https://doi.org/10.17221/224/2016-AGRICECON

Agricultural R&D, spatial spillover and regional economic growth in different R&D sectors of performance: evidence from a spatial panel in regions of the EU-28

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Anousheh S., Hojabr-Kiani K., Mojtahed A., Ranjbar H. (2018): **Agricultural R&D, spatial spillover and regional economic growth in different R&D sectors of performance: evidence from a spatial panel in regions of the EU-28**. Agric. Econ. – Czech, 64: 163–169.

Abstract: Agricultural R&D has been identified as an important determinant of economic output in the agricultural sector. Surprisingly, in previous studies, spatial spillover associated with R&D spending in the agricultural sector has not been taken into account. This paper investigates the effects of spatial spillover of agricultural R&D on regional economic growth across EU-28 NUTS-II regions in the period 1995–2014. In particular, we extend previous studies by considering spillover in all sectors of agricultural R&D performance including business enterprise, government and higher education. The spatial Durbin panel data model is employed to estimate brooders effect including direct and indirect effects. Empirical results show a positive effect of agricultural R&D and its spatial spillover on regional growth in all performance sectors. Moreover, the impact of spatial spillover of agricultural R&D on regional growth depends on the performance of the R&D sectors; positive spillovers are stronger in the business enterprise sector. Finally, the interaction effect between the economic output of the agricultural sector of each region with that of its neighbours is significantly positive.

Keywords: agricultural output, panel data, spatial Durbin model

Over the past two decades, a growing body of literature has contributed to establishing a new growth theory (Romer 1990) that emphasises that technological progress resulting from R&D activities is the major engine of growth (Romer 1990; Grossman and Helpman 1990; Aghion and Howitt 1992, 1998; Jones 1995). In these models, innovation either takes the form of improvements in quality to existing products (quality ladder) or introduction of new goods (expanding varieties) (Romer 1990). R&D activity creates technological knowledge, enhances the production and diffusion of innovations, and thus promotes productivity growth. Much empirical research has also pointed out the positive impact of R&D on productivity; see among others: Coe and Helpman (1995), Coe et al. (1997), Xu and Wang (1999), van Pottelsberghe de la Potterie and Lichtenberg (2001) and Frantzen (2002).

Innovation is not only of direct benefit; "spillovers" to other firms can occur, which contribute to raising the level of knowledge upon which new innovations can be based (Branstetter 2001). The theoretical literature on endogenous growth models has given considerable attention to the concept of knowledge and research spillovers (Romer 1990; Aghion and Howitt 1998). Grossman and Helpman (1991) showed that cross-country R&D spillovers are an important source of productivity growth.

Knowledge spillovers can be domestic (intranational) or public (international) in nature. Domestic spillovers,

https://doi.org/10.17221/224/2016-AGRICECON

which are locally bound, are based on the geographic proximity to innovative producers (Jaffe et al. 1993; Acs et al. 1994; Anselin et al. 1997), so as to allow for spillovers in knowledge across neighbouring regions (Bottazzi and Peri 1999). Although ignored in older studies, location and geographic space have now become key factors in explaining the determinants of innovation and technological change (Audretsch and Feldman 2004).

The role of international knowledge spillovers in generating endogenous economic growth has been highlighted in theoretical arguments, (Grossman and Helpman 1991; Rivera-Batiz and Romer 1991; Aghion and Howitt 1992; Coe and Helpman 1995; Eaton and Kortum 1996; Coe et al. 1997; Howitt 2000; Keller 2000) but there may be geographical boundaries to R&D spillovers particularly owing to tacit knowledge (Krugman 1998).

Jaffe et al. (1993) show that geography plays an important role in the positive spillovers that result from R&D. In fact, the marginal costs of transmitting tacit knowledge rise with distance because non-codified knowledge is vague and requires face-to face interaction (Funke and Niebuhr 2005). Many studies have emphasised that geographical proximity is significant for the transmission of knowledge (for a review see Audretsch and Feldman 2004). In fact, the relative impact of knowledge flow usually declines with geographic distance (Eaton and Kortum 1999; Carr et al. 2001), and its influence is more intranational rather than international in scope (Branstetter 2001). The international diffusion of technology is geographically localised, so that the effects of R&D on productivity decline with the geographic distance between countries (Keller 2002).

Recently, a growing number of empirical studies focusing on regional economic growth have considered spatial effects in empirical growth specifications (Carlino and Mills 1993, 1996; Armstrong 1995; Neven and Gouyette 1995; Bernat 1996; Chatterji and Dewhurst 1996; Sala-i-Martin 1996). One interesting characteristic of these analyses is that, as in the case of heterogeneous countries, regions have been considered as isolated economies; in other words, empirical specifications almost invariably exclude interactions across regions.

Consequentially, the interaction of R&D activities across regions has become an important issue in the study of regional economic growth. Following Bronzini and Piselli (2009), this study supposes that knowledge has a localised scope, and, on the basis of this assumption, we assess the role of regional R&D spillover in boosting regional economic growth in EU-28 regions. We consider this a plausible hypothesis. Proximity can encourage the circulation of ideas and the transmission of information and learning, thanks to face-to-face contacts and social interaction.

In the economic literature, R&D investment is considered as one of the most important factors in agricultural productivity and production (Alston et al. 1999; Pardey 2013). According to Pardey et al. (2013), countries with larger (smaller) agricultural economies are likely to invest more (less) in agricultural R&D. Previous studies analysing the output and productivity impact of agricultural R&D have not taken the spatial spillover effect of R&D into account, especially with respect to the performance of different agricultural R&D sectors. In this paper, we focus on the performance of different R&D sectors with reference to the spatial dimension of R&D investment. Also, we presume that different levels of R&D investment according to sector performance may not have the same effects on regional growth.

EMPERICAL MODEL

Model specification

In recent years, spatial models including more than one spatial interaction effect have been increasingly used. Here, we used the spatial econometric techniques developed by LeSage and Pace (2009), the so-called spatial Durbin model (SDM) that includes both a spatially lagged dependent variable and spatially lagged explanatory variables.

In this paper, we adopt a production function approach. We assume a standard Cobb-Douglas production function:

$$Y_i = AL_i^{\alpha L} K_i^{\alpha K} RD_i^{\alpha RD} \quad (1)$$

the log linear transformation of Equation (1) gives

$$LnY_i = \alpha + \alpha_L LnL_i + \alpha_K LnK_i + \alpha_b Ln(RD\_business) + \alpha_g Ln(RD\_government) + \alpha_h Ln(RD\_education) \quad (2)$$

Following Elhorst (2010), the SDM, which accommodates the spatial interaction effect from dependent and all the explanatory variables, was applied. The Cobb-Douglas production function of Equation (2) in an SDM framework can be specified as follows:

https://doi.org/10.17221/224/2016-AGRICECON

$$LnY_i = \alpha + \beta X_{it} + \rho \sum_{j=1}^{N} W_{ij} Y_{jt} + \theta \sum_{j=1}^{N} W_{ij} X_{jt} + \\ + U_i + \lambda_t + e_{it} \quad (3)$$

where ρ is the spatial autocorrelation coefficient, and Y represents the agricultural output for region i at time t. α is the constant term. $X_{jt} = [K_{it,} L_{it,} G_{it}]$, which is a 1 × 3 vector of explanatory variables containing capital labour and R&D input. β is a corresponding 3 × 1 vector of parameters. W_{ij} is the i and jth element of a $N \times N$ weight matrix, which represents the degree of connectedness between regions i and j. Variable $\sum_{j=1}^{N} W_{ij} Y_{jt}$ is the spatial lag in the dependent variable, which represents the spatially weighted average value of agricultural output from i's neighbouring states at time t. $\sum_{j=1}^{N} W_{ij} Y_{jt}$ is the spatial lag in the explanatory variables, and the corresponding coefficient θ represents the effect from the input of neighbouring regions on each region's agricultural output. e_{it} is the residual with a zero mean and constant variance. The SDM includes a spatial lag of the dependent variable (Wy) as well as spatial lagged explanatory variables (WX). An implication of this is that a change in the dependent variable for a single region may affect the dependent variable in all other regions by the network effect; meanwhile, a change in the explanatory variable for a single observation can potentially affect the dependent variable in all other observations. The type of spatial weights matrix is binary weight, in which $w_{ij} = 1$ if region i and j are neighbours and 0 otherwise. In order to normalise the influence on each region, the weight matrix is row-standardised; namely, the elements w_{ij} in each row add up to 1.

Direct and indirect (spillover) effects

In the spatial econometric model that incorporates spatial effects, the estimated parameters cannot be simply explained as a partial derivative of a dependent variable with respect to an explanatory variable (LeSage and Pace 2009). The best way to solve this problem and to capture marginal effects in the presence of spatial interaction effects, is to decompose the total marginal effect into direct and indirect effects (LeSage and Pace 2009). Estimates of direct effects measure the impact of changing an independent variable on the dependent variable of a spatial unit. This measure includes feedback effects, i.e., impacts passing through neighbouring regions and back to the region that instigated the change. Estimates of indirect effects measure the impact of changing an independent variable in a particular unit on the dependent variable in all other regions.

We can write the equation in vector form (Elhorst 2014):

$$Y = (I - \rho \mathrm{w})^{-1}(x\beta + wx\theta) + R \quad (5)$$

Where R specifies the intercept and error terms:

$$R = (I - \rho \mathrm{w})^{-1}\alpha I_N + (I - \rho \mathrm{w})^{-1}\varepsilon \quad (6)$$

Taking a partial derivative of the expected value of Y with respect to the explanatory value of X from unit 1 to unit N in time, we obtain the following matrix $N \times N$ that describes the marginal effects:

$$= \begin{bmatrix} \frac{\partial E(Y)}{\partial x_{1k}} \cdot \frac{\partial E(Y)}{\partial x_{Nk}} \end{bmatrix} = \begin{bmatrix} \frac{\partial E(Y_1)}{\partial x_{1k}} & \frac{\partial E(Y)}{\partial x_{Nk}} \\ \frac{\partial E(Y_{1N})}{\partial x_{1k}} & \frac{\partial E(Y_N)}{\partial x_{Nk}} \end{bmatrix}$$

$$= (1 - \rho W)^{-1} \begin{bmatrix} \beta_k & w_{12}\theta_k & \cdot & w_{1N}\theta_k \\ w_{21}\theta_k & \beta_k & \cdot & w_{2N}\theta_k \\ \cdot & \cdot & \cdot & \cdot \\ w_{N1}\theta_k & w_{N2}\theta_k & \cdot & \beta_k \end{bmatrix} \quad (7)$$

where β_k and θ_k are the coefficient estimates associated with the k^{th} explanatory variables, I is the identity matrix, I_N denotes an $N \times 1$ vector of ones and E is the error term.

This $N \times N$ matrix specifies that a one-unit change in a particular explanatory variable in a particular unit, will not only affect the dependent variable in that unit but also the dependent variable in all units.

The diagonal elements of the matrix show the direct effect, while the off-diagonal element describe the indirect effects. Because the direct and indirect effects are different for different units, we obtain K number of different $N \times N$ matrices of direct and indirect effects, making the results difficult to report. To solve this problem, LeSage and Pace (2009) proposed a summary indicator for both direct and indirect effects, which is based on the average of the diagonal elements and the average of the row sums or the column sums of the off-diagonal elements, respectively.

In the SDM model, the direct effect of the explanatory variable is equal to the coefficient estimate of the variable (β_k), while the indirect effect is equal to the coefficient estimate of its spatial lagged value (θ_k) (Elhorest 2014).

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DATA

Our sample consists of a panel of NUTS-II regions over 20 years from 1995 to 2014. The empirical analysis is based on the dataset elaborated by Cambridge Econometrics, sourced from Eurostat's REGIO database, the European Commission's (DG ECFIN) AMECO database and other sources of compiled data collected by Eurostat. The dataset consists of 276 regions. The NUTS classifications include NUTS-I, NUTS-II and NUTS-III. Owing to the lack of data for NUTS-III, we could either take the level of NUTS-I or NUTS-II. Although this choice is basically arbitrary, the NUTS-II level is usually considered as the appropriate level for analysing national and regional problems on the basis that such a level is used by member states for the application of their regional policies. The initial units of observation are 264 NUTS-II regions[1] belonging to twenty-one countries of the former EU-28; in fact, since our focus is on regional rather than national differences, the countries containing only one or two NUTS-II regions, including Estonia, Cyprus, Ireland, Latvia, Lithuania, Luxemburg and Malta, are not taken into account. The index of capital input is gross capital formation. In order to compute regional R&D capital stock, we use the methodology designed by Coe and Helpman (1995) who applied the perpetual inventory method to R&D investment data[2].

EMPIRICAL RESULTS

In this section, we discuss the empirical details of the estimation of the SDM model described in section Direct and indirect ... In this context, the panel data approach allows us fuller exploitation of both the spatial and temporal dimensions of the data. The spatial models are estimated using the maximum likelihood method (ML). The explanatory power of the model is good, as indicated by uniformly high adjusted R^2. Moran's I (Moran 1948), LM statistics (LM-error (Burridge 1980 and LM-sar (Anselin 1988a))[3] and other spatial-related tests such as Gary and Walds (Anselin 1988b) were applied to the panel data model in Table 1. The results are clear: LM-error and LM-SAR tests reject the null hypothesis of no spatial lag or no spatial error; also, Moran's I and Geary's C confirm spatial autocorrelation. The LM tests point to significant spatial spillovers.

In Table 2, we report the results of econometric estimates of our baseline model (4). We find that labour, private capital and R&D in the entire sector have a positive and significant effect on regional economic growth. Both the coefficient estimate of the spatially lagged dependent (WY) as well as R&D variables are significantly positive. The spatial autocorrelation coefficient of the lagged dependent variable, ρ, is also significantly positive. The estimated elasticities of output with respect to R&D in the business enterprise, government and higher education sectors are 0.026, 0.011 and 0.019, respectively.

Table 3 reports the summary direct, indirect and total impact measures for our SDM specification. The direct effect, i.e., the effect of a change of a R&D variable in a particular region on the economic growth of the same region is positive, so that a 1% increase in the R&D stock of each region in the business enterprise, government and higher education sectors increases the economic growth of the agricultural sector in the same region by 0.029, 0.018 and 0.021, respectively. The indirect (spillover) effects of the R&D

Table 1. Spatial autocorrelation tests

	LM-error (Robust)	LM-error (Burridge)	LM-SAR (Robust)	LM-SAR (Anselin)	Moran's I	Geary's C	Ord's G
Value	2.541	3.011	4.32	4.56	0.3714	0.4315	0.671
Probe	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*

*Statistical significance at the 5% level

Source: own calculations

[1]This is based on the current NUTS nomenclature, which subdivides the territory of the European Union into 98 regions at NUTS level 1, 276 at NUTS level 2 and 1342 at NUTS level 3.

[2]This method is standard in the literature. See, among others, Coe and Helpman (1995), Coe et al. (1997), Xu and Wang (1999), van Pottelsberghe de la Potterie and Lichtenberg (2001), Frantzen (2002) and Crispolti and Marconi (2005).

[3]Burridge (1980) developed a LM test for the case of spatial dependence within the error terms. Anselin (1988) later developed a LM test for the spatial lag model.

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Table 2. SDM results for the performance of different R&D sectors

Variables	Parameter
Constant	2.221 (9.23)*
Labour force	0.179 (12.41)*
Capital stock	0.119 (13.21)*
Business enterprise R&D	0.026 (16.25)*
Government R&D	0.011 (11.26)*
Higher education R&D	0.019 (10.92)*
W labour force	0.212 (14.31*)
W capital stock	0.192 (12.01)*
W R&D_business	0.0313 (11.92*)
W R&D_government	0.0221 (10.52)*
W R&D_higher education	0.024 (9.36)*
Spatial autoregressive	0.31* (4.25)
Sigma	0.023*
Log Likelihood Function(LLF)	20.24*

t-statistics are in parentheses
The variables W Labour, W capital stock, W R&D business enterprise, W R&D government and R&D higher education correspond to the spatial lag variables, of labour, capital stock, R&D stock in business enterprise, government and higher education, respectively .
*Statistical significance at the 5% level

Source: own calculations

variables on all the sector performance are positive and significant, which implies that an increase in the R&D stock in a business enterprise, government and higher education sector in a particular region will not only lead to increased agricultural economic output in the state itself, but also in nearby regions. Specifically, a 1% increase in the R&D stock in one region increases the agricultural economic growth of business enterprise, government and higher education sectors in all other region by an average of 2.6, 1.9 and 1.1, respectively. It is notable that the magnitude of spillover effects (indirect effects) are greater than that of a region's own R&D efforts (direct effects).

Table 3. Estimates of direct and indirect effects in the spatial Durbin model

Variables	Direct	Indirect	Total
Labour force	0.192 (0.000)*	0.241 (0.001)*	0.433 (0.001)*
Capital stock	0.122 (0.001)*	0.201 (0.002)*	0.323 (0.003) *
Business enterprise R&D	0.029 (0.003)*	0.341 (0.001)*	0.370 (0.004)*
Government R&D	0.018 (0.006)*	0.231 (0.000)*	0.249 (0.005)*
Higher education R&D	0.021 (0.000)*	0.0271 (0.002)*	0.581 (0.000)*

P-values are parentheses; *statistical significance at the 5% level

Source: Own calculations

CONCLUSION

In this study, we have evaluated the effect of agricultural R&D, as a crucial engine of growth, on the agricultural economic growth of EU-28 regions from 1995 to 2014. Our results suggest that encouraging agricultural R&D efforts can be considered as an effective strategy to boost economic output in the agricultural sector, which is consistent with previous empirical research showing that R&D plays a critical role in boosting agricultural economic growth. The potential existence of spatial spillovers from the performances of different R&D sectors was also considered by applying spatial panel data techniques. For regions of the EU-28, as Table 3 shows, the spillover effect (indirect effect) from the performance of all R&D sectors, including business enterprise, government and higher education, is statistically significant, and R&D stock does not only contribute to GDP in the agricultural sector directly but also indirectly through regional spillover effects. The effect of R&D investment and its spillover on regional agricultural growth depends on the performance of the various types of sector; thus, business enterprise may lead to significant benefits for the region in which it is located as well as to spillover to other regions. This is often explained by referring to high levels of expenditure within the business enterprise sector. Based on the empirical results, particular EU regions can benefit from the spillover effects of agricultural R&D investment in the region more than from their own R&D. In fact, learning has a localised scope and the location of research centres plays a substantial role in the development of the agricultural sector. On the other hand, benefits of investment in agricultural R&D will spread across regions and the choice of location of R&D activities will affect regional disparities. Therefore, policy-makers should take this aspect into account in designing regional development policies for the agricultural sector. In conclusion, the positive spatial dependence of agricultural economic growth found in the spatial Durbin model suggests the existence of geographical spillovers;

https://doi.org/10.17221/224/2016-AGRICECON

i.e., a given region's agricultural economic output can affect the economic output of the agricultural sector in other regions.

REFERENCE

Acs Z.J., Audretsch D., Feldman M.P. (1994): R&D spillovers and recipient firm size. Review of Economics and Statistics, 100: 336–367.

Acs Z.J., Audrestch D.B., Feldman M.P. (2004): R&D spillovers and innovative activity. Managerial and Decision Economics, 15: 131–138.

Aghion P., Howitt P. (1992): A model of growth through creative destruction. Econometrica, 60: 323–351.

Aghion P., Howitt P. (1998): Endogenous Growth Theory. MIT Press, Cambridge.

Anselin L. (1988a): Spatial Econometrics: Methods and Models. Kluwer Academic Publishers, Dordrecht.

Anselin L. (1988b): Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. Journal of Geographical Analysis, 20: 1–17.

Anselin L., Varga A., Acs Z. (1997): Local geographic spillovers between university research and high technology innovations. Journal of Urban Economics, 42, 422–448.

Armstrong H.W. (1995): Convergence among regions of the European Union, 1950–1990. Regional Science, 74: 143–152.

Audretsch D.B., Feldman M.P. (2004): Knowledge spillovers and the geography of innovation. In: Handbook of Regional and Urban Economics. Elsevier: 2713–2739.

Alston J.M., Pardey P.G., Smith V.H. (1999): Paying for Agricultural Productivity. Johns Hopkins University Press, Baltimore.

Bernat A. (1996): Does manufacturing matter? A spatial econometric view of Kaldor's laws. Journal of Regional Science, 36: 463–477.

Bronzini R., Piselli P. (2009). Determinants of long-run regional productivity with geographical spillovers: The role of R&D, human capital and public infrastructure. Regional Science and Urban Economics, 39: 187–199.

Bottazi L., Peri G. (1999): Innovation, Demand and Knowledge Spillovers: Theory and Evidence from European Regions. CEPR Discussion Papers No. 2279, London.

Branstetter L.G. (2001): Are knowledge spillovers international or intranational in scope? Microeconometric evidence from the U.S. and Japan. Journal of International Economics, 1: 53–79.

Burridge P. (1980): On the Cliff-Ord test for spatial autocorrelation. Journal of the Royal Statistical Society B, 42: 107–108.

Carlino G., Mills L. (1993): Are U.S. regional incomes converging? A time series analysis. Journal of Monetary Economics, 32: 335–346.

Carlino G., Mills L. (1996): Convergence and the US States: a time series analysis. Journal of Regional Science, 36: 597–616.

Carr D.L., Markusen J.R., Maskus K.E. (2001): Estimating the knowledge-capital model of the multinational enterprise. American Economic Review, 91: 693–708.

Chatterji M., Dewhurst J. (1996): Convergence clubs and relative economic performance in Great Britain: 1977–1991. Regional Studies, 30: 31–40.

Coe D.T., Helpmen E., Hoffmaister W.H. (1997): North-south R&D spillovers. The Economic Journal, 107: 13–49.

Coe D., Helpman E. (1995): International R&D spillover. European Economic Review, 39: 859–887.

Crispolti V., Marconi D. (2005). Technology transfer and economic growth in developing countries: an econometric analysis. Temi di discussione (Economic working papers) No. 564, Bank of Italy, Economic Research and International Relations Area.

Eaton J., Kortum S. (1999): International technology diffusion: theory and measurement. International Economic Review, 40: 537–570.

Elhorst J.P. (2010): Dynamic panels with endogenous interactions when T is small. Regional Science and Urban Economics, 40: 272–282.

Elhorst J.P. (2014): Spatial Econometrics: From Cross-Sectional Data to Spatial Panels. Springer, Heidelberg.

Grossman G.M., Helpman E. (1991): Innovation and Growth in the Global Econom. MIT Press, Cambridge.

Frantzen D. (2002): Cross-sector and cross-country technical knowledge spillovers and the evolution of manufacturing productivity: a panel data analysis. Economie Appliquée, 55: 31–62.

Funke M., Niebuhr A. (2005): Regional geographic research and development spillovers and economic growth. Regional Studies, 39: 143–153.

Howitt P. (2000): Endogenous growth and cross-country income differences. American Economic Review, 90: 829–846.

Jaffe A., Trajtenberg M., Henderson R. (1993): Geographic localization of knowledge spillovers as evidenced by patent citations. Quarterly Journal of Economics, 63: 577–598.

Jones C.I. (1995): R&D-based models of economic growth. The Journal of Political Economy, 103: 759–784.

Keller W. (2000): Do trade patterns and technology flows affect productivity growth. World Bank Economic Review, 14: 17–47.

https://doi.org/10.17221/224/2016-AGRICECON

Keller W. (2002): Geographic localization of international technology diffusion. American Economic Review, 92: 120–142.

Krugman P. (1998): What's new about the new economic geography? Oxford Review of Economic Policy, 14: 7–17.

LeSage J.P., Pace R.K. (2009): Introduction to Spatial Econometrics. CRC Press, Taylor.

Neven D., Gouyette C.(1995): Regional convergence in the European Community. Journal of Common Market Studies, 33: 47–65.

Rivera-Batiz L.A., Romer P.M. (1991): Economic integration and endogenous growth. The Quarterly Journal of Economics, 106: 531–555.

Romer P. (1990): Endogenous technological change. Journal of Political Economy, 98: 71–102.

Sala-i-Martin X. (1996): Regional cohesion: Evidence and theories of regional growth and convergence. European Economic Review, 40: 1325–1352.

Van Pottelsberghe de La Potterie B., Lichtenberg F. (2001): Does foreign direct investment transfer technology across borders? Review of Economics and Statistics, 83: 353–378.

Xu B., Wang J. (1999): Capital goods trade and R&D spillovers in the OECD. Canadian Journal of Economics, 32: 1258–1274.

Received July 17, 2016
Accepted October 3, 2016
Published online October 6, 2017