeterian growth theory against the predictions of semi-endogenous growth theory regarding the R&D–TFP relationship for developing economies, (*ii*) examine and compare the effects of domestic R&D and international R&D spillovers on TFP in developing countries, and (*iii*) examine differences in the effects of domestic R&D and international R&D spillovers on TFP between middle- and low-income countries.

Our results lead to the following conclusions: First, while the cross-sectional and time variation in the level and growth rate of TFP in developing countries can be explained by semi-endogenous growth models, Schumpeterian growth models are inconsistent with the data for developing countries. Specifically, our results suggest that an increase in the level (growth rate) of domestic R&D expenditures has a positive effect on the level (growth rate) of TFP, as semi-endogenous growth theory predicts. Second, while many imported goods and services are not a channel for international R&D spillovers, and while disembodied spillover effects are of minor or no importance for developing countries, machinery and equipment imports are important for technology transfer from developed to developing countries. However, and third, spillovers through machinery and equipment imports occur predominantly or exclusively between industrial and middle-income countries, whereas low-income countries in general do not benefit from R&D performed in industrial countries. Fourth, domestic R&D has a substantially greater effect on domestic TFP in developing countries, including middle-income countries, than foreign R&D. Fifth, while domestic R&D has a positive association with TFP in both middle-income and low-income countries, the impact of domestic R&D on TFP is greater in middle-income than in low-income countries.

Disclosure statement

I have no potential conflict of interest to report.

CRediT authorship contribution statement

Dierk Herzer: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization.

Acknowledgements

We thank two anonymous referees and an associate editor for suggestions which significantly improved the paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2021.105754.

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