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Revisiting Rates of Return to Agricultural R&D Investment

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ABSTRACT

There is a vast literature that shows that investment in agricultural research and development (R&D) has historically yielded very high rates of return, an indication of substantial underinvestment in R&D. Given these unusually high returns, several studies in the past have tried to answer the question of why governments do not allocate more funds to this activity. Recent studies have found that methods used in past analyses have systematically overstated the rates of return to R&D. We identified three major methodological issues mentioned in the literature as being behind the implausibly high rates of return to R&D. First, most previous studies have tried to model research lags using econometric methods, restricting lag length based on empirical reasons rather than on some positive theory. Second, the econometric estimation of the research elasticity (the percentage change in productivity with a 1 percent change in the stock of knowledge), entails omitted variables and time-series econometric issues that can bias the results. Third, the internal rate of return (IRR) was the predominant measure used in the past to calculate returns to R&D, despite the restrictive assumptions used in its calculation, mainly, the rate at which benefits are invested during the life of the project. To avoid the first two issues, this study proposes a new approach to determine research lags that is based on the use of partial least squares (PLS) to obtain the key parameters of the perpetual inventory method(PIM) of capital stock. With the PLS estimated knowledge stocks and data on TFP growth, it is straight forward to calculate R&D elasticities and use the modified internal rate of return (MIRR) to calculate rates of return to R&D. This approach seems to perform well in an application to global agriculture with relatively short time series and supports findings from the literature showing that research lags are longer than those normally assumed in econometric analysis. Using this method, we obtain an average R&D elasticity for low and middle-income (LM) countries of 0.23 and an average rate of return to R&D investment of 6.0 percent, bigger than the average discount rate of 4.2 percent for these countries. Results show that 60 percent of LM countries in our sample are underinvesting in agricultural R&D, with benefit-cost ratios for R&D investment greater than 2.

Keywords: agriculture, knowledge stock, modified internal rate of return, partial least squares, R&D investment, R&D elasticity, returns to R&D, total factor productivity

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ACRONYMS

ASTI	Agricultural Science and Technology Indicators
BC	benefit-cost ratio
Bioversity	International
CIAT	International Center for Tropical Agriculture
CIMMYT	International Maize and Wheat Improvement Center
CIP	International Potato Center
ESEA	East and Southeast Asia
ICARDA	International Center for Agricultural Research in the Dry Areas
ICRAF	World Agroforestry Center
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
IITA	International Institute of Tropical Agriculture
ILRI	International Livestock Research Institute
IRRI	International Rice Research Institute
IWMI	International Water Management Institute
LAC	Latin America and the Caribbean
LHS	left-hand side
LM	low- and middle-income countries
MIRR	modified internal rate of return
PC	principal components
PIM	perpetual inventory method
PLS	partial least squares
R&D	research and development
RHS	right-hand side
SA	South Asia
SDR	social discount rate
SSA	Africa south of the Sahara
TFP	total factor productivity
WANA	West Asia and North Africa

1. INTRODUCTION

There is a vast literature going back to 1958 that shows that investment in agricultural public research and development (R&D) has historically yielded very high rates of return, which should be indicative of substantial underinvestment in R&D. However, countries never responded to these high rates of return by increasing investment. Instead. what we observed in the past 40 years is a slowdown in the rate of investment in high-income countries and no major changes, at least until recently, in the rate of investment in developing countries, except for investment in Brazil, China, and India which accelerated in the late 1990s.

Given the unusually high returns to public R&D, several studies in the past have tried to answer the question of why governments do not allocate more funds to this activity. For example, Hurley, Rao and Pardey (2014) argue that the clear majority of rate-of-return estimates were implausibly high and that the most plausible answer to this question is that economists got it wrong, systematically overstating the rates of return to R&D. The problem according to Hurley, Rao and Pardey (2014) relates to key methodological conventions that have dominated the agricultural R&D literature that go back to Griliches (1958).

We identified three major methodological issues discussed in the literature as being behind the implausibly high levels of the rates of return to R&D observed in the past. First, Esposti and Pierani (2003), Alston and Pardey (2001), and Griliches (1979, 1994) argue that most previous studies have tried to model research lags using econometric methods which were mainly selected for empirical reasons rather than on the basis of some positive theory. Second, the econometric estimation of the research elasticity (the percentage change in productivity with a 1 percent change in the stock of knowledge), according to Andersen (2015), entails omitted variables and time-series econometric issues, such as autocorrelation in the error terms, that can bias the results. A third problem with the estimation of rates of return relates to the use of the internal rate of return (IRR) as the predominant measure used by economists in the past. The main problems of the IRR are the restrictive assumptions used in its calculation: the rate at which benefits are invested during the life of the project and the simultaneous equality of the reinvestment and borrowing rates.

Several solutions to improve the estimation of R&D elasticities and rates of return have been proposed in the literature, but most of these solutions still rely on quality data and long time-series to properly model the lag structure of investment. When working with data on developing countries, however, lack of quality data and of long time-series still limit the use of these improved approaches.

The focus of this study is the estimation of rates of return to public agricultural R&D in low- and middle-income countries using an approach that intends to contribute to the literature and that looks for new methods to overcome the problems found in the empirical econometric studies. Given the brevity of available time series, instead of recurring to some of the improved econometric procedures that rely on long time series panels like, for example, the one used by Alston et al. (2011), we use instead the analytical framework used by Esposti and Pierani (2003) that relies on the perpetual inventory method (PIM) to calculate knowledge stocks and combine it with partial least squares (PLS), an approach that is particularly suited to the problem at hand. This approach also allows us to recover the full set of basic parameters in the PIM and, with them, the lag structure linking R&D expenditure to the accumulation of the knowledge stock and its impact on productivity.

When using the PIM, the lagged effect of R&D investment on productivity depends on three key unknown parameters: a) the rate of decay or depreciation; b) the length of the gestation period of investment; and c) a parameter (B) that determines the shape of the gestation period of investment. We use PLS to estimate the PIM parameters, a method similar to principal components (PC) that unlike PC takes into consideration the variation of the right-hand side (RHS) variables together with the variation of the left-hand side (LHS) variable. This approach allows us to recover the parameters of the PIM model using data with many, noisy, collinear, and even incomplete variables while providing quantitative multivariate modelling methods, with inferential possibilities like those of multiple regression, t-tests, and ANOVA (Wold et al. 2001). With the estimated PIM parameters, we can calculate R&D stocks for each country that can then be used to calculate knowledge spillovers based on “proximity” or similarity between countries. Total knowledge stock available to a country results from aggregating stocks from own R&D investment and stocks from spillovers. R&D elasticities for each country are calculated, following Andersen (2015), as the ratio of changes in total factor productivity (TFP) and knowledge stocks. Finally, we use modified internal rates of return as in Alston et al. (2011) and Hurley, Rao and Pardey (2014) to calculate returns to R&D for different countries and regions, which overcomes the known problems of the IRR.

The study is organized as follows: in the next section, we discuss the conceptual framework for the analysis and calculation of the knowledge stocks. In Section 3, we present the statistical assumptions and limitations associated with the PLS approach, and how this approach is used to estimate the parameters needed to calculate the knowledge stock and productivity response to investment. An application of the proposed approach to global agricultural R&D is presented in sections 4 and 5, where knowledge stocks, R&D elasticities, and rates of returns to R&D investment are calculated for a sample of 71 low- and middle-income countries. The last section concludes.

2. CONCEPTUAL FRAMEWORK

The underlying assumption behind the measurement of the returns to R&D is that a string of R&D investments creates a stock of knowledge that yields returns into the future (Hall, Mairesse and Mohnen 2009). To construct such a stock, we need to determine how fast R&D investment enters and exits the stock of knowledge, and how the stock depreciates. Almost all studies reviewed by Hall, Mairesse and Mohnen (2009) have used a simple perpetual inventory or declining balance methodology with a single depreciation rate to construct the knowledge capital produced by R&D investments. We follow this literature and in particular the work by Esposti and Pierani (2003) and adopt the perpetual inventory method (PIM) to build the R&D knowledge stock in analogy with physical capital, assuming an infinite lag distribution that can be derived by looking at the R&D investment characteristics. The model requires little information: an initial value of the stock, the series of gross R&D investment, and three key parameters: a geometric depreciation or decay rate of the stock (δ), a stochastic gestation lag period (G), and a parameter (β) that defines the shape of the gestation period.

As in Griliches (1996) and in Alston, Craig and Pardey (1998), we assume that even though knowledge does not depreciate physically, some knowledge becomes obsolete. In this context, the decay rate applied to knowledge or technological stock means that when more recent knowledge becomes available, the utilization of "old" ideas decreases and part of the stock becomes obsolete, with new R&D investments partially or wholly substituting old ones. Obsolescence could also result from external conditions, such as consumer preferences, in which case knowledge stock may also become obsolete without vanishing. Under these assumptions, research effects diminish over time but potentially last infinitely (Esposti and Pierani 2003).

The gestation period (G) of an investment in period t is the time that takes a certain investment to become fully efficient. This means that, for example, only a small proportion (eventually zero) of the investment in t will contribute to the knowledge stock during the initial periods after the investment is made, increasing its contribution until t+G, the end of the gestation period, the moment at which the investment becomes fully efficient with its maximum contribution to the knowledge stock. After t+G periods, the weight or contribution of that investment to the knowledge stock decreases because of decay or obsolescence, as discussed above.

The age-effectiveness function represents the lag structure of R&D expenditure determining the flow of benefits of R&D investment used in the calculation of rates of return. The shape of this function depends on the assumptions about the gestation period and on the depreciation rate. Formally, and assuming, without loss of generality, that there is no contribution of R&D expenditure to knowledge stock during the gestation, the knowledge stock in period t can be represented as follows:

$$T_t = T_{t-1}(1-\delta) + R_{t-G} \tag{2.1}$$

where *t* is the current period, δ is the decay rate or "depreciation" and *G* the gestation period.[1] By backward substitution, equation (2.1) can be expressed as an infinite weighted sum of past investments:

$$T_t = R_{t-G} + (1-\delta)R_{t-(G+1)} + (1-\delta)^2 R_{t-(G+2)} + \cdots + (1-\delta)^{s-G} R_{t-s} + \cdots \tag{2.2}$$

where the weights are a function of the decay rate and of the age of the investment. Equivalently, we can express (2.2) as follows:

$$T_t = \omega_0 R_t + \omega_1 R_{t-1} + \omega_2 R_{t-2} + \cdots + \omega_s R_{t-s} + \cdots \tag{2.3}$$

where $\omega_s = (1\text{-}\delta)^{s\text{-}G}$ is a weight in the range of (0,1) and *s* is the investment's age. In equations (2.2) and (2.3), the weight ω_s=1 if s=G, ω_s=0 if s<G, and 0<ω_s<1 if s>G. The ω_s in (2.3) can be interpreted as the contribution (productivity) of different "vintages" of R&D investment to the knowledge stock. They can also be viewed as the weights used to aggregate different vintages into one technology stock. The knowledge stock in *t* is the sum of past R&D investments calculated in efficiency units using weights that reflect the productivity of different investments and hence their contribution to the knowledge stock. On this basis, T_t is a measure of the aggregate knowledge stock at time *t*, since it

[1] As discussed in Alston, Craig and Pardey (1998), the use of the term "depreciation" applied to knowledge stock is not adequate, conceptually. Knowledge does not depreciate as physical capital does. A more accurate description of the process is that the stock of old knowledge decays as new ideas replace old ones. In other words, the stock of knowledge does not change, what changes is the proportion of useful knowledge in the total stock.

indicates the amount of new capital required to obtain the same level of services as supplied by the old vintage capital still in use (see discussion in Esposti and Pierani 2003). The constant δ implies geometric decay of the knowledge stock, a faster reduction of efficiency in the early part of the service life.

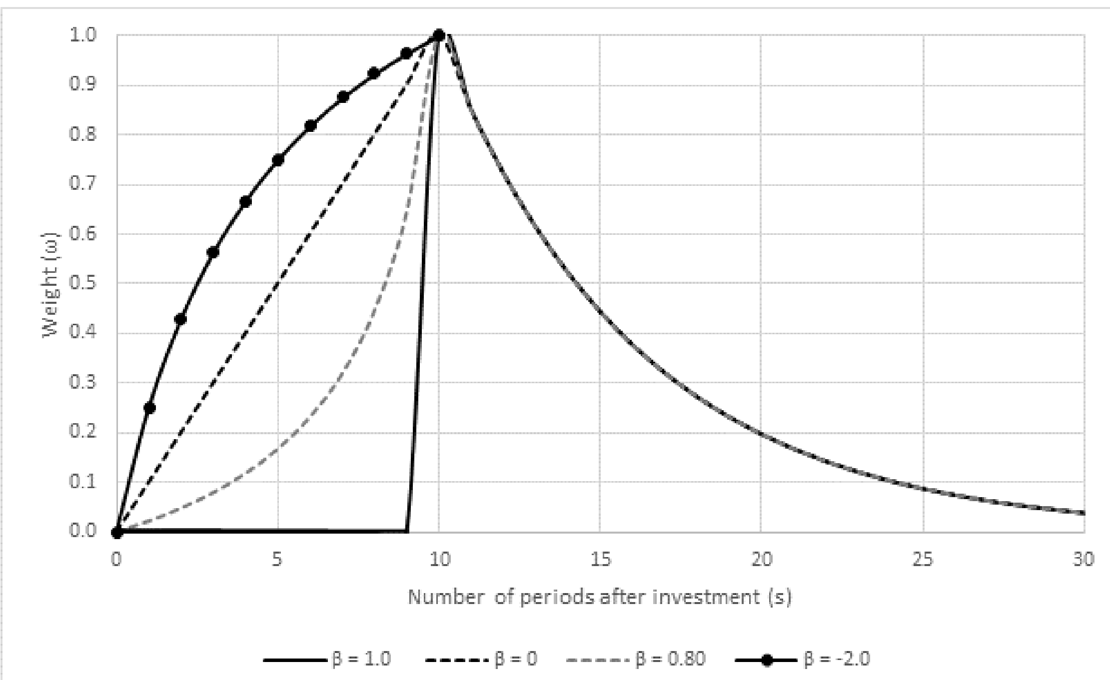
The case presented in equation (2.2), where $\omega_s=0$ if $s<0$, is only a particular case of a more general function that shapes the gestation period. This implies dividing the life of an investment into two periods. The first period, the gestation period, is finite and represents the period before full research results are obtained. The second phase or service life of the investment starts at period *G*, a period during which investment produces results that cumulate into knowledge stock and that could potentially last for infinite periods but with decreasing ω_s weights, if technological upgrading accelerates obsolescence. The contribution of a dollar invested in period $s=0$ to the knowledge stock in different years is what Esposti and Pierani (2003) called the *age/efficiency function* of R&D investment, a function that describes changes in the *effectiveness* of a single investment over the years and that also shows how different R&D investments are aggregated over vintages in one knowledge stock. Formally, this function can be represented by defining the ω_s weights as follows:

$$\begin{aligned}
&\omega_s = 0, \text{ if } s = 0 \\
&\omega_s = [(1-\beta)s]/[(G-\beta s)], \text{ if } 0 < s < G \\
&\omega_s = 1, \text{ if } s = G \\
&\omega_s = \prod_{i=G+1}^{s}(1-\delta_i),\ \forall i \in [G+1,\cdots,s], \text{ if } s > G
\end{aligned} \tag{2.4}$$

where *s* is age of the investment, *G* the gestation period, δ the decay rate, and β a curvature parameter incorporating different possible gestation periods (for $s<G$) as special cases. With $\beta=1$ we have the *"one-hoss shay"* form: no contribution of the R&D investment to knowledge stock until period *G,* which was the case represented in equation (2.2) and (2.3). As the value of β approaches zero, the contribution of a particular investment to the stock during gestation occurs at an increasing rate, reaching its maximum in G. The case where $\beta=0$ corresponds to the straight-line distribution, which results in the constant growth rate $1/G$. If $0<\beta<1$, the curve is convex: most efficiency gains occur towards the end of the gestation period, and the closer β is to 1 the more pronounced the efficiency gain is in the later years of gestation. Finally, β<0 results in a concave curve. Figure 2.1 shows the shape of *age/efficiency functions* of R&D investment differing only in the value of the parameter β, assuming values of G=10 and δ=0.15 for all curves. According to Esposti and Pierani (2003), the convex distribution seems to be the natural candidate to describe the early years of many research projects.

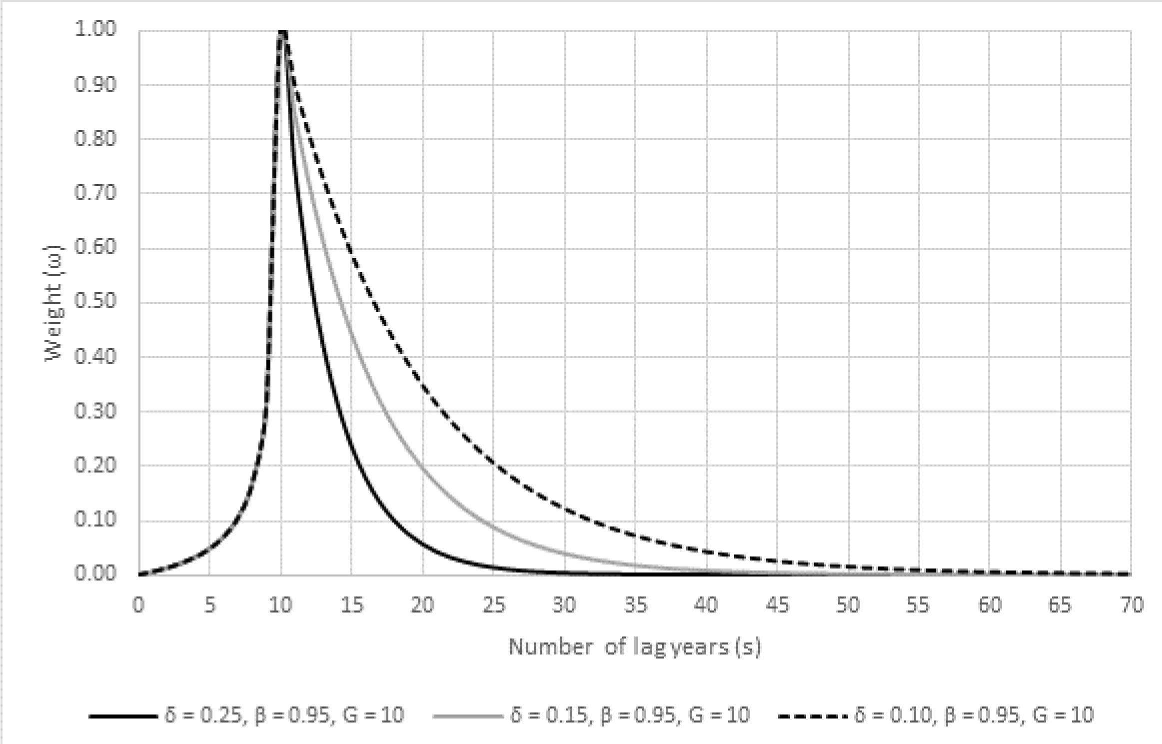
As in Figure 2.1, Figure 2.2 compares three age/effectiveness functions but in this case with the same gestation period and the same value of β (G=10 and β=0.95) but different decay rates. The curve on the left assumes a decay rate δ=0.25. The curve on the right shows the lowest decay rate δ=0.10 while the remaining curve is defined with δ=0.15. After twenty years with δ=0.25, the effect of R&D on productivity is almost extinguished, whereas there is still an appreciable effect even after 35 years when δ= 0.10. Note that the weight reaches its maximum value of 1 at the end of the gestation period, followed by decreasing weights, determined by the decay rate δ.

Figure 2.1 Shapes of the gestation curve with different values of "β"



Source: Elaborated by authors

Figure 2.2 Shapes of the decay curve with different decay rates (δ)



Source: Elaborated by authors.

Note: G is the gestation period, the decay rate is defined by δ, while β defines the characteristics of the gestation period.

The more general representation of the R&D stock

$$T_t = T_{t-1}(1-\delta) + \Omega R_{t-G} \text{ with } \Omega\text{=1 if t=G and } \Omega\text{=[(1-}\beta\text{)t] / [(G- }\beta\text{t)] if t<G} \quad (2.5)$$

The constant decay rate δ implies geometric decay of the knowledge stock, which is equivalent to assuming that most innovations are incremental and will be replaced fast. The value of this rate will depend on the speed at which new knowledge can be produced. In the case of fast technological upgrading, we expect the decay rate to be only initially constant, increasing with the speed of knowledge production. In that case, the decay rate is expected to be research-specific and endogenous to the research effort. However, the speed of technological upgrading and its relationship with the decay rate is difficult to measure empirically, so it is usually assumed that the constant δ is a long-run real decay rate (Alston et al. 1998).

Results of research efforts are not certain, which means that there is risk associated with R&D investment. When a research project starts, we do not necessarily know with certainty how long would it take to get results. This risk could affect both timing and outcome of investment. To account for risk in the investment process, Esposti and Pierani (2003) introduce uncertainty in the length of the gestation period, under the assumption that some projects may fail. The gestation period defined in (2.4) is now assumed to be stochastic, which implies that the service life of the investment has a random starting date, with *G* being a random variable that we assume here to have a triangular distribution with mean μ and a range of possible values $\mu \pm \Delta$. Formally, the age/efficiency function with a stochastic gestation period is expressed as:

$$\omega(s\backslash\beta,\Delta,\mu) = \int_{\mu-\Delta}^{\mu+\Delta} \omega(s\backslash\beta,G)P(G\backslash\Delta,\mu)dG, \qquad (2.6)$$
$$(s\backslash\beta,\mathrm{G}) = 0 \text{ when } s > G \text{ and } G = \mu + \Delta$$

where $\omega(\cdot)$ is the age/efficiency function, and $P(\cdot)$ is the density generating the weights, given μ and Δ. The second line in (2.6) considers the failure of the research program whenever its gestation exceeds the maximum length (μ+Δ), also called the break-up period. Note that in equation (2.6), there is only one year in which, for any possible event, full efficiency ($\omega_s = 1$) is reached, and this year differs according to the event. This means that when assuming *G* as a random variable, the expected value of the age/efficiency function never reaches unity.

To use the model in (2.6) we need to define values for the different parameters β, Δ, μ and δ, expressing technical and economic properties of the research program. As discussed above, β sets up the form of the efficiency gains during the gestation period; Δ sets up the length of both the research program gestation and breakup; μ is the mean gestation period around which there exists some distribution whose dispersion ($\pm\Delta$) indicates the risk associated with that specific investment, and δ is the decay rate (Esposti and Pierani 2003).

Esposti and Pierani (2003) conceptually link values of the parameters of the PIM model with the type of research the model represents. They distinguish three main categories: basic, applied, and developmental research and look at the literature for the parameter values of each category. They report that few studies explicitly estimate the decay rate δ (see Alston et al. 1998) and that none of them refer to agriculture. The values for δ that Esposti and Pierani (2003) found in the literature go from 0.12 to 0.36, with 0.15 as the most frequently assumed value in empirical research. They also found that in general, δ values depend on the type of research: the more basic the research, the smaller the δ and the larger the μ. The literature does not give clear-cut indications on the remaining parameters.

Based on this information and in general considerations, Esposti and Pierani (2003) define parameters as follows: δ=0.1 for basic research, δ=0.2 for applied, and δ=0.25 for developmental research; $\mu=7$ for basic, $\mu=6$ for applied and $\mu=4$ for developmental; the standard deviation of the distribution of the gestation period is a function of μ, considering that the more theoretical, original, and borderline a research program is, the greater the uncertainty and therefore the risk. Finally, they assumed that the value of β is close to the *one-hoss shay* case, and the more this holds true the more basic the research program: 0.98 for basic, 0.95 for applied, and 0.90 for developmental research.

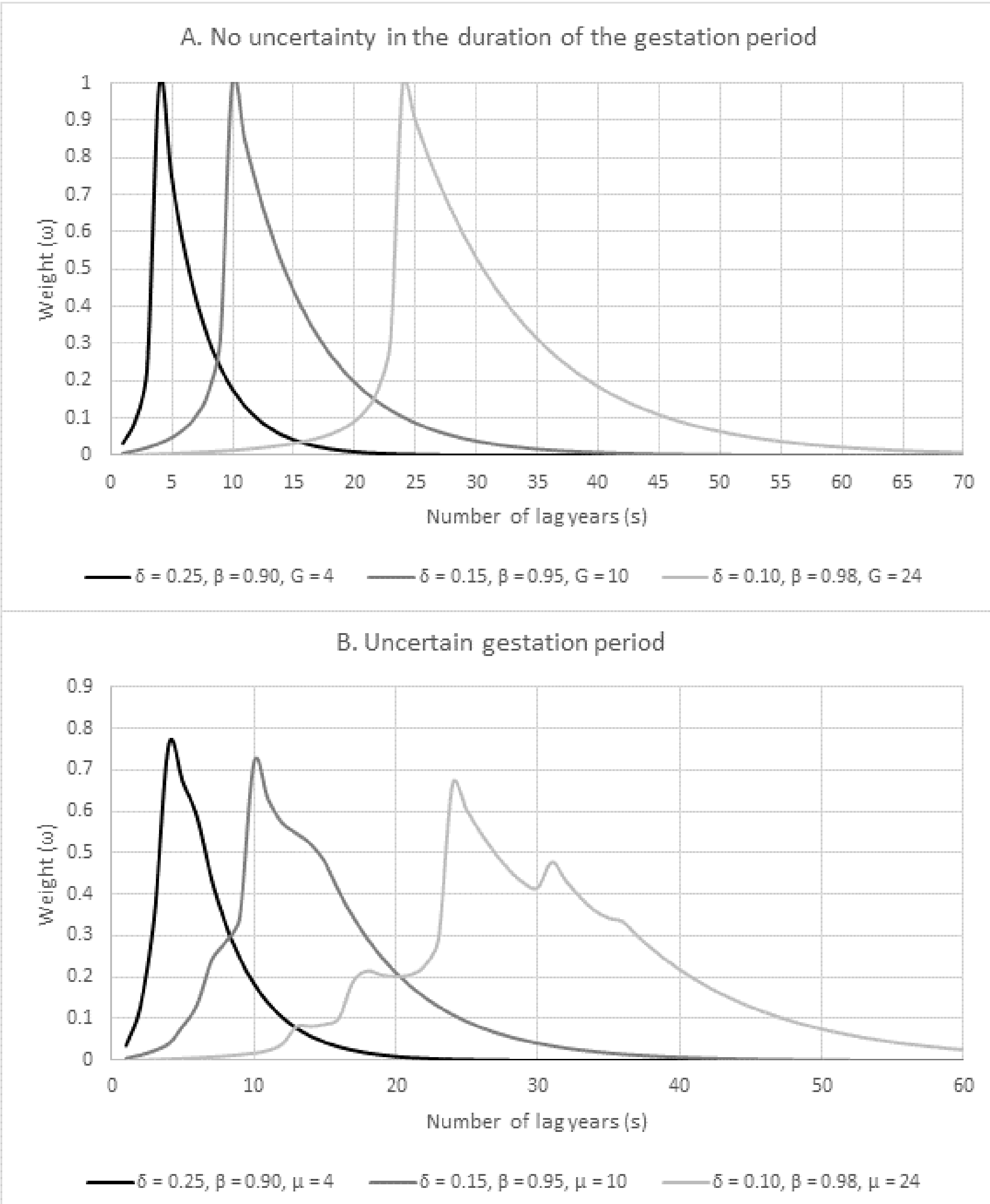
Looking at the applied literature on agriculture, for the specific case of crop breeding, Brennan and Byerlee (1991) found an average lag, for different crops, between investment and adoption of seven to eight years. Brennan (1991) discusses the concept of a "planned level of capability" in research introduced by Javier (1987). It implies that a country determines in advance (at the time of research resource allocation) the desired extent of research into a commodity. Following Javier (1987) and Dagg (1988), the levels of capability in research can be considered as: 1) the capability to monitor technological developments elsewhere, to keep up with world knowledge; 2) the capability to introduce and test a technology under local conditions; 3) the capability to carry out adaptive research to adapt technologies to local conditions; 4) the capability to carry out applied research to generate new technology; and 5) the capability to conduct basic and strategic research on agricultural problems. Adapting this classification to plant breeding, Brennan (1991) defines the following levels with their respective lags between investment and the final relevant returns of the new variety: 1) the capability to introduce and test a crop under local conditions, using international nurseries: 10 years; 2) the capability to carry out adaptive breeding, involving the selection of earlier-generation material provided by international or other national programs under local conditions: 12 years; and 3) the capability to carry out a full crossing and breeding program to generate new local varieties: 14 years. Notice that these periods correspond to the gestation period (G) in our conceptual framework.

For the case of agricultural R&D investment in the United States, Alston et al. (2011) found a gestation period of 24 years and effects of research that extend beyond 40 years after investment—much longer than the 7 years assumed by Esposti and Pierani (2003) for the case of basic research. Because of these findings by Alston et al. (2011) we expand the range of possible age/effectiveness functions beyond those considered by Esposti and Pierani (2003) to include longer gestation periods.

Using Brennan's (1991) classification and findings by Alston et al. (2011), we expect countries to show lengths of the gestation period between 10 and 25 years, depending on the capabilities and development of their research systems. We also expect that the more developed the research system and the higher the human capital, the smaller the observed decay rate of research, which means that research by more developed research systems will generate more complex outputs, which will require longer gestation periods but with long-lasting effects on productivity (lower decay rates).

Figure 2.3 compares three different profiles of the age/effectiveness function defined using different parameter values without considering uncertainty (2.3.A) and with uncertainty in the gestation period. The curve on the left in Figure 2.3.A assumes a gestation period of four years (μ=4), a decay rate (δ) of 0.25, and a value of β equal to 0.90. The curve on the right represents an age/effectiveness function with a 24-year gestation period, a decay rate of 0.10 and β=0.98. Parameters for the intermediate case are μ=10, δ=0.15 and β=0.95. There are marked differences across the three curves and we can think of them, from left to right, as particular cases of lag distributions for developmental, applied and basic research, respectively. After twenty years, the effect of development research is almost extinguished, whereas applied research still has an appreciable effect. The effect of basic research is still high after 50 years. Note that the weight reaches its maximum value of 1 at the end of the gestation period, followed by decreasing weights, determined by the decay rate δ. Figure 2.3.B shows the same age/effectiveness curves as in Figure 2.4 but in this case, uncertainty is assumed for the duration of the gestation period. Note that with uncertainty, the age/effectiveness function is always less than 1, but the lower the risk (proportional to the length of the gestation period), the closer the maximum weight is to unity.

Figure 2.3 Age/effectiveness functions for different parameter values



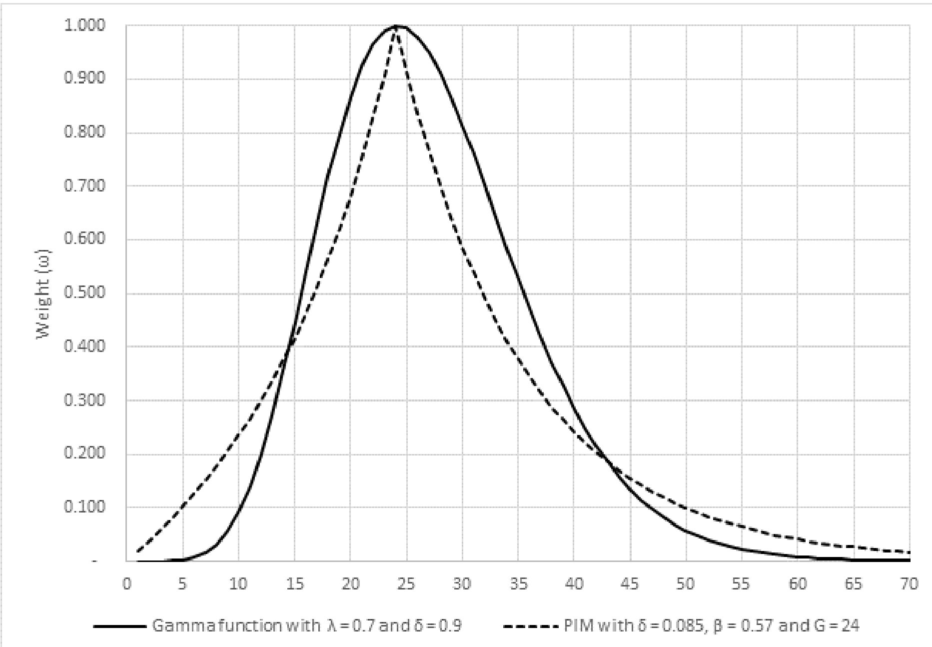
Source: Elaborated by authors.
Note: The gestation period is defined by G under certainty and by μ when we assume it as a random variable, the decay rate is δ, while β defines the characteristics of the gestation period.

Figures 2.4 and 2.5 show how the approach used in this paper, adapted from Esposti and Pierani (2003), can reproduce specifications of the lag structure when using other methods. Figure 2.4 compares the lag distribution of the gamma function estimated by Alston et al. (2011) for the United States with a PIM age/effectiveness function with a similar shape, while Figure 2.5 shows a similar comparison but in this case of the trapezoidal lag structure used by Fuglie and Rada (2012) for Africa south of the Sahara (SSA). To make the values of the weights in these studies comparable with lag distributions as defined here using different parameter values, we normalize the weights in Alston et al. (2011) and Fuglie and Rada (2012) relative to the value of the peak lag year in each study.

As shown in Figure 2.4, the gamma function with λ=0.4 and δ=0.9 can be approximated by an age/effectiveness function with G=24, β=0.57 and δ=0.085. The gestation period of the trapezoidal shape in Fuglie and Rada (2012) can be closely approximated defining β=-1.0. The concave curve after the maximum value cannot be replicated assuming a single value for δ. On average, the best fit is a PIM curve with depreciation 0.12. The assumption behind the trapezoidal lag structure is that depreciation is low in the first four years and accelerates in the second half of the depreciation period. We replicate almost exactly the trapezoidal lag structure by assuming a variable δ. The depreciation starts at 0.03 in periods 10 and 11 and increases exponentially, reaching 0.5 in the last year.

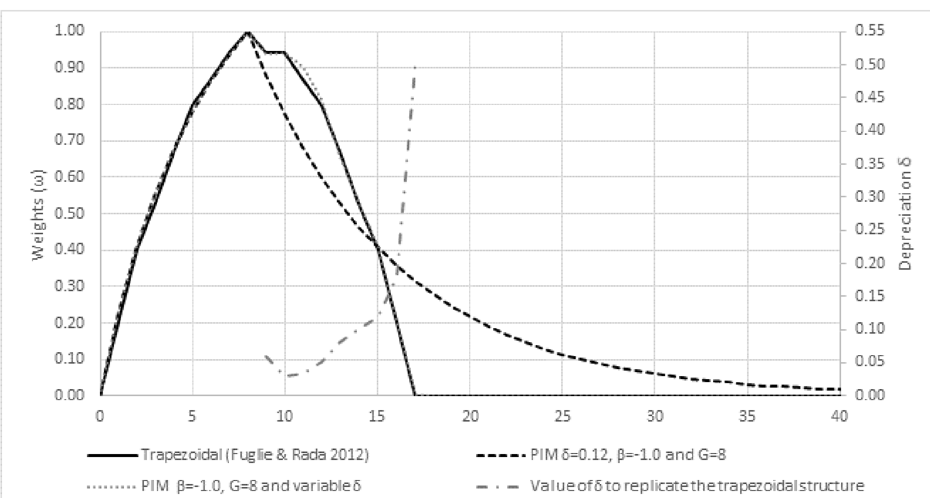
We should offer a final comment on the rate of decay. Esposti and Pierani (2003) highlight the fact that a constant decay rate is often thought of as a working parameter to be assumed and used mostly for convenience, when, in fact, it contains a body of economic information. First, and based on the literature, Esposti and Pierani (2003) argue that equation (2.2) can be viewed as a Taylor series, a linear approximation to the unknown stock derived from a theoretical information model of how a firm uses R&D investment to develop the desired technology. Second, a constant decay rate implies geometric depreciation: a more rapid reduction of efficiency during the early part of the investment service life. This is in general considered implausible for physical assets, but in the case of knowledge stock, Esposti and Pierani (2003) argue that this is to be expected because only a few research projects produce innovations of enduring impact, which means that in aggregated terms, geometric decay applied to the knowledge stock is theoretically sound. This is one more advantage of the PIM and the gamma models over the ad hoc models like the trapezoidal representation of lagged effects of R&D investment.

Figure 2.4 Gamma and PIM age/effectiveness functions



Source: Elaborated by authors
Note: G is the gestation period, the decay rate is defined by δ, while β defines the characteristics of the gestation period.

Figure 2.5 Trapezoidal and PIM age/effectiveness functions



Source: Elaborated by authors
Note: G is the gestation period, the decay rate is defined by δ, while β defines the characteristics of the gestation period.

3. METHODOLOGY

As discussed in the previous sections, the use of the PIM to estimate R&D stocks leaves us with the problem of choosing the values of the parameters that determine the shape of the age/efficiency function of R&D investment and the transformation of investment into knowledge stock: the decay or depreciation rate δ, the expected length, and the shape of the gestation period defined by μ, Δ. and β as seen in the previous section. According to Hall et al (2009), determining the decay rate econometrically is difficult if not impossible and there has not been yet a satisfactory solution to this problem.

Owing to the problems discussed in Hall et al. (2009), few studies explicitly estimate the decay rate δ, and none of them refer to agriculture (Alston et al. 1998). Most applications assume the decay rate based on ad hoc considerations, and similar practices have been adopted for the other parameters. In general, and according to Esposti and Pierani (2003), values of the parameters are defined based on the type of research; they assume that the more basic the research, the smaller the δ and the larger the μ, but there is no clear-cut indication about the remaining parameters.

Esposti and Pierani (2003) followed this same approach but went a step further by calibrating the PIM model using the nonparametric least squares criterion and assuming as known the lag structure of R&D investment in Italian agriculture based on assumptions of the type of research conducted by different institutions. Given that this lag structure depends on unknown parameters δ, μ, Δ, and β, they argue that it should be possible to estimate the unknown parameters as a weighted sum of the research specific lag structures (basic, applied, and developmental research).

As acknowledged by Esposti and Pierani (2003), this approach has several limitations and usually the solution to this problem is not empirically feasible. First, a reliable estimation of the actual lag structure should be obtained, but this kind of estimation is usually based upon some assumption regarding the lag profile. Second, the non-linearity in the parameters and the inadequacy of the traditional econometric tools also makes this estimation difficult. Major identification problems occur: for example, the observed lag structure is determined by a set of parameters that does not correspond to any of the three research types. In this context, they propose to fit the model using a grid of the parameter values and choose, among the possible combinations of parameters, the one with the smallest sum of square errors. Using this calibration method, they confirmed the "mixed" character of the underlying public agricultural research investments in Italy.

In this study, we propose an econometric method to identify the relevant parameters defining the lag structure of R&D in the knowledge stock. The method is feasible under the use of limited data, as is the case in developing countries, without the need to subordinate the results to data constraints, which allow us to check our empirical results against what is expected by the conceptual framework of the PIM. Our method relies on generating a large number of different knowledge stocks using different combinations of parameter values and determining which stock or linear combination of stocks defined in this way better explain the TFP response of different countries. To deal with this problem, the selected method needs to be able to handle many explanatory variables that are significantly redundant (collinear) and do not have a well-understood relationship to the dependent variable and to identify among this wide range of different R&D stocks those that better fit the TFP data.

Partial least squares (PLS) is a method that derives its usefulness from its ability to analyze data with many, noisy, collinear, and even incomplete variables in both independent (*X)* and dependent (*Y)* variables. This method models not only the relationship between two matrices, *X* and *Y*, but in addition models the structure of these matrices, which gives richer results than the traditional multiple regression approach, providing quantitative multivariate modelling methods, with inferential possibilities like multiple regression, t-tests, and ANOVA (Wold et al. 2001).

To form a relationship between the dependent variable (*Y*) and explanatory variables *X* ($X_1,..,X_m$), PLS constructs new explanatory variables, called factors, latent variables, or components, where each component is a linear combination of the explanatory variables *X*. Standard regression methods are then used to determine equations relating the components to the dependent variable. The method can be seen essentially as a combination of multiple regression analysis and principal components regression (PCR), where principal components form the independent variables in a regression. The major difference is that with PCR, principal components are determined solely by the data values of the X variables, whereas with PLS, the data values of both the X and Y variables influence the construction of components. The intention of PLS is to form components that capture most of the information in the X variables that is useful for predicting Y, while reducing the dimensionality of the regression problem by using fewer components than the number of X variables. PLS is considered especially useful for constructing prediction equations when there are many explanatory variables and comparatively little sample data (Garthwaite 1994, Hoskuldsson 1988).

In what follows we provide a simple interpretation of PLS based on the paper by Garthwaite (2001). We start from a sample of size *n* from which to estimate a linear relationship between Y and X, where Y is a $n\times 1$ vector and X is an $n\times m$ matrix that can be represented by *m* vectors $[X_1, \ldots, X_m]$. PLS reduces the number of regressors by defining *p* components *C* that are fewer than the number of X variables ($p<m$). This is achieved by allowing variables X to influence Y only through the components C_g with $g=[1, 2,\ldots,p]$.

PLS works with centered variables *U* and V_h, with $U=(Y-\bar{y})$ and $V_h = (X_h - \bar{x}_h)$. The sample means of vectors *U* and V_h are 0, and their components are denoted by *u* and v_h. The method works by sequentially defining the different components. The first component, C_1, is constructed as a linear combination of the V_h by regressing *U* against each of the V_h in turn, running *m* regressions of the form:

$$U_{(h)} = b_h V_h \tag{3.1}$$

with each of the *m* equations in (3.1) providing an estimate of U. C_1 is then defined as a weighted average of predictors of *U*[2]:

$$C_1 = \sum_{h=1}^{m} w_{1,h} b_{1h} V_h \tag{3.2}$$

As such, C_1 should itself be a useful predictor of U and hence of Y. But the X variables potentially contain useful information for predicting Y beyond the information contained in C_1. The

[2] A wide range of possibilities for constructing C_l are offered, depending on the weights that are used. A discussion on different types of weights and their effects can be found in Garthwaite (2001, 124)

information in X that is not in C_1 may be estimated by the residuals from a regression of X, on C_1; these residuals are identical to the residuals from a regression of V on C_1. Similarly, variability in Y that is not explained by C_1 can be estimated by the residuals from a regression of U on C_1. These residuals will be denoted by V_2 and U_2, respectively. This procedure continues iteratively using equations (3.1) and (3.2) to estimate the parameters of regressions between U_2 and vectors in V_2, to obtain component C_2, and so forth to obtain component C_g, where each component is determined from the residuals of regressions on the preceding component, with residual variability in Y being related to residual information in the Xs. In general, the Vs are defined as:

$$V_{(g+1)h} = V_{gh} - \left\{\frac{c_g' v_{gh}}{c_g' c_g}\right\} C_g \tag{3.3}$$

with the term in brackets being the coefficients obtained from regressing V_{gh} on C_g. Similarly, U is defined as:

$$U_{(g+1)} = U_g - \left\{\frac{c_g' u_g}{c_g' c_g}\right\} C_g \tag{3.4}$$

where the term in brackets includes coefficients from regressing U_k on C_g. C_{g+1} is then obtained as in (3.2):

$$C_{g+1} = \sum_{h=1}^{m} w_{(g+1),h} b_{(g+1)h} V_{(g+1)h} \tag{3.5}$$

With p components, the PLS regression equation takes the form:

$$\hat{Y} = \alpha_0 + \alpha_1 C_1 + \alpha_2 C_2 + \cdots + \alpha_p C_p \tag{3.6}$$

The components C in (3.6) are orthogonal vectors because $V_{(g+1)h}$ is uncorrelated with C_g for all h and each of the components C_g are a linear combination of the $V_{(g)h}$ so they are uncorrelated with C_k. After an estimate of the regression model has been determined, we can express the model in terms of the original variables X, rather than the components C_k. This gives a more convenient equation for estimating Y for further samples based on their X values.

An alternative way of seeing how the PLS approach works is to consider the Spectral Theorem for Symmetric Matrices, according to which a symmetric $n \times n$ matrix A has n real eigenvalues, and also to consider that the corresponding eigenvectors are orthogonal. The symmetric matrix A can be orthogonally diagonalized as follows: $A=UDU^T$, where U is a matrix made of the eigenvectors of A and D is the diagonal matrix made up of the eigenvalues of A. Another property of symmetric matrices is that the solution to the optimization problem: $Max\ [\mathbf{x}^T A \mathbf{x}]\ s.t.\ ||\mathbf{x}||=1$ is given by the largest eigenvalue of A (λ_{max}), with x being equal to the eigenvector of A corresponding to λ_{max}.

Based on these properties it can be shown that what PLS analysis does is to find in each iteration a ***t*** vector that maximizes the covariance of $Y^T X$. In other words, PLS computes the largest eigenvalue-eigenvector pair (t and λ) for the symmetric $X^T Y Y^T X$ matrix, which is the solution to the maximization problem: $Max\ [t^T X^T Y Y^T X t],\ s.t.\ ||t||=1$. In this way the $n \times k$ T matrix is chosen so that:

$$cov(Y^T XT, Y^T xT) = D' \tag{3.7}$$

where $D' = diag(\lambda'_1, \lambda'_2, \lambda'_3, ..., \lambda'_k)$ with $\lambda'_1 > \lambda'_2 > \lambda'_3 > \ldots > \lambda'_k$.

A PLS model is not complete until the number of factors ***t*** (the value of *k*) is chosen. With numerous and correlated X-variables there is a substantial risk for over-fitting, that is, getting a well-fitting model with little or no predictive power. Hence, a strict test of the predictive significance of each PLS component is necessary, stopping the iterative process when components start to be non-significant. Cross-validation (CV) (Clark and Cramer 1993, van der Voet 1994, Wakeling and Morris 1993, and Wold et al. 2001) has become the standard method to test the predictive significance of the model. CV is performed by dividing the data in Z groups and then developing Z different parallel models, each of them estimated with one of the groups deleted. Differences between actual and predicted Y-values are calculated for each of the groups, and the sum of squares of these differences is computed and collected from all the parallel models to form the predictive residual sum of squares (PRESS), which estimates the predictive ability of the model. One way of defining the number *k* of components is to calculate the ratio

$PRESS_k/SS_{k-1}$ after each component, judging the component as significant if this ratio is smaller than 0.9 (Wold et al. 2001).

The cross-validated R^2 (Q2) is defined for the final model with the estimated number of significant components as Q2 = (1-PRESS)/SS, where SS is the sum of squares of *Y* corrected for the mean. CV is also used to validate the model, by simulating how well the model predicts the data (Wold et al. 2001).

The PLS analysis is conducted for a sample of 71 developing countries covering the period 1981-2011, plus the United States and Canada, countries used as reference to compare the results of our approach to those in Alston et al. (2011). TFP values were obtained using the same growth-accounting approach as the one in Nin-Pratt (2015), based on Eberhardt and Teal (2013). Data on R&D expenditure to calculate knowledge stocks is from ASTI (2016). The PLS approach is implemented using SAS. By default, SAS displays the amount of predictor and response variation accounted for by each factor. The package also provides a summary of the cross validation for each number of factors, along with information about the optimal number of factors and details of the fitted model for each successive factor.

With the number of factors determined, additional tests can be performed to increase the amount of variability explained by the factors in the dependent variable. One key component of this process is identifying the predictors that play a relevant role in explaining the variance. SAS' output for PLS analysis includes the regression coefficient profile and the variable importance plot that gives a direct indication of which predictors are most useful for predicting the dependent variable. The regression coefficients represent the importance each predictor has in the prediction of just the response (*Y*). The variable importance plot, on the other hand, represents the contribution of each predictor in fitting the PLS model for both predictors and response (*X* and *Y*). It is based on the Variable Importance for Projection (VIP) statistic of Wold, Johansson and Cochi (1993), which summarizes the contribution a variable makes to the model. If a predictor has a relatively small coefficient (in absolute value) and a small value of VIP (a critical value of 0.9 is suggested), then it is a prime candidate for deletion. Variables that do not reach the critical value are dropped and the model is re-estimated. The VIP test is applied as many times as needed until all variables reach the critical value of 0.8. By applying the VIP test, it is also possible to establish whether the effect of a given variable on the dependent variable is positive or negative. Specifically, the VIP shows whether the selected stocks of R&D affect TFP in a positive or negative fashion. We have selected only stocks that affect TFP positively. Negative impacts of some of the R&D stocks on TFP are likely to capture the effects of factors other than R&D and therefore are not relevant to our goal.

4. AN APPLICATION TO GLOBAL AGRICULTURE

To link knowledge stock and production we use the neo-classical production function as in Griliches (1995), where output (Y) is a function of inputs (X) and the technological stock (T):

$$Y = F(X, T) \tag{4.1}$$

For simplicity, we assume that the production function in (4.1) is represented by the Cobb-Douglas function with constant returns to scale on conventional inputs and where α and γ are parameters:

$$Y = \prod_{j=1}^{n} X_j^{\beta j}\, T^{\gamma} \tag{4.2}$$

From equation (2.8) we define TFP as follows[3]:

$$TFP = \frac{Y}{\prod_{j=1}^{n} X_j^{\beta j}} = T^{\gamma} \tag{4.3}$$

As a result, TFP growth is a function of changes in the knowledge stock:

$$\frac{dTFP}{TFP} = \gamma \frac{dT}{T} \tag{4.4}$$

Equation (4.4) represents the relationship between the benefits and costs of R&D investment, where the benefits are given by the growth of *TFP*, and the costs result from R&D expenditure in previous periods that contribute to a change in total knowledge stock in the year of analysis. As noted by Esposti and Pierani (2003), the change in T (dT/T) represents a change in the capacity of a country to produce "new ideas," while the impact of "new ideas" on productivity is given by the parameter γ.

Own R&D investment is not the only source that contributes to knowledge stocks. Since the seminal article by Griliches (1992), R&D spillovers have been found to be a major source of agricultural productivity growth. For example, Alston et al. (2011) show that for the case of the United States knowledge spillovers between states cannot be ignored. They found that each dollar spent on research in a state has spillover benefits to other states with a value of US$6 to US$16. In states having small

[3] TFP is calculated by estimating the βj parameters of a global Cobb-Douglas production function, and these parameters are used to calculate an input index for each country, denominator in equation (4.3). Details of the econometric estimation of the production function can be found in Appendix A.

agricultural sectors, the spillover benefits accounted for most of the national benefits. The evidence from developing countries also shows that own R&D investment alone cannot explain TFP growth. For example, Johnson and Evenson (1999) traced n*ew technology introduced for use in the agricultural and food processing sectors in 14 less developed and newly industrialized countries and compared the regional and industrial sources of these inventions across time. They found that both international and interindustry spillovers from public and private sources added to agricultural total factor productivity. Similarly, Alston (2002) showed that* international spillovers from public agricultural R&D investments accounted for half or more of the total measured productivity growth, with implications for measures of research impacts on productivity and on the implied rates of return to research, as well as for national and international agricultural research policy. Gutierrez and Gutierrez (2003), using panel cointegration techniques, analyzed the effect of agricultural international technological spillovers on total factor productivity growth for a sample of 47 countries between 1970 and 1992 and found that total factor productivity was influenced by domestic as well as foreign public R&D spending in agriculture. They also found that countries located in temperate zones benefit more from international spillovers than countries located in tropical zones and that the rate of return to agricultural R&D spending is higher in tropical countries. Evenson (2000) also found that geography matters, offering empirical evidence that foreign agricultural research is protected by patent in less developed countries that are similar in output choice, climate and soil type, education levels, and market size to countries developing new technologies. Evenson's (2000) results also show that Africa is far away from the nations performing most R&D and that African nations did not benefit from domestic or foreign spillovers.

Another source of agricultural knowledge spillovers is the CGIAR, a global public player in agricultural R&D that includes 15 research centers and is home to more than 8,000 scientists, researchers, technicians, and staff. Renkow and Byerlee (2010), reviewing evidence on the impacts of CGIAR research published since 2000, found that CGIAR's research contributions to crop genetic improvement, pest management, natural resources management, and policy resulted in strong positive impacts relative to investment, with crop genetic improvement research standing out because of the most rigorously documented positive impacts.

In recent years, the accelerating growth of domestic private R&D capacity directed to crop genetics, farm machinery, and food processing, mostly in the larger middle-income countries, has reduced the preponderance of public-sector research in food and agriculture, raising the importance of international private R&D as a driver of TFP (Pardey et al. 2016). Pray, Fuglie, and Johnson (2007) refer to studies looking at the impacts of agricultural research that show that private sector research is making an important contribution to agricultural productivity growth in some countries and could make an even larger impact if government policies were more favorable. More recently, Pray and Fuglie (2015) refer to the growing importance of the private sector in developing improved technology for food and agriculture, with private agricultural R&D spending growing faster than public R&D spending over the past several decades. However, Pray and Fuglie (2015) argue that this growing importance of private R&D does not imply a diminished role of the public sector, as most empirical evidence points to complementarities between public and private agricultural R&D.

Spillovers from Other Countries

In the case of spillovers from other countries' public R&D, we combine three different measures of distance which we calculate separately by assuming that spillover potential depends on the "distance" between pairs of countries measured by the similarity of their agricultural sectors. As in Alston et al. (2011), we define a spillover coefficient ω_{ij} between countries *i* and *j* as 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:*

$$\omega_{ij} = \frac{\sum_{m=1}^{M} q_{mi} q_{mj}}{\left(\sum_{m}^{M} q_{mi}^{2}\right)^{1/2} \left(\sum_{m}^{M} q_{mj}^{2}\right)^{1/2}} \qquad (4.5)$$

where q_{mi} represents the share of output *m* in country's *i* agricultural output. Calculated in this way, ω_{ij} can be interpreted as a multivariate correlation coefficient that varies between zero and unity: a high value indicates high similarity in output in the two countries (Eberhardt and Teal 2013). Potential spillovers for country *i* result from the product of ω_{ij} and the knowledge stock in country *j*.

To calculate the distance between countries we combine three different measures of distance. The first measure is based on output composition, which we calculate using data on 61 commodities or groups of commodities (M=61) from FAO (2016). The second measure uses the Köppen climate classification scheme that divides climates into five main climate groups: A (tropical), B (dry), C (temperate), D (continental), and E (polar), which are further divided into sub-groups based on precipitation (see for example Kottek et al. 2006). Finally, the third measure of distance is based on similarity of the input mix used in production: we compare countries based on the relative amounts of labor, capital and materials they use per hectare of agricultural area. The input mix of different countries should reflect differences in the relative prices of inputs and, if this is the case, technologies developed in the United States should be easier to adapt by countries with similar relative prices. The literature on "appropriate technology" (for example, Basu and Weil 1998) argues that technology improvements will diffuse slowly even without barriers to technology transfer and that developing countries might refrain from using a new technology until they reach a level of development at which this technology would be appropriate to their needs. The final "similarity" coefficient is calculated as the product of these three values:

$$\Omega_{ij} = \prod_v \omega_{ij}^v \quad \text{where v=\{output composition, climate, input composition\}} \tag{4.6}$$

The knowledge spillovers received by country i from other countries is then calculated as the sum of stocks from all other countries weighted by the aggregated distance coefficient:

$$Tcsp_{i,t} = \sum_j \left(\Omega_{ij} \times T_{j,t-1}\right) \tag{4.7}$$

where *Tcsp* is knowledge from other countries spilling-in to country *i* in period *t* expressed as the weighted sum of knowledge stocks from *j*, where the weight is the distance between *i* and *j*.

R&D Investment and Spillovers from the CGIAR

To calculate the CGIAR's knowledge stock we use data of R&D expenditure by CGIAR centers for the period 1971-2012 (ASTI 2016). Spending by center is further disaggregated by region, for example, spending by the International Center for Tropical Agriculture (CIAT) in SSA, Asia, MENA and LAC. Separate knowledge stocks are calculated by center and region using a simple PIM method:

$$Tcg_{c,r,t} = Tcg_{c,r,t-1} \times (1 - \delta) + R_{c,r,t-10} \tag{4.8}$$

where $Tcgc_{,r,t}$ is the knowledge stock of center *c* in region *r* and period *t*. The decay rate δ is assumed to be 0.12 and R&D spending is incorporated into the knowledge stock with a ten-year lag ($R_{c,t,t-10}$). The impact of CGIAR's knowledge stock on productivity in a particular country is defined based in the importance of the CGIAR crops in that country, the distance of the country to the different CGIAR centers, and the level of the knowledge stock in each center, which depends on R&D spending by center.

Information on research activities in each center was used to define the main crop and livestock activities in which the different centers do research (Table 4.1) and then each center is mapped into countries where their headquarters are located and other countries where centers have offices, research facilities, or major projects (Table 4.2). The final step is to calculate the knowledge stock of each center based on equation (4.3) and R&D spending by center. The spillovers from different centers to a country are calculated by adding the R&D stocks of the centers located in that country's region weighted both by the inverse of the distance between the country and the countries where centers are located and by the importance of the crop and livestock activities of those centers in total output of the country.

Table 4.1 Main crop and livestock activities for CGIAR research centers

	Center	Crops and livestock
1	Africa Rice	Rice
2	Bioversity	Agriculture
3	CIAT	Beans, cassava, tropical forages, and rice
4	CIMMYT	Wheat and maize
5	CIP	Potato and sweet potato
6	ICARDA	Wheat, other cereals and pulses, livestock
7	ICRAF	Agroforestry
8	ICRISAT	Sorghum, millet, and pulses (pigeon pea, chickpea, and groundnuts)
9	IFPRI	Agriculture
10	IITA	Banana and plantain, cassava, cowpea, maize, soybean, and yam
11	ILRI	Tropical livestock (beef and dairy, sheep and goats)
12	IRRI	Rice
13	IWMI	Agriculture

Source: Elaborated by authors.
Note: To quantify the importance that research conducted in the centers has for a particular country we use the share in total output of the crops centers specialized in that particular country. For example, the more important wheat and maize are for a country, the more relevant research by CYMMYT for that country. The share of agriculture in the economy is used in the case of centers not doing research in specific crops or livestock.

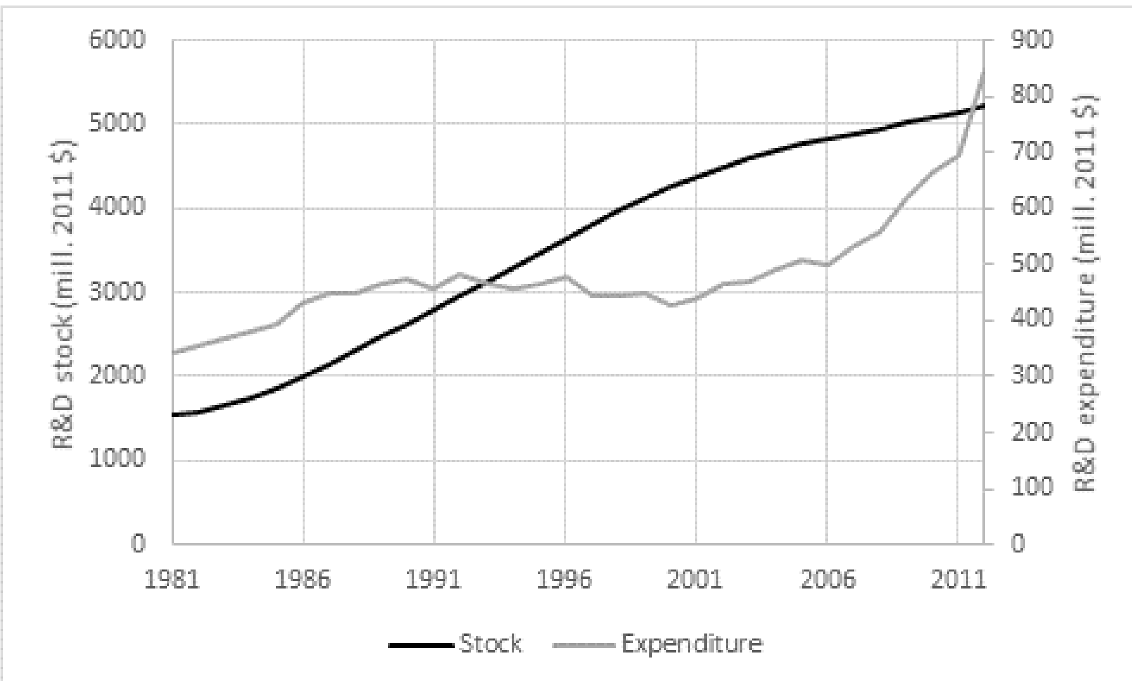
Table 4.2 Main countries where CGIAR research centers operate

	Center	Countries
1	Africa Rice	Côte d'Ivoire, Nigeria, Senegal, and United Republic of Tanzania
2	Bioversity	Italy, Colombia, Costa Rica, India, Nepal, Uzbekistan, China, Philippines, Benin, Cameroon, Burundi, Ethiopia
3	CIAT	Colombia, Peru, Nicaragua, Kenya, Democratic Republic of the Congo, Ethiopia, Malawi, Rwanda, United Republic of Tanzania, Uganda, Zimbabwe, China, Viet Nam, Lao People's Democratic Republic, Philippines
4	CIMMYT	Mexico, Guatemala, Colombia, Ethiopia, Kenya, Zimbabwe, Turkey, Iran, Afghanistan, Pakistan, India (New Delhi), Nepal, Bangladesh, China (Beijing)
5	CIP	Peru, Ecuador, Kenya
6	ICARDA	Jordan, Iraq, Syria, Lebanon, Palestine, Cyprus, Algeria, Libya, Mauritania, Morocco, and Tunisia, Nile valley: Egypt, Sudan, Ethiopia, Eritrea
7	ICRAF	Kenya
8	ICRISAT	India (Hyderabad), Mali, Niger, Nigeria (Kano), Malawi, Ethiopia, Kenya, Mozambique, Zimbabwe
9	IFPRI	United States, Egypt, Ghana, Nigeria, Ethiopia, Uganda, Malawi, Bangladesh, India (New Delhi), Pakistan, China
10	IITA	Nigeria (Ibadan), Democratic Republic of the Congo, United Republic of Tanzania, Zambia
11	ILRI	Kenya, Ethiopia, Burkina Faso, India
12	IRRI	Philippines, Southeast Asia, Bangladesh, Burundi, and Mozambique
13	IWMI	Sri Lanka, Egypt, Ghana, Ethiopia, South Africa, Uzbekistan, Pakistan, Nepal, Lao People's Democratic Republic, Myanmar, India

Source: Elaborated by authors.

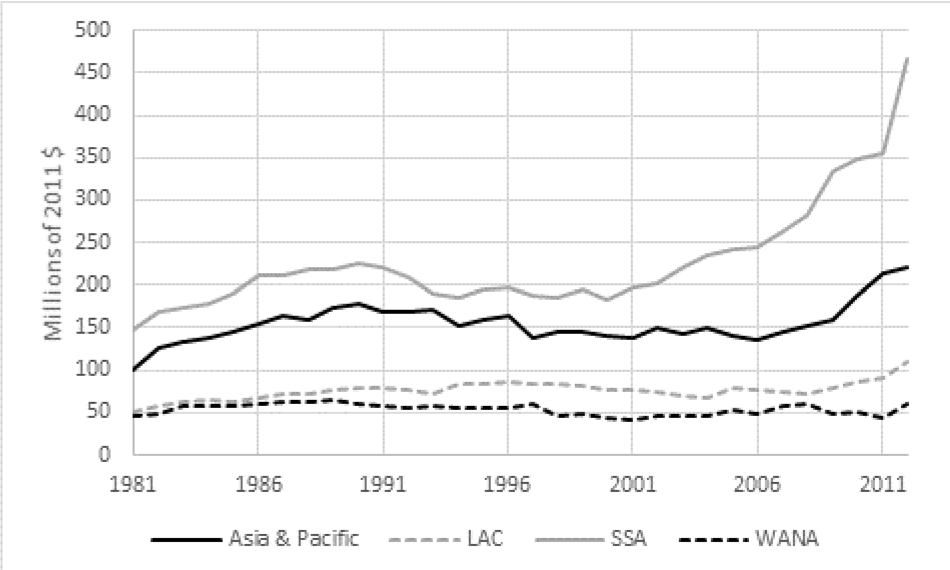
Trends of R&D spending by CGIAR are presented in Figures 4.1 and 4.2. After a period of stagnation, R&D spending by CGIAR resumes growth in 2000, first at an annual rate of 2.6 percent, taking off after 2006 at an average rate of 9.3 percent (Figure 4.1). Increased R&D spending in the 2000s targeted mostly SSA and, to a lesser degree, Asia (mainly South Asia), with LAC and WANA decreasing their share in CGIAR's total spending. The slowdown in spending of the 1990s is clearly reflected in the lack of growth in the R&D knowledge stock observed in the 2000s, as shown in Figure 4.3. The increase in spending during this same period should result in growing knowledge stocks in the coming decade.

Figure 4.1 Trends in R&D spending by the CGIAR and evolution of R&D stock



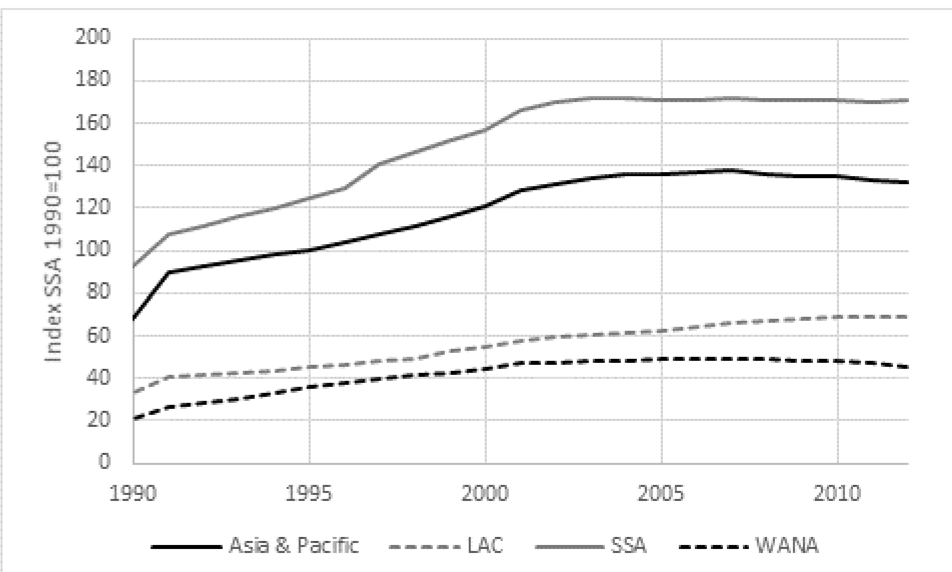
Source: Elaborated by authors using data from ASTI (2016).
Note: R&D = research and development.

Figure 4.2 Trends in CGIAR's R&D spending by region



Source: Elaborated by authors using data from ASTI (2016).
Note: LAC = Latin America and the Caribbean; R&D = research and development; SSA = Africa south of the Sahara; WANA = West Asia and North Africa.

Figure 4.3 Evolution of CGIAR's R&D stock by region

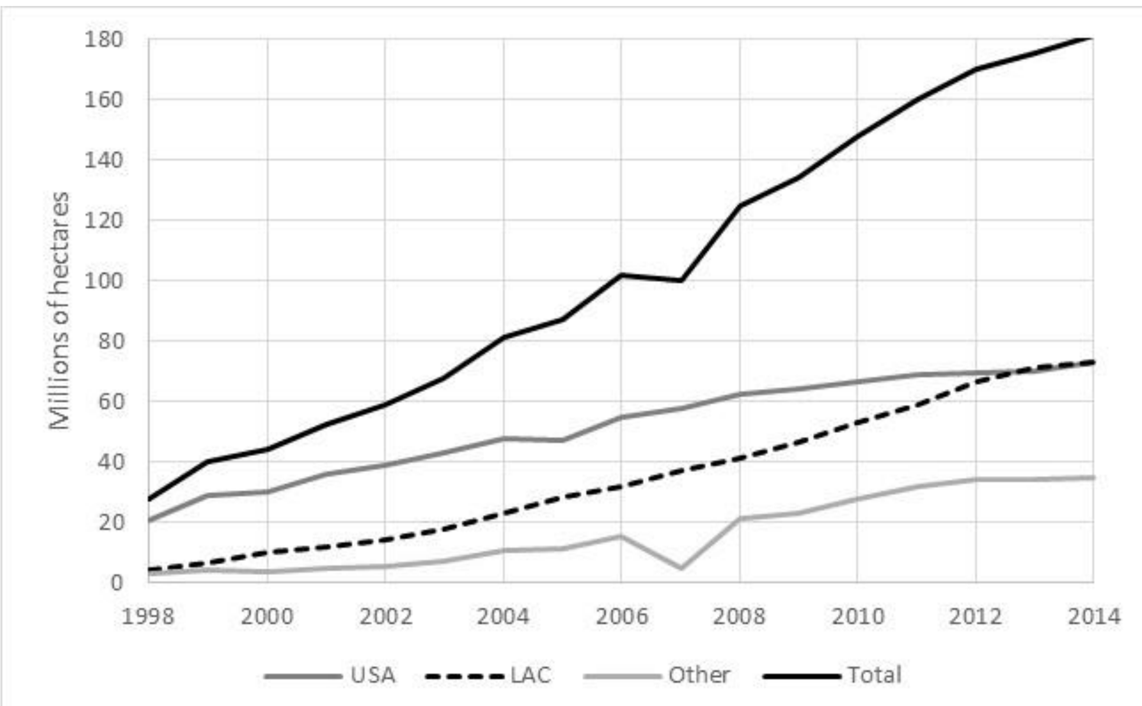


Source: Elaborated by authors using data from ASTI (2016).
Note: LAC = Latin America and the Caribbean; R&D = research and development; SSA = Africa south of the Sahara; WANA = West Asia and North Africa.

Agricultural R&D Investment of the Six Major Biotech Firms

One of the major changes in global agriculture in the last 20 years has been the growing role that the private sector, mostly through R&D investments of the large multinational biotech companies, have played in the process of technical change. The evolution of the total area under biotech crops is presented in Figure 4.4. Commercialization of biotech crops started in 1996 and the area allocated to these crops has seen sustained growth until the present, increasing from 1.7 million hectares in 1996 to 181.5 million hectares in 2014. Among LM countries, LAC has played a major role in the global expansion of these crops. In 1998, the total area of biotech crops in LAC was 4 million hectares, compared to 21 million hectares in the United States. In 2014, LAC was already catching-up to the area in the United States, reaching 73 million hectares. The area of these crops has increased in other regions from 3 million to 34 million hectares between 1998 and 2014.

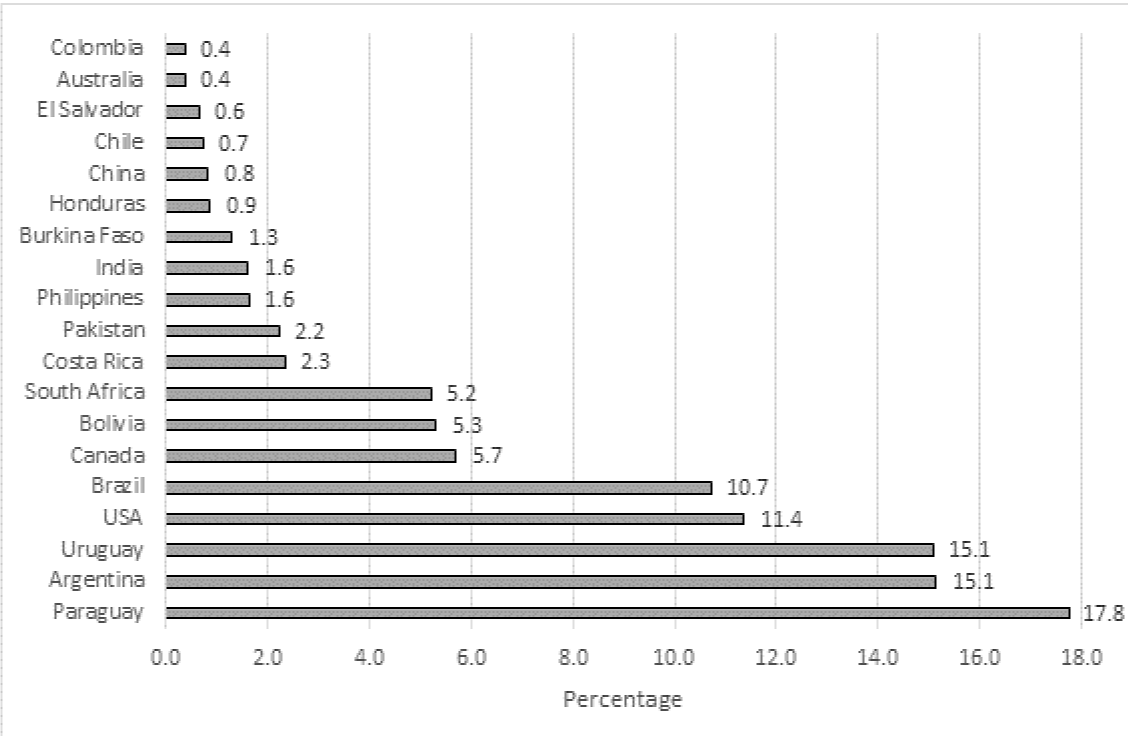
Figure 4.4 Area of Biotech crops



Source: Elaborated by authors using data from James (2014)
Note: LAC = Latin America and the Caribbean; USA = United States.

Figure 4.5 shows that Paraguay, Argentina, Uruguay, Brazil, and Bolivia are the LM countries with the highest share of biotech crops in total crop area, while Brazil and Argentina are the most important producers of biotech crops, with 65 of the 73 million hectares of biotech crops in LM countries in 2014. The main biotech crops are soybean, maize, cotton, and canola, but there are also biotech varieties of alfalfa, eggplant, papaya, squash, sugar beets, sweet pepper, and tomato.

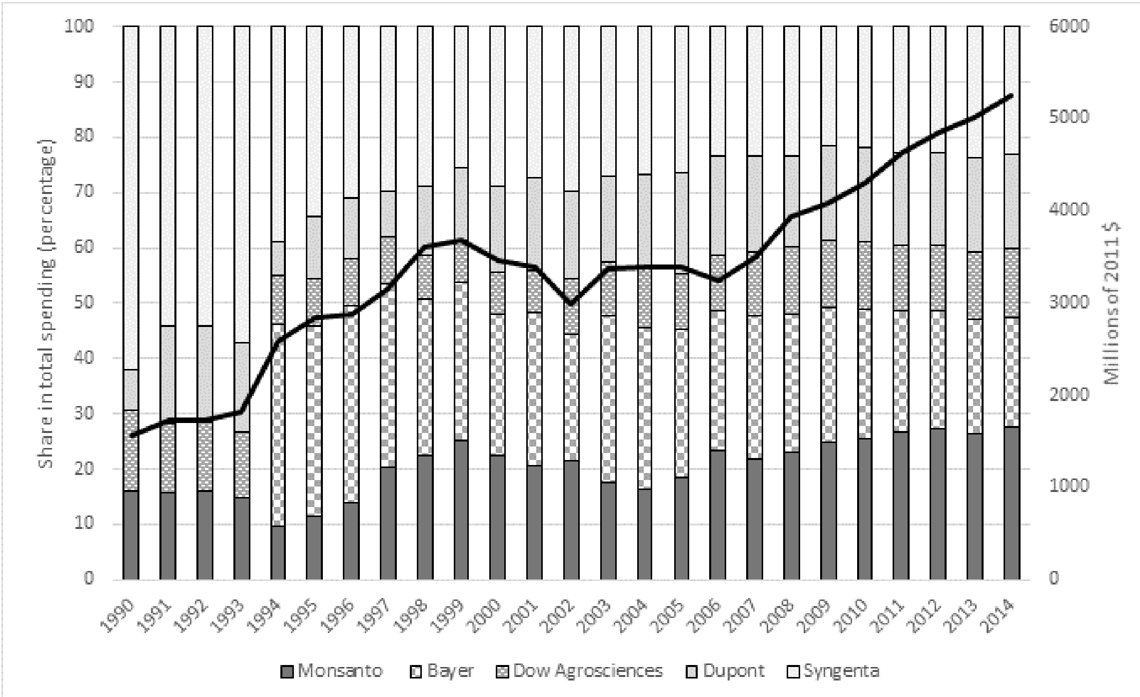
Figure 4.5 Share of the area of biotech crops in total crop area in major producing countries, 2011-2014



Source: Elaborated by authors using data from James (2014).

The world's six largest seed, agrochemical and biotech firms are behind the global development of these technologies and the expansion of biotech crops: BASF, Bayer, Dow Agrosciences, DuPont, Monsanto, and Syngenta. Together, these six firms spent US$5.2 billion (2011 US$) in R&D in 2014, compared to US$1.5 billion in 1990 (Figure 4.6). Notice that in 1990 Syngenta was the largest R&D investor among the six major firms, accounting for 60 percent of total spending. In 2014, Monsanto shows the largest share in total spending (28 percent) while Syngenta's share was down to 23 percent.

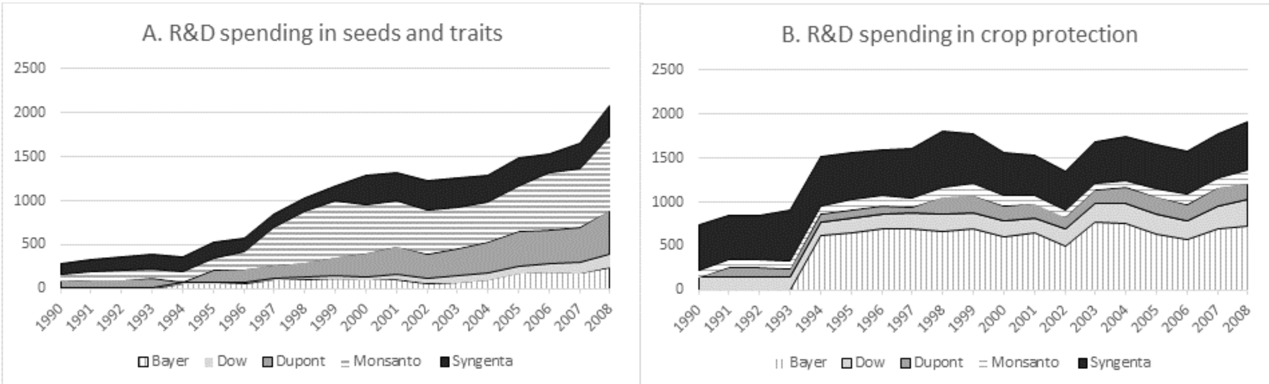
Figure 4.6 R&D spending by the six major biotech companies



Source: Elaborated by authors using information from ISAAA (International Service for the Acquisition of Agri-biotech Applications).

The changes in the share of R&D spending shown in Figure 4.6 do not tell the full story of the transformation of private R&D investment in this area. Monsanto played a major role in the transformation of the seed sector globally, as the result of strategic choices made by the company. The most important of these choices was to invest in research to develop seeds and traits instead of investing in developing agrochemicals for crop protection. Differences in R&D spending between major companies are presented in Figure 4.7. It is clear from the comparison of Figures 4.7A and 4.7B the importance that Monsanto gave to development of new varieties since 1996. Other companies increased spending in seeds and traits only after 2000, and thus Monsanto has been the leading firm in this area, ahead of its rivals by at least 6 years (Wilson and Dahl 2010).

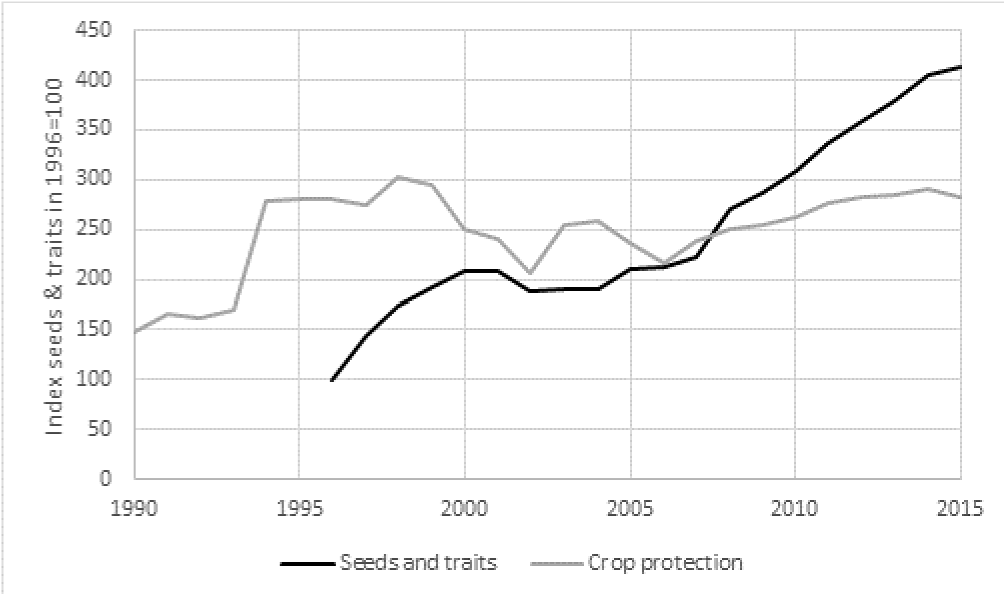
Figure 4.7 R&D spending in seeds and traits and in crop protection by biotech companies (millions of 2011 US$)



Source: Elaborated by authors using information from ISAAA (International Service for the Acquisition of Agri-biotech Applications) and Wilson and Dahl (2010).

R&D stock of biotech companies was calculated using a simple PIM method like the one used for the CGIAR but, in this case, we built two separate stocks: knowledge stock in seeds and traits and knowledge stock in crop protection. The spillovers to countries were determined by a) calculating the share of all countries in the global use of chemical pesticides and herbicides and using these shares as weights for the crop protection R&D stock of biotech companies; and b) calculating the share of all countries in the global area of GMO crops and using the share as weights for the seeds and traits R&D stock of biotech companies. The evolution of the seeds and traits and crop protection knowledge stocks are presented in Figure 4.8. Commercialization of biotech crops started in 1996 and since then the stock increased by more than four times its level in that year.

Figure 4.8 Evolution of the knowledge stock in seeds and traits and in crop protection of biotech companies, 1990-2015



Source: Elaborated by authors.

5. R&D STOCKS AND RETURNS TO R&D INVESTMENT IN LOW AND MIDDLE-INCOME COUNTRIES

This section presents the results derived from the application of the conceptual framework and methodology developed in sections 2 and 3 to the global agricultural R&D investment and TFP data discussed in the previous section. These results include the PIM parameters obtained using the PLS approach, the calculation of knowledge stocks, R&D elasticities, and the marginal returns to R&D investment for individual countries.

The PLS analysis is implemented using SAS and applied to different groups of countries, covering the period 1981-2011. TFP values were obtained using a growth-accounting approach described in Nin-Pratt et al. (2015), based on Eberhardt and Teal (2013). Data on R&D expenditure to calculate knowledge stocks are from ASTI (2016). Parameter estimates were obtained for North America (United States and Canada), Asian and LAC countries with large or more developed R&D systems (Advanced Asia and Advanced LAC, respectively), other Asian and LAC countries, and a group of SSA countries.

Table 5.1 presents the PLS results. The first column of the table shows the number of factors or components that result in the best fit of the model for each group of countries. Each component combines different R&D stocks, each of them calculated using different parameters of the PIM model. The second column shows total variation of the independent variables (X) used to predict the dependent variable Y (TFP), while the third column shows the total variation of TFP accounted for by the X variables, determined by the size and significance of the regression coefficients. As explained in Section 3, if a predictor has a relatively small coefficient (in absolute value) and a small value of VIP, then it is a prime candidate for deletion. The last three columns in Table 5.1 show the estimated parameters of the PIM knowledge stock for each group of countries.

Notice that estimates for North America required only three factors that account for 95 percent of the variation of TFP. In contrast with those results, 12 to 15 factors were selected to account for the variation of TFP in LM countries, with varied results in terms of the total TFP variation accounted for. Recall that only own-country R&D investment is used to calculate R&D stocks, so the total TFP variation accounted for could be reflecting the importance of R&D own-investments explaining TFP variation. Own investment explains most of TFP variation in North America and Advanced Asia, while in the case of SSA and Other Asian countries, the LPS model using knowledge stock with own investment only explains 39 and 42 percent of TFP variation, respectively. Results for LAC countries fall between these extremes, with the model explaining 66 to 73 percent of TFP variation in Advanced and Other LAC, respectively.

Table 5.1 Estimated parameters of the PIM knowledge stock model

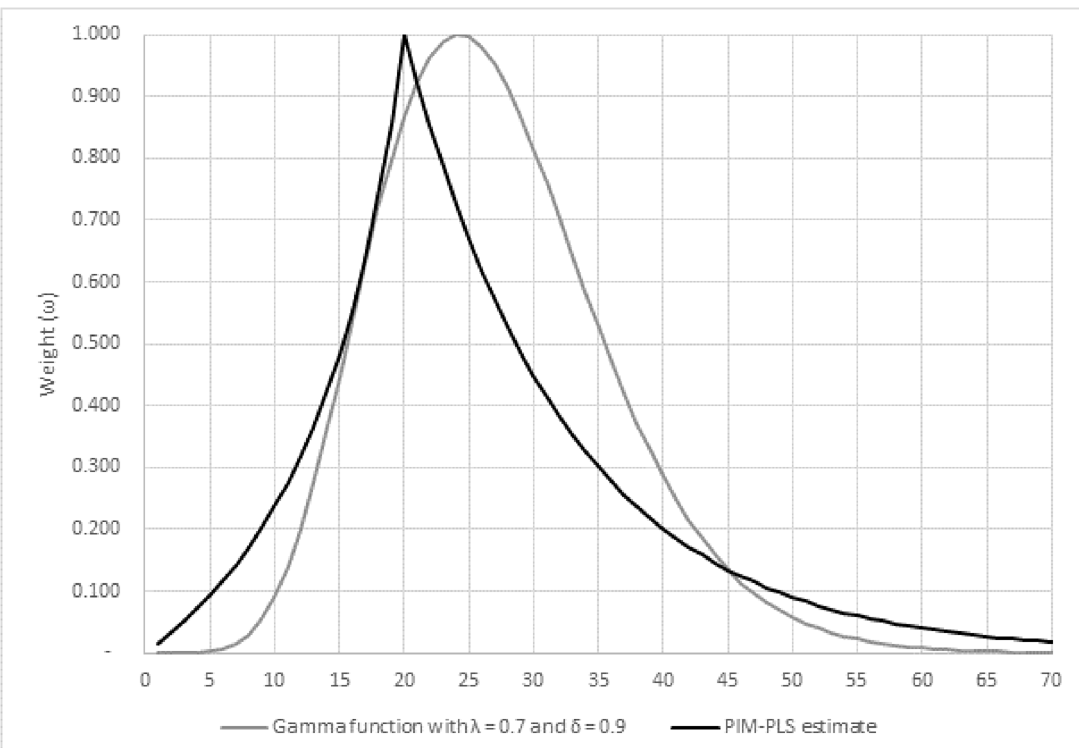
				PIM Parameters		
	Number of extracted factors	Total X variation accounted for	Total Y variation accounted for	Depreciation (δ)	Gestation period (G)	β
North America	3	99.9	94.6	7.7	20	69
Advanced Asia	15	100.0	90.0	11.6	17	63
Advanced LAC	15	100.0	66.1	15.3	17	62
Other Asia	12	100.0	42.5	14.5	14	57
Other LAC	15	100.0	73.3	16.0	12	62
SSA	12	100.0	39.1	13.1	12	74

Source: Estimated by authors
Notes: LAC = Latin America and the Caribbean; PIM = perpetual inventory method; SSA = Africa south of the Sahara.

As discussed in Section 2, we expected smaller depreciation rates and larger gestation periods in regions with more advanced R&D systems. Research from these regions is expected to have longer lasting effects, which is assumed to be related to more basic research. Our results show that North America, with a depreciation of 7.7 percent and a gestation period of 20 years clearly stands apart from the LM regions. Among these regions, Advanced Asia and Advanced LAC show the highest gestation period (17 years), in clear contrast with Other LAC and SSA (12 years), while the length of the gestation period for Other Asia is 14 years. Depreciation values do not seem to be correlated with the development and size of the R&D systems. Advanced Asia shows the lowest depreciation value (11.6 percent), but this is similar to the value obtained for SSA (13.1 percent), while the highest value is found in Other LAC (16 percent). All values for LM regions are around the 15 percent depreciation value normally used in the literature. Similarly, no clear pattern is found for the value of β determining the shape of the gestation period, which fall between 0.57 (Other Asia) and 0.74 (SSA), and are smaller than the values of 0.9 or bigger assumed by Esposti and Pierani (2003).

Another way to partially verify our results is to compare the age/effectiveness function obtained for North America with the gamma function estimated by Alston et al. (2011). In their article, Alston et al. argue that the lagged effects of research last longer than those normally assumed in econometric studies due to data constraints. The similar shape of the age/effectiveness obtained using the PLS approach to that of the estimated gamma function by Alston et al. (2011) shown in Figure 5.1 support their conclusions. Notice also that our results were obtained using only 30 years of data at the aggregated country level, while Alston et al. (2011) worked with a detailed panel of state-level data, including annual state-specific data on agricultural productivity for each of the 48 contiguous U.S. states over the years 1949–2002.

Figure 5.1 Age/effectiveness functions for the USA from econometric estimates using a Gamma function and 150 years of data and for USA-Canada using the PIM-PLS approach and 30 years of data



Source: Elaborated by authors.
Note: PIM-PLS = perpetual inventory method-partial least squares.

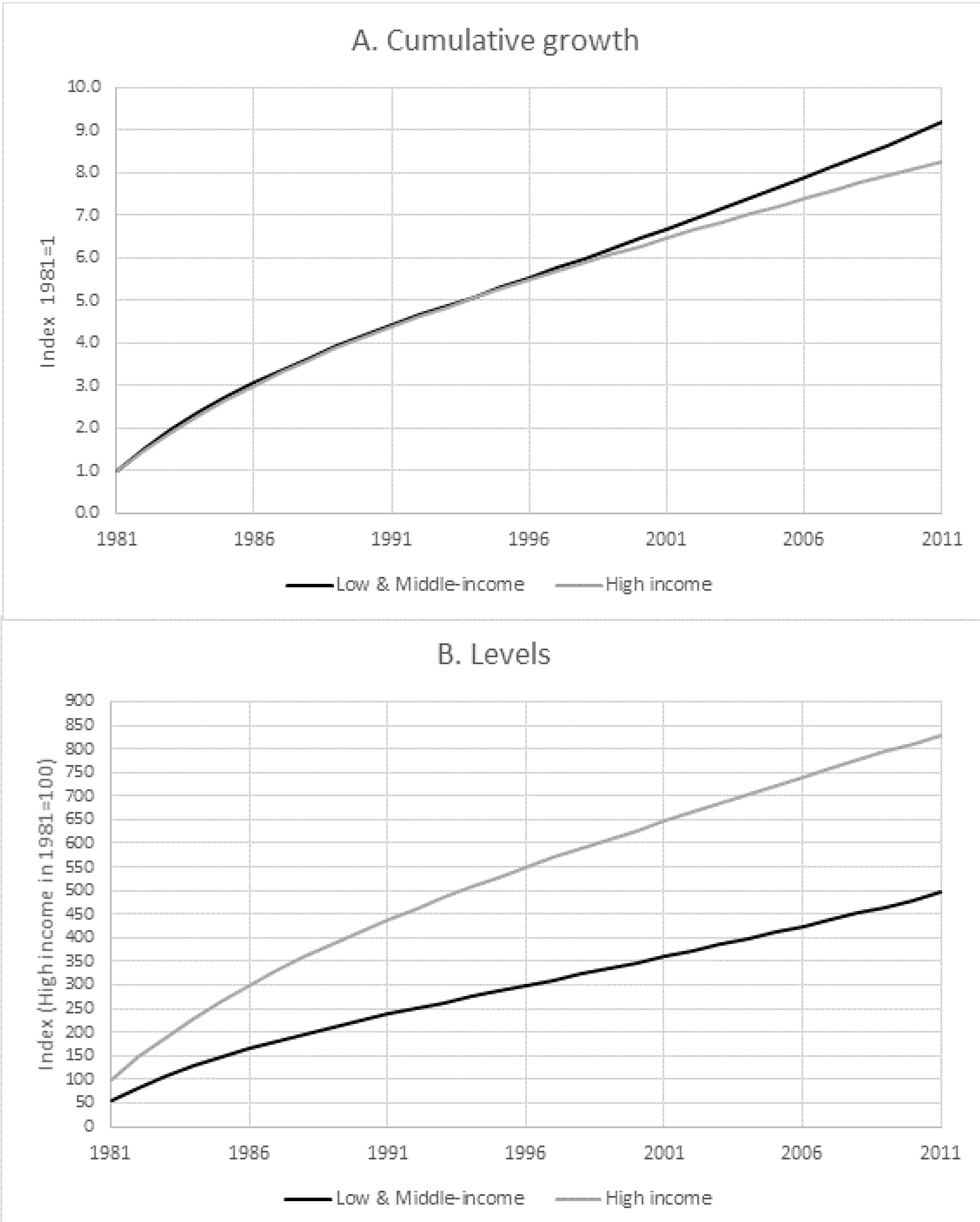
The estimated parameters in Table 5.1 are used to calculate the R&D stocks for countries in each group, but the final knowledge stock is calculated by adding to own R&D investment stock, knowledge spillovers from other countries, plus spillovers from CGIAR and private investments.

Knowledge Stocks

Figure 5.2 shows the evolution of total knowledge stock in high income and developing countries. In all cases, the R&D stock includes own investments, knowledge spillovers from other countries, spillovers from knowledge generated by biotech firms, and spillovers from CGIAR investment in the region.[4] The results show that the knowledge stock of LM countries was more than 9 times bigger in 2011 than its level in 1981. Growth of the knowledge stock in high-income (HI) countries was slightly smaller than that in LM countries, becoming 8 times larger in 2011 than its own level in 1981 (Figure 5.2A). As a result, no significant change occurred in the global share of knowledge generated in LM and HI countries. In 1981, this share for LM countries was 35 percent, increasing to 37 percent in 2011. This is reflected in the proportional growth of the knowledge stock levels of LM and HI shown in Figure 5.2B.

[4] It was assumed that CGIAR spillovers only benefit LM countries and not high-income countries.

Figure 5.2 Levels and cumulative growth of R&D knowledge stocks for low and middle-income and high-income countries, 1981-2011

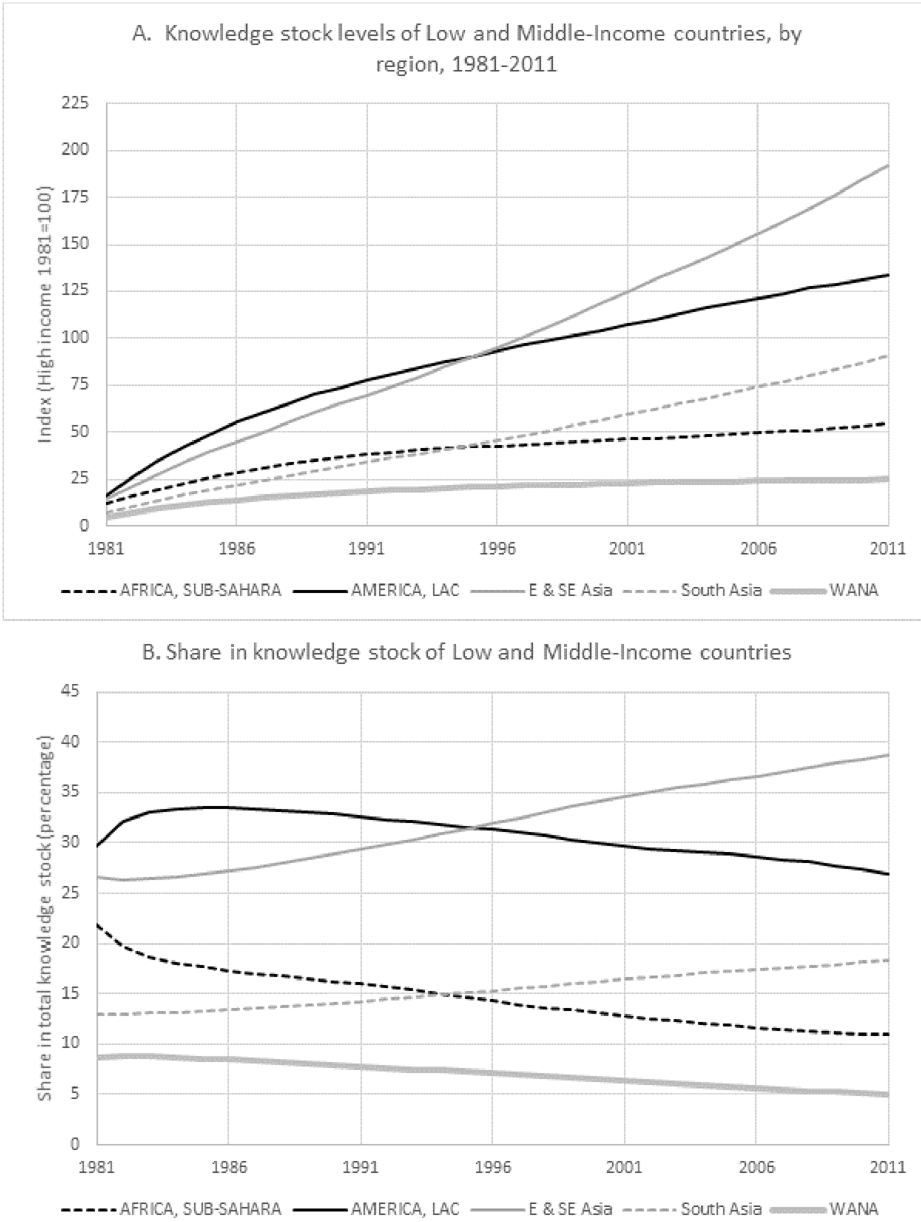


Source: Elaborated by authors

Note: Knowledge stocks include country stocks and spill-ins from other countries, from CGIAR investments in the region and knowledge from biotech firms.

Growth in knowledge stock varies by country and region. East and Southeast Asia (ESEA) and South Asia (SA) were the regions driving growth of the knowledge stock in developing countries, with stock levels reaching values that were respectively 13 and 12 times bigger in 2011 than at the beginning of the period (Figure 5.3A). Knowledge stock in Latin America and the Caribbean (LAC) also increased significantly, but to a level 8 times bigger in 2011 than in 1981, slower than growth in Asia. Growth in SSA and WANA was relatively low, close to half of that in LAC. As the result of this differential growth, the share of ESEA in total knowledge stock of LM countries increased from 27 percent in 1981 to almost 40 percent in 2011, while the share of SA in total stock went from 13 to 18 percent in 1981 and 2011, respectively. Note that in 1981, the largest knowledge stock was in LAC, and that SSA's knowledge stock was larger than that of SA and WANA. In 2011, the largest stock is in ESEA, the level of the stock in SA is bigger than that of SSA and WANA, and LAC, SSA and WANA decreased their share in total knowledge stock, from 60 percent for these three regions in 1981 to 43 percent in 2011 (Figure 5.3B).

Figure 5.3 R&D knowledge stock levels in low and middle-income countries by region and regional share in total knowledge stock, 1981-2011



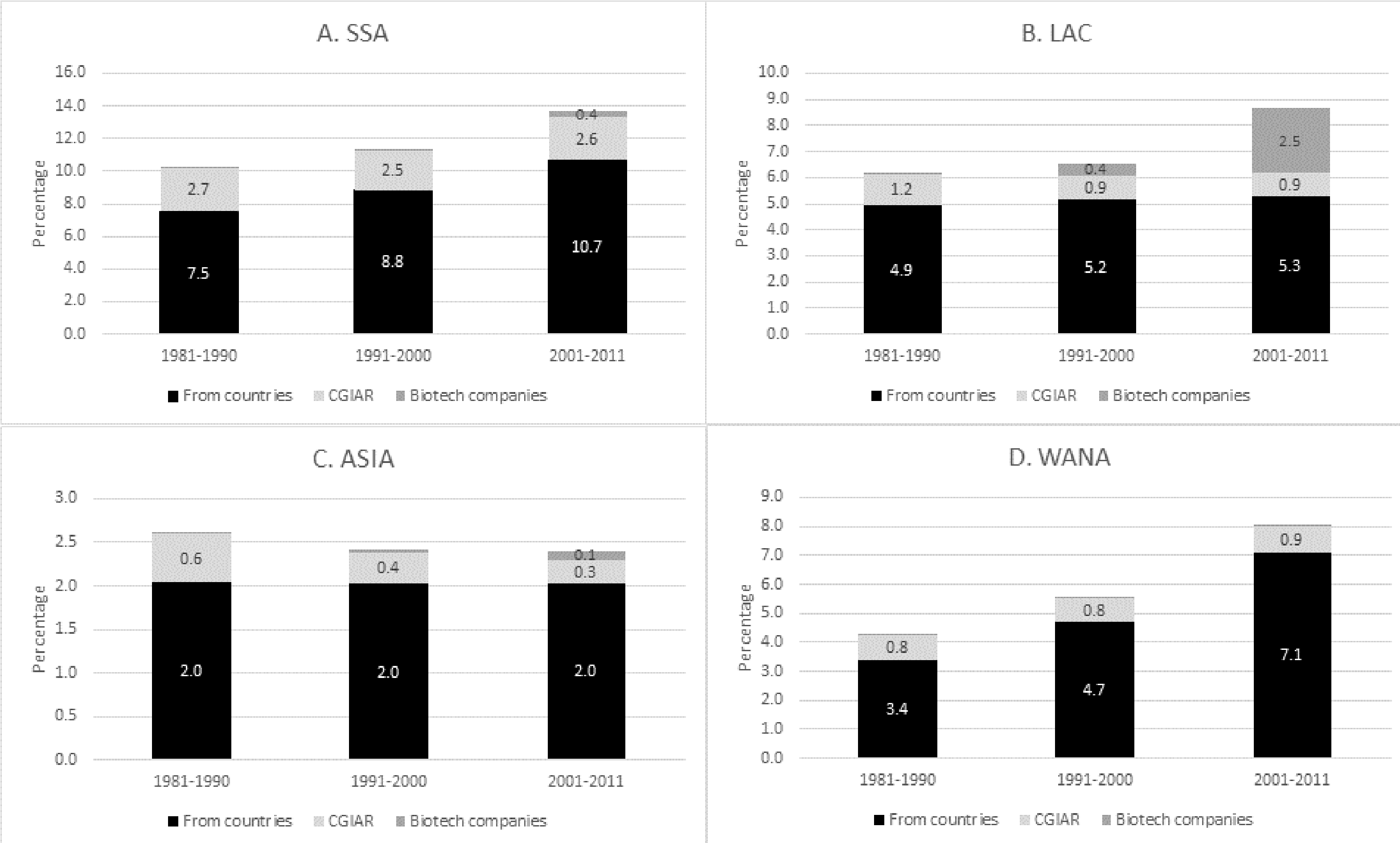
Source: Elaborated by authors
Note: Africa, Sub-Sahara = Africa south of the Sahara; America, LAC = Latin America and the Caribbean; E & SE Asia = East and Southeast Asia; WANA = West Asia and North Africa. Knowledge stocks include country stocks and spill-ins from other countries, from CGIAR investments in the region and knowledge from biotech firms.

What is the importance of different sources of spillovers relative to own investment in agricultural R&D at the country level? Except for Asia (ESEA and SA), the contribution of spillovers to the knowledge stock increased between 1981 and 2011 although their relative importance varies by region (Figure 5.4A). SSA is the region benefiting the most from spillovers (14 percent on average for the period

2001-2011). Spillovers also contribute significantly to knowledge stock in LAC and WANA (9 and 8 percent, respectively). In Asia on the other hand, the contribution of spillovers to knowledge stock remained below 2.6 percent without major changes during the period. Spillovers resulting from research by the CGIAR are most important in SSA, while those from private biotech companies have the largest impact in LAC.

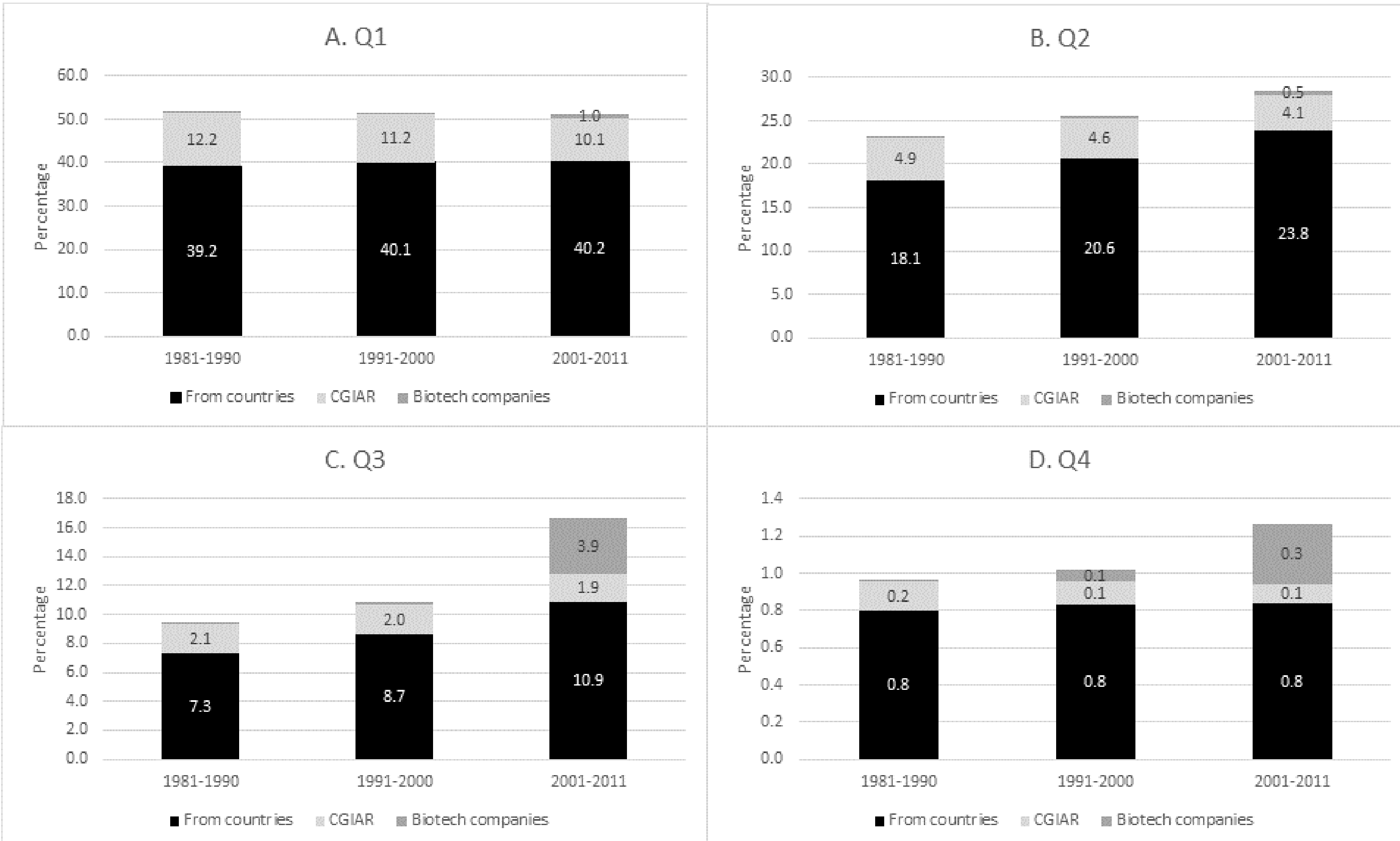
Figure 5.5 presents the same results shown in Figure 5.4 but with countries grouped by quantile of the average size of their knowledge stock between 1981 and 2011. The figure shows the relative importance of spillovers in countries with small research systems (Q1 and Q2). About 50 percent of the knowledge stock in Q1 countries is coming from research in other countries, while in the case of Q2, the share of knowledge from spillovers in total stock is 25 percent. In contrast, the share of knowledge spillovers in the group of countries with large stocks (Q4) is only 1 percent.

Figure 5.4 Contribution of different sources of spillovers to total knowledge stock



Source: Elaborated by authors.
Note: LAC = Latin America and the Caribbean; SSA = Africa south of the Sahara; WANA = West Asia and North Africa.

Figure 5.5 Contribution of different sources of spillovers to total knowledge stock



Source: Elaborated by authors.
Note: Q = quantile of the average size of countries' knowledge stock between 1981 and 2011.

R&D Elasticities and Returns to R&D Investment

Using TFP changes and changes in total knowledge stock for each country over the period 1981-2011 we obtain the R&D elasticity for each individual country. As discussed in Section 4, R&D elasticities measure the percentage increase in TFP that results from a 1 percent increase in knowledge stock and are calculated by dividing TFP growth between 1981 and 2011 by growth of the knowledge stock during the same period. Elasticity values together with average TFP and knowledge stock growth rates by region and for the period 1981-2011 are shown in Table 5.2. A similar table for all LM countries in our sample can be found in Appendix A.

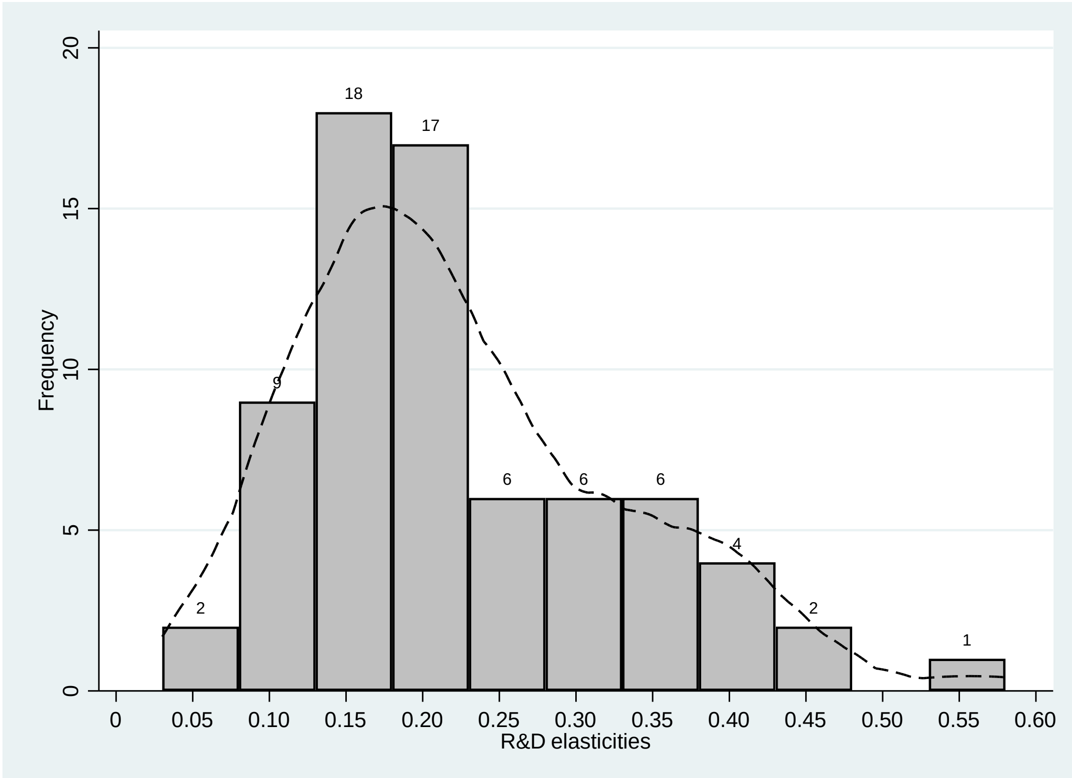
The calculated average R&D elasticity for LM countries is 0.23 (last row in Table 5.2). SSA, LAC and ESEA show average elasticities between 0.25 and 0.30. The lowest elasticity is observed in SA (0.18) and the highest in WANA (0.37). Average TFP growth rate for LM countries during 1981-2011 was 1.85 percent, while the knowledge stock in these countries increased at an average rate of 8.1 percent. Figure 5.6 shows the distribution of calculated R&D elasticities for all LM countries. Elasticities take values between 0.06 and 0.56 with an average of 0.23 as shown in Table 5.2. Figure 5.7 plots growth rates of R&D stocks and TFP for LM countries showing a highly significant correlation between growth in knowledge stock and TFP for our sample of countries.

Table 5.2 R&D elasticities and average growth of TFP and of the knowledge stock by region, 1981-2011

Region	R&D elasticity	TFP	Knowledge stock
SSA	0.30	1.40	5.34
LAC	0.29	2.02	7.03
E & SE Asia	0.25	2.45	9.58
South Asia	0.18	1.63	9.06
WANA	0.37	2.12	5.73
Low & Middle-Income	0.23	1.85	8.10

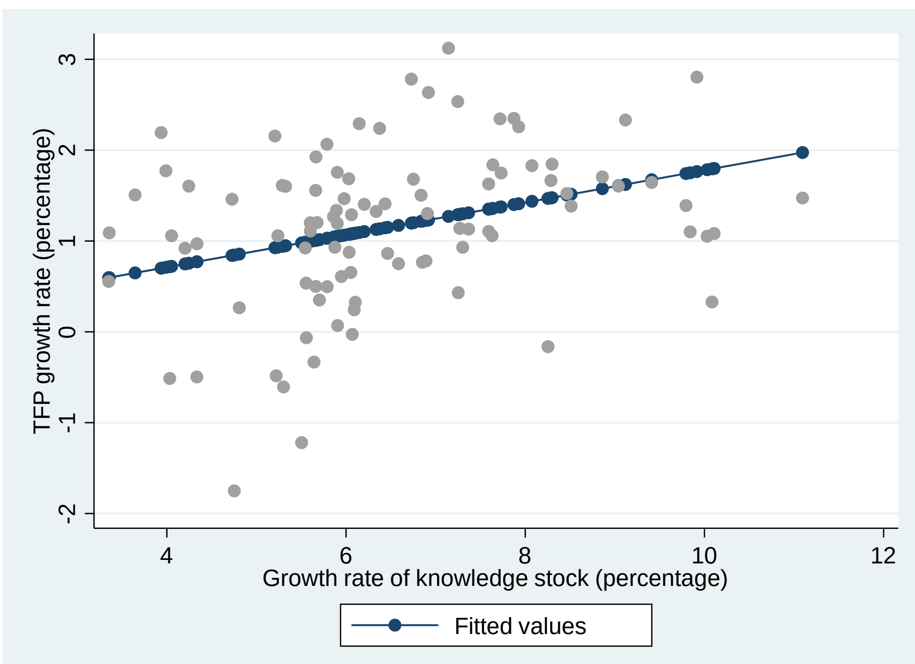
Source: Elaborated by authors
Note: E & SE Asia = East and Southeast Asia; LAC = Latin America and the Caribbean; SSA = Africa south of the Sahara; WANA = West Asia and North Africa. Knowledge stocks include country stocks and spill-ins from other countries, from CGIAR investments in the region, and from biotech firms. Elasticities measure the percentage growth in TFP as the result of a 1 percent growth in knowledge stocks. Averages for all groups and totals are weighted averages with weights calculated as the share of the country's knowledge stock in the region and in LM, respectively.

Figure 5.6 Distribution of R&D elasticities of 71 Low and Middle-Income countries, 1981-2011



Source: Elaborated by authors based on Andersen (2015) and own calculations using ASTI (2016).

Figure 5.7 Relationship between growth in knowledge stock and TFP growth using values for 71 low and middle-income countries, average values, 2001-2011



Source: Elaborated by authors

Note: TFP = total factor productivity.

Using the calculated R&D elasticities together with the age/effectiveness curves presented in Section 2, we calculate rates of return and benefit-cost ratios (BC) of an extra dollar of R&D investment for each LM country in the sample.[5] In this analysis, the cost is the investment of 1 dollar in the initial period, and benefits in the future are determined using the formula proposed by Alston Craig and Pardey (1998):

$$\varepsilon_j \frac{y}{k} \sum_s \frac{w_{j,s}}{(1+r)^s} = 1 \tag{5.1}$$

where ε_j is the R&D elasticity of country *j*, *y* and *k* are agricultural output and the R&D stock in the initial period, w_s are the values of the age/effectiveness curves (investment efficiency coefficients), *s* is the period after investment, and *r* is the modified internal rate of return measure (MIRR), the variable to be determined in equation (5.1). Refer to section 4 and to Appendix C for details on the calculation of the MIRR and the BC. Results of these calculations are presented in Table 5.2, including average values of the social discount rate, modified rates of return (MIRR), benefit-cost ratios (BC) by region, and confidence intervals for the regional averages.[6] Figures 5.7 and 5.8 show the distribution of MIRR and BC values calculated for all LM countries.

Results in Table 5.3 show that the average LM country is expected to obtain a relatively high return from R&D investment, with benefits almost four times bigger than costs (row 4 in Table 5.3). Results also show that the average BC value for LM countries falls between 2.7 and 5.3 with a confidence of 99 percent. The same conclusion can be reached by looking at the estimated MIRR. The average MIRR for LM countries is 5.96 percent and we expect the value of the MIRR for the average LM country to fall between 5.24 and 6.68 percent with a 99 percent confidence, with the minimum value of this range being greater than the average discount rate of 4.2 percent. At the regional level, the highest BC is observed in Asia (4.57), with LAC and Africa showing similar values (3.71 and 3.94, respectively). The highest value

[5] A length of 50 years of the age/effectiveness function is considered for these calculations.
[6] See Appendix B for details on the calculation of the discount rate.

of the BC for Asia corresponds to the highest MIRR (6.09 percent) and the lowest discount rate (3.9 percent) among all regions. In the case of Africa, returns to R&D are bigger than the discount rate (4.6 percent), with a 99 percent confidence 4.99 to 6.92 percent). This means that we can say with a 99 percent confidence that the average African country is underinvesting in R&D. The same conclusion applies to LAC and Asia. If we arbitrarily assume that countries are not willing to invest in R&D unless benefits are at least as twice as big as costs (BC ≥ 2), we can still say with a 99 percent confidence that Africa is underinvesting.[7] However, using this same standard, we can say that, on average, LAC and Asia are also underinvesting but with a 90 percent confidence interval.[8]

Table 5.3 Average values and confidence intervals for MIRR and BC ratios for low and middle-income countries, total and by region, 2001-2011

	Obs	Discount rate	Mean	Std. err.	[90% CI]	[99% CI]
BC						
Africa	35	4.6	3.94	0.62	[2.90–4.99]	[2.26–5.63]
Latin America & Caribbean	23	4.0	3.71	0.99	[2.01–5.42]	[0.91–6.51]
Asia	13	3.9	4.57	1.24	[2.36–6.79]	[0.78–8.37]
Low- & middle-income	**71**	**4.2**	**3.98**	**0.49**	**[3.16–4.80]**	**[2.68–5.29]**
MIRR						
Africa	35	4.6	5.95	0.35	[5.36–6.55]	[4.99–6.92]
Latin America & Caribbean	23	4.0	5.89	0.57	[4.92–6.87]	[4.29–7.49]
Asia	13	3.9	6.09	0.59	[5.03–7.15]	[4.27–7.91]
Low- & middle-income	**71**	**4.2**	**5.96**	**0.27**	**[5.51–6.41]**	**[5.24–6.68]**

Source: Elaborated by authors.
Note: BC = benefit-cost ratio; CI = confidence interval; MIRR = modified internal rate of return. Africa includes 30 countries from Africa south of the Sahara, plus Egypt, Morocco, Tunisia, and two West Asian countries: Jordan and Turkey.

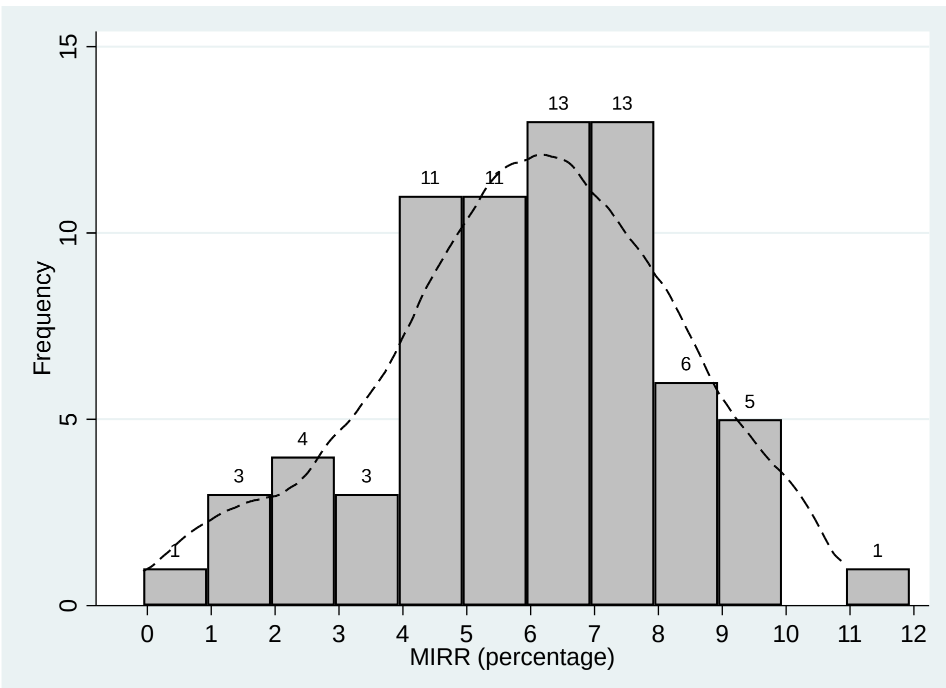
Figure 5.8 shows that only 22 of 71 LM countries in our sample show MIRR values below 5 percent. The distribution of BC values is shown in Figure 5.9. If, as before, we assume that governments would be willing to invest in R&D only if benefits double costs (BC ≥ 2), we observe that 37 countries show BC values between 0 and 2.5, with 29 of these countries having BC ratios smaller than 2 (not shown in the figure). This still leaves us with 42 countries with BC ≥ 2. These results suggest that about 60

[7] BC ≥ 2 is a more demanding standard than the alternative measure of whether MIRR is greater than the discount rate.
[8] This is because the lower value of the 99 percent confidence interval for these two regions is less than 2.

percent of low- and middle-income countries are underinvesting in R&D. These countries can get higher returns by investing in R&D than in activities that return the social discount rate.

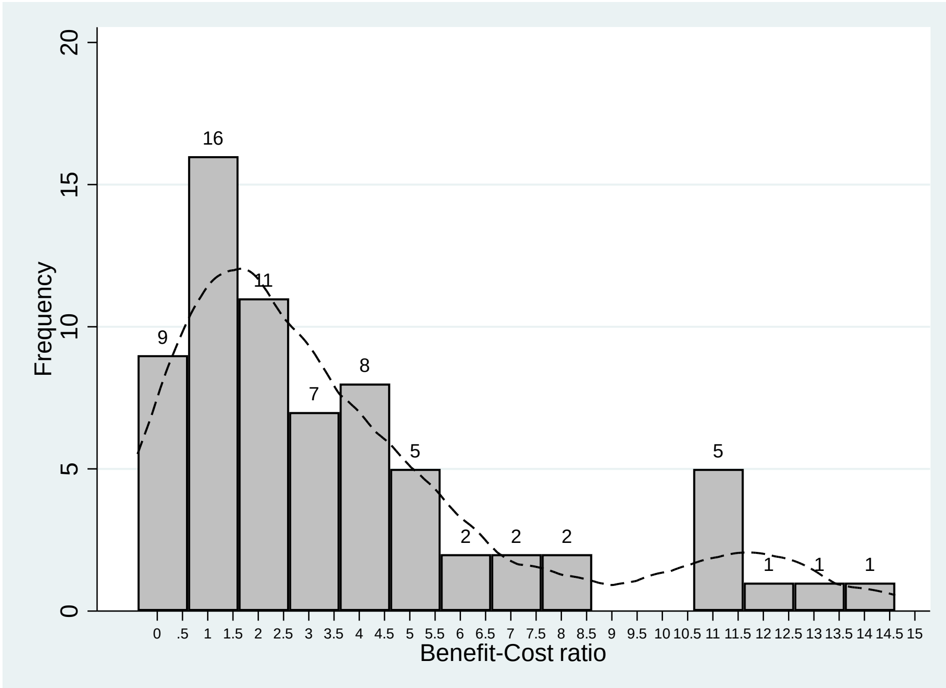
Which countries are the most likely under investors? Values of MIRR and BC for individual countries are presented in Tables 5.4 and 5.5, with Table 5.4 showing countries with BC ratios smaller than 2 (countries with lowest returns to R&D) and Table 5.5 showing countries with BC ratios equal or bigger than 2, sorted by BC values. Observe that large agricultural countries like China, India, and Brazil, big investors in the past decade, can still obtain large returns from R&D investment, so we could expect them to continue to expand investment in the coming years.

Figure 5.8 Distribution of the values of the MIRR obtained for 71 low and middle-income countries



Source: Elaborated by authors.
Note: MIRR = modified internal rate of return.

Figure 5.9 Distribution of the values of BC obtained for 71 low and middle-income countries



Source: Elaborated by authors.

Table 5.4 Discount rates and values of the MIRR and the BC ratio for low and middle-income countries with BC ratios smaller than 2, 2001-2011

Country	Discount rate	MIRR	BC
Barbados	5.0	0.4	0.1
Trinidad & Tobago	5.0	1.2	0.2
Belize	4.5	1.5	0.2
Botswana	5.0	2.3	0.3
Gambia	3.7	1.2	0.3
Namibia	4.5	2.0	0.3
Suriname	5.0	2.9	0.4
Sri Lanka	3.7	2.0	0.4
Uruguay	5.0	3.9	0.6
Senegal	4.5	3.7	0.7
Jamaica	4.5	4.0	0.8
Mauritius	3.7	3.3	0.8
Malaysia	5.0	4.9	1.0
El Salvador	4.5	4.5	1.0
Colombia	4.5	4.6	1.1
Indonesia	3.7	3.9	1.1

Table 5.4 Continued

Country	Discount rate	MIRR	BC
Guinea	3.7	4.0	1.2
Lao People's Democratic Republic	3.7	4.2	1.3
Kenya	3.7	4.3	1.3
South Africa	5.0	5.6	1.4
Gabon	5.0	5.6	1.4
Uganda	3.7	4.4	1.4
Thailand	4.5	5.2	1.4
Burundi	3.7	4.4	1.4
Togo	3.7	4.5	1.5
Panama	4.5	5.5	1.6
Philippines	4.5	5.5	1.7
Tunisia	4.5	5.8	1.9
Zimbabwe	3.7	5.1	1.9

Source: Elaborated by authors.
Note: BC = benefit-cost ratio; MIRR = modified internal rate of return.

Table 5.5 Discount rates and values of the MIRR and the BC ratio for low and middle-income countries with BC ratios greater than 2, 2001-2011

Country	Discount rate	MIRR	BC	Country	Discount rate	MIRR	BC
Madagascar	3.7	5.2	2.0	Côte d'Ivoire	4.5	7.7	4.5
Paraguay	4.5	6.0	2.1	Zambia	3.7	6.9	4.7
Chile	4.5	6.0	2.1	Nepal	3.7	7.0	4.8
Mexico	5.0	6.5	2.1	Bangladesh	3.7	7.0	4.9
Congo, Republic of	4.5	6.1	2.1	Nicaragua	3.7	7.1	4.9
Pakistan	3.7	5.4	2.2	India	3.7	7.1	5.0
Burkina Faso	3.7	5.6	2.5	Venezuela	5.0	8.7	5.7
Rwanda	3.7	5.7	2.6	United Republic of Tanzania	3.7	7.4	5.8
Dominican Republic	4.5	6.6	2.7	Niger	3.7	7.9	7.3
Jordan	4.5	6.7	2.8	Benin	3.7	7.9	7.3
Argentina	5.0	7.3	3.1	Turkey	4.5	8.9	7.9
Mali	3.7	6.1	3.1	Guatemala	4.5	9.0	8.3
Malawi	3.7	6.3	3.5	Mozambique	3.7	8.8	11.0
Honduras	3.7	6.4	3.6	China	3.7	8.8	11.2
Bolivia	4.5	7.3	3.7	Cambodia	3.7	8.8	11.2
Brazil	5.0	7.8	3.7	Sudan	3.7	8.8	11.3
Sierra Leone	3.7	6.5	3.8	Peru	4.5	9.7	11.5
Costa Rica	4.5	7.6	4.3	Morocco	4.5	9.9	12.4
Ghana	3.7	6.8	4.3	Viet Nam	3.7	9.2	13.3
Egypt	3.7	6.9	4.5	Nigeria	3.7	9.4	14.4
Ethiopia	3.7	6.9	4.5	Ecuador	4.5	11.1	21.5

Source: Elaborated by authors.
Note: BC = benefit-cost ratio; MIRR = modified internal rate of return.

6. CONCLUSIONS

This study proposes the use of PLS to determine the key parameters of the PIM model of capital stock as a new approach to calculate R&D knowledge stocks and R&D elasticities. This approach avoids most of the major problems encountered in the literature that lead to obtaining very high and implausible rates of return to agricultural R&D. The proposed method performs well in an application to global agriculture with relatively short time series. Results support findings from the literature showing that research lags are longer than those normally assumed in econometric analysis, which restricted lag length for empirical reasons. Results showing relatively long research lags apply not only to high-income but also to low- and middle-income countries. Using this approach, we obtain an average R&D elasticity for LM countries of 0.23 and an average rate of return to R&D investment of 6.0 percent, bigger than the average discount rate of 4.2 percent for these countries. Results show that 60 percent of LM countries in our sample are underinvesting in agricultural R&D, as they can get higher returns by investing in this activity than in activities that return the social discount rate.

APPENDIX A: TFP, INPUT ELASTICITIES, AND THE COBB-DOUGLAS PRODUCTION FUNCTION

The empirical framework to estimate input elasticities of the Cobb-Douglas production function follows Eberhardt and Teal (2013) and builds on a common factor representation of the log-linearized production function, allowing one to accommodate non-stationarity and correlation across panel members. Borrowing notation from Eberhardt and Teal (2013) we represent the Cobb-Douglas production function in logs as follows:

$$y_{it} = \beta_i{}' x_{it} + \mu_{it} \tag{A.1}$$
$$\mu_{it} = \alpha_i + \lambda_i' f_t + \varepsilon_{it} \tag{A.2}$$

The Cobb-Douglas production function (A.4) has observed output (y_{it}) and observed inputs (x_{it}) including labor, crop capital stock, livestock capital stock, fertilizer, feed, and agricultural land (all in logarithms). The constant term is represented by a combination of country-specific effects (α_i) and a set of common factors f_t, which can have different effects across countries (i).

The model allows for endogeneity as the input variables x_{it} are driven by a set of common factors g_{jt} and by the set (or subset) of factors f_t influencing output in equations (A.4) and (A.5), which means that some unobserved factors driving agricultural production are likely to drive, at least in part, the evolution of the inputs:

$$x_{ijt} = \pi_{ij} + \delta'_{ij} g_{jt} + \phi_{ij} f_t + v_{ijt} \tag{A.3}$$

Finally, equation (A.7) indicates that the latent factors are persistent over time, which allows for the setup to accommodate non-stationarity in factors ($\varrho = 1$, $\kappa = 1$).

$$f_t = \varrho' f_{t-1} + \epsilon_t \text{ and } g_t = \kappa' g_{t-1} + \epsilon_t \tag{A.4}$$

The parameter of interest for TFP calculation in this study is the mean effect β. As in Eberhardt and Teal (2013), we consider different models to estimate β. These models deal with unobserved heterogeneity, cross-section dependence, and dependence due to latent common factors. We divide these models into two groups: a) pooled models assume parameter homogeneity: all countries share the same slope parameters ($y_{it} = \beta' x$); and b) heterogeneous slopes models ($y_{it} = \beta i' x$). These models accommodate the type of endogeneity presented in the original model (equations A.4 to A.7) to arrive at consistent estimates for common slope coefficients calculated as the mean of heterogeneous β_i. Results for the best-performing models are presented in Table A.1. The preferred model is AMG2 and the elasticities used to calculate the input index used in TFP calculation are those with CRS imposed. For further discussion on these estimates see Nin-Pratt (2016).

Table A.1 Best performing models, unrestricted and with CRS imposed

	CCEPn		CCEPd		CMGn		AMG2	
	Unrestricted	**CRS-Imposed**	**Unrestricted**	**CRS-Imposed**	**Unrestricted**	**CRS-Imposed**	**Unrestricted**	**CRS-Imposed**
Labor	-0.106		-0.241*		-0.203		-0.0389	
	(0.218)		(0.135)		(0.138)		(0.124)	
Crop capital	0.0829***	0.0863***	0.0946**	0.124**	0.143***	0.177***	0.189***	0.178***
	(0.0283)	(0.0282)	(0.0475)	(0.0566)	(0.0513)	(0.0464)	(0.0512)	(0.0482)
Livestock capital	0.229***	0.263***	0.307***	0.341***	0.196***	0.259***	0.234***	0.270***
	(0.0651)	(0.0590)	(0.0386)	(0.0358)	(0.0306)	(0.0325)	(0.0298)	(0.0299)
Fertilizer	0.0133	0.0135*	0.0131**	0.0155***	0.0131**	0.0119	0.0228***	0.0267***
	(0.00747)	(0.00784)	(0.00504)	(0.00494)	(0.00649)	(0.00653)	(0.00625)	(0.00652)
Land	0.134	0.206***	0.134	0.239***	0.124	0.105	0.112	0.132
	(0.175)	(0.0784)	(0.0953)	(0.0748)	(0.118)	(0.0730)	(0.117)	(0.0812)
Feed	0.230***	0.230***	0.130***	0.136***	0.204***	0.224***	0.152***	0.171***
	(0.0538)	(0.0516)	(0.0276)	(0.0282)	(0.0215)	(0.0224)	(0.0185)	(0.0203)
Constant	-5.923***	1.722***	-3.520***	-0.943***	-0.391	2.709***	5.582***	4.958***
	(1.666)	(0.233)	(0.819)	(0.0614)	(1.528)	(0.278)	(1.085)	(0.205)
Implied labor coeff.	0.20	0.20	0.08	0.15	0.117	0.224	0.251	0.222
Returns [a.]	CRS	-	CRS	-	CRS	-	CRS	-
RMSE	0.075	0.078	0.063	0.066	0.047	0.050	0.057	0.060
Stationarity [b.]	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Mean ρij [c]	0.131	0.138	0.146	0.151	0.124	0.126	0.133	0.139
CD(p) [d.]	2.08	2.23	-1.26	-2.13	-0.6	-0.59	-0.33	-0.77
CD p value	0.038	0.026	0.207	0.033	0.549	0.556	0.739	0.442
Observations	6,171	6,171	6,171	6,171	6,171	6,171	6,171	6,171
Number of countries	121	121	121	121	121	121	121	121

Notes: Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.
Dependent variable is log output per worker in all models. CCEPn and CCEPd are the common correlated effects pooled estimators using the cross-section averages of the observed output and input variables of contiguous neighbors and the cross-section averages calculated using the population-weighted geographic distance between countries, respectively. The CMGn model is the heterogeneous version of the common correlated effects model with individual country regressions augmented by cross-section averages of dependent and independent variables using the data for the entire panel, in this case using neighboring countries as weights. The AMG2 is the Augmented Mean Group model with the dynamic process variable imposed in every country regression with a unit coefficient.
a. CRS refers to constant returns to scale.
b. Pesaran (2007) CIPS test results: I(0) stationary, I(1) non-stationary.
c. Mean absolute correlation coefficient.
d. Pesaran CD test, H0: no cross-section dependence.

Table A.2 R&D elasticities and average growth rates of TFP and of R&D stock, 1981-2011

Country	R&D elasticity	TFP	R&D stock	Country	R&D elasticity	TFP	R&D stock
Argentina	0.25	1.68	6.75	Malaysia	0.22	1.85	8.30
Bangladesh	0.18	1.52	8.46	Mali	0.22	0.97	4.34
Barbados	0.19	-0.33	5.64	Mauritania	0.16	-0.48	5.22
Belize	0.09	0.50	5.66	Mexico	0.19	1.30	6.91
Benin	0.35	2.24	6.37	Morocco	0.44	3.12	7.14
Bolivia	0.28	1.69	6.03	Mozambique	0.25	1.47	5.98
Botswana	0.11	0.65	6.05	Namibia	0.16	-1.22	5.50
Brazil	0.35	2.53	7.25	Nepal	0.23	1.83	8.07
Burkina Faso	0.20	1.06	5.24	Nicaragua	0.30	1.61	5.29
Burundi	0.16	-0.50	4.34	Niger	0.28	1.56	5.66
Cambodia	0.30	2.35	7.87	Nigeria	0.44	1.77	3.99
Chile	0.28	2.26	7.93	Pakistan	0.21	1.63	7.59
China	0.28	2.80	9.92	Panama	0.19	-0.61	5.30
Colombia	0.13	0.93	7.30	Paraguay	0.18	1.60	9.04
Congo, Republic of	0.38	1.60	4.24	Peru	0.36	2.07	5.79
Costa Rica	0.38	2.63	6.92	Philippines	0.14	1.06	7.63
Côte d'Ivoire	0.32	1.09	3.36	Rwanda	0.11	0.75	6.59
Dominican Republic	0.13	0.86	6.46	Senegal	0.16	-0.51	4.03
Ecuador	0.37	2.29	6.15	Sierra Leone	0.22	1.27	5.86
Egypt	0.41	2.16	5.21	South Africa	0.21	1.20	5.60
El Salvador	0.09	0.50	5.79	Sri Lanka	0.10	0.61	5.95
Ethiopia	0.13	1.47	11.09	Sudan	0.41	1.51	3.65
Gabon	0.22	0.92	4.20	Suriname	0.19	-0.03	6.07
Gambia	0.16	-1.75	4.75	United Republic of Tanzania	0.20	1.19	5.90
Ghana	0.26	2.33	9.12	Thailand	0.11	1.08	10.11
Guatemala	0.26	1.06	4.05	Togo	0.17	0.55	3.35
Guinea	0.06	0.27	4.81	Trinidad & Tobago	0.31	1.46	4.73
Honduras	0.15	0.88	6.03	Tunisia	0.21	1.20	5.68
India	0.17	1.64	9.41	Turkey	0.34	1.93	5.66
Indonesia	0.16	1.14	7.27	Uganda	0.06	0.35	5.70
Jamaica	0.16	0.93	5.88	Uruguay	0.10	1.05	10.03
Jordan	0.41	2.78	6.73	Venezuela	0.23	1.40	6.20
Kenya	0.22	1.41	6.44	Viet Nam	0.14	1.39	9.79
Lao People's Democratic Republic	0.15	1.10	7.59	Zambia	0.56	2.19	3.94
Madagascar	0.10	0.54	5.55	Zimbabwe	0.16	-0.06	5.56
Malawi	0.20	1.11	5.60				

Source: Elaborated by authors
Note: R&D = research and development; TFP = total factor productivity. R&D elasticities for countries with average negative TFP growth for the period are average elasticities of the country's region.

APPENDIX B: SOCIAL DISCOUNT RATE

There are two approaches for discounting future benefits, one consumption- and the other investment-based. The consumption rate of discount reflects the rate at which society is willing to trade consumption in the future for consumption today. This approach places a lower value on the consumption of future generations, because it assumes that future generations will be wealthier than we are and that the utility people receive from an extra dollar of consumption declines as their level of consumption increases. On the other hand, under the investment approach, the discount rate is the rate of return on investment. Without market distortions or inefficiencies, the consumption rate of discount would equal the rate of return on investment; however, there are many reasons why the two may differ. For the analysis in this study, we follow Moore, Boardman, and Vining (2013) and use a social discount rate (SDR) that reflects the weight that society puts on present and future consumption flows, which is equivalent to maximizing a social welfare function that equals the present (discounted) value of current and future utilities from consumption. It can be shown that this rate is

$$r=\rho+g\varepsilon \tag{B.1}$$

where ρ is the rate of decrease in the utility of incremental consumption just because it is in the future, sometimes called the pure rate of time preference; g is the percentage change in per capita consumption; and ε is the absolute value of the elasticity of the marginal utility of consumption with respect to consumption. Although ρ, g or ε could vary over time periods, we will assume that they are constant and, therefore, r is constant, at least within a generation (see Moore, Boardman, and Vining 2013). We refer to r as the rate at which consumption should be discounted for society to maximize the present value of utility from its current and future per capita consumption flows. This means that society achieves the optimal growth rate of consumption when the real return to investment equals r. To calculate r, we assume ρ=1.0 percent and ε=0.0135 as discussed in Moore, Boardman, and Vining (2013), but project growth using data from World Bank (2016) on consumption per capita for each country to determine the value of g.

APPENDIX C: MODIFIED INTERNAL RATE OF RETURN

In practical terms, the calculation of the MIRR proceeds as follows:

First, determine the present value of all future benefits:

$$PVB = \sum_{s=1}^{50} \frac{y}{k} \bar{\varepsilon}/(1+i)^s \tag{C.1}$$

where i is a real discount rate assumed as 5 percent in this analysis; y is output in the initial period; k is R&D stock, also in the initial period; $\bar{\varepsilon}$ is the R&D elasticity; and s are the periods after investment during which the dollar invested in s=0 generates increases in TFP.

The future value of all benefits after 50 years is then

$$FVB = PVB(1+i)^{50} \tag{C.2}$$

Given that the present value of the cost of the investment (PVC) is equal to US$1 (we are investing an extra dollar in R&D in the initial period), the MIRR is calculated as

$$MIRR = \left[\frac{FVB}{PVC}\right]^{1/50} - 1 = [FVB]^{1/50} - 1 \tag{C.3}$$

The BC is equal to

$$BC = \frac{PVB}{PVC} = \frac{PVB}{1} \tag{C.4}$$

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