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R&D Investments, technology spillovers and agricultural productivity, case of the Czech Republic

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Abstract: The objective of the paper is to quantify the effect of the R&D investments on agricultural productivity in the Czech Republic using the co-integration analysis. The effect of the R&D investments is measured by a knowledge stock constructed using a gamma distribution with lags ranging from 7 to 15 years. The relationship between the total factor productivity in agriculture, the domestic knowledge stock and the foreign R&D spillovers approximated by the imports of agricultural technologies is examined using an error correction model. Whereas the estimates confirm that domestic research plays a positive role in agricultural productivity, the results for the foreign R&D spillovers are rather weak. Furthermore, there is little evidence that either length of time or the functional form of weights plays a major role in assessing the dependence of the productivity on R&D investments; however, the models with the knowledge distribution lags longer than 7 years perform better.

Key words: agricultural research, co-integration analysis, knowledge stock, total factor productivity

The EU as well as the Czech development strategy puts great emphasis on the R&D activities with the expected effect on economic growth, sustainability and wellbeing of citizens. In the Czech Republic, both public and private gross R&D expenditures doubled in the last decade. Particularly in agriculture, public expenditures increased in the nominal terms by 91% between 2000 and 2012[1] and are about twice as large as the private ones (CSO 2013a). In light of this, the Czech government is increasingly concerned with an assessment of the effectiveness and the efficiency of the public R&D outlays, as well as with getting evidence that the R&D policy has also stimulated the private sector involvement in the financing of research activities.

There is theoretical reasoning and empirical evidence that the R&D investments play a positive role in the economy. Numerous studies have analysed the R&D effects in the agricultural sector and derived predominantly positive returns from the public R&D spending, usually by examining long time series, which allow capturing the lags between R&D activities and the responses. Unlike the essentially continuous evolution of the R&D policy in countries like the UK, the US and Australia, the Czech science and technology have experienced dramatic changes induced by the economic transition since 1990. While the rapid productivity growth in all sectors, including agriculture, is likely mainly due to the institutional reforms in the early 1990s (e.g. Rizov 2005, Ratinger et al. 2006), the further productivity improvements should be attributed to the transfer of knowledge and technology.

The objective of this paper is to analyze the development of agricultural productivity within the context of the structural transformation, and to examine whether the positive evidence found in other studies for the role of R&D in agricultural productivity can be applied to the case of the Czech Republic, taking into account the specific development that the country has gone through. It refers in particular to the transition from a centrally planned to a free-market economy

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[1]By 57% in real terms using the GDP deflators (CSO 2013d).

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resulting in a radical contraction of the agricultural sector and a massive inflow of technology and expertise from the Western neighbours in the process of structural transformation. The transition also implied a certain degree of misfit of the agricultural R&D stocks accumulated in the past and the needs of the transforming sector. In addition, there is an inevitable inconsistency of the national statistics and thus a constrained possibility to use solid time series.

The above-mentioned caveats are reflected in the methodological approach of this paper. Due to the constrained availability of data, the Total Factor Productivity (TFP) could be computed only from 1993 on, when the economic accounts that followed the EUROSTAT standards were constructed. In order to address the dramatic inflow of the R&D from abroad, the R&D-embodied imports of agricultural technologies are included in the estimated Equation, following the assumption that international trade is a vehicle of knowledge spillover (Van Meijl and Van Tongeren 1999) and that under massive international spillovers, the national agricultural research might act as a free rider (as pointed out by Esposti 2002).

EMPIRICAL EVIDENCE OF THE EFFECTS OF R&D PRODUCTIVITY ON AGRICULTURE

There is convincing empirical evidence that the cumulative domestic R&D and knowledge stocks are important determinants of productivity. The effect of R&D investments on productivity was studied as early as in the 1960s by Griliches (1964), Mansfield (1965) and Evenson (1968). These pioneering works were often based on the evidence from the agricultural sector – for instance, Griliches (1958) derived a 40% return on public R&D in the hybrid corn, and Evenson (1968) derived a 50% aggregate rate of return on the public R&D in agriculture.

There are certain characteristics that distinguish agriculture from other sectors when measuring the effects of R&D on productivity. First of all, most studies are based on the aggregated data at the sector level, since the expenditures of firms on R&D in agriculture are usually not available. Second, the public sector plays a principal role in financing agricultural research, and therefore most of the studies quantify the social rates of return that are larger than the private rates captured at the micro-level. Most importantly, contrary to the industrial research, which has a more experimental and hence a short-term character, the R&D investments in agriculture have a lengthy gestation period which requires the adoption of specific approaches to constructing knowledge stocks in agriculture.

Alston et al. (2000) conducted a meta-analysis of the returns on agricultural R&D based on the results of 289 studies and concluded that the average returns on R&D in agriculture reach 82% (mean) and 44% (median). They also pointed out that, contrary to the common belief, there was no evidence of falling returns in agriculture, and thus advocated for continuous public investments in agricultural R&D. Similar conclusions were derived by Johnson and Evenson (1999), who investigated the role of the public research in 6 OECD countries from 1973–1986 and found that the public R&D has a direct impact on the agricultural TFP, whereas the private domestic R&D has only an indirect impact, and therefore it is necessary to continuously support public research in agriculture. However, the recent evidence shows that the public sector's share in the R&D expenditures has fallen at the expense of a rapid concentration of the private sector research conducted by the multinationals, as discussed in Piesse and Thirtle (2010). The relationship between the and public research in agriculture was also studied by Alfranca (2005), who pointed out that there were substantial differences in the proportions of the private and public R&D across the EU countries. Moreover, due to the high diversity of agriculture in Europe, the applied research has predominantly local effects, which makes it an impure public good. Alfranca found that the public sector may have been over-investing in applied discoveries with a strong protection of property rights, which resulted in the crowding out of the private R&D. On the other hand, protecting discoveries in the basic and general sciences is more complicated, which justifies the public role in R&D investments.

Besides the debate on the role of the public sector in financing agricultural research, there is also an extensive discussion on the proper way to estimate the R&D stocks in agriculture. As Alston et al. (2008) point out, many researchers underestimate the time lags between the initial research investments and the ultimate economic impacts. Alston explains these long lags using the development of a new crop variety as an example. As shown in Figure 1, research and development might take 5–10 years before the variety is adopted, due to the time spent on experimental trials and regulatory approvals. After the variety is adopted, the farmers have to learn how to

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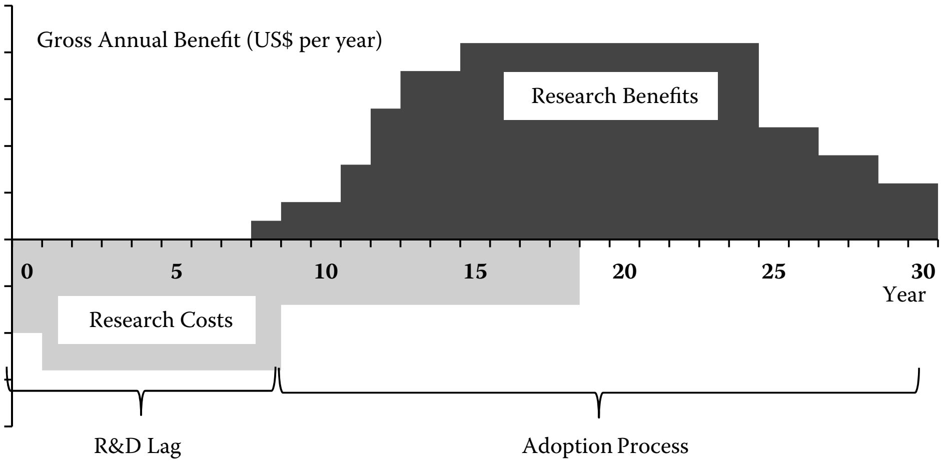

Figure 1. Stylized representation of research benefits and costs of developing a new crop variety

Source: Alston et al. (2008)

produce it, and the consumers have to accept the new product innovation in the market. Therefore, the peak of benefits only comes 15–25 years after the initial investment. Eventually, the variety may become obsolete, as it may be less effective against the evolving pests or diseases.

Unlike in agriculture, the adoption of R&D in industry does not involve lags because the benefits of investing in a new machine accrue immediately; however, the service life of the investment is short. This process can be best described by a geometric model. It is apparent that this model is not suitable for the R&D processes in agriculture. Instead, a trapezoidal lag model and the gamma lag distributions are recommended for modelling the R&D stocks in agriculture. The trapezoidal model was first introduced by Huffman and Evenson (1983, cit. in Alston 2009) and allows for the longer life of R&D investments, although the peak comes in as little as 10 years, compared to the gamma distribution. As Thirtle, Piesse and Schimmelpfennig (2008) further comment, the gamma distribution is of interest since it offers the smooth form of a trapezoid, which can be estimated rather than imposed.

By fitting the knowledge stocks calculated from the alternative distribution specifications in a TFP regression, Alston (2009) found that in a double log function, a gamma distribution with a maximum 50-year lag and peak after 24 years yields the best result. For the calculation of the knowledge stock with this distribution, Alston used the following formulas:

$$SR_{i,t} = \sum_{k=0}^{50} b_k \cdot \left(R_{i,t-k}\right)$$

$$\text{where } \sum_{k=0}^{50} b_k = 1 \text{ and } b_k = \left(k+1\right)^{\frac{\delta}{1-\delta}} \cdot \lambda^k \qquad (1)$$

where $SR_{i,t}$ represents the accumulated knowledge stock per state, $R_{i,t-k}$ represents the R&D expenditures in lagged period $t-k$, b_k are weights that sum to one, k is the maximum lag of the distribution and l and d are the gamma distribution parameters[2].

Various studies have adopted the above-mentioned distributions in modelling the R&D stocks. For instance, Sheng et al. (2011) tested 10 different alternatives of gamma, trapezoidal and geometric distribution for constructing the stocks in Australian agriculture from 1953–2007. The authors concluded that the gamma distribution with a peak after 7 years and a lag of 35 years performed the best. Under this distribution, the estimated elasticity of TFP with respect to the public R&D knowledge stocks was 0.23%, with an internal rate of return on the public R&D reaching 28%. Similarly, Hall and Scobie (2006) found a 17% rate of return on the public R&D in New Zealand agriculture, using the perpetual inventory method, a Koyck transformation and a polynomial lag structure on the annual data from 1927–2000.

In the European literature, modelling of the R&D stocks also raised attention among researchers. Esposti (2001) questions the high rates of return reported in the Alston's meta-analysis, which he attributes to an ad-hoc measurement of knowledge stocks, and de-

[2]According to Alston's findings, the parameters of the preferred gamma distribution of the US knowledge stocks are d = 0.8 and l = 0.7.

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velops a new analytical framework with a stochastic gestation period and an adoption period that follows a geometric distribution. However, due to the lack of data, the basic parameters of his proposed model are difficult to estimate empirically.

Recently, Thirtle et al. (2008) investigated the impact of R&D on agricultural productivity in the UK from 1953–2005. By regressing the Thornquist-Theil TFP index on the lagged public R&D expenditures, mechanical and technical patents as proxy to the private R&D and farm size, the authors found highly significant results, with the strongest R&D lag of 12 years. Consequently, Thirtle et al. confirmed a co-integrating relationship between the TFP and the explanatory variables, with the Granger causality from R&D to TFP. Instead of developing an error correction model (ECM), the authors investigated different knowledge stock distributions, such as the polynomial, trapezoidal, gamma and beta distributions, and showed that they lead to different estimates of the R&D rates of return..

R&D EXPENDITURES AND AGRICULTURAL PRODUCTIVITY IN THE CZECH REPUBLIC

Evolution of agricultural R&D expenditures and imports of technologies

The first attention to research and development in Czechoslovakia can be dated back to 1952, when the Czechoslovakian Academy of Sciences was established. Although the research efforts might have existed in the previous periods, when Czechoslovakia was part of the Austro-Hungarian Empire and later after 1918 when the independent Czechoslovak Republic was established, there are no available statistics on the R&D expenditures or number of workers in agricultural sciences. Moreover, the occurrence of two world wars in the first half of the 20th century negatively affected any research efforts that might have existed.

According to the Historical Statistical Yearbook of Czechoslovakia (FSO 1985), an important moment for stimulating research was the establishment of the Science and Technology Fund in 1962, which became an instrument for implementing the state research policy. Statistical data on science and technology was reported in the statistical yearbooks from 1966 in an aggregated form for Czechoslovakia. Between 1966 and 1983, the nominal expenditures on science and technology in Czechoslovakia increased by 158%, and the number of workers employed in research grew by 37%. Despite this positive trend, in 1983 only 32% of all scientific workers were university educated, out of which only 19% had scientific qualifications[3]. Therefore, the marginal productivity of the R&D workers in science was very low.

From 1975, the statistical yearbooks provide the R&D expenditures and sector-specific data on the R&D employment separately for the Czech and Slovak Republics. Based on this data, it was possible to derive expenditures on science and technology in agriculture, following the assumption that the share in the R&D expenditures follows the share in the R&D employment (Figure 2).The R&D expenditures in agriculture

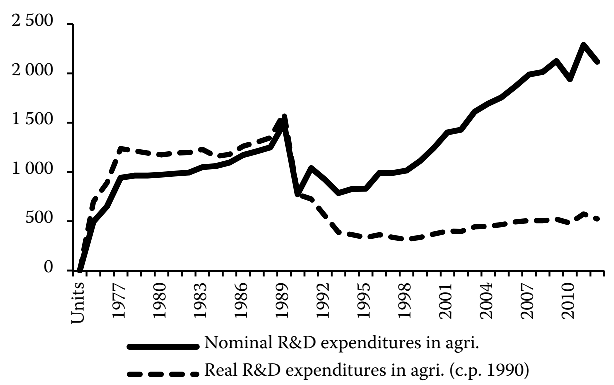

Figure 2. The evolution of nominal and real R&D expenditures in agriculture (CZK Mln.)

Source: FSO (1985–1993), CSO (2013a) (1994–2012)

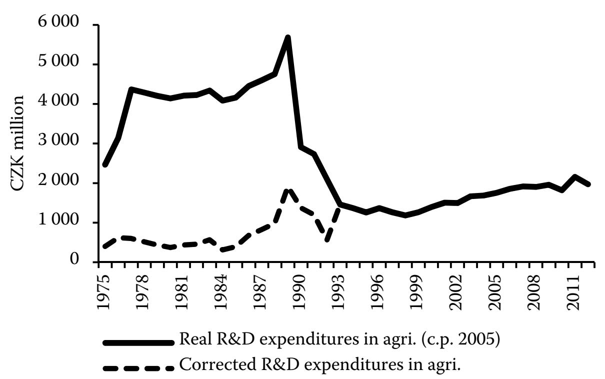

Figure 3. Correction of the R&D expenditures in agriculture (CZK Mln.)

Source: Own calculation based on trend analysis

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grew quickly after 1975 due to a 50% increase in the number of scientific workers in agriculture during this period. The value of the R&D investments in agriculture culminated at the end of the 1980s as the result of an overall boom in science and technology spending in Czechoslovakia.

After 1989, dramatic changes connected with the aftermath of the Velvet Revolution affected the development of the whole economy. This was reflected in a sudden fall of the governmental expenditures on agricultural research by almost 50% between 1989 and 1990. The situation became stabilized after 1994, when the economy started to recover from the shocks associated with the rapid liberalization of the economy. After 2000, the nominal R&D expenditures on agriculture grew steadily by 6% annually.

When converting the nominal R&D investments to the real investments corrected by the GDP deflator, the real R&D investments in agriculture seem to be far below the pre-transformation levels, as displayed in Figure 2. It can be argued that although the nominal level of R&D investments was higher before 1989, the real contribution of agricultural research to the economy was actually much smaller due to a large share of non-scientific workers employed in agricultural research, as mentioned above. After 1989, when the centrally planned economy was abandoned, the artificially employed workers were rapidly expelled from the research sector to other industries. In order to capture this notion in our dataset, the time series of the real R&D expenditures was corrected by shifting the over-estimated level downwards, such that the corrected time series captures the initial trends but is increasing in time, as shown in Figure 3. The corrected data for the R&D expenditures was consequently used in the econometric estimation, as described in the next chapter.

After 1989, the agricultural sector faced increasing exposure to spillovers from the foreign R&D, embedded in the imports of agricultural technologies. Between 1993 and 2012, the total nominal imports of agricultural technologies increased by 200% (Figure 4). The most significant increase was registered in the case of imports of the genetic materials for crops (+913%), as well as tractors (+608%) and fertilizers (+481%). Figure 4 also shows that the largest value of the imported technologies can be attributed to equipment, which accounts for almost 50% of all imports, followed by pesticides and fertilizers, which contribute to the total imports by 20% each.

Evolution of agricultural productivity

After 1989, agricultural production faced a dramatic decline caused by the liberalization of the economy, including the rapid abolition of the past system of heavy agricultural subsidies. The subsequent structural adjustment led to the shed of labour from agriculture to other sectors. Between 1990 and 1991, the gross agricultural production expressed in constant prices of 2005 a shrank by 30%. The decline of agriculture continued until the end of the 1990s. After 2000, the agricultural production partially recovered, but at the beginning of the second decade of the new millennium, the agricultural production remained by 70% below the pre-transitional level (i.e. in 1989 and 1990). In the effect, the share of agriculture on

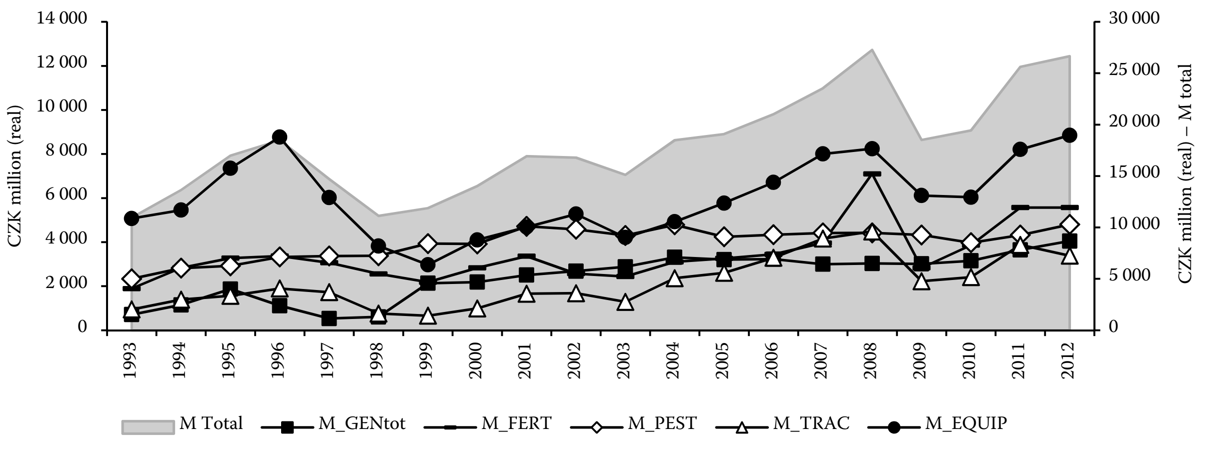

Figure 4. The evolution of imports of technologies for agriculture

Source: CSO (2013c)

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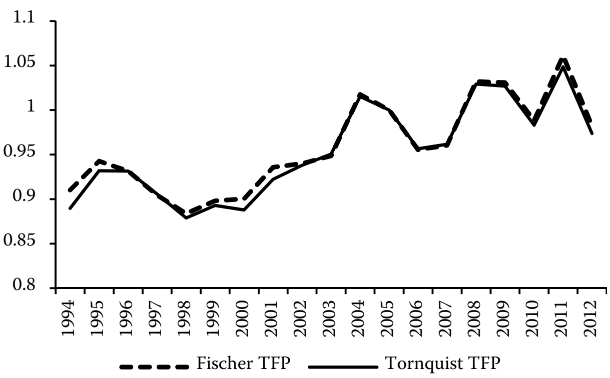

Figure 5. The evolution of theTFP indices

Source: CSO (2013b) (1994–2012) and Ratinger (1995)

the GDP dropped to 2%, which corresponds to the shares typical for the OECD countries.

The economic pressure of the transition and later of the common market required an adjustment of factors, such as a reduction in agricultural employment as well as the more rapid and extensive deployment of knowledge and up-to-date technologies. This process is embodied in the growth of productivity in agriculture, which can be measured by the total factor productivity indices such as the Tornquist TFP and the Fischer indices (e.g. Antle and Capalbo 1998). In our analysis, we constructed the Tornquist TFP and the Fischer indices based on the data from the Economic Accounts for Agriculture (EAA), which have been published since 1998 by the Czech Statistical Office. In the period 1994–1997, the Czech EAA were built by the Research Institute of Agricultural Economics (VUZE) in a pilot project (Ratinger et al. 1995). Using a backward prediction, we finally obtained the Tornquist TFP and Fischer indices for the period 1993–2012 (Figure 5). Both indices show an increasing trend in the total factor productivity, with some fluctuations in specific years.

DESCRIPTION OF THE METHODOLOGICAL APPROACH APPLIED IN THE PAPER

We follow the assumption that agricultural productivity is driven by technology, and that technology is a result of the national R&D spending and the R&D spillover from abroad. We measure the R&D expenditures as expenditures to agricultural sciences (Frascati manual, OECD 2002) which comprise both public and private spending. Our methodological approach follows Thirtle et al. (2008) and Alston et al. (2011), who analyzed the R&D effects on agriculture in the UK and the USA, respectively. To our knowledge, there has not been any recent study performed on the countries in the Central and Eastern Europe, which is probably due to the lack of a consistent time series. In spite of the substantially different socio-economic context prior to 1989, we nevertheless followed the above-mentioned approaches, with some modifications reflecting the specific conditions of our research case.

First, we investigated whether there is a significant relationship between the simple productivity indicators and the R&D spending (current or lagged but not accumulated) over the long term (1975–2012), and we determined the appropriate lag in the R&D spending. Second, we constructed the accumulated knowledge (i.e., knowledge stock) by weighting lagged spending. Consequently, we assessed the relationship between the TFP and the knowledge stock using the co-integration analysis framework (e.g., Charemza and Deadman 1992). Besides the cumulated domestic R&D expenditures, we also considered spillover effects from the rest of the world. These spillovers are represented by the the import of technologies employed in agricultural production.

Definition of the empirical form of the model

The empirical form of our model is provided in Equation 2:

$$\ln TFP_t = \alpha_0 + \alpha_1 \cdot \ln KnSt_t + \alpha_2 \cdot \ln MSt_t + \varepsilon_t \tag{2}$$

where TFP_t is the a total factor productivity index, $KnSt_t$ denotes the knowledge stock calculated as a weighted sum of past investments in agricultural research *R_DAgr*, and MSt_t is the imported technology (knowledge) stock. Parameters α_1 and α_2 represent the elasticity of productivity with respect to the domestic and foreign knowledge stock.

Two indices were considered in calculating the total factor productivity – the Tornquist TFP index and Fischer index. Data for calculating the TFP was obtained from the Economic Accounts for Agriculture.

The Tornquist-TFP index was calculated as follows:

$$\ln(TFP_t) = \frac{1}{2}\sum_{i=1}^{n}\left(R_{i,t} + R_{i,0}\right)\ln\left(\frac{Q_{i,t}}{Q_{i,0}}\right) - \\ - \frac{1}{2}\sum_{j=1}^{m}\left(S_{j,t} + S_{j,0}\right)\ln\left(\frac{X_{j,t}}{X_{j,0}}\right) \tag{3}$$

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where Q_i and X_j denote the multiple outputs (crop production, livestock production and other production) and inputs (labour, land, consumption of gross fixed capital and operational capital), respectively, and R_i and S_j the shares in revenue and costs, respectively.

Similarly, the Fischer TFP index was calculated according to formula 4:

$$FIS_t = \left(\frac{\boldsymbol{P}_0'\boldsymbol{Q}_t}{\boldsymbol{P}_0'\boldsymbol{Q}_0}\frac{\boldsymbol{P}_t'\boldsymbol{Q}_t}{\boldsymbol{P}_t'\boldsymbol{Q}_o}\right)^{\frac{1}{2}}\left(\frac{\boldsymbol{W}_0'\boldsymbol{X}_0}{\boldsymbol{W}_0'\boldsymbol{X}_t}\frac{\boldsymbol{W}_t'\boldsymbol{X}_0}{\boldsymbol{W}_t'\boldsymbol{X}_t}\right)^{\frac{1}{2}} \quad (4)$$

where $\boldsymbol{Q}$ and $\boldsymbol{X}$ are the vectors of multiple outputs and inputs, and $\boldsymbol{P}$ and $\boldsymbol{W}$ are the respective vectors of prices. Zero index indicates the base year; in our case we used the year 2005, and thus $TFP_{2005}=FIS_{2005}=1$. Since the Tornquist TFP and Fischer TFP indices are almost identical, we present the analysis using only the Tornquist TFP.

Time series analysis

The regression analysis employs the time series data which requires the adoption of common procedures of the time series analysis, carried out in the following three steps:

(1) Proving that the dependent (*TFPt*) and independent variables (R_DAgr_t, $KnSt_t$ and MSt_t) are integrated of order 1 by using an Augmented Dickey-Fuller unit root test (ADF).

(2) Estimating the co-integrating vector and testing whether the error correction term is of order 0.

(3) Estimating the error correction model:

$$\Delta y_t = \alpha_0 + \alpha_1 \cdot \Delta x_t + \beta\left(y_{t-1} - \delta \cdot x_{t-1}\right) + \varepsilon_t \quad (5)$$

where $\left(y_{t-1} - \delta \cdot x_{t-1}\right)$ is an error correction term and the corresponding parameter β provides an estimate of the speed of adjustment towards the long-run equilibrium.

Compared to the other studies, we have relatively short time series (1975–2012, or 38 years). They do not allow for lags of 50 or more years, as in Alston et al. (2011) or Thirtle et al. (2008). This limits our analysis; however, we believe that the transfer of knowledge could accelerate in the focus period due to several factors: in the 1970s and 1980s agriculture was one of the few sectors exhibiting substantial dynamics and growing income. A number of collective farms were able to absorb even the non-agricultural technologies: food processing, construction, various manufacturing processes and the ICT. In the transition period, we could observe a further and rapid upgrading of technologies, probably induced by the urgent need to enhance the competitiveness of agricultural production. the

Following these assumptions, the knowledge stock accumulation was approximated by a gamma distribution under the alternative parameter values, following Alston (Equation 1).

Estimation of returns on research

There are various methods for calculating the returns on research as well as various indicators. Most authors cited in section 2 provide estimates of the internal rate of return, which measures the attractiveness of one dollar or other currency equivalent invested in R&D.

The derivation of the internal rate of return applied in this paper is provided below. The approach follows Alston (1998), who estimates the internal rate of return from the R&D investment based on the knowledge accumulation function, and Thirtle and Bottomley (1998).

The parameter δ from the co-integration Equation indicates a long-term elasticity in labour productivity TFP_t to knowledge $KnSt_t$, which can be written as:

$$\delta = \frac{dTFP_t}{dKnSt_t} \cdot \frac{KnSt_t}{TFP_t} \quad (6)$$

The increase in the knowledge stock in the period $t+k$ ($dKnSt_{t+k}$) from a unit change in the R&D investments in period t is given by:

$$dKnSt_{t+k} = b_k \cdot dRD_t \quad (7)$$

Solving for the change in the total factor productivity $dTFP_t$ from Equation 6 and substituting for $dKnSt_{t+k}$ yields:

$$dTFP_{t+k} = \frac{\delta \cdot TFP_{t+k} \cdot dKnSt_{t+k}}{KnSt_{t+k}} = \frac{\delta \cdot TFP_{t+k} \cdot b_k \cdot dRD_t}{KnSt_{t+k}} \quad (8)$$

The marginal increase in the total factor productivity per unit of the R&D investment thus reads as:

$$\frac{dTFP_{t+k}}{dRD_t} = \frac{\delta \cdot TFP_{t+k} \cdot b_k}{KnSt_{t+k}} \quad (9)$$

A simplified version of the Tornquist-Thile index with one output and input (i = 1, j = 1) can be expressed as:

$$\ln TFP_t = \ln\frac{Q_t}{Q_o} - \ln\frac{X_t}{X_o} \quad (10)$$

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Differentiating Equation 10 with respect to output yields:

$$\frac{d\ln TFP_t}{dO_t}=\frac{1}{TFP_t}\cdot\frac{dTFP_t}{dQ_t}=\frac{d\ln\frac{Q_t}{Q_0}}{dQ_t}=\frac{d\left(\ln Q_t-\ln Q_0\right)}{dQ_t}=\frac{1}{Q_t} \quad (11)$$

From Equation 11, the derivative of TFP can be obtained as:

$$dTFP_t = dO_t\cdot\frac{TFP_t}{Q_t} \quad (12)$$

Substituting for $dTFP_{t+k}$ from Equation 12 enables us to derive the marginal product of R&D investment:

$$MP_{t+k}=\frac{dQ_{t+k}}{dRD_t}=\frac{\delta\cdot TFP_{t+k}\cdot b_k\cdot Q_{t+k}}{TFP_{t+k}\cdot KnSt_{t+k}}=\frac{\delta\cdot Q_{t+k}\cdot b_k}{KnSt_{t+k}} \quad (13)$$

The expression in Equation 13 shows that the marginal product of one unit of R&D investment is calculated as the elasticity of knowledge multiplied by the average product of knowledge distributed over k periods corresponding to the lag in R&D investment.

The marginal product of the R&D investment in Equation 13 represents the marginal benefit enjoyed in year $t+k$ of one dollar or, in our case, one Czech crown, spent on the R&D investments in year t. The marginal internal rate of return r is thus estimated from Equation 14:

$$\sum_{k=0}^{n}\frac{MP_{t+k}}{(1+r)^k}-1=\delta\cdot\sum_{k=0}^{n}\frac{Q_{t+k}\cdot b_k}{KnSt_{t+k}}\cdot\frac{1}{(1+r)^k}-1=0 \quad (14)$$

By assuming a constant share of output to knowledge, Equation 14 can be further simplified using the average values of output and knowledge:

$$\delta\cdot\frac{\overline{Q}_{t+k}}{\overline{KnSt}_{t+k}}\sum_{k=0}^{n}\frac{b_k}{(1+r)^k}-1=0 \quad (15)$$

RESULTS

The analysis is divided into three parts. In the first part, we construct the domestic knowledge stock from the national R&D expenditures covering 1975–2012. In the second part, we model the agricultural productivity using the TFP indices, calculated for the period 1993–2012. Finally, in the third part we introduce the R&D spillovers from abroad into the model and estimate their effect on the total factor productivity of Czech agriculture. We then derive returns on research based on our elasticity estimates.

Construction of knowledge stocks from agricultural R&D investments

Prior to considering the impact of the accumulated knowledge stock, an auxiliary regression was performed to assess the impact of the current and lagged R&D investments (with a maximum lag of 15 years) on simple measures of productivity (labour productivity, cereal and milk yields) that have been available since 1975[4]. Based on these results, it was concluded that the effect of the R&D investments on labour productivity and yields is delayed by more than 10 years.

This finding was used for constructing the knowledge stock based on the accumulated R&D investments in the lagged periods. Various forms of the gamma distribution were tested by varying the lag of the distribution and the parameters d and l. An illustration of the gamma distribution forms applied in the regression analysis is provided in Figure 6. It can be observed that different values of the gamma parameters significantly affect the shape of the distribution curve, in terms of both kurtosis and skewness. For instance, the application of the gamma distribution d(0.1)l(0.8) implies a slowly accumulating knowledge with the highest power in t+15, whereas the version d(0.8)l(0.4) assumes the strongest peak in t+11 periods, after which the knowledge stock rapidly diminishes. These different alternatives of a gamma distribution were consequently applied to our regression analysis in order

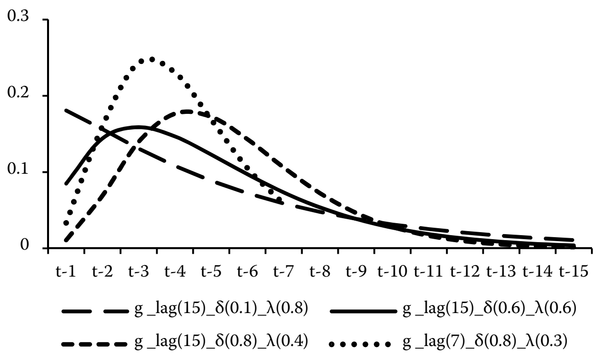

Figure 6. Gamma distribution forms applied in the regression analysis

Source: own calculation

[4]The regression with cereal yields brought the best ECM results for the highest lag of 15 years.

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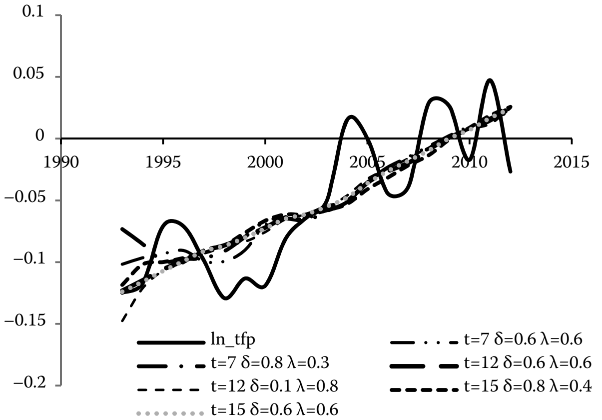

Figure 7. The development of the domestic knowledge stocks by functional forms

Source: own calculation

to find a co-integration relationship between the knowledge stock and productivity.

Impact of domestic R&D investments on total factor productivity in agriculture (1993–2012)

As shown in Figure 5, the difference between the Tornquist TFP index and the Fischer index is negligible; we therefore present the analysis only for the Tornquist TFP index, referred to hereafter as TFP.

Based on the previous chapter, we selected 6 internal knowledge stock aggregations of lengths (t) 7, 12 and 15, and using the gamma distribution of weights given three combinations of δ and λ (0.1, 0.8), (0.6, 0.6) and (0.8, 0.4) (Figure 7).

In the first two steps, we estimated the co-integrating vector (1,–β) for *ln(TFP)* and *ln(KnSt),* where *KnSt* stands for the knowledge stock generated by either of the selected aggregation functions. The values of the estimated parameter β [b] range from 0.246 to 0.276 depending on the construction of the knowledge stock variable. All the residuals of the co-integrating regressions are stationary I(0) conducting the ADF, all are significant at the 0.01 level).

In the third step – the application of the error correction model – we introduced three dummy variables to capture the short-term effects of weather and the overall economic conditions on agricultural productivity: *Econ_Slowdown* relating to the slowdown of the Czech economy since 2008, *Econ_Crises* considering the years 1998, 2008 and 2012 as years of economic recession, and *Weather* relating to years of significant weather disasters (1997, 2006 and 2007). The resulting error correction model takes the form of:

$$\Delta\ln(TFP_t) = \alpha_1 \cdot \Delta\ln(Knst_t) + \\ + \alpha_2\left[\ln(TFP_{t-1}) - b\cdot\ln(KnSt_{t-1})\right] + \alpha_3 \cdot dummy + \varepsilon_t \quad (16)$$

where $\ln(TFP_{t-1}) - b\cdot\ln(KnSt_{t-1})$ is the lagged error correction term (*L.ercorr*) and (1,–*b*) is a co-integrating vector from step 1.

All error correction models are significant at the 0.01 level. The residuals are stationary (by the ADF test at the 0.01 level) and there is no signal for the serial correlation (D-W statistics is around 2). We can argue that the model with the weather dummy

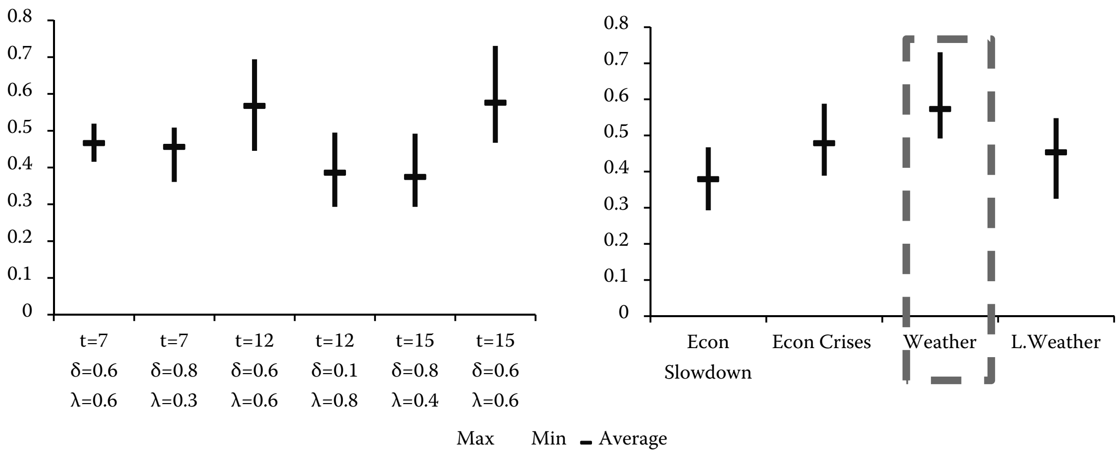

Figure 8. Variation of the parameter at D.ln(KnSt*) in the ECM

Note: Significant only in the ECM with the weather dummy (the rectangle in the right-hand chart).

Source: own calculation

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Table 1. Elasticities of TFP with respect to knowledge stock in the long- and short-term perspective

	t = 7 δ = 0.6 λ = 0.6	t = 7 δ = 0.8 λ = 0.3	t = 12 δ = 0.6 λ = 0.6	t =12 δ =0.1 λ = 0.8	t =15 δ = 0.8 λ = 0.4	t = 15 δ = 0.6 λ = 0.6
Long term	0.276	0.265	0.260	0.246	0.268	0.259
Short term	0.519	0.509	0.694	0.495	0.492	0.731

Source: own calculation

performs the best; all parameters are significant in the respective sub-models except the model which considers the knowledge stock distribution, given by t = 7, δ = 0.8 and λ = 0.4 (see Appendix 1 for detailed results).

Although the coefficients at the first difference of the R&D stock (*D.ln(KnSt*)*) are rarely significant, they exhibit a certain level of stability; the values depend on the functional form (the lag length and gamma distribution parameters), but also markedly on the inclusion of the dummy variable (Figure 8).

There is a rather considerable difference between the parameters (elasticities of TFP with respect to the knowledge stock) obtained from the first and second step, i.e., referring to the long- and short-term perspectives (Table 1).

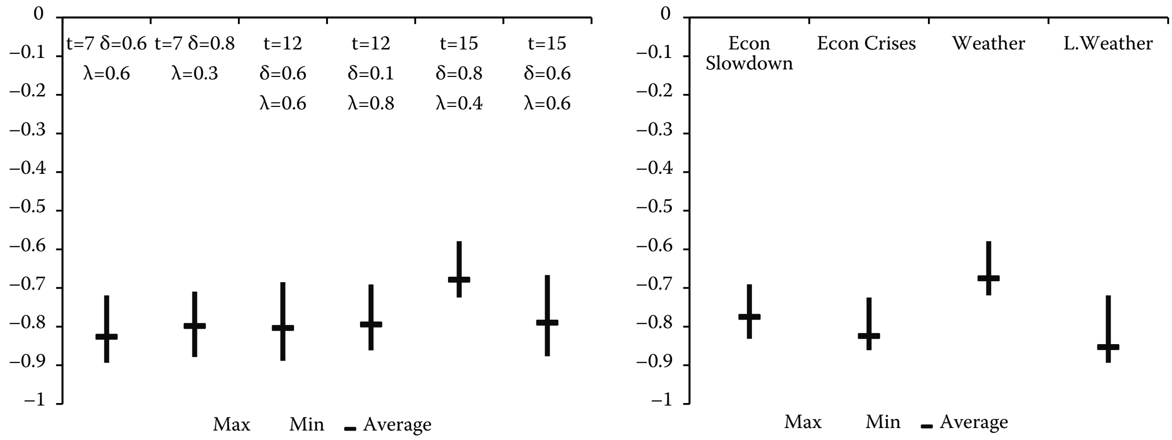

Figure 9. Variation of the coefficient at the lagged error term (L.(ln(TFP)-ln(KnSt_*))

Note: The error correction term is defined as ln(TFP) – b ln(KnSt_*), where (1,–b) is a co-integrating vector.

Source: own calculation

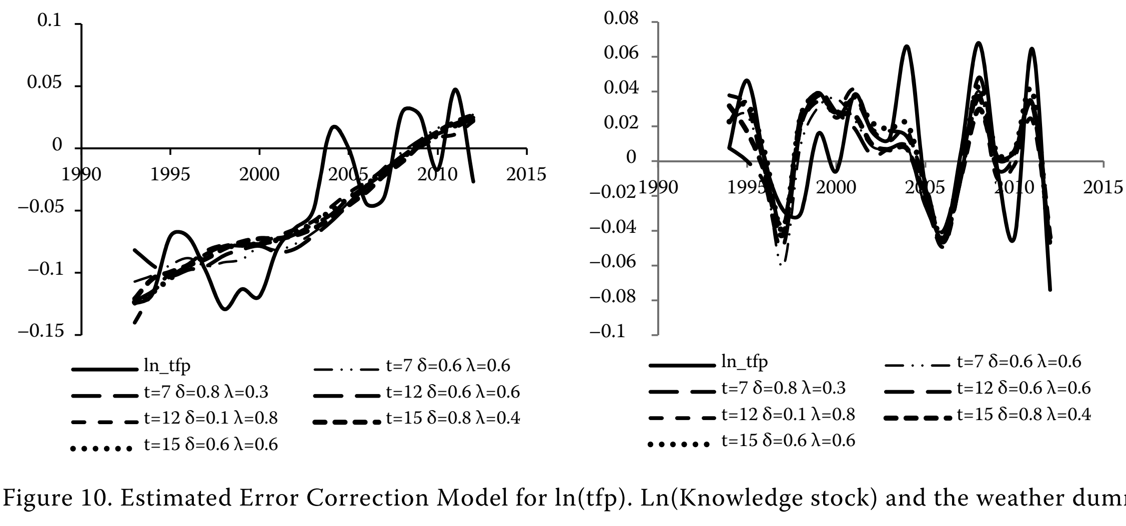

Figure 10. Estimated Error Correction Model for ln(tfp). Ln(Knowledge stock) and the weather dummy

Source: own calculation

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The parameter at the error correction term is significant in all the presented models. The values of the parameter exhibit a relatively narrow range (–0.86 to –0.58) across all models, and between –0.71 and –0.58 in the set of models with the weather variable. Keeping in mind that this coefficient provides an estimate of the speed of adjustment towards the long-run equilibrium, we can conclude that the models exhibit a rather strong adjustment power (Figure 9).

Figure 10 illustrates how well the knowledge stock models fit the TFP development. Obviously, there is not much difference between the presented alternatives of the knowledge stock, in terms of either time span or functional form; however, from the attempts we made with other time lengths and the gamma function parameters, we can assert that the models with $t. \leq 5$ and peaks of the gamma distribution close to the current year perform worse than those presented here.

Model with the approximated external R&D spillovers

We have tried to approximate the R&D spillover by imports of technologies, i.e., the genetic material, pesticides, fertilizers, tractors, machinery and equipment. We approached the imported technology (R&D spillover) in a similar way as the domestic knowledge stock; the R&D spillover is the sum of the recent imports, the lag is much shorter (2–4 years), and the respective weights are 1/length for $k = 0$, ½ for the most distant year and 1 in between. The development of the R&D spillover is illustrated in Figure 11. It is obvious that imports of technologies are highly variable and more dynamic than the TFP index.

Similarly to the previous three assessments, we conducted the analysis in three steps. In the first two steps, we assessed the integration order of the

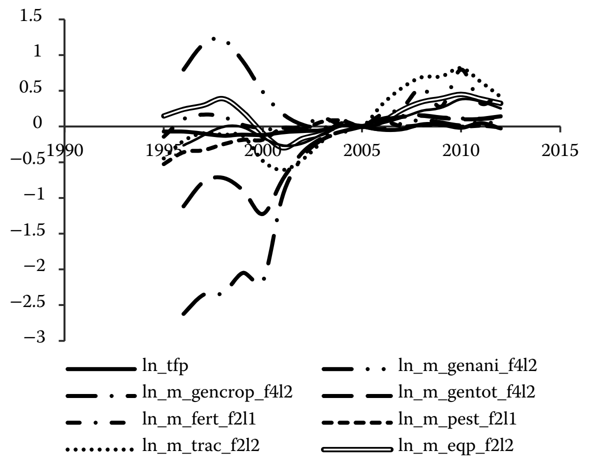

Figure 11. The R&D Spillover (a logarithmic transformation)

Source: own calculation based on trade data (CSO 2013)

time series and estimated the long-term relationship between the total factor productivity index *(ln(TFP))* and the two explanatory variables *(ln(KnSt*)* and *ln(M_tech))*.

The respective ECM model (step 3) is defined as follows:

$$\Delta \ln(TFP_t) = \alpha_1 \cdot \Delta \ln(KnSt_t) + \alpha_2 \cdot \Delta \ln(M\_tech_t) + \\ + \alpha_3 \left[\ln(TFP_{t-1}) - b_1 \cdot \ln(KnSt_{t-1}) - b_2 \cdot \ln(M\_tech_{t-1} \right] + \varepsilon_t \quad (17)$$

where $[\ln(TFP_{t-1}) + b_1 \cdot \ln(KnSt_{t-1}) - b_2 \cdot \ln(M\_tech_{t-1})]$ is the lagged error correction term and $(1,-b_1, -b_2)$ is a co-integrating vector.

All the time series are integrated of order 1 (ADF test significant at the level 0.05). Nevertheless, the parameters estimated in the second step exhibited a negative relationship for four of the eight proxies of the external R&D spillover. Hence, we continued our analysis only for the imports of the plant genetic material, the total genetic material, pesticides and

Table 2. Parameters of the ECM with the external R&D spillovers

		$t = 7$ $\delta = 0.6$ $\lambda = 0.6$	$t = 7$ $\delta = 0.8$ $\lambda = 0.3$	$t = 12$ $\delta = 0.6$ $\lambda = 0.6$	$t = 12$ $\delta = 0.1$ $\lambda = 0.8$	$t = 15$ $\delta = 0.8$ $\lambda = 0.4$	$t = 15$ $\delta = 0.6$ $\lambda = 0.6$
ln_m_gentot_f4l2	D. Know_Stock	0.091	0.056	0.084	0.083	0.050	0.110
ln_m_trac_f2l2	D. Know_Stock	0.184	0.107	0.126	0.125	0.035	0.159
ln_m_gentot_f4l2	D. Gen_Total	0.067*	0.070*	0.066	0.064	0.069*	0.064
ln_m_trac_f2l2	D. Gen_Tract	0.057	0.063	0.062	0.060	0.071	0.060
ln_m_gentot_f4l2	L.ErCorTerm	–1.128***	–1.099***	–1.101***	–1.106***	–1.097***	–1.103***
ln_m_trac_f2l2	L.ErCorTerm	–0.843**	–0.761**	–0.771**	–0.817**	–0.734**	–0.792**

Source: own calculation

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tractors. However, the estimated coefficients of the plant genetic material and pesticides appeared to be negative in the error correction model. In the view of this, the analysis is reported only for two variables (the total imports of genetic material and tractors). These models are significant (*F*-test) at the level 0.05 (detailed regression results are included in Appendix 2).

No knowledge stock parameter is significant in either sub-model, and all are much lower than those estimated in the previous model. The R&D spillover parameters are significant only for the imports of the total genetic material in the three sub-models (Table 2). In contrast, the lagged error correction term (*L.ercor*) is significant in all the sub-models at the level 0.01, and is high.

Estimation of returns on research

The results of the co-integration analysis were used to calculate the marginal rate of return on the R&D investments in agriculture, following Equations 14 and 15. For this purpose, the model with gamma distribution d(0.8)l(0.4) was applied, and the returns were calculated for the models discussed in previous chapters. The calculated rates of return are reported in Table 3. Concerning the TFP model with the domestic R&D, the estimated average return on knowledge reaches 40% if calculated from both the annual data (Equation 14) and the average data (Equation 15) over the period. However, this result is subject to overestimation due to the omission of the R&D spillover from abroad. The model which includes technology imports provides more realistic estimates of the returns on the domestic agricultural research. The calculations show that one Czech crown invested in R&D in agriculture between 1993–2012 brought an approximately 30% return. This result corresponds to the results derived by other authors, such as Shenget al. (2011) for Australia, Alston et al. for the USA (2000) and Thirtle et al. (2008) for the case of the UK.

CONCLUSIONS

The rich empirical evidence on the positive role of R&D in agricultural productivity, together with the increasing interest from policy makers, provided a motivation to investigate whether the positive R&D benefits can also be confirmed in the case of the Czech Republic.

The underlying assumption of this paper is that agricultural productivity is driven by technology, and that technology is a result of the domestic R&D spending and the spillover from abroad. Our effort was to demonstrate that the data exhibit it taking into account time lags between the generation of knowledge (≈ technology) and its realization in the practice. Due to the unavailability of the long time series commonly used in the studies of Alston, Thirtle and other authors, the methodological approach was adjusted to our specific case. The application of the co-integration analysis confirmed the long-term positive effect of knowledge stocks, approximated by the gamma distribution with a 15-year lag. Consequently, the effects of the R&D investments were investigated using the total factor productivity indicators. In addition, the foreign R&D spillovers measured as the accumulated imports of technologies were included

Table 3. Estimation of the marginal internal rates of return

IRR from R&D	TFP with only domestic R&D $\delta = 0.268$		TFP also with R&D spillovers $\delta = 0.164$	
	based on the annual share	based on the average share	based on the annual share	based on the average share
IRR 93-07	0.423	0.425	0.332	0.34
IRR 94-08	0.411	0.413	0.323	0.33
IRR 95-09	0.401	0.401	0.315	0.32
IRR 96-10	0.392	0.391	0.308	0.311
IRR 97-11	0.384	0.381	0.301	0.302
IRR 98-12	0.375	0.373	0.293	0.295
Average IRR	0.4	0.4	0.31	0.32

Source: own calculation

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in the Equation. We could confirm that productivity is driven by the domestic R&D expenditures; however, the results on the external spillovers are rather weak. One of the reasons might be the approximation of the R&D spillover by imports. As already pointed out by Van Meijl (1995), not all technological innovations lead to user-producer relationships and thus the real magnitude of pure knowledge spillovers might be underestimated when using the trade-embodied approach. Thus, various scholars proposed alternative approaches to measure the R&D spillovers rather than the trade channels such as the technology proximity based on patents, the FDI or the geographic proximity (for instance Verspagen 1997, Cincera 2005 or Krammer 2010). Another reason can be the level of aggregation, whereas on the aggregated level, the accumulated imported technology is not reflected in a higher TFP, on a farm-level data, we might observe a positive relationship.

Another conclusion that came out of our analysis is that in all models, there is little evidence that either the length of time or the functional form of weights plays a major role in assessing the dependence of productivity on R&D investments, which contradicts the recent evidence in the literature (see for instance Thirtle et al., 2008).

Although the returns on agricultural research are estimated to be high, we cannot deny that they exhibit a declining tendency (Table 3). We can also see from Figure 5 that the TFP loses its dynamics after the EU accession. This could be just a temporal phenomenon associated with the economic crisis in Europe, but it could also be explained by the structural break in financing and in the coordination of research in the Czech Republic after the political changes in 1989. One could argue that the sector benefited in the late 1990s from the large R&D outlays of the 1980s, and it is now going to feel the consequences of the disruption of agricultural research during the transition.

From this point of view, we need to understand the results of our investigation as indicative, and definitely suggesting that more research is needed in this area. In particular, the effect of the foreign R&D spillovers on agricultural productivity should be better understood.

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Appendix 1. Results of the co-integration analysis for models with ln(knowledge stock) and weather dummy

	Know_st	t = 12 δ = 0.1 λ = 0.8		Know_st	t = 15 δ = 0.1 λ = 0.8		Know_st	t = 12 δ = 0.6 λ = 0.6	
	–B1			–B1			–B1		
Co-integrating vector	–0.246			–0.242			–0.260		
	n	ADF_stat	P	*n*	ADF_stat	P	*n*	ADF_stat	P
ADF (residuals)	19	–3.038	**0.007**	19	–3.131	**0.006**	19	–2.875	**0.010**

	Know_st	t=12 δ=0.1 λ=0.8		Know_st	t=15 δ=0.1 λ=0.8		Know_st	t=12 δ=0.6 λ=0.6	
	coef	se	P	coef	se	P	coef	se	P
D.ln_knowstock	0.495	0.188	**0.018**	0.480	0.183	**0.019**	0.694	0.237	**0.010**
Weather	–0.042	0.016	**0.020**	–0.041	0.016	**0.022**	–0.047	0.017	**0.012**
L.ercor	–0.691	0.232	**0.009**	–0.683	0.232	**0.009**	–0.685	0.226	**0.008**
_cons									
Number of observations	19			19			19		
df_m	3			3			3		
df_r	16			16			16		
F	6.319		**0.005**	6.644		**0.004**	6.817		0.004
R2	0.542			0.555			0.561		
Adjusted R2	0.456			0.471			0.479		

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	n	ADF_stat	P	*n*	ADF_stat	P	*n*	ADF_stat	P
ADF (residuals)	18	−4.524	**0.000**	18	−4.547	**0.000**	18	−4.405	**0.000**
	Know_st	*t* = 15 δ = 0.8 λ = 0.4		Know_st	*t* = 5 δ = 0.8 λ = 0.3		Know_st	*t* = 7 δ = 0.8 λ = 0.3	
	−B1			−B1			−B1		
Cointegrating vector	−0.268			−0.231			−0.265		
	n	ADF_stat	P	*n*	ADF_stat	P	*n*	ADF_stat	P
ADF (residuals)	19	−2.752	**0.013**	19	−3.232	**0.005**	19	−3.078	**0.006**
	Know_st	*t* = 15 δ = 0.8 λ = 0.4		Know_st	*t* = 5 δ = 0.8 λ = 0.3		Know_st	*t* = 7 δ = 0.8 λ = 0.3	
	coef	se	P	coef	se	P	coef	se	P
D.ln_knowstock	0.492	0.250	**0.066**	0.143	0.171	0.416	0.509	0.259	**0.067**
Weather	−0.039	0.018	**0.046**	−0.028	0.018	0.152	−0.036	0.017	**0.053**
L.ercor	−0.579	0.240	**0.028**	−0.526	0.264	**0.063**	−0.709	0.254	**0.013**
_cons									
Number of observations	19			19			19		
df_m	3			3			3		
df_r	16			16			16		
F	4.502		**0.018**	2.756		**0.076**	4.498		0.018
R2	0.458			0.341			0.458		
Adjusted R2	0.356			0.217			0.356		
	n	ADF_stat	P	*n*	ADF_stat	P	*n*	ADF_stat	P
ADF (residuals)	18	−4.274	**0.001**	18	−3.844	**0.001**	18	−3.941	**0.001**
	Know_st	*t* = 7 δ = 0.8 λ = 0.4							
	−B1								
Co-integrating vector	−0.277								
	n	ADF_stat	P						
ADF (residuals)	19	−2.840	**0.011**						
	Know_st	*t* = 7 δ = 0.8 λ = 0.4							
	coef	se	P						
D.ln_knowstock	0.219	0.210	0.312						
Weather	−0.028	0.018	0.133						
L.ercor	−0.567	0.247	**0.035**						
_cons									
Number of observations	19								
df_m	3								
df_r	16								
F	3.412		0.043						
R2	0.390								
Adjusted R2	0.276								
	n	ADF_stat	P						
ADF (residuals)	18	−3.907	**0.001**						

Source: own calculation

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Appendix 2. Results for models including imports as the external knowledge spillover

	Know_16	t =12 δ = 0.1 λ = 0.8		Know_stock	t =15 δ = 0.1 λ = 0.8		Know_stock	t =12 δ = 0.6 λ = 0.6	
	–B_knst	–B__gent		–B_knst	–B__gent		–B_knst	–B__gent	
Co-integrating vector	–0.098	–0.065		–0.113	–0.060		–0.090	–0.069	
	n	ADF_stat	P	n	ADF_stat	P	n	ADF_stat	P
ADF (residuals)	16	–4.306	**0.001**	16	–4.327	**0.001**	16	–4.283	**0.001**

	Know_stock t = 12 δ = 0.1 λ = 0.8			Know_stock t = 15 δ = 0.1 λ = 0.8			Know_stock t = 12 δ = 0.6 λ = 0.6		
	coef	se	P	coef	se	P	coef	se	P
D.ln_knowstock	0.083	0.272	0.765	0.045	0.273	0.872	0.084	0.264	0.757
D.ln_m_gentot_f4l2	0.064	0.042	0.155	0.064	0.043	0.158	0.066	0.041	0.129
L.ercor	–1.106	0.286	**0.002**	–1.115	0.281	**0.002**	–1.101	0.284	**0.002**
_cons									
Number of observations	16			16			16		
df_m	3			3			3		
df_r	13			13			13		
F	5.202		**0.014**	5.422		**0.012**	5.170		0.014
R2	0.546			0.556			0.544		
Adjusted R2	0.441			0.453			0.439		
DW	1.99424097			1.99629526			1.98919148		
	n	ADF_stat	P	n	ADF_stat	P	n	ADF_stat	P
ADF (residuals)	15	–3.739	**0.002**	15	–3.741	**0.002**	15	–3.730	**0.002**

	Know_stock t = 15 δ = 0.8 λ = 0.4			Know_stock	t = 5 δ = 0.8 λ = 0.3		Know_stock	t = 7 δ = 0.8 λ = 0.3	
	–B_knst	–B__gent		–B_knst	–B__gent		–B_knst	–B__gent	
Co-integrating vector	–0.084	–0.071		–0.048	–0.078		–0.087	–0.068	
	n	ADF_stat	P	n	ADF_stat	P	n	ADF_stat	P
ADF (residuals)	16	–4.277	**0.001**	16	–4.268	**0.001**	16	–4.232	**0.001**

	Know_stock t = 15 δ = 0.8 λ = 0.4			Know_stock	t = 5 δ = 0.8 λ = 0.3		Know_stock	t = 7 δ = 0.8 λ = 0.3	
	coef	se	P	coef	se	P	coef	se	P
D.ln_knowstock	0.050	0.247	0.844	–0.028	0.176	0.876	0.056	0.224	0.806
D.ln_m_gentot_f4l2	0.069	0.039	**0.097**	0.075	0.042	**0.096**	0.070	0.039	**0.093**
L.ercor	–1.097	0.281	**0.002**	–1.048	0.275	**0.002**	–1.099	0.283	**0.002**
_cons									
Number of observations	16			16			16		
df_m	3			3			3		
df_r	13			13			13		
F	5.220		**0.014**	5.043		**0.016**	5.195		0.014
R2	0.546			0.538			0.545		
Adjusted R2	0.442			0.431			0.440		
DW	1.99373026			1.99982824			1.97232246		
	n	ADF_stat	P	n	ADF_stat	P	n	ADF_stat	P
ADF (residuals)	15	–3.737	**0.002**	15	–3.745	**0.002**	15	–3.696	**0.002**

	Know_stock t = 7 δ = 0.8 λ = 0.4

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	–B_knst	–B__gent	
Co-integrating vector	–0.094	–0.069	
	n	ADF_stat	P
ADF (residuals)	16	–4.209	**0.001**
	Know_stock	t = 7 δ = 0.8 λ = 0.4	
	coef	se	P
D.ln_knowstock	0.038	0.199	0.853
D.ln_m_gentot_f4l2	0.069	0.039	0.104
L.ercor	–1.123	0.284	**0.002**
_cons			
Number of observations	16		
df_m	3		
df_r	13		
F	5.398		0.012
R2	0.555		
Adjusted R2	0.452		
DW	1.96126139		
	n	ADF_stat	P
ADF (residuals)	15	–3.673	**0.003**

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