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Comparing Apples to Apples

A New Indicator of Research and Development Investment Intensity in Agriculture

Alejandro Nin-Pratt

Environment and Production Technology Division

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

AUTHOR

Alejandro Nin-Pratt (a.ninpratt@cgiar.org) is a senior research fellow in the Environment and Production Technology Division of the International Food Policy Research Institute, Washington, DC.

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ABSTRACT

It has been apparent for more than a century that future economic progress in agriculture will be driven by the invention and application of new technologies resulting from expenditure in research and development (R&D) by governments and private firms. Nevertheless, it is conventional wisdom in the economic development literature that there is a significant underinvestment in agricultural R&D in developing countries. Evidence supporting this belief is provided, first by a vast literature showing returns on R&D expenditure to be so high as to justify levels of investment in multiples of those actually found, and second, from available data showing low research effort in developing countries as measured by the intensity ratio (IR), that is, the percentage of agricultural gross domestic product invested in agricultural R&D (excluding the for-profit private sector). This paper argues that the IR is an inadequate indicator to measure and compare the research efforts of a diverse group of countries and proposes an alternative index that allows meaningful comparisons between countries. The proposed index can be used to identify potential under-investors, determine intensity gaps, and quantify the R&D investment needed to close these gaps by comparing countries with similar characteristics. Results obtained using the new R&D intensity indicator with a sample of 88 countries show that the investment effort in developing countries is much higher than the one observed using the conventional IR measure. The new measure finds that countries like China, India, Brazil, and Kenya have similar levels of R&D intensity to those in the United States. To close the R&D intensity gap measured by the new index, developing countries will need to invest US$7.1 billion on top of the $21.4 billion invested on average during 2008–2011, an increase of 33 percent of total actual investment.

Keywords: agriculture, investment intensity, research and development

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ACRONYMS

AgGDP	agricultural gross domestic product
AII	ASTI intensity index
ASTI	Agricultural Science and Technology Indicators
DEA	data envelopment analysis
DI	diversification index
ESEA	East and Southeast Asian countries
GDP	gross domestic product
HI	high-income
IG	intensity gap
IR	intensity ratio (R&D spending/AgGDP)
LAC	Latin America and the Caribbean
LP	linear programming
OECD	Organisation for Economic Co-operation and Development
OLS	ordinary least squares
PIR	potential intensity ratio
PPP	purchasing power parity
R&D	research and development
SA	South Asia
SSA	Africa south of the Sahara
TFP	total factor productivity

1. INTRODUCTION

It has become widely accepted among stakeholders in economic development that there is a significant underinvestment in public agricultural research and development (R&D) in developing countries. This concern is supported by a vast literature showing returns on R&D expenditure to be so high as to justify levels of investment at multiples of those actually found (see, for example, Alston and others (2000a and 2000b) for an analysis and comparisons of results from this literature). Evidence of agricultural R&D underinvestment also comes from available data on R&D investment showing low agricultural R&D intensity as measured by the intensity ratio (IR) in developing countries. This measure is often used as an indicator of the research effort made by an economy and is defined as the percentage of agricultural gross domestic product invested in agricultural R&D (excluding the for-profit private sector). For example, IR values for the period 2001–2011 calculated using Agricultural Science and Technology Indicators data from 2016 show an average IR of 2.76 percent for Organisation for Economic Co-operation and Development (OECD) countries, 1.17 percent for upper-middle-income countries, and only 0.43 percent for low-income countries. Given that estimated returns on R&D are expected to rise with distance from the technological frontier, reflecting the gains that follower countries can make from catching up (Griffith, Redding, and Van Reenen 2004), the observed low levels of research intensity reinforce the results from the rates-of-return literature, suggesting that returns on R&D investment should be truly large and that developing countries should increase research intensity in agriculture.

Different types of R&D intensity measures are calculated in many countries and areas to monitor progress toward meeting R&D policy objectives and, in some cases, explicit targets. For example, governments at the Rio+20 conference in 2012 agreed to develop a universally applicable set of sustainable development goals to promote coherent action on development with a strong focus on agriculture, food systems, and nutrition outcomes, areas linked to the goal of eradicating hunger and poverty (Legget and Carter 2012). Among the targets defined under this general goal, there is a call for a minimum of 5 percent annual growth in agricultural R&D spending in low- and middle-income countries over the next decade to reach an IR value of at least 1 percent.

This widespread agreement on the need to promote agricultural R&D investment could have a significant impact on future allocation of scarce public resources in low-income countries, so it justifies a second look at the R&D underinvestment hypothesis, especially because this proposition rests on very weak assumptions, mainly the high rates of return on agricultural R&D found in the literature and the low intensity of investment as measured by the IR.

With respect to the high rates of return on R&D argument, Alston, Craig, and Pardey claimed in a 1998 paper that the evidence in previous studies has been severely biased. They showed that when the effects of research on production are measured more appropriately, the estimated rate of return on research is closer to a normal market rate of return than to the very high rates that predominate in the literature. More recently, Alston and others (2011) contended that many of the estimated rates of return, in particular some very large estimates of internal rates of return on aggregate R&D investments, are simply implausible and, if taken literally, imply unbelievable impacts of agricultural research over lengthy time periods. According to Alston and others (2011), these high rates result from data limitations that require the imposition of restrictive assumptions and also from particular modeling choices that were not made necessary by data constraints. According to Alston and others (2011), these very high rates of return from the literature might have damaged the case for public support of R&D.

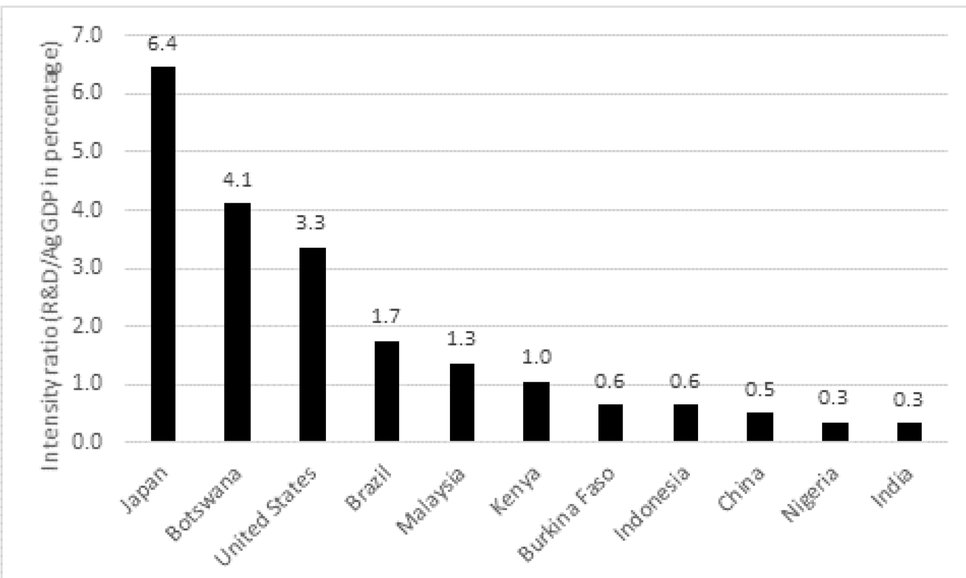
If rates of return on agricultural R&D appear not to be as high as they were assumed to be in the past, how does this finding relate to the low research intensities observed in developing countries as measured by the IR? Is R&D investment in developing countries as low as this indicator seems to show? This paper is concerned with the meaning and measurement of IR at the country level as an indicator of research intensity and its use to define policy targets or conduct cross-country comparisons. Main goals of the study are, first, to look at the correlation between IR and a series of structural variables to determine to what extent IR depends on country characteristics not controlled by policy makers, making it an inadequate indicator to compare research effort between countries. The second goal of the study is to develop an index of R&D intensity that would allow us to (1) unequivocally rank and compare countries according to R&D intensity levels, (2) identify underinvesting countries by comparing countries with similar characteristics, and (3) use this information to determine intensity gaps and quantify R&D investment needs for different countries and regions. Results of this study show that the IR is an inadequate indicator to measure and compare the research efforts of a diverse group of countries. Large, low-income economies with a relatively large agricultural sector invest far less in R&D as a share of their gross domestic product (GDP) than small, rich economies where agriculture represents a small share of GDP. Also, countries with potential to benefit from technology spill-ins and those with less diversified agricultural production tend to show lower IRs because they can rely on technologies developed elsewhere and concentrate research efforts in fewer activities to achieve results similar to those of countries with low potential for spill-ins and a more diversified agriculture. Results obtained using the proposed R&D intensity indicator show that the investment effort in developing countries is much higher than the one observed using the conventional IR measure.

The rest of the paper is organized as follows. The next section looks at the correlation between the IR measures and structural characteristics of countries, and proposes an index that controls for these characteristics, improving on past measures of the research effort made by countries. This is followed by the conceptual framework, the methodological approach, and data used in the study to build the new intensity index. Section 4 presents results and country comparisons, and quantifies the intensity gap using the proposed index. Section 5 concludes.

2. THE INTENSITY RATIO AND COUNTRY COMPARISONS

A simple comparison of average IR values of 11 selected countries for the period 2001–2011 (Figure 2.1) is sufficient to show some of the difficulties that arise when using the IR to measure the intensity of research and development (R&D) investment. Assuming that the IR is a good measure to compare research intensity between countries, Figure 2.1 shows that high-income countries like Japan and the United States make a much higher effort in agriculture R&D investment than most developing countries, which is normally expected. But take, for example, the cases of China, India, and Brazil. These countries show IR values that are only a small fraction of those of Botswana, with Brazil's IR three times larger than China's, and India's research effort only half of that of China. Why these differences between Brazil, China, and India, and why are their IR values smaller than Botswana's when it is well established that these three countries are leading agricultural research–developing countries with comparably large, relatively developed, and successful R&D systems (Fan 2000; Fan, Qian, and Zhang 2006; Pal 2008; Pal and Byerlee 2006; Beintema, Pardey, and Dias Avila 2009)?

Figure 2.1 Intensity ratio (agricultural R&D spending/AgGDP) for 11 selected countries, average values 2001–2011



Source: Created by author, based on ASTI (2016), and World Bank (2015) data.
Note: AgGDP = agricultural gross domestic product; R&D = research and development. Figure excludes agricultural R&D spending by the for-profit private sector.

This study argues that the IR is an inadequate indicator to measure and compare the research efforts of a diverse group of countries, which makes the comparison in Figure 2.1 a completely misleading exercise. The reasons for the inadequacy of the IR as a measure of R&D investment effort can be found in the more general literature on R&D investment at the firm level. This literature shows that poor countries invest far less in R&D as a share of their gross domestic product (GDP) than rich countries. One explanation for this fact, relevant for our analysis, is that the necessary complementarities to R&D expenditure are likely to diminish with distance from the income frontier and hence reduce the efficacy of a given unit of R&D. In other words, the efficacy of R&D investment in developing countries is much lower than in high-income countries due to any number of institutional and educational factors that can offset the Schumpeter catch-up effect and significantly reduce the returns on R&D (Goñi and Maloney 2014).

Lederman and Maloney (2003) looked at the links between development and R&D investment and found that R&D rises exponentially with the level of development as measured by GDP per capita, mainly because high-income countries tend to have higher government capacity to mobilize public R&D expenditures and, in all likelihood, a better quality of research institutions. Private R&D is also higher in rich countries because they have better intellectual property protection and deeper credit markets. Other authors have emphasized the importance of market size as a determinant of innovative activity. For example, Eaton, Gutierrez, and Kortum (1998) found that Europe's research intensity was lower than that of the United States because Europe suffers from having smaller and more fragmented markets for innovations than the United States. Notice that in this case, market size is related to the absolute value of R&D investment, not to the IR. As will be discussed below, the actual size of the economy could be negatively related to the IR.

A first conclusion derived from the literature on R&D investment is that richer economies are expected to show higher IR values. If this conclusion also applies to R&D in agriculture, it could be at least a partial explanation of observed heterogeneity in IR between countries. At the sectoral level, there are other factors that could potentially affect IR. In the case of agriculture, one of these factors is the size of the agricultural sector relative to the economy. A country with a smaller share of agriculture in its GDP could potentially allocate relatively large amounts of resources to agricultural R&D investment given that the investment needed is small relative to GDP. This could contribute to explaining why, in general, IR is higher in high-income countries than in developing countries, inasmuch as the share of agriculture decreases with income growth. This explanation could also apply to developing countries with small agricultural sectors relative to GDP, as in the case of Botswana, shown in Figure 2.1.

As in the more general literature on R&D, the size of the economy should be another factor affecting agricultural R&D investment and IR. A large economy could facilitate the development of innovation activities in agriculture due to a larger market for innovations, not only in agriculture but in other sectors. However, the effect of a large economy doesn't necessarily result in higher IR levels. Economies with large markets for innovation might depend less on investment from the public sector and nonprofit organizations, which might result in less R&D investment relative to agricultural GDP (AgGDP). However, this could also be affected by other variables like income per capita, spill-ins, and the relative size of agriculture, making it difficult to determine a priori the sign of its effect on IR.

The potential of a country to benefit from spillovers from other countries (spill-ins) is another factor that could affect IR. For example, countries with similar output compositions (reflecting similar agroecologies and natural resources) and similar use of capital and land per worker in agriculture are "closer" to each other than to countries in different agroecologies and with different relative factor prices (for example, land- and capital-abundant countries compared with land-scarce and labor-abundant countries). Countries with high potential of receiving spill-ins from other countries could show lower IRs (a negative correlation) because they can rely on technologies developed elsewhere that can be adapted to their own conditions with a lower research effort than countries with low potential for spill-ins. The negative correlation between spill-ins and IR could be expected if there is a simple linear relationship between these variables. However, this relationship could be more complex because countries might need to invest in R&D to take advantage of spill-ins, and the level of investment needed could vary along the distribution of IRs.

Finally, diversification or specialization within agriculture is another factor with potential impact on the intensity of R&D investment as measured by the IR.[1] In terms of absolute levels of R&D investment, we could assume that the more diversified agricultural production is, the more R&D investment is needed, assuming other factors are equal. This is because countries need a much-diversified portfolio with sufficient investment in each of its components to have the same impact at the sectoral level than more specialized countries. An example of this situation could be the rice economies of East and Southeast Asia compared with the diversity of agroecologies and production systems in West Africa.

[1] The author would like to thank Douglas Gollin, who suggested this as a potential factor affecting R&D intensity.

African countries will need to invest more to have a similar impact on productivity than the Asian countries, ceteris paribus.

However, when thinking of the correlation between diversification and IR, it is more difficult to have clear hypotheses about the sign of the correlation between these variables. Countries have limited resources to invest in R&D, which means that they will not invest proportionally in all activities, setting investment priorities independently of the degree of diversification of their agricultural sectors. If this is the case, we could observe a negative correlation between IR and diversification, with countries still investing in a limited number of activities independently of the level of diversification of their agricultural sector.

The purpose of the discussion so far has been to show the different variables that could affect IR values at the country level and the difficulties of trying to determine the sign of the correlation between IR and other variables, assuming that there is no simple linear relationship between them. The last part of this section shows the results of different measures that try to capture the correlation between the IR and the five factors assumed to affect its value: income, size of the economy, relative size of the agricultural sector, potential to receive spill-ins, and specialization in agriculture. GDP per capita is used as a proxy for the country's income, GDP is a proxy for the size of the economy, and the share of agriculture in GDP looks at the effect of the relative size of the agricultural sector. In the case of potential spill-ins, this study uses a similar approach to that of Jaffe (1986, 1989), Alston and colleagues (2011), and Eberhardt and Teal (2013) to calculate the "distance" between agriculture in different countries. As in Alston and colleagues (2011), the measure of spill-in potential in this study is based on the similarity of the commodity composition of output between pairs of countries, but unlike in Alston and colleagues (2011), the output measure is complemented with an input measure based on the similarity of input composition. The reason for this is that differences in relative factor prices and the different intensities in factor use between countries are also barriers that make adaptation and adoption of technologies generated in other countries more difficult. The seminal paper by Hayami and Ruttan (1970) is a good example of this, showing how the United States and Japan adapted agricultural technology to their sharply contrasting factor proportions. Finally, the Herfindahl-Hirschman index, which is frequently used to measure industrial concentration and corporate diversification (Jacquemin and Berry 1979) is adapted to create a diversification index (DI). The DI takes values between 0 and 1, with 1 being the highest level of diversification (see Appendix A for details on the calculation of the potential spill-in and diversification indicators).

Table 2.1 shows the correlation coefficients between IR and the five variables. Data used are for 88 countries from 1981 to 2011. R&D data are from Agricultural Science and Technology Indicators (ASTI 2016), GDP and AgGDP are from World Bank (2015), and the diversification and specialization indexes are built using data from FAO (2015). The same data and sources used in this section are used in Section 4 to construct the new intensity index. The pairwise correlation measures the strength and direction of the linear relationship between two variables and is defined as the (sample) covariance of the variables divided by the product of their (sample) standard deviations. The partial correlation between IR and one particular variable is the correlation that would be observed between IR and that variable if other variables do not vary. Finally, the semipartial correlation between IR and one particular variable is the correlation that would be observed between IR and that variable if the effects of all other variables were removed from the variable of interest (but not from IR).

The pairwise correlation is highly significant in all cases (at the 0.1 percent level) and with very high coefficients for the share of agriculture in GDP (-0.70) and income (0.60). Once we control for the effects of other variables using the partial and semipartial correlations, the correlation coefficients are smaller but still highly significant, with the only exception being the correlation between IR and DI, which becomes statistically nondifferent from 0. The results show a positive correlation of IR with income, GDP, and potential spill-ins. The share of agriculture in GDP and the DI show negative correlation with IR.

Table 2.1 Correlation coefficients between IR and different variables, 88 countries, 1981–2011

Variable	Pairwise correlation	Partial correlation	Semipartial correlation
GDP per capita	0.595***	0.260***	0.094***
	0.000	0.000	0.000
Share of agriculture in GDP	-0.70 1***	-0.513***	-0.185***
	0.000	0.000	0.000
GDP	0.323***	0.106***	0.038***
	0.000	0.000	0.000
Diversification index	-0.120***	-0.023	-0.008
	0.000	0.241	0.241
Potential spill-ins	0.178***	0.115***	0.042***
	0.000	0.000	0.000

Source: Created by author, based on ASTI (2016), FAO (2015), and World Bank (2015) data.

Note: R&D date are from ASTI. GDP and agricultural GDP are from the World Bank. Diversification and specialization indexes are from FAO. p-values are given below the correlation coefficients; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Pairwise correlation = the (sample) covariance of the variables divided by the product of their (sample) standard deviations; partial correlation = correlation that would be observed between IR and a variable if other variables do not vary; semipartial correlation = correlation that would be observed between IR and a variable if the effects of all other variables were removed from the variable of interest (but not from IR). GDP = gross domestic product; IR = intensity ratio.

As in Lederman and Maloney (2003), ordinary least squares (OLS) and quantile regressions (including median regressions) are used to model conditional quantiles of the joint distribution of IR and the independent variables. This approach allows the estimation of multiple coefficients and provides a more complete picture of the relationship between IR and other variables. Median regression is more robust to outliers than OLS, and it avoids assumptions about the parametric distribution of the error process, while quantile regressions allow us to describe the relationship between IR and the independent variables at different points in the conditional distribution of IR (see, for example, Koenker and Hallock 2001). Separate regressions are run between IR and each of the independent variables (Table 2.2), and these are compared with the simultaneous regression between IR and the five independent variables (Table 2.3) and of IR with all independent variables plus interaction terms (Table 2.4). Variables that capture country and year fixed effects are used in all regressions.

It is clear from Table 2.2 that IR increases with income and decreases with the relative size of the agricultural sector. For these variables, results hold for the correlation coefficients in Table 2.1 and at all values of the conditional distribution of IR in Table 2.2. All coefficients are highly significant and show the expected sign. The quantile regressions show that the relationship between IR and GDP, IR and DI, and IR and the index measuring the potential of receiving technology spill-ins is more complex. The correlation between IR and GDP is positive and significant, as shown by the OLS regression, but the quantile regressions show no significant coefficients. On the other hand, IR and DI show no significant coefficients and no evidence of correlation. In the case of the index of potential spill-ins, coefficients are consistently positive with the OLS and the quantile regressions. Only the coefficient at the lowest decile of the IR distribution is positive but not significantly different from 0.

Table 2.2 Estimated coefficients of median and quantile regressions of the intensity ratio against GDP per capita, share of agriculture in GDP, GDP level, production diversification, and potential spill-ins, 88 countries, 1981–2011

Variable	Ordinary least squares	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
GDP per capita	0.614***	0.469***	0.509***	0.625***	0.371***	0.243***
	(12.07)	(5.05)	(5.76)	(7.41)	(4.61)	(4.98)
Share of agriculture in GDP	-1.007***	-1.073***	-1.125***	-1.056***	-0.959***	-0.938***
	(-28.66)	(-24.45)	(-24.78)	(-23.74)	(-25.16)	(-28.94)
GDP	0.259***	0.085	0.057	0.113	0.130	0.014
	(5.19)	(0.89)	(0.57)	(1.39)	(1.90)	(0.21)
Diversification index	-0.061	-0.105	-0.086	-0.030	0.117	-0.032
	(-1.01)	(-1.47)	(-1.33)	(-0.43)	(1.44)	(-0.31)
Potential spill-ins	4.313***	1.724	3.064*	4.376***	2.719**	2.400*
	(5.51)	(1.25)	(2.54)	(4.85)	(2.63)	(2.33)

Source: Created by author, based on ASTI (2016), FAO (2015), and World Bank (2015) data.
Note: R&D date are from ASTI. GDP and agricultural GDP are from the World Bank. Diversification and specialization indexes are from FAO. *t* statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All models include dummy variables for countries and years; coefficients not shown. GDP = gross domestic product.

What happens to the results when regressing IR against all variables simultaneously and when we add interaction terms looking at the joint effect of different variables? These results are shown in Tables 2.3 and 2.4. The first result to notice is that coefficients obtained for income and the share of agriculture in GDP are robust in all specifications: the effect of income on IR is consistently positive while that of the share of agriculture in GDP is negative. For other variables, the sign of the coefficients and their significance change in the different specifications, a result that might reflect multicollinearity problems in the simple models being compared. When controlling for the effect of other variables, as is the case in the results in Table 2.3, the effect of GDP on IR becomes consistently negative, and DI shows negative and significant coefficients with the OLS and the Q(0.10) regressions only. Coefficients of the potential spill-in index become not significantly different from 0.

Table 2.3 Estimated coefficients of median and quantile regressions of the IR against GDP per capita, share of agriculture in GDP, GDP levels, production diversification, and potential spill-ins, 88 countries, 1981–2011

Variable	Ordinary least squares	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
GDP per capita	0.643***	0.895***	0.812***	0.895***	0.599***	0.307**
	(6.52)	(5.77)	(7.88)	(8.34)	(4.36)	(2.69)
Share of agriculture in GDP	-0.906***	-1.054***	-1.073***	-0.984***	-0.955***	-0.984***
	(-25.58)	(-18.15)	(-26.24)	(-23.13)	(-28.71)	(-28.57)
GDP	-0.549***	-1.066***	-0.940***	-0.914***	-0.688***	-0.464***
	(-5.79)	(-7.47)	(-9.68)	(-8.17)	(-5.07)	(-4.22)
Diversification index	-0.201***	-0.151**	-0.131*	-0.068	-0.054	-0.053
	(-3.79)	(-2.61)	(-2.38)	(-1.26)	(-1.29)	(-1.38)
Potential spill-ins	0.238	-2.637*	-1.459	-0.694	-0.898	-1.062
	(0.31)	(-2.29)	(-1.33)	(-0.82)	(-1.12)	(-1.32)
Number of observations	2,728	2,728	2,728	2,728	2,728	2,728
R^2 / pseudo R^2	0.907	0.866	0.887	0.895	0.88	0.869

Source: Created by author, based on ASTI (2016), FAO (2015), and World Bank (2015) data.
Note: R&D date are from ASTI. GDP and agricultural GDP are from the World Bank. Diversification and specialization indexes are from FAO. t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All models include dummy variables for countries and years; coefficients not shown. Pseudo R-squared = square of the correlation between the fitted values and the dependent variable in the quantile regression. Standard errors of quantile regressions are asymptotically valid under heteroskedasticity and misspecification (Machado, Parente, and Santos Silva 2011). GDP = gross domestic product. IR = intensity ratio.

Finally, Table 2.4 introduces interactions to the model in Table 2.3. The problems with multicollinearity are likely to have increased in this model, but we still observe many significant coefficients and the confirmation of some of the robust results observed with the previous models. For example, coefficients for income (GDP per capita) are still highly significant and positive except at the highest deciles of the IR distribution. The share of agriculture in GDP is, as before, negative and significant in the OLS regression and around the median of the IR distribution, while the effect of GDP is now negative and highly significant in all regression results. Some interesting changes occur in the results for the diversification and spill-in indexes. The relationship between the IR and the DI is now positive and significant in the OLS regression, around the median and at higher deciles of the distribution. On the other hand, high potential spill-ins result, in most cases, in lower IR values (negative and significant coefficients). Coefficients obtained for the interaction terms mainly show that after reaching median levels of IR, richer countries with larger agricultural sectors tend to show higher IRs while big economies with large agricultural sectors tend to have smaller IRs. Also interesting is the result showing that at low IR levels, the higher the diversification of agriculture and the higher the potential to receive spill-ins, the lower the value of the IR.

Table 2.4 Estimated coefficients of median and quantile regressions of the IR against GDP per capita, share of agriculture in GDP, GDP levels, production diversification, and potential spill-ins, including interaction terms, 88 countries, 1981–2011

Variable	Ordinary least squares	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
GDP per capita	1.347***	1.147***	0.912**	0.836**	0.570	0.395
	(5.32)	(3.71)	(2.91)	(2.59)	(1.48)	(1.13)
Share of agriculture in GDP	-0.879*	-0.946	-1.112*	-1.234*	0.009	0.434
	(-2.30)	(-1.83)	(-2.24)	(-2.20)	(0.02)	(0.58)
GDP	-1.109***	-1.551***	-1.174***	-1.210***	-0.711*	-0.347
	(-7.97)	(-6.17)	(-5.37)	(-5.04)	(-2.54)	(-1.68)
Diversification index	2.083**	-0.809	0.594	1.816*	2.199*	2.247**
	(3.02)	(-0.71)	(0.64)	(2.52)	(2.42)	(2.75)
Potential spill-ins	-0.671	-3.453**	-1.578	-2.483*	-2.456*	-1.333
	(-0.83)	(-2.84)	(-1.32)	(-2.40)	(-2.29)	(-1.29)
Income * Ag. share	0.025	0.032	0.046	0.178***	0.127**	0.059
	(0.73)	(0.77)	(1.14)	(4.11)	(2.76)	(1.43)
Ag. share * GDP	-0.011	-0.023	-0.010	-0.065*	-0.098***	-0.073*
	(-0.54)	(-0.97)	(-0.39)	(-2.38)	(-3.50)	(-2.43)
Ag. share * diversification	-0.251***	-0.062	-0.131	0.029	-0.004	-0.149
	(-3.30)	(-0.59)	(-1.43)	-0.35	(-0.04)	(-1.79)
Ag. share * spill-ins	0.110***	0.069*	0.029	0.035	0.068	0.042
	(4.57)	(2.17)	(0.87)	(1.11)	(1.78)	(1.31)
Income * diversification	-0.088	0.022	0.000	0.107	0.066	-0.045
	(-1.04)	(0.23)	0.00	(1.04)	(0.61)	(-0.46)
GDP * diversification	-0.020	0.043	0.004	-0.110*	-0.101**	-0.043
	(-0.62)	(0.95)	(0.08)	(-2.36)	(-2.87)	(-1.12)
Diversification * spill-ins	-0.097*	-0.090*	-0.106**	-0.038	-0.080	-0.119*
	(-2.41)	(-2.36)	(-3.12)	(-0.80)	(-1.56)	(-2.40)
Observations	2,728	2,728	2,728	2,728	2,728	2,728
R^2 /pseudo R^2	0.91	0.87	0.89	0.90	0.88	0.87

Source: Created by author using ASTI (2016), FAO (2015), and World Bank (2015) data.

Note: R&D date are from ASTI. GDP and agricultural GDP are from the World Bank. Diversification and specialization indexes are from FAO. *t* statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All models include dummy variables for countries and years; coefficients not shown. Pseudo R-squared = square of the correlation between the fitted values and the dependent variable in the quantile regression. Standard errors of quantile regressions are asymptotically valid under heteroskedasticity and misspecification (Machado, Parente, and Santos Silva 2011). GDP = gross domestic product; IR = intensity ration.

To conclude, results in Tables 2.1 to 2.4 show that the IR depends on structural variables (not controlled by policy makers): income, size of the economy, size of the agricultural sector, agricultural diversification, and potential for technology spill-ins. The effect of these variables on IR is not linear but changes with the particular level and combination of the five variables. This explains why IR is a misleading measure of research intensity and cannot be used to determine the intensity gaps of individual countries. For the IR to be a good measure of R&D investment intensity, the size of the agricultural sector should be the major, if not the only, indicator of R&D investment intensity. In other words, when using IR as a measure of R&D intensity, the implicit assumption is that R&D investment depends only on the size of the agricultural sector and also that optimal investment is proportional to the size of the sector. To put it differently, the IR can be thought of as a misleading measure of research intensity in the same way that labor or land productivity is not necessarily a good proxy for total factor productivity (TFP).

Due to the limitations of the traditional IR as an indicator of R&D intensity and as a tool to compare and rank countries according to their effort in R&D investment, this study proposes a multiratio indicator of R&D intensity that combines R&D investment with AgGDP, GDP, income, agricultural specialization, and potential spill-ins. The procedure used to calculate this indicator is similar to the one used to build a TFP index. For example, given the evidence on the relationship between agricultural R&D and the five variables of interest, the proposed indicator could be seen as a TFP measure of a production process wherein countries "produce" R&D expenditure using different combinations of these five "inputs." The actual maximum R&D intensity that can be achieved will depend on the particular mix of inputs in each country. Countries with the same mix of inputs are expected to show similar levels of R&D investment. On the other hand, differences in R&D expenditure between countries with a similar mix of inputs will indicate higher "productivity" by the country with higher expenditure. In this analogy, higher "productivity" means that the country is investing more than expected given its particular structural characteristics. This leads to a conceptually meaningful definition of the R&D intensity gap: the difference between the R&D investment of a particular country and the highest investment among all countries with the same mix of agricultural GDP, GDP, income, agricultural specialization, and spill-in potential.

A major difficulty in building this index is to define the weights necessary to aggregate the individual indicators into a single measure of R&D intensity. These weights should reflect the importance that the five determinants of R&D have as constraints of R&D investment in each country. For example, R&D investment in a small, high-income economy could be constrained by the relative size of GDP, by a very small agricultural sector, or both, so these two variables should enter the intensity index with a higher weight than income to reflect the importance of these constraints on R&D intensity. Technical details of the approach followed to build the index are discussed in the next section.

3. APPROACH AND DATA

The data envelopment analysis (DEA) approach is used to obtain a multifactored research and development (R&D) intensity measure called the ASTI (Agricultural Science and Technology Indicators) intensity index (AII). This index calculates the R&D investment of a particular country relative to the main structural factors affecting intensity: gross domestic product (GDP), agricultural GDP (AgGDP), income per capita, agricultural specialization, and potential spill-ins. In generic form, this measure can be represented as

$$AII_i = f\left(\frac{R\&D_i}{GDP_i}, \frac{R\&D_i}{AgGDP_i}, \frac{R\&D_i}{y_i}, \frac{R\&D_i}{DI_i}, \frac{R\&D_i}{SP_i}\right), \tag{1}$$

where AII_i is the ASTI intensity index of country *i, R&D* is expenditure in agricultural research and development, *y* is income per capita, *DI* (diversification index) is a measure of output diversification, *SP* measures potential spill-ins, and $f[\bullet]$ is a function aggregating the five IRs into a single number that measures the R&D investment intensity of country *i*. This problem is equivalent to that of estimating an index of input quantities when no prices are available, where the main difficulty is to determine the weights to be used to aggregate the five partial intensity measures.

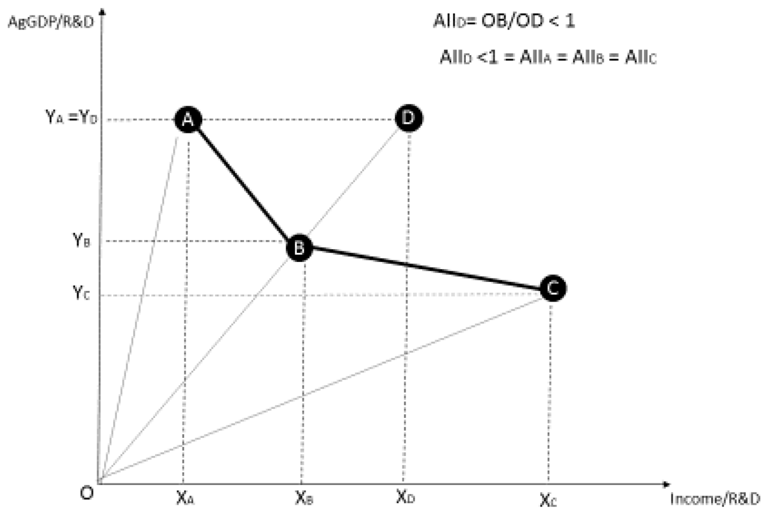
A well-known feature of DEA is that it looks for endogenous weights that maximize the overall score for each decision-making unit given a set of other observations, yielding the most favorable country-specific weights. The DEA approach has been extensively used to solve this problem in production analysis when prices of inputs or outputs are not available, and it has been extended more recently to build indexes that comply with characteristics required by index theory. The approach used by Whittaker and colleagues (2015) is adapted here to build a multifactored measure of R&D intensity.

The multifactored measure of intensity is equivalent to a measure of technical efficiency, whereby total R&D investment is a function of the particular mix of "inputs" used. The intuition behind the proposed index is shown in the example in Figure 3.1. The axes in the figure represent values of R&D investment relative to two variables, GDP per capita and AgGDP. The use of two inputs in the figure is only for illustrative purposes, but the analysis will be presented more formally later in this section and extended to *n* variables.

Thinking of the example in Figure 3.1 as a production efficiency problem, each point in the figure represents a production unit (countries) using two inputs (coordinates): AgGDP/R&D and income/R&D, in the vertical and horizontal axes, respectively. Notice that these coordinates represent the inverse of partial IRs, with the measure in the vertical axis being the inverse of the IR normally used to measure the intensity of agricultural R&D investment. Also notice that the farthest a country is from the origin, the lower its R&D intensity. For example, point *B* and point D have the same proportion of AgGDP and income (they are in the same ray from the origin), but the level of AgGDP and income per unit of R&D invested is lower in *B* than in *D*. This means that the R&D intensity of point *B* is higher than that of *D*. Countries *A*, *B*, and *C* are the countries with highest R&D intensity because there is no other country with the same proportion of AgGDP and income closer to the origin than these countries.

Investments by countries *A*, *B*, and *C* are equally intensive and outline the "intensity frontier" or the benchmark isoquant. This frontier defines the space of investment intensity for the sample of countries, with the highest intensity defined by points *A*, *B*, and *C*, and by all linear combinations of these three points (the lines connecting *A*, *B*, and *C*). Countries with less intensive investment are located in the space above and to the right of the frontier.

Figure 3.1 Example of the multifactored R&D intensity index using two partial measures of intensity: R&D spending/agricultural gross domestic product and R&D spending/income



Source: Created by author.

Note: The intensity ratios are expressed as the inverse of R&D spending / AgGDP and R&D/income, to represent the analysis as an input-oriented problem, where A, B, and C determine the unit isoquant, showing the value of AgGDP and income per unit of R&D invested. AgGDP = agricultural gross domestic product; AII = ASTI (Agricultural Science and Technology Indicators) intensity index; R&D = research and development.

The DEA approach uses the piecewise linear frontier as the benchmark curve and measures distances of country vectors relative to this frontier. The distance of each country from the frontier is calculated as the proportional reduction of AgGDP and income needed to bring each point in the "intensity space" to the frontier. For example, the intensity measure for country *D* can be calculated as $AII_D = OB/OD$, which is the distance of country *D* from the frontier. The result of multiplying the values of the AgGDP and the income of country *D* by *OB/OD* is the coordinates of country *B*, that is, the value of AgGDP and income of vector *B*, the point on the frontier with the same proportion of AgGDP and income as country *D*. In this way, the multifactored intensity measure for country *D* (AII_D) is calculated as the distance between *D* and a similar point at the frontier. Notice that this distance is a measure of the difference of investment intensity between *D* and the maximum potential investment (investment at the frontier). Also notice that countries at the frontier have, by definition, values of the intensity index equal to 1 because the distance of each of these countries from the frontier is $AII_A = OA/OA = AII_B = OB/OB = AII_C = OC/OC = 1$. Countries in the intensity space above the frontier will show values of AII between 0 and 1. Comparing frontier countries with country *D* in Figure 3.1, we get intensity indexes $AII_A = AII_B = AII_C = 1 \geq AII_D \geq 0$. The closer the AII is to 1, the higher the investment intensity of that country, which is to say, the higher R&D investment relative to the value of AgGDP and income.

Notice that countries are compared with countries that have the same proportion of AgGDP relative to income. In Figure 3.1, country *A* could represent a low-income country (a small value on the horizontal axis) with a large agricultural sector. On the other extreme, the particular mix of income and AgGDP of country *C* could represent that of a high-income country with a relatively small agricultural sector. Country *D* is compared with *B*, the country with the same ratio of AgGDP to income. This is important because it means that the DEA approach allows us to determine the maximum potential intensity that a country can reach (given observed intensities of all countries), and as a corollary of this, it allows us to obtain the actual intensity gap for that country, which can be measured as the difference between maximum potential intensity and actual intensity.

Since AII_D measures the proportional reduction of AgGDP and income needed to reach maximum potential intensity, the product of each of the two intensity measures ($AgGDP_D/R\&D_D$ and $income/R\&D_D$) with AII_D gives the maximum potential value of the two partial intensity measures for country *D*. This allows us to express the potential intensity and the intensity gap in terms of the conventional IR. For example, the potential intensity of country *D* can be seen as the maximum reduction of AgGDP that allows it to "obtain" one unit of R&D. In the example in Figure 3.1, this is the AgGDP coordinate of point *B*, the point at the frontier, which can be seen as the potential intensity ratio (PIR) of country *D*: $PIR_D = AgGDP_D * AII_D$. In Figure 3.1, $PIR_D = Y_B$, which is the actual value of the inverse of the IR of the reference point *B* at the frontier. The intensity gap for country *D* in Figure 3.1 can then be measured in percentage points of AgGDP: $IG_D = (1/Y_B) - (1/Y_D)$.

Because the interest here is in the actual intensity measures and not in their inverses, potential intensity can then be calculated as the maximum increase in R&D investment, given AgGDP, to reach the frontier, and we can express the PIR as $PIR_D = (R\&D_D/AgGDP_D)/AII_D$, or $PIR_D = 1/Y_B$ in the example in Figure 3.1, and as before, we can measure the intensity gap in percentage points.

The rest of this section presents a formal approach to the construction of the AII, taking advantage of the similarity between the index problem and the problem of measuring production efficiency. To do this, we consider a set of countries that define the space of R&D investment values for different levels of *GDP*, *AgGDP*, income per capita (*y*), *DI*, and *SP*. We can think of this set as the technology for a given production process, defined as follows:

$$T = \{z: (z, Y)\ z\ \mathit{can\ produce}\ Y\}, \tag{2}$$

where *z* is a vector of inputs (*GDP, AgGDP, y, DI, SP*) and *Y* is a single output (R&D investment). The production technology is assumed to satisfy the usual axioms, such as convexity and strong disposability. If *Y* is fixed, then the input requirement set is

$$L(Y) = \{z: (z, Y) \in T\}. \tag{3}$$

This input set shows all possible combinations of inputs belonging to *T (z, Y)* that can produce *Y*. Rather than working with absolute values of *Y* and *z*, the problem is defined in terms of the inverse of individual intensity indexes, with the input set representing in this case all feasible combinations of *GDP*, *AgGDP*, *y, DI*, and *SP* per unit of R&D invested, where $x_n = X_n/Y$. Further,

$$L(1) = \{x: (x, 1) \in T_1\}. \tag{4}$$

L(1) is the set of all observed input combinations required to produce one unit of output (R&D). The lower bound of this set is what we call the benchmark isoquant (the *ABC* line in Figure 3.1). These are the minimum observed input combinations required to achieve one unit of output. We can calculate the distance of each input vector *x* from the benchmark isoquant using Shephard's distance function (Shephard 1970), as in Whittaker and colleagues (2015).

$$D(1, x_k) = sup\left\{\theta: \frac{x_k}{\theta} \in L(1)\right\}, \tag{5}$$

where θ is a positive scalar defining the proportional reduction that is needed to reduce the input vector to the benchmark curve, and *x* is the vector of inputs of country *k (k = 1, …, K)*. For example, in the case of country *D* in Figure 3.1, θ = *OD/OB*. The distance function, D(1, *x*), is nondecreasing, positively linearly homogeneous, and concave in *x*. The value of the distance will be equal to 1 or greater than 1 if the input vector, *x*, is an element of the feasible input set L*(1)*: $D(1, x) \geq 1$ *if* $x \in L(1)$.

The distance function is used (assuming homotheticity) to build a multifactored R&D intensity measure that compares two input vectors. As in Whittaker and others (2015) and following Caves, Christensen, and Diewert (1982), the following expression is obtained:

$$AII(x_i, x_j) = \frac{D(1,x_i)}{D(1,x_j)}, \tag{6}$$

where x_i and x_j are two input vectors, representing countries *i* and *j*, respectively, to be compared. The distances in equation (5) are calculated using linear programming (LP), and the approach used here defines the "technology" space using observations of all available countries and years. This means that all countries are compared with a unique isoquant, or equivalently, the benchmark isoquant is the same for all countries and years and represents the highest observed R&D intensity for the set of analyzed countries in all periods. The intensity index for a particular country *i* in period t_o is calculated using the following LP problem:

$$\begin{aligned}
&D^{-1}_{(1,x_{i,to})} = \min_{\theta,\lambda} \theta \\
&s.t. \textstyle\sum_{k=1}^{K} \sum_{t=1}^{T} \lambda_{k,t} x_{n,k,t} \leq \theta x_{n,i,to} \ \ with\ n = 1, 2, \ldots, N \\
&\textstyle\sum_{k=1}^{K} \sum_{t=1}^{T} \lambda_{k,t} = 1 \\
&\lambda_{k,t} \geq 0 \ \ t = 1, \ldots, T \ and\ k = 1, \ldots, K.
\end{aligned} \tag{7}$$

$D^{-1}_{(1,x_{i,to})}$ is the inverse of Shephard's distance and has an upper limit of 1, representing the highest R&D intensity, while values close to 0 represent low intensity. The index calculated in this way compares the intensity of country *i* with the intensity of a country that has the same proportion of *GDP*, *AgGDP*, *y, DI*, and *SP* in the benchmark isoquant. The final AII measure is represented as an index that compares the inverse of the Shephard distance obtained from LP problem (7) relative to the distance of a reference country and year (k^*, t^*): $AII(x_{i,to}\ x_{k^*,t^*}) = D^{-1}(x_i,t_o)/D^{-1}(x_{k^*,t^*})$, where $D^{-1}(x_i,t_o)$ is obtained from linear problem (7) and $D^{-1}(x_{k^*}, t_*)$ is calculated using the same problem (7) but replacing $x_{n,I,to}$ with x_{n,k^*,t^*}, that is, the input vector of the reference country (k^*) in the reference year (t^*).

The AII allows the comparison of intensity values of different countries in different periods because it satisfies a number of desirable properties that an index formulation should possess according to the axiomatic approach to index numbers (in, for example, Diewert 1987). The properties used to evaluate alternative indexes with the axiomatic approach are proportionality, time reversibility, transitivity, and dimensionality (Diewert and Lawrence 1999). The proportionality condition implies that if the index value that results from comparing $x_{i,to}$ and x_{k^*,t^*} is $AII(x_{i,to}\ x_{k^*,t^*})$, then the index comparing $(\alpha\ x_{ito})$ with $x_{k^*t^*}$ is $AII(\alpha x_{i,to}\ x_{k^*,t^*}) = \alpha AII(x_i,t_o\ x_{k^*,t^*})$; that is, the index obtained is a proportional increase to the overall index when one of the input vectors increases.

Reversibility guarantees that if $AII(x_{i,to}\ x_{k^*,t^*}) = AII(x_{i,to})/AII(x_{k^*,t^*})$, then $AII(x_{i,to}\ x_{k^*,t^*}) = AII(x_{k^*,t^*}\ x_{i,to}) = AII(x_{k^*,t^*})/AII(x_{i,to}) = 1/AII(x_{i,to}\ x_{k^*,t^*})$. This means that if the quantity for one country and time period is exchanged with another, the resulting index is the reciprocal of the original index. The transitivity property means that whether a fixed base or a chain of observations is used to calculate the index, the result will be the same. For example, the difference in intensity for the same country between two periods will be equivalent to $AII(x_{i,t1}\ x_{k^*,t^*}) \times AII(x_{i,t2}\ x_{k^*,t^*}) = AII(x_{i,t1}\ x_{i,t2})$. Finally, dimensionality means that when changing the units of measurement of each input by the same positive number α, the index remains unchanged: $AII(\alpha x_{i,to}\ \alpha x_{k^*,t^*}) = AII(x_i,t_o\ x_{k^*,t^*})$.

The same framework is used to determine the intensity gap for an individual country, but rather than comparing all observations with a unique benchmark isoquant, we calculate distances for a particular period, defining benchmark isoquants by year. The intensity gap (IG) expresses the increase in R&D investment (in percentage of present annual investment) that is needed to close the gap between actual and potential intensity, with potential intensity measured annually:

$$IG(x_{i,to}) = 100 * (1 - D^{-1}_{(1,x_{i,to})}). \tag{8}$$

For this particular analysis, $D^{-1}_{(1,x_{i,to})}$ is calculated as

$$\begin{aligned} & D^{-1}_{(1,x_{i,to})} = \min_{\gamma,\delta} \gamma \\ & s.t. \textstyle\sum_{k=1}^{K} \delta_{k,to} x_{n,k,to} \leq \gamma x_{n,i,to} \text{ with } n = 1, 2, \ldots, N \\ & \textstyle\sum_{k=1}^{K} \delta_{k,to} = 1 \\ & \delta_{k,to} \geq 0 \text{ with } k = 1, \ldots, K. \end{aligned} \tag{9}$$

Note that in the LP problem (9), the comparison is between $x_{i,to}$ and other countries' vectors but only for year t_o instead of including observations of all years, as in problem (7). The decision variables (γ and δ) in problem (9) are different from those in (7) (θ and λ) to highlight the fact that (7) and (9) are different problems leading to different solutions. Results from (9 determine the distance to the maximum potential intensity, the IG, for each country in every year and trace the evolution of this gap. The solution of problem (9) also provides the potential intensity for each country, so changes in the IG for a particular country can be decomposed into intensity changes in that particular country and changes in the potential intensity, which means that countries with the highest intensities (defining the benchmark isoquant in each year) are reducing R&D investment relative to changes in *GDP*, *AgGDP*, *y*, *DI*, and *SP*.

As mentioned before, problem (7) gives a measure of the distance from vector $x_{i,n,to}$ to the frontier, that is, a measure of country *i*'s total input per unit of R&D investment relative to that of the country with the lowest aggregated input per unit of R&D investment among those countries with the same input mix as country *i*. However, it is not clear from problem (7) how the different intensity components are aggregated to obtain the measure of total input that allows this comparison. To better understand this, it is convenient to present the dual to problem (7). The dual LP problem (10) generates the same result as problem (7) but better shows the intuition of the method employed to build the AII. The dual problem is as follows:[2]

$$\begin{aligned} & \min_{u,v} \Theta_i = \textstyle\sum_{n=1}^{N} v_{i,n} x_{i,n} \\ & s.t. \textstyle\sum_{n=1}^{N} v_{j,n} x_{j,n} \geq 1 \text{ with } j = 1, \ldots, K \\ & v \geq 0. \end{aligned} \tag{10}$$

The objective function in problem (10) is the weighted sum of the inverse of the different IRs, where $N = 5$ in the particular case of the AII, as defined here. Solving problem (10) finds the weights or shadow prices $v_{i,n}$ for all inputs in country *i* that minimize expression Θ. We define the shadow price of input *n* ($v_{i,n}$) as the achievable rate of increase in the objective function per unit increase in input *n*. Formally stated, the shadow price of input *n* is defined as

$$v_{i,n} = \frac{\partial \Theta^*}{\partial v_{i,n}}, \tag{11}$$

where Θ^* denotes the optimal value of the objective function, provided only increases in $v_{i,n}$ are allowed. Translating this to the particular problem in this study, the shadow price gives a measure of how much country *i* can increase output (R&D) by increasing one unit of input *n* (*GDP, AgGDP, income, DI*, or *SP*). Equivalently, the shadow price of decision unit *i* is a measure of how much *i* is willing to pay for an extra unit of input *n*. The higher the shadow price, the more constraining the input is, the bigger the increase in intensity with a change of this input, and the more *i* is willing to pay for this input.

[2] This particular form of the dual problem has an infinite number of solutions, so to solve this problem we need to impose the constraint that $v'x_i = 1$ and modify the problem accordingly.

Data on agricultural expenditures of 88 developing and high-income countries[3] were obtained from Agricultural Science and Technology Indicators (ASTI 2016); data on GDP, AgGDP, and GDP per capita are from World Bank (2015); and detailed agricultural production data at the crop and livestock activity level to calculate diversification and distance between countries are from FAO (2015). The dataset covers the period 1981–2011. All figures were converted to 2011 purchasing power parity (PPP) US dollars.[4] The next section looks at the results of the calculation of the intensity index and the IGs for developing countries. It also looks at shadow prices to see how the different subindexes constrain research intensity in different regions and at different levels of development.

[3] The list of countries, together with average values of the variables used in the analysis, can be found in Appendix B.

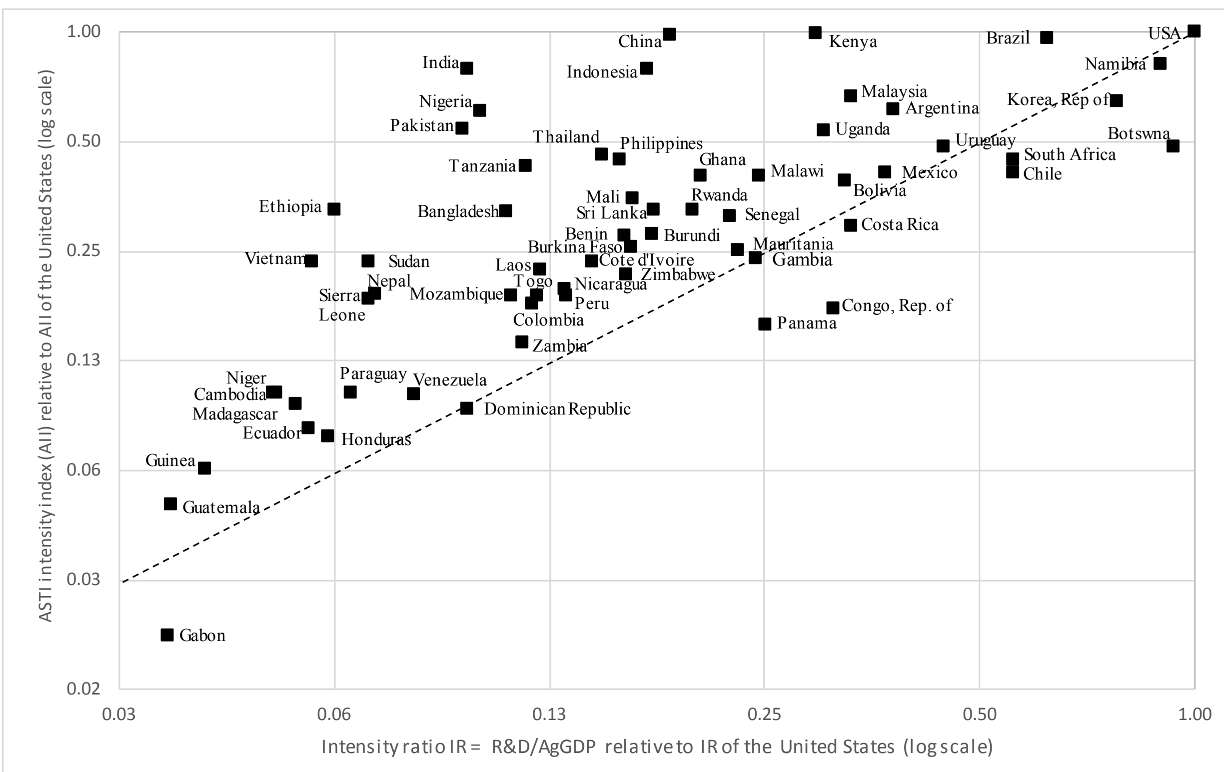
[4] Unless otherwise stated, all dollar values in this document are in 2011 PPP US dollar exchange rates, which reflect the purchasing power of currencies more effectively than do standard exchange rates because they compare the prices of a broader range of nontradable—as opposed to internationally traded—goods and services.

4. RESULTS

Figure 4.1 compares the proposed ASTI (Agricultural Science and Technology Indicators) intensity index (AII) measure with the conventional IR measure using data for developing countries. The AII and IR are shown as the coordinates of the country points in the vertical and horizontal axes, respectively. Values of the IR and AII are shown as relative to those of the United States to facilitate comparisons (US coordinates in the figure are (1, 1)). The 45^{o} line shows the points where the two measures take the same value as a proportion of US values.

The correlation between the two indicators in Figure 4.1 is 0.54 (recall that IR is one of the components of AII), but the two measures result in very different country rankings of research and development (R&D) intensity. Large Asian countries like China, India, and Indonesia show IR values that are less than 25 percent of those of the United States (10 percent in the case of India). The developing countries showing the highest IR are Botswana and Namibia, middle-income countries with small economies and relatively small agricultural sectors. These two countries are followed by Brazil, South Africa, and Chile, all with intensities greater than 50 percent of that of the United States.

Figure 4.1 The ASTI intensity index and the R&D IR for developing countries and regions compared to the United States, average 2001–2011



Source: Created by author, based on ASTI (2016), FAO (2015), and World Bank (2015) data.

Note: Agricultural expenditures data are from ASTI. GDP and AgGDP data are from the World Bank. Agricultural production data are from FAO. AgGDP = agricultural gross domestic product; ASTI = Agricultural Science and Technology Indicators; GDP = gross domestic product; IR = intensity ratio; R&D = research and development. The figure shows average values for the period 2001-2011 to better reflect the effect of increased R&D investment in developing regions in recent years.

The R&D intensity ranking using the AII shows a very different picture of R&D investment effort than does the conventional IR calculation. First, there are more countries with intensities higher than 50 percent of US intensity (12 instead of only 6 when using IR). For example, China's AII is almost the same as that of the United States (0.98); India's and Indonesia's are both 0.80, and Nigeria's is 0.61. When using the IR, all these countries are less than 18 percent of US values (China), and as low as 10 percent (India and Nigeria). Brazil and Kenya also show intensity values equivalent to those of the United States (AII close to 1), compared with 62 and 30 percent, respectively, when using the IR. Other countries also showing high R&D intensity as measured by the AII are Malaysia, Argentina, Pakistan, Uganda, Namibia, and the Republic of Korea. Second, with a few exceptions, most countries are above the 45° line, meaning that they show higher levels of R&D investment intensity when the AII is used instead of the IR. Exceptions include Botswana, whose R&D intensity falls to 48 percent of that of the United States when using the AII, compared with 93 percent when using the IR. Also with lower intensity than that shown by the IR are South Africa, the Republic of the Congo, and Panama. Finally, several countries with very low IR values (less than 25 percent of US values) are shown to have much higher intensity values when measured by the AII. Among these countries, Ethiopia, with an IR of 6 percent, shows an AII of 35 percent of that of the United States. Other countries for which the AII shows a much higher intensity than that shown by the IR are Tanzania, Bangladesh, Thailand, the Philippines, Ghana, Malawi, Mali, and Sri Lanka, to name a few.

Figure 4.2 shows the evolution of weighted averages[5] of the AII, IR, and yearly R&D expenditure, all values relative to those of the United States in 2005. As in the case of individual countries in Figure 4.1, the AII gives a very different picture of intensity levels and their trends between regions. The AII is presented in Panel A of Figure 4.2. It comes as a surprise that the East and Southeast Asian countries (ESEA) are the region consistently showing the highest R&D investment intensity over the last 30 years. In 1981, the AII for this region was 77 percent of that of the United States in 2005, and it increased to 90 percent by 2011. Intensity in high-income (HI) countries in 1981 was 60 percent, and it had increased to 80 percent of the US 2005 value by 2011. South Asia (SA), Latin America and the Caribbean (LAC), and Africa south of the Sahara (SSA) show similar values of AII in 1981, all between 40 and 50 percent of US 2005 values, but the path followed by the AII in the past 30 years has been very different for the three regions. First, SA increased its intensity significantly during the period, growing from 47 percent of US 2005 values in 1981 to 64 percent in 1990, and accelerating after 1996 to catch up to the intensity levels of ESEA and HI countries by 2005. In the case of SSA, the AII actually decreased, reaching its lowest level (29 percent of the US 2005 value) in 1994, and recovered after 1996, reaching a peak of 61 percent of the US 2005 value in 2008. After that, the data show a sharp decrease in intensity for SSA that takes the value of its AII to 42 percent of the US 2005 value, almost the same level as in 1981. Finally, LAC shows an intermediate path between those of SA and SSA, with AII values moving around an average of 50 percent of US 2005 values, although the last few years show a steady growth in intensity. Given the changing economic prospects for the region, we might see changes in this trend in the coming years.

Figure 4.2, Panel B compares the levels of R&D investment between regions and helps us visualize how the AII measures intensity relative to the structural characteristics of each region. Notice that R&D investment for HI countries is shown in the secondary vertical axis for comparison with the R&D values of developing regions. The level of R&D investment by HI countries in 1981 was 4 times greater than that of ESEA and LAC (2.0, compared with 0.5) and 7 times greater than the AII in SSA and SA. By the end of the period, ESEA had reached the investment levels that HI countries had in 1981 (4 times their levels in 1981). In the case of SA, investment at the beginning of the period was below that of SSA, but by 2011 it was twice as large as SSA's investment and almost the same as LAC's. Investment in LAC and SSA in 2011 was roughly 1.5 times bigger than investment in 1981, which explains why LAC

[5] Agricultural gross domestic product is used as a weight to calculate regional averages, so results should be driven by countries like the United States, Japan, China, India, Brazil, Indonesia, and Nigeria, among other large economies within each region.

fell behind ESEA and was caught up with by SA, and why SSA fell behind SA. These results are already showing which regions are more likely to be underinvesting in R&D.

Finally, Panel C of Figure 4.2 shows the contrasting picture that we obtain when using the IR instead of AII as a measure of intensity. In this case, HI countries show the highest intensity, several times larger than the IR of LAC, the developing region with the highest IR (close to 35 percent of the US 2005 value, compared with 80–120 percent for HI countries). SSA and ESEA show similar IRs throughout the period (only 17 percent of US 2005 values), which are higher than SA's IR values. SA shows the lowest IR (8 percent of US 2005 in 1981, increasing to 14 percent in 2011).

Figure 4.2 Indexes showing the evolution of R&D investment, AII, and IR, measured as a weighted average of the values for countries in each region, 88 countries, 1981–2011

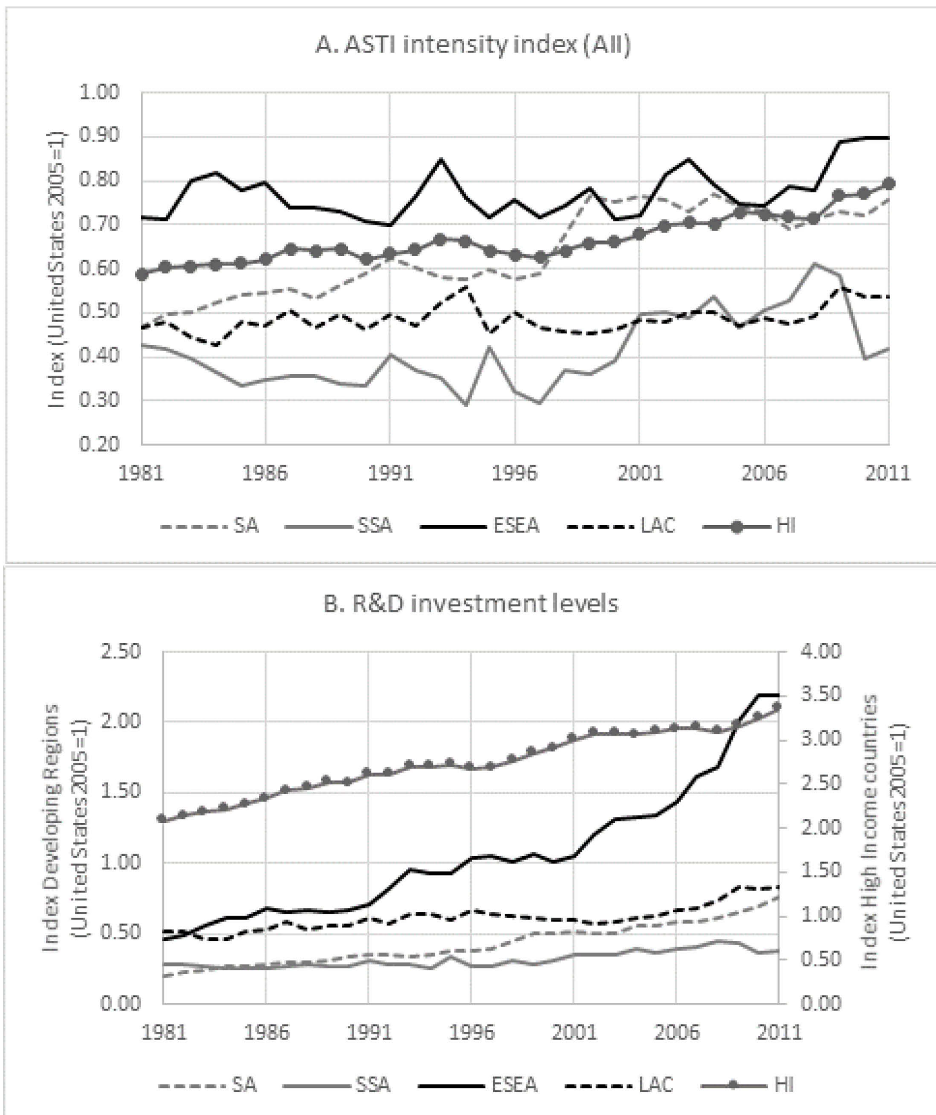
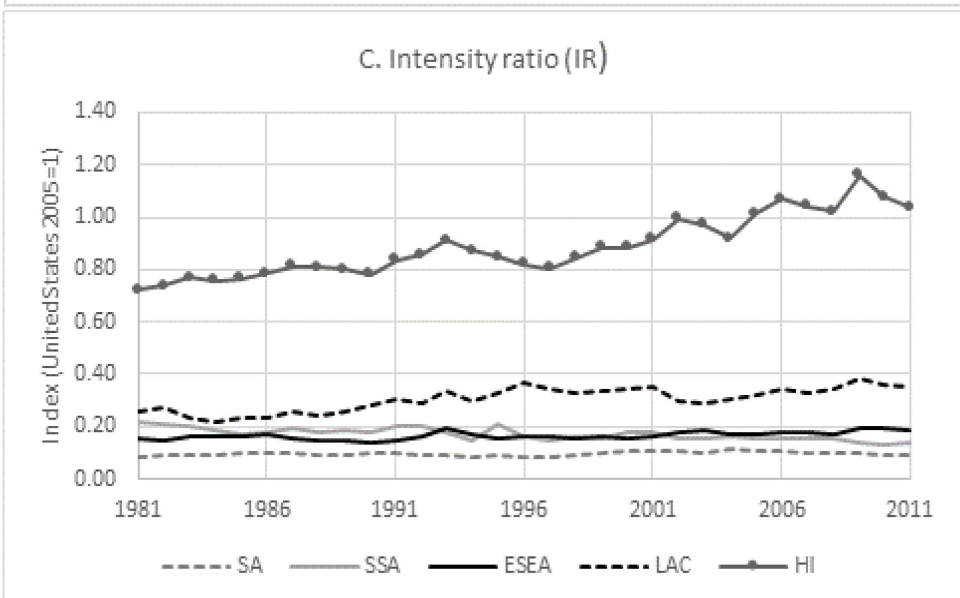


Figure 4.2 Continued

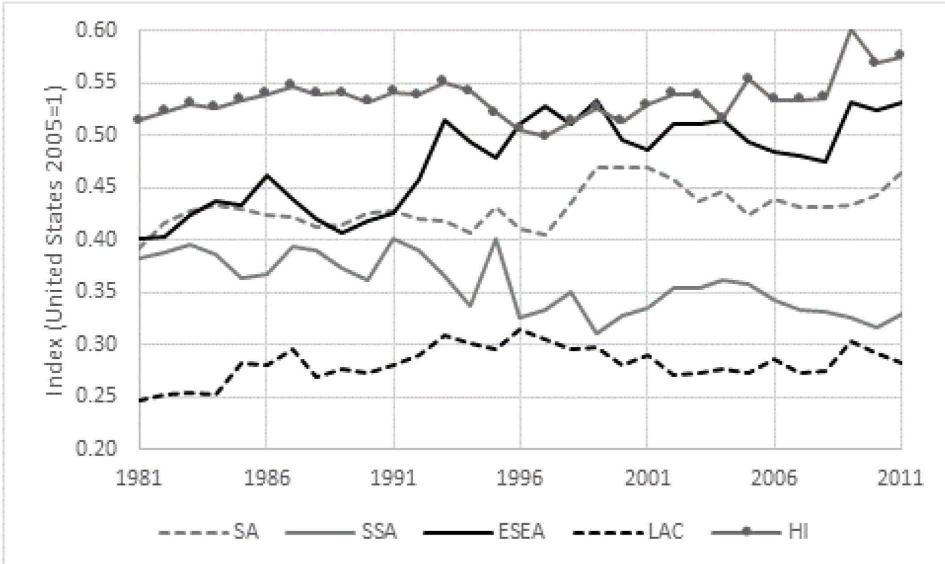


Source: Created by author, based on ASTI (2016), FAO (2015), and World Bank (2015) data.
Note: Agricultural expenditures data are from ASTI. GDP and AgGDP data are from the World Bank. Agricultural production data are from FAO. AII = ASTI (Agricultural Science and Technology Indicators) intensity index; ESEA = East and Southeast Asian countries; IR = intensity ratio; LAC = Latin America and the Caribbean; R&D = research and development; SA = South Asia; SSA = Africa south of the Sahara. Values are weighted averages of the different measures, with agricultural gross domestic product used as weight. All values are relative to those of the United States in 2005.

Figure 4.3 shows levels and trends of the AII for the period 1981–2011, as in Panel A of Figure 4.2, but this time using simple averages of AII values.[6] According to the AII values shown in the figure, R&D intensity is very low in LAC and SSA, and has even decreased during the period. For example, the AII for SSA measured relative to that of the United States in 2005 decreased from 0.38 to 0.33 between 1981 and 2011, equivalent to a -0.5 percent yearly growth rate. LAC also reduced R&D intensity, but negative growth occurred only after 1996. Intensity in ESEA shows significant growth during the 1980s (from 0.40 to 0.52 of the US 2005 level), and we also see a modest increase in SA in the second half of the 1990s, though SA's intensity remains below 0.50. Comparing Figure 4.3 with Panel A of Figure 4.2, which shows the weighted averages of AII, yields a very different picture. The low values and slower or negative growth obtained with the simple average AIIs suggest that countries with the largest agricultural sectors are the ones increasing intensity, while countries with smaller agricultural sectors are falling behind.

[6] The simple average better reflects the average performance of all countries in each region by giving the AII of large and small countries the same weight.

Figure 4.3 Evolution of AII measures as a simple average of countries in each region, 88 countries, 1981–2011

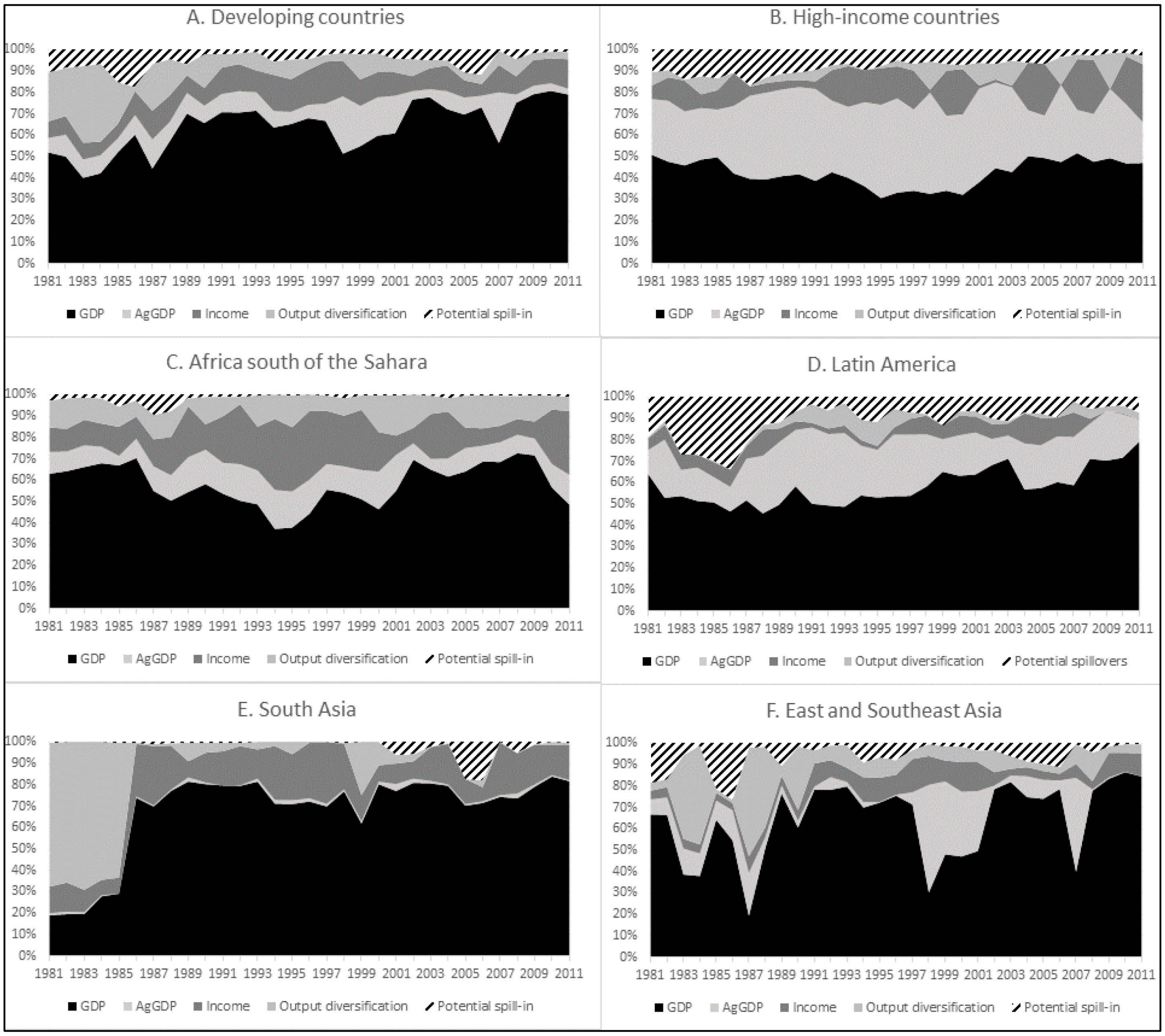


Source: Elaborated by author using ASTI (2016), FAO (2015), and World Bank (2015) data.
Note: Agricultural expenditures data are from ASTI. GDP and AgGDP data are from the World Bank. Agricultural production data are from FAO. AII = ASTI (Agricultural Science and Technology Indicators) intensity index; ESEA = East and Southeast Asian countries; HI = high-income countries; LAC = Latin America and the Caribbean; SA = South Asia; SSA = Africa south of the Sahara. All values are relative to those of the United States in 2005.

One of the features of the AII calculated in this study is the weights used to aggregate the five IRs, which are determined endogenously by the linear programming (LP) problem used by the data envelopment analysis approach. As discussed before, if we think of the LP problem as a production process in which we use agricultural gross domestic product (AgGDP), gross domestic product (GDP), income, a diversification index, and an indicator of potential spill-ins to "produce" R&D investment, then the weights from the LP problem can be thought of as shadow prices of the inputs of this problem. These prices can be interpreted as the price each country is willing to pay at the optimum for one extra unit of each input to increase R&D. The higher the price of a particular input, the higher is the increase in the objective function as a result of adding an extra unit of the input (that is, the higher the increase in R&D investment). Using these shadow prices and the quantities of each of the inputs, we can calculate the contribution of each of the five individual ratios to the total intensity index. The larger the share, the greater the weight of the individual ratio on the overall intensity index.

Figure 4.4 plots the evolution of average shadow shares in developing and HI countries and in four regions: SA, SSA, ESEA, and LAC. GDP has the largest share in all regions, but patterns and trends in the importance of the different ratios vary by region. For example, the size of the economy has been a major and growing constraint on intensity in developing countries (Panels A and B of Figures 4.4), while the size of the agricultural sector is a main constraint on increasing R&D intensity in HI countries.

Figure 4.4 Level and evolution of shadow shares of GDP, AgGDP, income, output diversification, and potential spill-in, average for developing and high-income countries and developing regions, 88 countries, 1981–2011



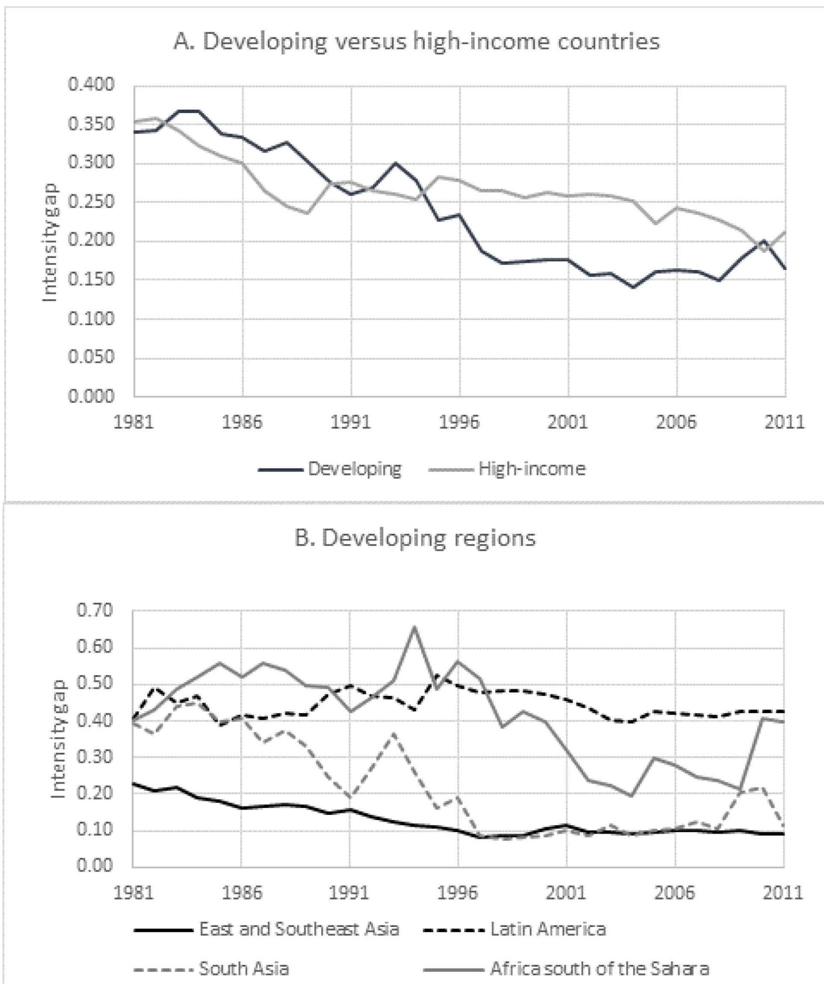
Source: Created by author; based on ASTI (2016), FAO (2015), and World Bank (2015) data.
Note: Agricultural expenditures data are from ASTI. GDP and AgGDP data are from the World Bank. Agricultural production data are from FAO. AgGDP = agricultural gross domestic product; GDP = gross domestic product.

Looking at developing regions, we find that the size of the economy is a major factor determining intensity in all regions, while income is an important constraint on intensity in SSA and SA. The size of the agricultural sector plays an important role in LAC and is also important in SSA, while ESEA shows periods during which this factor was an important constraint. Production specialization was a major factor determining intensity in SA and in ESEA in the early 1980s and still plays a role in SSA but has little importance in LAC. On the other hand, potential spill-ins affect intensity mostly in LAC and to a lower degree in ESEA.

We now present the intensity gap of R&D investment at the regional level. The gap is determined by comparing the multifactored intensity of each country, with the same mix of the five IRs included in the multifactored index, against that of countries with the highest intensity. These are the countries that define the "intensity frontier" for different mixes of the IRs. Panel A of Figure 4.5 shows the evolution of the intensity gap for HI and developing countries, while Panel B of Figure 4.5 shows the gap for different developing regions. The gap is defined as in problem (9) and is the difference between the maximum potential intensity (taking a value of 1) and the actual intensity measured relative to the potential intensity.

Panel A of Figure 4.5 shows a decreasing trend of the intensity gap for all developing regions, but with a change in the speed at which regions were reducing the gap in the early years of this century. This change is related to accelerated growth of AgGDP, GDP, and income, rather than to a slowdown in R&D investment, as shown before. LAC shows the highest gap among all regions, reaching 50 percent of potential intensity in the mid-1990s and decreasing to 40 percent 10 years later. SA and SSA started with very similar intensity gaps in 1981 (around 40 percent of potential intensity), but in the case of SSA, the gap increased to the highest value among developing regions (60 percent) by 1996 and then decreased to 20 percent after the turn of the millennium. The gap in SA decreased to 10 percent after 1996 and has remained at this level, with some fluctuations, especially in the most recent years. The region with the smallest intensity gap is ESEA, starting at 20 percent in 1981, reaching 10 percent in 1996, and remaining at that level until recent years.

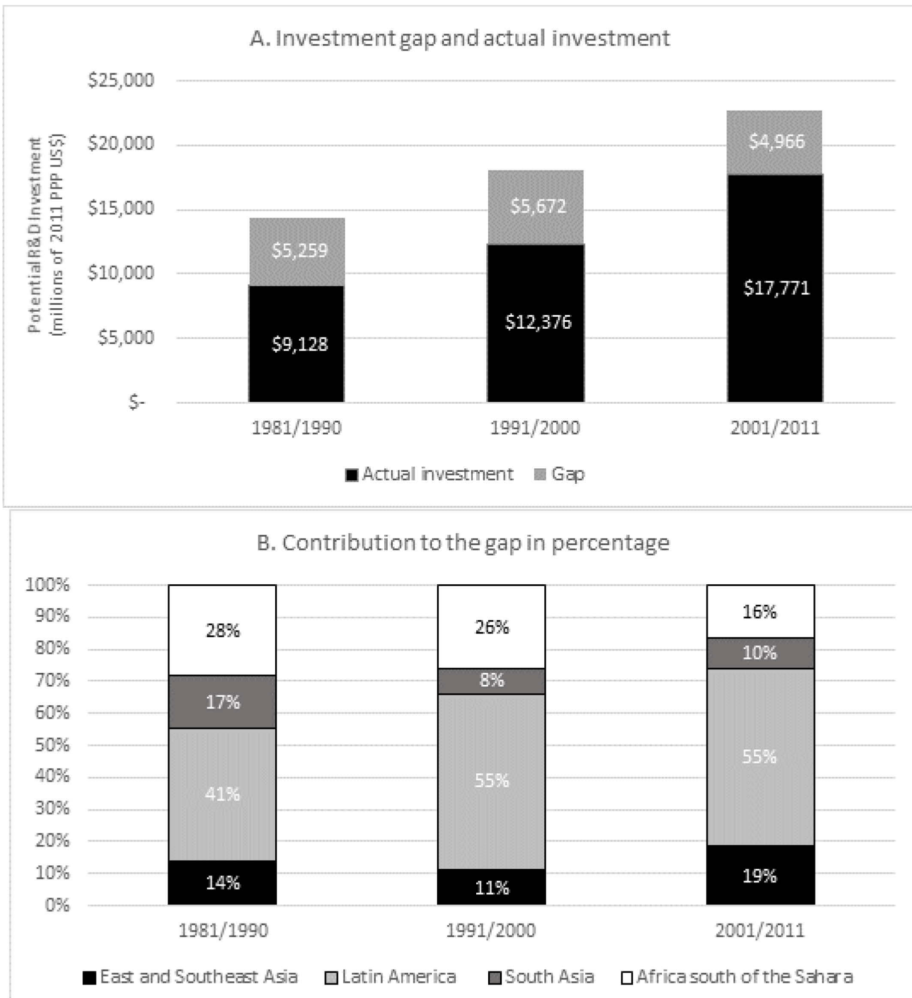
Figure 4.5 Evolution of the intensity gap, total of developing versus high-income countries (Panel A), and comparison of developing regions (Panel B), weighted averages, 1981–2011



Source: Created by author, based on ASTI (2016), FAO (2015), and World Bank (2015) data.
Note: Agricultural expenditures data are from ASTI. GDP and AgGDP data are from the World Bank. Agricultural production data are from FAO. Averages are calculated using agricultural gross domestic products as weights.

How much R&D investment is needed to close the intensity gap shown in Figure 4.5? We answer this question in Figure 4.6. The total investment gap has not changed significantly in absolute terms in the last 30 years: $5.3 billion, $5.7 billion, and $5.0 billion (US dollars, 2011 purchasing power parity) in the 1980s, 1990s, and first decade of this century, respectively (Panel A of Figure 4.6). Most important, total R&D investment in developing countries almost doubled in the last 30 years, from $9.1 billion to $17.8 billion. This growth reduced the gap from almost 57 percent of total investment in the 1980s to only 28 percent in the first decade of the 21st century.

Figure 4.6 Investment gap and actual investment (Panel A), and relative contributions to the gap (Panel B), developing countries, weighted averages 2006–2011



Source: Created by author, based on ASTI (2016), FAO (2015), and World Bank (2015) data.
Note: Agricultural expenditures data are from ASTI. GDP and AgGDP data are from the World Bank. Agricultural production data are from FAO. Averages are calculated using agricultural gross domestic products as weights. PPP = purchasing power parity; R&D = research and development; SSA = Africa south of the Sahara.

Historically, LAC is the region that contributes the most to the investment gap, explaining about half of the total gap in developing countries in the last 30 years (Panel B of Figure 4.6). SSA's intensity gap in the first decade of this century, representing 16 percent of the total gap, is down from 28 percent in the 1980s. SA has also reduced its share in the global gap from 17 percent in the 1980s to 10 percent in the first decade of this century. On the other hand, ESEA, the region with highest investment intensity, has increased its share in the total gap from 14 to 19 percent in the last 30 years.

Table 4.1 displays the average 2008–2011 values of the AII, the IR, and the investment gap, as well as the target values of the AII and IR needed by different countries to close the R&D investment gap. The table also shows the actual investment and the amount of investment needed to close the gap. Results show that that larger or richer countries have the highest target values of the AII (more than 0.80, or 80 percent of the US value). This is the case for China, Indonesia, the Republic of Korea, Brazil, Egypt, Mexico, and Turkey. Alternatively, small or low-income economies, like Ethiopia, Madagascar, Senegal, Zimbabwe, Bangladesh, Burkina Faso, Guinea, Mozambique, Mauritania, Malawi, Mali, Gambia, Rwanda, Niger, Benin, Sierra Leone, Togo, and Burundi, need to reach values below 0.50 of the US AII value to close the intensity gap. Within this group, low-income but relatively large economies like Ethiopia and Madagascar show the highest potential values (around 0.50). On the other hand, low-income and small economies like Rwanda, Niger, Benin, Sierra Leone, Togo, and Burundi have AII target values below 0.30. The countries at the top and bottom of the table represent about one-third of the countries in our sample. Table 4.1 also shows the average IR for each country (2008–2011) and the IR needed to close the investment gap. The large Asian countries that are big R&D investors, such as China and India, are able to close the investment gap by reaching IR values of 0.56 and 0.33, respectively. This doesn't mean that these countries cannot reach a 1 percent IR target but rather that there are no countries with their characteristics investing at higher intensity. On the other hand, a country like Brazil needs an IR of almost 2 percent to close the investment gap.

Which are the countries explaining most of the gap of about US$7.0 billion (last row of Table 4.1)? Three-quarters of the total investment intensity gap in 2008–2011 was concentrated in 17 countries: Mexico, Venezuela, Colombia, Republic of Korea, Thailand, Vietnam, India, the Philippines, South Africa, Peru, Pakistan, Argentina, Sudan, Ecuador, Nigeria, Bangladesh, and Guatemala. In contrast, the 30 countries at the bottom of Table 4.1 account for only 11 percent of the gap, and 25 of these countries are from SSA.

Table 4.1 Investment gap and R&D investment needed to close the gap, in millions of 2011 US dollars, average values 2008–2011

			R&D expenditure (millions of 2011 PPP US$)				Intensity ratio (IR), percentage	
Region	**Country**	**All**	**Actual**	**Potential**	**Actual/ Potential**	**Gap**	**Actual**	**Target**
Africa south of the Sahara	Benin	0.27	28	41	0.69	13	0.5	0.73
	Botswana	0.47	23	31	0.74	8	2.93	3.96
	Burkina Faso	0.25	26	52	0.5	26	0.51	1.01
	Burundi	0.27	15	17	0.83	3	0.55	0.66
	Congo, Rep. of	0.17	8	29	0.27	21	0.98	3.57
	Côte d'Ivoire	0.23	57	128	0.44	72	0.45	1.02
	Ethiopia	0.32	82	137	0.6	55	0.2	0.33
	Gabon	0.02	1	38	0.03	36	0.12	3.36
	Gambia	0.23	4	7	0.57	3	0.77	1.35
	Ghana	0.39	138	182	0.76	44	0.64	0.84
	Guinea	0.06	4	33	0.12	29	0.13	1.07
	Kenya	0.97	247	247	1	0	0.93	0.93
	Madagascar	0.09	14	77	0.18	62	0.17	0.94
	Malawi	0.39	25	29	0.87	4	0.77	0.88
	Mali	0.34	46	59	0.79	13	0.51	0.65
	Mauritania	0.24	12	24	0.5	12	0.72	1.44
	Mozambique	0.18	23	56	0.4	33	0.35	0.86
	Namibia	0.79	45	45	1	0	2.82	2.82
	Niger	0.1	8	34	0.25	26	0.16	0.66

Table 4.1 Continued

Region	Country	All	R&D expenditure (millions of 2011 PPP US$) Actual	Potential	Actual/ Potential	Gap	Intensity ratio (IR), percentage Actual	Target
Africa south of the Sahara	Nigeria	0.59	721	893	0.81	172	0.32	0.39
	Rwanda	0.32	27	35	0.78	8	0.62	0.8
	Senegal	0.3	32	57	0.57	24	0.7	1.23
	Sierra Leone	0.18	10	20	0.47	11	0.22	0.47
	South Africa	0.44	301	569	0.53	268	1.75	3.31
	Sudan	0.23	82	293	0.28	210	0.22	0.78
	Tanzania	0.42	105	211	0.5	106	0.37	0.73
	Togo	0.18	10	21	0.48	11	0.38	0.79
	Uganda	0.52	119	124	0.96	5	0.95	1
	Zambia	0.14	18	72	0.24	55	0.36	1.49
	Zimbabwe	0.21	15	38	0.39	23	0.5	1.3
	Total	n.a.	21,429	28,471	n.a.	7,042	n.a.	n.a.
East and South east Asia	Cambodia	0.1	21	91	0.23	70	0.16	0.71
	China	0.95	7,059	7,059	1.00	0	0.58	0.58
	Indonesia	0.77	1,513	1,631	0.93	118	0.54	0.58
	Korea, Rep. of	0.63	908	1,297	0.70	388	2.44	3.49
	Lao	0.22	30	62	0.49	32	0.38	0.79
	Malaysia	0.65	599	607	0.99	8	1.04	1.05
	Philippines	0.43	322	598	0.54	276	0.49	0.92
	Thailand	0.45	467	856	0.55	388	0.46	0.85
	Vietnam	0.23	136	479	0.28	343	0.18	0.64
Latin Americ a and Caribb ean	Argentina	0.6	580	798	0.73	218	1.19	1.64
	Bolivia	0.38	56	85	0.66	29	1.02	1.55
	Brazil	0.94	2,390	2,390	1.00	0	1.96	1.96
	Chile	0.4	186	318	0.59	132	1.75	2.99
	Colombia	0.18	122	567	0.22	445	0.37	1.72
	Costa Rica	0.28	38	82	0.46	44	1.04	2.25
	Dominican Rep.	0.09	20	133	0.15	113	0.30	2.04
	Ecuador	0.08	24	198	0.12	174	0.18	1.49
	Guatemala	0.05	13	155	0.08	142	0.12	1.41
	Honduras	0.08	8	59	0.13	52	0.19	1.52
	Mexico	0.4	693	1,589	0.44	896	1.16	2.66
	Nicaragua	0.18	16	52	0.31	35	0.41	1.32
	Panama	0.15	16	65	0.24	50	0.79	3.28
	Paraguay	0.1	18	100	0.18	83	0.21	1.19
	Peru	0.19	80	338	0.24	257	0.41	1.74
	Uruguay	0.47	67	85	0.80	17	1.40	1.76
	Venezuela	0.1	63	516	0.12	453	0.25	2.08
South Asia	Bangladesh	0.31	224	395	0.57	171	0.34	0.60
	India	0.77	2,845	3,144	0.90	299	0.30	0.33
	Nepal	0.19	41	132	0.31	91	0.22	0.72
	Pakistan	0.53	522	748	0.70	226	0.30	0.43
	Sri Lanka	0.32	107	245	0.44	138	0.55	1.26

Source: Created by author, based on ASTI (2016), FAO (2015), and World Bank (2015) data.
Note: Agricultural expenditures data are from ASTI. GDP and AgGDP data are from the World Bank. Agricultural production data are from FAO. AII = ASTI (Agricultural Science and Technology Indicators) intensity index; n. a. = not applicable; PPP = purchasing power parity; R&D = research and development.

5. CONCLUSIONS

This paper argues that the IR is an inadequate indicator to measure and compare agricultural research effort at the country level. This is because this measure assumes that the level of research and development (R&D) investment in every country should be proportional to the size of its agricultural sector. The literature on R&D investment and the analysis conducted in this paper show that the capacity of countries to invest does not depend only on the size of their agricultural sector but also on other structural variables not controlled by policy makers. As a result, the capacity of countries to invest changes with the particular levels and combination of these variables, which explains why the IR in most cases does not reflect the investment effort made by countries.

To overcome the problems of the conventional measure of R&D intensity, this study proposes a multifactored indicator of R&D intensity that combines five different IRs, each of them relating R&D investment to one of five variables that are proxies for structural characteristics that affect a country's possibilities for investment. These variables are agricultural gross domestic product (AgGDP), representing size of the agricultural sector; gross domestic product (GDP) as a proxy for the size of the economy; GDP per capita as a measure of income; an index used to measure diversification in agricultural production; and a measure of potential spill-ins that measures the distance between countries based on similarities in their mix of outputs and inputs used in agricultural production. The main difficulty in building this indicator is to define the weights to use to aggregate the five partial intensity measures into a single index of intensity. These weights should reflect the importance that each of the five individual ratios included in the index has as a constraint on investment in each country. We solve the problem of defining these weights by using a data envelopment analysis approach. This method is ideally suited for the task at hand because it yields the most favorable country-specific weights for the different components of the proposed intensity measure.

Our results show that the ASTI (Agricultural Science and Technology Indicators) intensity index (AII) provides a very different picture of international agricultural R&D investment intensity than the one obtained using the conventional IR. When using the IR as the research intensity indicator, high-income countries show the highest levels of R&D intensity, most of them with values greater than 1 percent (in many cases greater than 2 or 3 percent), while most developing countries show IRs lower than 1 percent, with the lowest values observed among Asian countries (lower than 0.6 percent). In contrast, when we use the AII as the measure of investment intensity, we find developing countries like Brazil, China, Kenya, Indonesia, and India at the highest levels of R&D intensity.

We used the same methodology to determine the potential intensity of R&D investment that countries can reach given their economic size, income, specialization, and potential to receive technology spill-ins. We find that Brazil, Namibia, Kenya, and China, with intensity gaps equal to 0, are the developing countries with the highest intensity values in most years for the period 1981–2011. Other countries showing high R&D investment and low intensity gaps are Malaysia, Nigeria, and Uganda.

The intensity gap in developing countries decreased by half between 1981 and 2011 (from 35 to 17 percent of potential investment), a reduction explained by increased investment in all developing regions. Comparing intensity levels in different regions for the most recent years, we observe that investment intensity in Asian countries is on average closer to potential intensity than in other regions. To close the R&D intensity gap in developing countries as measured by the AII, countries will need to invest $7.1 billion more than the $21.4 billion (US dollars, 2011 purchasing power parity) invested on average in 2008–2011, an increase of 33 percent of total actual R&D investment.

APPENDIX A: SIMILARITY AND DIVERSIFICATION

To measure "similarity" between countries, a linear country-to-country spillover relationship is assumed, and a spillover coefficient ω_{ij} is defined as the geometric mean of an output spillover coefficient ω^{o}_{ij} and an input spillover coefficient ω^{f}_{ij}. This coefficient is a weight that measures the potential contribution of a unit of the knowledge stock created in country *j* to the knowledge stock used in country *i*:

$$\omega_{ij} = \left(\omega_{ij}^{q} \times \omega_{ij}^{f}\right)^{1/2} = \left(\frac{\sum_{m=1}^{M} q_{mi} q_{mj}}{\left(\sum_{m}^{M} q_{mi}^{2}\right)^{1/2}\left(\sum_{m}^{M} q_{mj}^{2}\right)^{1/2}} \times \frac{\sum_{n=1}^{N} f_{ni} f_{nj}}{\left(\sum_{n}^{N} f_{ni}^{2}\right)^{1/2}\left(\sum_{n}^{N} f_{nj}^{2}\right)^{1/2}}\right)^{\frac{1}{2}}, \qquad \text{(A.1)}$$

where q_{mi} represents the share of output *m* in country *i*'s agriculture, and f_{ni} is the amount of input *n* used per worker in country *i*. Calculated in this way, ω_{ij} can be interpreted as a multivariate correlation coefficient that varies between 0 and 1: a high value indicates high similarity in output and in the intensity of the use of different inputs in the two countries (Eberhardt and Teal 2013). Potential spill-ins for country *i* result from the product of ω_{ij} and the knowledge stock in country *j*, approximated using the perpetual inventory method, assuming a 10-year lag between the investment period and the period in which this investment has an effect on productivity, and a decay rate of the knowledge stock of 15 percent.[7]

As a proxy for diversification in agriculture, the Herfindahl-Hirschman index, which is frequently used to measure industrial concentration and corporate diversification (Jacquemin and Berry 1979), is adapted to define a diversification index taking a value between 0 and 1 (with 0 being the highest specialization):

$$DI_i = 1 - \sum_{m=1}^{M} q_{im}^{2} \qquad \text{(A.2)}$$

where q_{im} is again the share of output *m* in country *i*'s agricultural production.

[7] See discussion in Esposti and Pierani (2003, 45).

APPENDIX B: COUNTRIES AND REGIONS

The sample of countries used in this study includes a total of 88 countries in four groups. The complete list of countries is shown in Table B.1.

Table B.1 Average values of variables used in the analysis by country and region relative to United States values, 1981–2011

Region/country	R&D	AgGDP	GDP	GDP per capita	Diversification	Potential spill-ins
Africa south of the Sahara	***38***	***236***	***13***	***13***	***29***	***174***
Benin	0	2	0	4	96	264
Botswana	0	0	0	22	80	168
Burkina Faso	1	2	0	3	102	166
Burundi	1	2	0	2	85	247
Congo, Rep. of	0	1	0	13	94	365
Côte d'Ivoire	2	8	0	8	97	265
Ethiopia	1	16	0	2	104	121
Gabon	0	1	0	45	95	389
Gambia	0	0	0	4	84	286
Ghana	2	11	0	5	99	312
Guinea	0	1	0	3	101	149
Kenya	5	14	1	5	102	103
Madagascar	0	5	0	4	97	123
Malawi	1	2	0	1	100	149
Mali	1	4	0	3	102	151
Mauritania	0	1	0	6	98	277
Mozambique	0	2	0	1	95	257
Namibia	1	1	0	16	77	180
Niger	0	2	0	2	98	181
Nigeria	9	96	4	8	101	268
Rwanda	0	2	0	2	85	240
Senegal	1	2	0	5	94	175
Sierra Leone	0	2	0	3	95	159
South Africa	7	12	4	26	101	87
Sudan	2	20	1	7	102	139
Tanzania	1	13	0	4	102	108
Togo	0	1	0	3	99	203
Uganda	1	6	0	2	90	192
Zambia	1	3	0	6	99	112
Zimbabwe	0	3	0	5	99	118

Table B.1 Continued

Region/country	R&D	AgGDP	GDP	GDP per capita	Diversification	Potential spill-ins
East and Southeast Asia	***129***	***775***	***68***	***15***	***98***	***109***
Cambodia	0	5	0	4	71	166
China	64	465	40	9	102	89
Indonesia	28	132	10	13	92	144
Korea, Rep. of	12	29	7	43	99	87
Lao PDR	1	4	0	5	74	165
Malaysia	10	26	3	33	84	225
Philippines	6	39	3	11	99	131
Thailand	8	42	4	20	96	117
Vietnam	1	33	2	6	83	130
Latin America and Caribbean	***74***	***249***	***45***	***29***	***100***	***99***
Argentina	9	25	5	35	96	106
Bolivia	1	3	0	10	101	103
Brazil	40	83	16	27	100	101
Chile	3	7	2	31	102	95
Colombia	3	26	3	20	100	110
Costa Rica	1	2	0	22	96	148
Dominican Republic	1	4	1	18	102	112
Ecuador	1	10	1	19	94	114
Guatemala	0	9	1	15	102	127
Honduras	0	2	0	9	98	97
Mexico	11	46	12	33	103	75
Nicaragua	0	2	0	9	99	87
Panama	0	1	0	24	92	108
Paraguay	0	4	0	15	96	133
Peru	1	9	2	17	104	83
Uruguay	1	3	0	28	86	125
Venezuela	1	12	3	37	99	86
South Asia	***52***	***545***	***29***	***6***	***99***	***122***
Bangladesh	3	34	2	4	63.2	234
India	34	411	22	6	102	107
Nepal	1	9	0	4	96	128
Pakistan	11	80	4	8	100	154
Sri Lanka	2	11	1	11	93	132

Source: Elaborated by author using ASTI (2016), FAO (2015), and World Bank (2015) data.
Note: AgGDP = agricultural gross domestic product; GDP = gross domestic product; R&D = research and development.

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