

Adjustment costs and efficiency in Polish agriculture: a dynamic efficiency approach

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Published online: 28 January 2015
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Abstract This paper aims to understand the state of adjustment processes and dynamic structure in Polish agriculture. A dynamic cost frontier model using the shadow cost approach is formulated to decompose cost efficiency into allocative and technical efficiencies. The dynamic cost efficiency model is developed into a more general context with a multiple quasi-fixed factor case. The model is empirically implemented using a panel data set of 1,380 Polish farms over the period 2004–2007. Due to regional differences and a wide variety of farm specializations, farms are categorized into two regions and five types of farm production specializations. The estimation results confirm our observation that adjustment was rather sluggish, implying that adjustment costs were considerably high. According to this study, it will take up to 30 years for Polish farmers to reach their optimal level of capital and land input. Allocative and technical efficiency widely differ across regions. Moreover, efficiencies prove rather stable over time and among farm specializations, although the results indicate that the regions with larger farms performed slightly better.

Keywords Polish agriculture · Dynamic efficiency · Adjustment cost · Shadow cost approach

JEL classification D21 · D61 · Q12

1 Introduction

During the socialist era, Polish agriculture did not experience fundamental restructuring processes as in other centrally planned economies. Consequently, farm structures in 1990 were just the same as before World War II, especially due to the socialist government having prohibited structural changes in private agriculture. Compared to other countries in the EU, Polish agriculture is greatly dominated by small holdings, with comparatively low levels of specialization and a relatively low degree of market integration. In the 1990 s, it was expected that overdue adjustment processes would be set in motion after 50 years' backlog of reforms, bringing about substantial change in farm structure. Given the poor economic development in the 1990s, the constancy in farm structures came as no surprise since the absorption capacity of the other sectors for labor was rather limited. However, the situation has changed over the past decade, as the economy has been prospering and offering plenty of alternative possibilities to earn a living outside agriculture. This demand pull has posed a competitive threat to labor input in agriculture. In addition, this situation has been further compounded by a supply push resulting from intensified competition within the sector after Poland's accession to the EU. Despite these obvious drivers of change, empirical evidence only supports the assumption that the structural adjustment process and its agricultural change have been rather sluggish. In the first years after EU accession, a change in agriculture could not be observed, with neither a pronounced trend in farm growth leading to a higher degree of specialization, nor changes in the specialization in production.

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The persistence of farm structures suggests that adjustment costs in Polish agriculture might be decisive. In order to reap the benefits from larger holdings, especially economies of scale, farmers would be required to change their entire production program. However, it can be assumed that these fundamental changes would have entailed disproportionately high adjustment costs. Thus, the role of adjustment costs and dynamic cost structure should be increasingly brought into focus in investigating the performance of Polish agriculture. Moreover, it is also of interest to policymakers whether adjustment costs are significant, and if so whether they can be regarded as a source of the sluggish adjustment processes.

The main purpose of this paper is to understand and analyze the state of adjustment processes and dynamic structure in Polish agriculture. For this purpose, the paper extends the adjustment costs model with technical and allocative inefficiency of Rungsuriyawiboon and Stefanou (2007) to a more general context with a multiple quasi-fixed factor case. The model is empirically implemented using a panel data set of 1,380 Polish farms over the period 2004–2007. The study period allows for the examination of the post-accession performance of Polish farms. Due to large differences across regions and a wide variety of farm specializations, the study focuses on two regions (i.e. Northwest and Southeast) and five types of farm production specialization (i.e. field crops, dairy cattle, other grazing livestock, granivores, mixed farm). The production technology of Polish farms is represented by one output variable (aggregate of crop and livestock), four variable inputs (labor, overheads, fertilizer, livestock) and two quasi-fixed factors (land and capital).

In their dynamic efficiency model, Rungsuriyawiboon and Stefanou (2007) integrated two strains of literature: the shadow cost approach for estimating technical and allocative inefficiencies in the context of static production models (Kumbhakar and Lovell 2000) and the dynamic duality model of intertemporal decision making (Epstein and Denny 1983; Vasavada and Chambers 1986; Howard and Shumway 1988; Luh and Stefanou 1991, 1993; Fernandez-Cornejo et al. 1992; Manera 1994; Pietola and Myers 2000). The model is formulated assuming that firms minimize the net present value of production costs. The relationship between an actual and behavioral Hamiltonian Jacobi Bellman or dynamic programming equation (DPE) is used to estimate factor demand functions, as well as allocative and technical efficiencies. Dynamic efficiency measurement as proposed in Rungsuriyawiboon and Stefanou (2007) can be considered a structural approach because it does not directly specify or estimate production technology.¹

¹ However, recent studies including Emvalomatis et al. (2011) and Serra et al. (2011) have presented a parametric reduced-form

It is worth noting that the vast literature on dynamic duality models of intertemporal decision making is based on only a few assumptions: first, economic agents are risk neutral; second, price expectations are static in the sense that the decision maker expects current real prices and technology to persist indefinitely in each base period; and third, the adjustment cost function is strictly convex to allow quasi-fixed inputs to adjust smoothly to their optimal level over time. The existence of irregularities (such as the fixed cost of adjustment and irreversibility) might lead to a non-smooth adjustment of quasi-fixed inputs, causing the asset fixity problem. More recent developments in the context of dynamic dual models of investment that have considered the influence of price risk and uncertainty on capital investment in agriculture include the works of Pietola and Myers (2000), and Serra et al. (2009). The stochastic dual model of investment of Pietola and Myers (2000) allows for asymmetry in investment response during phases of capital expansion and contraction. In their dynamic setting, irreversibility, risk and uncertainty are defined as stochastic variables and risk-neutral firms are assumed to have rational expectations regarding the future evolution of these variables. Serra et al. (2009) extended the dynamic dual model of investment under uncertainty developed by Sckokai (2005). They have allowed for non-static price expectations and risk in a dynamic setting in order that risk-averse firms seek to maximize the discounted utility over an infinite horizon. By considering irregularities in the capital stock adjustment cost function, they adopted the threshold regression methods to assess the existence of irregularities on production decisions. By following these previous studies, the dynamic efficiency model can also be extended to allow for the existence of risk, uncertainty and irregularities on investment decisions. Recently, Huettel et al. (2011) have extended the Rungsuriyawiboon and Stefanou (2007) model by developing a theoretical framework of a dynamic efficiency measurement and optimal investment under uncertainty.

While parametric dynamic measures of production efficiency have continuously been developed in recent years, a few studies modeling dynamic production with adjustment costs have used non-parametric approaches, e.g. Nemoto and Goto (2003) and Silva and Stefanou (2003, 2007). Nemoto and Goto (2003) translated the data envelopment analysis (DEA) model into a dynamic framework in order that investment behavior can be modeled within the conventional DEA framework. Silva and Stefanou (2003) developed a non-parametric dynamic dual

Footnote 1 continued

approach in which dynamic efficiency measurements are derived on the basis of production technology and the duality between this function and the optimal value function.

cost approach for production analysis. Based on this work, they proposed non-parametric measures of dynamic efficiency in the context of an adjustment-cost technology and intertemporal cost minimization (Silva and Stefanou 2007).

The remainder of the paper is organized as follows. The next section presents the theoretical framework and mathematical derivations of the dynamic efficiency model for the multiple quasi-fixed factor case. The third section discusses the data set and defines the variables used in this study. Section 4 elaborates the econometric model of the dynamic efficiency model with the two-quasi-fixed factor case. The results of the empirical analysis are presented and discussed in the ensuing section, before the final section summarizes and concludes.

2 Theoretical framework and model specification

2.1 Intertemporal decision making of the cost minimizing firm

In this section, a dynamic measure of production efficiency in the context of intertemporal cost minimization is developed. Consider a market in which products are not differentiated, customers are homogeneous and firms minimize costs to maintain and improve their long-term competitiveness. The dynamic economic decision problem can be addressed by assuming that the firms plan investments, e.g. changes in the quasi-fixed factor use, and variable input use such that the net present value of production costs is minimized over an infinite horizon. Investments have two countervailing effects: first, the cost increase resulting from accompanying learning processes or modifications of the farm’s production processes; and second, the reduction of production costs after full adjustment.

The underlying idea behind an optimal investment path is to substitute lower cost decreases due to a reduction of investment by cost savings resulting from the split of an investment over several periods. Analytically, the dynamic decision problem can be solved using the dynamic duality approach, which allows the use of appropriate static optimization techniques as expressed in the DPE or Hamilton–Jacobi–Bellman equation (Epstein and Denny 1983). The solution consists of optimal levels of variable input use and the optimal transition path of quasi-fixed factors from the initial state to their desired long-run levels. The assumptions that the cost function is convex in investment and concave in the level of the quasi-fixed factor ensure that a solution for the decision problem exists.

Let \mathbf{x} and \mathbf{q} denote non-negative $(N \times 1)$ and $(Q \times 1)$ vectors of variable and quasi-fixed inputs, respectively. Factor prices are given by strictly non-negative vectors

\mathbf{w} for variable inputs and \mathbf{p} for quasi-fixed factors with appropriate dimensions.

The DPE for the intertemporal cost minimization can be expressed as

$$rJ(\mathbf{w}', \mathbf{p}', \mathbf{q}', y, t) = \min_{\mathbf{x}, \mathbf{q} > 0} \{ \mathbf{w}'\mathbf{x} + \mathbf{p}'\mathbf{q} + \nabla_{\mathbf{q}}J'\dot{\mathbf{q}} + \gamma(y - F(\mathbf{x}', \mathbf{q}', \dot{\mathbf{q}}', t)) + \nabla_t J \}, \quad (1)$$

where r is the constant discount rate; y is output; t is the time trend variable; $\nabla_{\mathbf{q}}J$ is a $(Q \times 1)$ strictly non-negative vector of the marginal valuation of the quasi-fixed factors; $\dot{\mathbf{q}}$ is a $(Q \times 1)$ non-negative vector of net investment in quasi-fixed factors; γ is the Lagrangian multiplier associated with the production function; $F(\mathbf{x}', \mathbf{q}', \dot{\mathbf{q}}', t)$ is the single output production function; and $\nabla_t J$ is the shift of the value function due to technical change.

Equation (1) can be interpreted as the dynamic intertemporal model of a firm’s cost minimization problem in the presence of perfect efficiency. When a firm neither minimizes its factor inputs, given output levels, nor uses the factors according to respective prices and production technology, it is operating inefficiently, both technically and allocatively. A measure of inefficiency can be obtained by adopting a shadow price approach, as described in Kumbhakar and Lovell (2000).

Figure 1 illustrates the presence of technical and allocative inefficiency in the dynamic cost minimization framework. The curve XX represents the isoquant, and thus all curves lying to the southeast of XX represent higher output levels. Given that $\nabla_{\mathbf{x}}F > 0$ and $\nabla_{\dot{\mathbf{q}}}F < 0$, the isoquant is downward sloping, and, since $\nabla_{\mathbf{xx}}F < 0$ and $\nabla_{\dot{\mathbf{q}}\dot{\mathbf{q}}}F < 0$, it is also concave.² The line YY represents the isocost curve derived from the long-run shadow cost function in Eq. (1). According to the definition, the costs are increasing in variable inputs and higher net investments. Point E displays the least cost combination, e.g. the point where the factor price relation equals the marginal rate of substitution $\nabla_{\mathbf{x}}\dot{\mathbf{q}} = -(\mathbf{w}'/\nabla_{\mathbf{q}}J) = -(\nabla_{\mathbf{x}}F/\nabla_{\dot{\mathbf{q}}}F)$; $\nabla_{\mathbf{q}}J < 0$.

Consider point A , where a firm uses the bundle of inputs $(\mathbf{x}^A, \dot{\mathbf{q}}^A)$ available at prices $(\mathbf{w}, \nabla_{\mathbf{q}}J)$ to produce output y according to the XX curve. Given the input price $(\mathbf{w}, \nabla_{\mathbf{q}}J)$, a minimum cost of $(\mathbf{w}'\mathbf{x}^E + \nabla_{\mathbf{q}}J'\dot{\mathbf{q}}^E)$ will occur at point E . However, at point A the firm is technically inefficient because production is not on the XX curve. Consequently, the use of both variable input as well as dynamic factor can be reduced, and thus costs can be saved without reducing production (e.g. moving from point A to

² Totally differentiating $y = F(\mathbf{x}, \mathbf{q}, \dot{\mathbf{q}}, t)$ leads to $\nabla_{\mathbf{x}}F d\mathbf{x} + \nabla_{\mathbf{q}}F d\mathbf{q} + \nabla_{\dot{\mathbf{q}}}F d\dot{\mathbf{q}} + \nabla_t F dt = 0$. Given $d\mathbf{q} = 0$ and $dt = 0$, the slope of the isoquant yields $-\nabla_{\mathbf{x}}F/\nabla_{\dot{\mathbf{q}}}F = \nabla_{\mathbf{x}}\dot{\mathbf{q}}$. Differentiating the slope of the isoquant with respect to \mathbf{x} provides $\nabla_{\mathbf{xx}}\dot{\mathbf{q}} = -[(\nabla_{\dot{\mathbf{q}}}F \nabla_{\mathbf{xx}}F - \nabla_{\mathbf{x}}F \nabla_{\dot{\mathbf{q}}\dot{\mathbf{q}}}F) / (\nabla_{\dot{\mathbf{q}}}F)^2] < 0$.

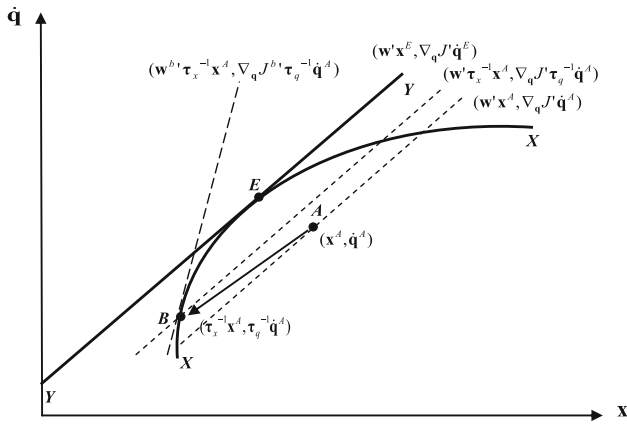


Fig. 1 The dynamic intertemporal cost model in the presence of inefficiency. *Source* own presentation

point *B* in Fig. 1). Let τ_x^{-1} and τ_q^{-1} denote input-oriented measures of technical efficiency for variable and dynamic factors, respectively; thus, the technically efficient production point is $(\tau_x^{-1}x^A, \tau_q^{-1}q^A)$. While the firm is technically efficient at *B*, it is still allocatively inefficient because the marginal rate of substitution at *B* differs from the actual input prices $(w, \nabla_q J)$. However, the firm is allocatively efficient relative to shadow input prices $(w^b, \nabla_q J^b)$. The shadow prices (internal to the firm) are defined as input prices forcing the technically efficient input vector to be the cost-minimizing solution for producing a given output. Shadow prices will differ from market (actual) prices in the presence of allocative inefficiency.

The main difference between the conventional approach to the analysis of cost efficiency and the shadow cost approach is that the latter gives factor-specific efficiency scores averaged over all firms, whereas the former provides firm-specific efficiency scores averaged over all inputs. From this conceptual difference, it follows that the scores cannot be directly compared; in fact, they might be significantly different. In Fig. 1, technical efficiency is achieved at point *B*. According to the shadow price approach, input use can be reduced by more than 50 %, while the conventional approach only provides a relatively small decrease of costs. Moreover, the shadow cost approach does not measure allocative efficiency at point *E*, as the conventional approach does, but rather at point *B*, where the isocost line only becomes tangent to the isoquant suitable rotation.

2.2 Derivation of dynamic efficiency model

In the presence of inefficiency, the dynamic efficiency model can be formulated employing the shadow price approach. One of the basic ideas underlying the construction of the dynamic efficiency model is to define the relationship between actual and shadow (behavioral) value functions of

the DPE for the firms' intertemporal cost minimization behavior. The behavioral value function of the DPE is expressed in terms of shadow input prices, quasi-fixed factors and output, whereas the actual value function can be viewed as the perfectly efficient condition. The shadow input prices are constructed to generate an optimality relationship. Moreover, as the shadow input prices will differ from market (actual) prices in the presence of inefficiency, a firm's inefficiency can be estimated and evaluated as the deviation between the behavioral and actual value function.³

Let x^b and q^b denote nonnegative $(N \times 1)$ and $(Q \times 1)$ vectors of behavioral variable and quasi-fixed inputs, respectively. Following the shadow price approach, x^b and q^b can be expressed in terms of actual variable and dynamic factors as $x^b = \tau_x^{-1}x$ and $q^b = \tau_q^{-1}q$, respectively, where τ_x and τ_q represent inverse producer-specific scalars providing input-oriented measures of the technical efficiency in variable input and dynamic factor use, respectively.

Let w^b and $\nabla_q J^b$ denote strictly non-negative vectors of behavioral variable input prices and behavioral dynamic factors with appropriate dimensions. The behavioral prices can be expressed in terms of actual prices of variable inputs $w^b = \Lambda_w w$ and dynamic factors $\nabla_q J^b = \Sigma_q \nabla_q J^a$, where Λ_w and Σ_q are allocative inefficiencies of the variable and quasi-fixed inputs, respectively.

Given behavioral input prices and quantities, the DPE for the firms' intertemporal cost minimization behavior can be expressed as

$$rJ^b(w^b, p', q', y, t) = w^b x^b + p' q + \nabla_q J^b q^b + \gamma^b (y - F(x^b, q', q^b, t)) + \nabla_t J^b, \quad (2)$$

where γ^b is the behavioral Lagrangian multiplier defined as the short-run, instantaneous marginal cost; and $\nabla_t J^b$ is the shift of the behavioral value function.

Differentiating (2) with respect to p and w^b yields the behavioral conditional demand for the dynamic and variable factors, respectively. Using $q^b = \tau_q^{-1}q^\circ$ and $x^b = \tau_x^{-1}x^\circ$, with superscript *b* denoting the behavioral value and superscript \circ indicating the optimal value, the optimized demand for the dynamic and variable factors are $q^\circ = \tau_q q^b = \tau_q (\nabla_{qp} J^b)^{-1} (r \nabla_p J^b - q - \nabla_{pt} J^b)$ (3)

³ This model assumes that economic agents are risk neutral and that their price expectations are static. However, if these restrictive assumptions are relaxed investments under uncertainty can be derived within the dynamic duality model of intertemporal decision making. In the intertemporal model setting, risks and uncertainties can be defined as stochastic variables about which firms are assumed to have rational expectations regarding the future evolution of these variables. For more details about non-static price expectations and risk in the dynamic dual model of investment, see Luh and Stefanou (1996) and Pietola and Myers (2000).

$$\mathbf{x}^\circ = \boldsymbol{\tau}_x \mathbf{x}^b = \boldsymbol{\tau}_x \boldsymbol{\Lambda}_n^{-1} (r \nabla_w J^b - \nabla_{\mathbf{wq}} J^b \dot{\mathbf{q}}^b - \nabla_{\mathbf{wr}} J^b), \tag{4}$$

where $\nabla_{\mathbf{wb}} J^b = \boldsymbol{\Lambda}_w^{-1} \nabla_w J^b$.

The value function in actual prices and quantities (indicated by superscript a) at the optimal level can be defined as

$$rJ^a(\cdot) = \mathbf{w}' \mathbf{x}^\circ + \mathbf{p}' \mathbf{q} + \nabla_{\mathbf{q}} J^a \dot{\mathbf{q}}^\circ + \nabla_t J^a. \tag{5}$$

Differentiating (5) with respect to \mathbf{p} and \mathbf{w} and applying the same steps as before in the behavioral value function of Eq. (2) yields

$$\dot{\mathbf{q}}^\circ = (\nabla_{\mathbf{qp}} J^a)^{-1} (r \nabla_{\mathbf{p}} J^a - \mathbf{q} - \nabla_{\mathbf{pr}} J^a) \tag{6}$$

$$\mathbf{x}^\circ = (r \nabla_w J^a - \nabla_{\mathbf{qw}} J^a \dot{\mathbf{q}}^\circ - \nabla_{\mathbf{wr}} J^a) \tag{7}$$

Inserting the behavioral demand function (5) in (6) and (7), the value function in actual prices and quantities (5) can be rewritten as

$$\begin{aligned} rJ^a(\cdot) = & \mathbf{w}' \boldsymbol{\tau}_x \boldsymbol{\Lambda}_w^{-1} \left(r \nabla_w J^b - \nabla_{\mathbf{qw}} J^{b'} \left[(\nabla_{\mathbf{qp}} J^b)^{-1} (r \nabla_{\mathbf{p}} J^b - \mathbf{q} - \nabla_{\mathbf{pr}} J^b) \right] \right. \\ & \left. - \nabla_{\mathbf{nw}} J^b \right) + \mathbf{p}' \mathbf{q} + \sum_q \nabla_{\mathbf{q}} J^{b'} \boldsymbol{\tau}_q \left[(\nabla_{\mathbf{qp}} J^b)^{-1} (r \nabla_{\mathbf{p}} J^b - \mathbf{q} - \nabla_{\mathbf{pr}} J^b) \right] + \nabla_t J^b, \end{aligned} \tag{8}$$

where $\nabla_{\mathbf{r}} J^a = \nabla_{\mathbf{r}} J^b$ implies that the shift in the behavioral value function is proportional to that in the actual value function.

Differentiating (8) with respect to \mathbf{p} , \mathbf{q} and t (neglecting third derivative) and substituting into (6) yields

$$\begin{aligned} & \left[\mathbf{i}' / r + \boldsymbol{\tau}_q \sum_q \left(\nabla_{\mathbf{qp}} J^b + \nabla_{\mathbf{qq}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b - \mathbf{i}' / r \right) - \sum_q \nabla_{\mathbf{qp}} J^b \right] \dot{\mathbf{q}}^\circ \\ & = \left[r \boldsymbol{\tau}_x \boldsymbol{\Lambda}_n^{-1} \left(\nabla_{\mathbf{wp}} J^b - \nabla_{\mathbf{qw}} J^{b'} (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b \right) \mathbf{w} \right. \\ & \quad \left. + \boldsymbol{\tau}_q \sum_q \left[r (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b \nabla_{\mathbf{q}} J^b - (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pp}} J^b \nabla_{\mathbf{qr}} J^b \right] \right. \\ & \quad \left. + (\mathbf{i} - \boldsymbol{\tau}_q \boldsymbol{\Sigma}_q^{-1}) \nabla_{\mathbf{pr}} J^b \right] \end{aligned} \tag{9}$$

where \mathbf{i} is a unit vector of appropriate dimension.

Similarly, differentiating (8) with respect to \mathbf{w} , \mathbf{q} and t (neglecting third derivatives) and substituting into (7) yields

$$\begin{aligned} \mathbf{x}^\circ = & \boldsymbol{\tau}_x \boldsymbol{\Lambda}_w^{-1} \left[r \left[\nabla_{\mathbf{ww}} J^b - \nabla_{\mathbf{qw}} J^{b'} (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{wp}} J^b \right] \mathbf{w} + r \nabla_w J^b \right. \\ & \left. - \nabla_{\mathbf{wr}} J^b + \nabla_{\mathbf{qw}} J^{b'} (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{pr}} J^b \right. \\ & \left. + \boldsymbol{\tau}_q \sum_q \left[r \nabla_{\mathbf{wp}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{q}} J^b - \nabla_{\mathbf{wp}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{qr}} J^b \right] \right. \\ & \left. - \boldsymbol{\tau}_x \boldsymbol{\Lambda}_w^{-1} \left[\nabla_{\mathbf{qw}} J^{b'} - \nabla_{\mathbf{qw}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} (\nabla_{\mathbf{qp}} J^b - \mathbf{i} / r) + \boldsymbol{\tau}_q \nabla_{\mathbf{qw}} J^{b'} \right] \dot{\mathbf{q}}^\circ \right. \\ & \left. - \boldsymbol{\tau}_q \sum_q \left[\nabla_{\mathbf{wp}} J^b (\nabla_{\mathbf{qp}} J^b)^{-1} \nabla_{\mathbf{qq}} J^b \right] \dot{\mathbf{q}}^\circ \right] \end{aligned} \tag{10}$$

The dynamic efficiency model in the presence of inefficiencies consists of the actual conditional demands for dynamic factors in Eq. (9) and variable inputs in Eq. (10).

The dynamic efficiency model is developed under a condition that firms can operate technically and allocatively inefficient in the production. It allows one to measure both firm’s technical and allocative inefficiency in variable input and dynamic factor. This dynamic efficiency model can be considered as the perfectly inefficient model. When all inefficiency parameters in the model are equal to one, (9) and (10) reduces to the optimal input demand functions presented in Epstein and Denny (1983).

3 Data discussions

3.1 Definition of variables

The empirical analysis focuses on agricultural production in Poland using a balanced subpanel of the Polish FADN data set for the period 2004–2007.⁴ In our analysis, the production technology of Polish farms is represented by one output (y), four variable inputs x_n (i.e. $x_1 =$ labor, $x_2 =$ crop input, $x_3 =$ livestock input, $x_4 =$ overheads) and two quasi-fixed factors q (i.e. $q_1 = l =$ land, $q_2 = k =$ capital).⁵ Labor and land are given in physical inputs, e.g. the total labor input expressed in annual work units (= full-time person equivalent) and the total utilized agricultural area in hectares, respectively. All other inputs and outputs are provided in nominal monetary values. Capital input comprises land improvement, permanent crops, farm buildings, machinery, equipment and breeding livestock. Material input in crop production reflects the aggregate expenditure for fertilizer, seed, pesticides and other inputs for crop production. Material input in livestock production comprises expenditures for feed and other inputs for livestock production. Overheads include expenditures for energy, maintenance, purchased services and other unspecified inputs.

⁴ The Farm Accountancy Data Network (FADN), Source: <http://ec.europa.eu/agriculture/rica/>.

⁵ We follow the conventional dynamic analysis of production structures and consider capital as one of the quasi-fixed factors to capture possibly resulting adjustment costs to which the producer can appropriately respond and minimize entailed losses by dividing their investment requirement into several steps. Land was also considered as a quasi-fixed factor, given that farm structures are rather stable, which implies that changing the amount of cultivated acreage will entail considerable costs so that the adjustment of farm structures is only of minor importance/relevance. It is often argued that labor also belongs to the group of quasi-fixed inputs. In Poland, however, labor input reacts rather flexible and thus might considerably change following the overall economic situation. Correspondingly, part-time farming is a widespread phenomenon in Poland, thus implying that labor is more a flexible than a quasi-fixed input (Csaki and Lerman 2001).

The volume of capital input was calculated as the quotient of the capital input and price index of fixed assets. This index was only available for the national level. Rental prices for capital were approximated the sum of the depreciation rate and nominal interest rate times the price index of fixed assets (Jorgenson 1963). The latter two variables were calculated from the data set.⁶ Price indices for variable inputs were only available at the national level.⁷ Farm-specific price indices were derived in the three-step procedure as follows: first, we calculated the volume of the individual inputs by dividing the data in current prices by the corresponding price index at the national level; second, the corresponding inputs were aggregated for each of the three categories; and third, the relations of input in current and constant prices constitute the farm-specific price indices.

No reliable price information for land and labor was available from Polish statistics. However, the data set contained information on land rents and wages paid for some farms. Farm-specific prices were calculated in the following manner. After the available information was regressed on several farm specific indicators,⁸ the information obtain was subsequently taken to find the best fit between prices and regressors in a stepwise procedure. The estimation results were then used to determine the factor prices for each farm.

We used information on farm products at regional price levels to construct multilateral consistent Theil-Törnquist price indices for crop, animal and total output (Caves et al. 1982). For comparability, we finally computed real price-adjusted volumes for crop, animal and total production by dividing the production values in current prices by the corresponding calculated price indices.

3.2 Selection of regions

While the data set covers all Polish FADN regions, due to marked differences across regions, this paper focuses on farms located in two regions: Pomorze and Mazury (785) in the northwest, and Malopolska and Pogórze (800) in the southeast of Poland (Fig. 2). For convenience, the first region is called Northwest (Pomorze and Mazury) and the second Southeast (Malopolska and Pogórze) throughout the remainder of this article. A total number of 1,380 farms were extracted from the data: 763 in the region Northwest

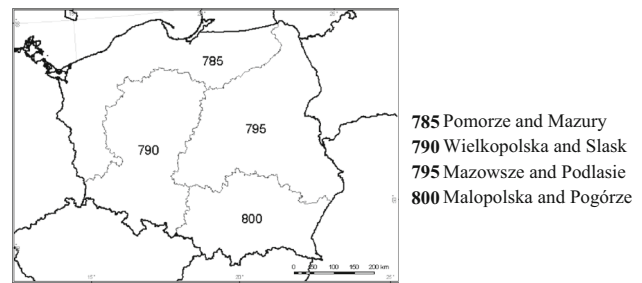


Fig. 2 Polish FADN regions. Source http://ec.europa.eu/agriculture/ricea/regioncodes_en.cfm?CodeCountry=POL

and 617 in the region Southeast. These regions were selected due to the pronounced differences in production structures (Table 1).

The Northwest is characterized by comparatively large enterprises, while the Southeast is dominated by rather small farms. This farm structure finds its expression not only in the production volume but also in the intensity of used inputs. To put this into perspective, although labor input is around the same in the two regions, agriculture in the Southeast produces more labor intensive than agriculture in the Northwest. Moreover, these inter-regional differences in input use are reflected in corresponding differences in the amount of production and productivities. Compared to the Southeast, farms in the Northwest have higher labor and capital productivities: labor productivity (y/x_l) is around 65 % higher and capital productivity (y/k) 7 %, while land productivity (y/l) is around 23 % lower. In addition, the average value share of material inputs in the Northwest is also slightly higher than in the Southeast (58 vs. 52 %).⁹

In terms of types of production, there is no pronounced regional specialization of production. In both regions, around 40 % of total production results from crop production. Table 2 compares the different types of farm production specialization by region and over the study period. Farms in both regions tend to specialize, predominantly in raising dairy cattle, other grazing livestock, granivores (pigs and poultry), a variety of field crops or mixed farming; indeed, farming is the most frequent specialization, accounting for nearly 50 % in the Northwest and more than 50 % in the Southeast. Apart from this “number one” specialization, the Northwest specializes in dairy cattle, accounting for 20 %, followed field cropping, granivores and (other) grazing livestock. By contrast, the Southeast showing a slightly different order, with field cropping accounting for 20 %, followed by dairy cattle, granivores and (other) grazing livestock. Despite this clear ranking, mixed farming tends to decrease over the years in both regions, while raising dairy cattle and granivores tend to increase. Therefore, farms have

⁶ The depreciation rate was obtained by relating depreciation to fixed assets. The interest rate was obtained by the relation between interest paid and the amount of proportion of interest paid on long and medium-term loans.

⁷ All price indices were taken from national statistics and the EUROSTAT website.

⁸ These include dummy variables on specialization, farm size in European Size Units, location by Wojwodship (e.g. region), altitude of the farm, the existence of environmental limitations, the availability of structural funds and the education level of the farmer.

⁹ Partial productivity and value shares were computed using the information given in Table 1.

Table 1 Descriptive statistics of the variables, 2004–2007

Variable	Northwest (Pomorze and Mazury)				Southeast (Malopolska and Pogórze)			
	Mean	Std	Min	Max	Mean	Std	Min	Max
p_c P_CROP	1.003	0.200	0.749	1.477	1.037	0.200	0.731	1.488
p_a P_ANIM	1.026	0.039	0.910	1.457	0.971	0.044	0.378	1.072
p_y P_OUT	1.017	0.102	0.767	1.408	0.999	0.101	0.771	1.357
y_c X_CROP	80,498	137,764	341	3,555,780	44,965	75,273	739	1,289,640
y_a X_ANIM	123,552	274,984	40	5,539,070	68,915	129,130	521	2,256,540
Y X_OUT	204,050	339,487	10792	6,063,050	113,880	176,891	2,727	2,529,410
Share of crop production	42.2 %	22.7 %	0.2 %	100.0 %	43.3 %	21.8 %	0.4 %	99.1 %
w_1 P_LAB	13,966	813	12,010	17,739	14,195	937	12,010	19,140
w_2 P_CRP_I	1.002	0.056	0.927	1.173	1.002	0.061	0.929	1.186
w_3 P_ANI_I	1.003	0.074	0.925	1.083	1.003	0.074	0.925	1.083
w_4 P_OVER	0.988	0.035	0.915	1.082	0.987	0.036	0.916	1.242
p_l P_LAN	225	41	116	340	227	51	113	374
p_k P_CAP	0.924	0.521	0.006	4.370	1.093	0.611	0.033	3.607
x_1 X_LAB	2.075	1.148	0.510	16.900	1.916	1.048	0.250	18.420
x_2 X_CRP_I	31,279	50,165	228	1,080,980	15,130	27,013	105	442,185
x_3 X_ANI_I	69,638	183,282	88	3,450,370	33,569	66,487	264	823,026
x_4 X_OVER	21,217	29,872	849	733,522	11,395	17,707	647	316,292
L X_LAN	48.9	58.3	2.0	699.1	21.2	25.2	0.4.2	253
K X_CAP	764,458	745,718	28,719	1,0948,300	458,427	529,251	49,035	8,947,220

Total of 5,480 observations; 3,012 for the Northwest region and 2,468 for the Southeast region

Source own calculations

Table 2 Farm specialization in each region, 2004–2007 (percentage share)

Specialization	Year							
	2004		2005		2006		2007	
	North-west	South-east	North-west	South-east	Northwest	South-east	North-west	South-east
Field crops	18.5	21.8	17.7	19.4	17.2	17.8	17.0	21.5
Dairy cattle	20.3	8.9	21.1	9.7	21.9	11.0	21.7	12.0
Grazing livestock	2.8	4.9	2.5	5.8	3.2	6.3	5.3	6.8
Granivores	8.8	7.6	10.2	8.3	10.6	8.9	10.9	9.1
Mixed farming	49.6	56.8	48.4	56.8	47.1	56.0	45.1	50.6

Source own calculations

necessarily been switching from one type of production to another: more precisely, 243 farms in the Northwest and 210 farms in the Southeast switched specializations in both regions over the entire study period.

4 Econometric model

Equations (9) and (10) constitute a system of quasi-fixed and variable factor demands that can be estimated using appropriate econometric procedures. However, before going into details about the estimation strategy, it is

helpful to make a few remarks regarding the empirical implementation. Our empirical model distinguished the two quasi-fixed factors of net investment and land. or convenience of the derivation and empirical setup, we assume that both net investment and land are independent.¹⁰ Under this simplifying assumption, $\nabla_{qp}J^b, \nabla_{qq}J^b$

¹⁰ In the context of this study, when firms decide to increase farm land, net investment will not be simultaneously affected; rather, it might take several periods for net investment to adjust. Therefore, the decision to increase farm land is not fully dependent on the decision to increase a firm’s net investment. Over the study period, average

and $\nabla_{pp}J^b$ are diagonal matrices, e.g. the off-diagonal elements $J^b_{kp_l}, J^b_{lp_k}, J^b_{kl}$ and $J^b_{p_k p_l}$ are each equal to zero. Using this information, the demand Eq. (9) becomes:

$$\begin{aligned} & \left[1/r + \tau_q \sum_k^{-1} \left(J^b_{kp_k} + J^b_{kk} \left(J^b_{kp_k} \right)^{-1} J^b_{p_k p_k} - 1/r \right) - \sum_k^{-1} J^b_{kp_k} \right] k^o \\ &= [r\tau_x \Lambda_n^{-1} \left(J^b_{wp_k} - J^b_{kw} \left(J^b_{kp_k} \right)^{-1} J^b_{p_k p_k} \right)'] \mathbf{w} \\ &+ \tau_q \sum_k^{-1} \left[r \left(J^b_{kp_k} \right)^{-1} J^b_{p_k p_k} J^b_k - \left(J^b_{kp_k} \right)^{-1} J^b_{p_k p_k} J^b_{tk} \right] \\ &+ (1 - \tau_q \Sigma_k^{-1}) J^b_{p_k t} + \varepsilon_1 \end{aligned} \tag{11}$$

$$\begin{aligned} & \left[1/r + \tau_q \sum_l^{-1} \left(J^b_{lp_l} + J^b_{ll} \left(J^b_{lp_l} \right)^{-1} J^b_{p_l p_l} - 1/r \right) - \sum_l^{-1} J^b_{lp_l} \right] l^o \\ &= [r\tau_x \Lambda_n^{-1} \left(J^b_{wp_l} - J^b_{lw} \left(J^b_{lp_l} \right)^{-1} J^b_{p_l p_l} \right)'] \mathbf{w} \\ &+ \tau_q \sum_l^{-1} \left[r \left(J^b_{lp_l} \right)^{-1} J^b_{p_l p_l} J^b_l - \left(J^b_{lp_l} \right)^{-1} J^b_{p_l p_l} J^b_{tl} \right] \\ &+ (1 - \tau_q \Sigma_l^{-1}) J^b_{p_l t} + \varepsilon_2 \end{aligned} \tag{12}$$

where ε_1 and ε_2 are the two-sided error terms representing random errors which $\varepsilon_1 \sim \text{iid } N(0, \sigma_1^2)$ and $\varepsilon_2 \sim \text{iid } N(0, \sigma_2^2)$. ε_1 and ε_2 are distributed independently of each other, and of the regressors.

In addition, the demand for variable inputs (10) is given by:

$$\begin{aligned} x^o &= \tau_x \Lambda_n^{-1} \left[\begin{aligned} & (rJ^b_{ww} \mathbf{w} - rJ^b_{kw} \left(J^b_{kp_k} \right)^{-1} J^b_{wp_k} \mathbf{w} - rJ^b_{lw} \left(J^b_{lp_l} \right)^{-1} J^b_{wp_l} \mathbf{w} \\ & + rJ^b_w - J^b_{wi} + J^b_{kw} \left(J^b_{kp_k} \right)^{-1} J^b_{p_k i} + J^b_{lw} \left(J^b_{lp_l} \right)^{-1} J^b_{p_l i} \end{aligned} \right] \\ &+ \tau_k \sum_k^{-1} \left[rJ^b_{wp_k} \left(J^b_{kp_k} \right)^{-1} J^b_k - J^b_{wp_k} \left(J^b_{kp_k} \right)^{-1} J^b_{kt} \right] \\ &+ \tau_l \sum_l^{-1} \left[rJ^b_{wp_l} \left(J^b_{lp_l} \right)^{-1} J^b_l - J^b_{wp_l} \left(J^b_{lp_l} \right)^{-1} J^b_{lt} \right] \\ &- \left[\begin{aligned} & \tau_x \Lambda_n^{-1} \left[J^b_{kw} - J^b_{kw} \left(J^b_{kp_k} \right)^{-1} \left(J^b_{kp_k} - 1/r \right) + \tau_q J^b_{kw} \right] \\ & + \tau_k \sum_k^{-1} \left[J^b_{wp_k} \left(J^b_{kp_k} \right)^{-1} J^b_{kk} \right] \end{aligned} \right] k^o \\ &- \left[\begin{aligned} & \tau_x \Lambda_n^{-1} \left[J^b_{lw} - J^b_{lw} \left(J^b_{lp_l} \right)^{-1} \left(J^b_{lp_l} - 1/r \right) + \tau_q J^b_{lw} \right] \\ & + \tau_l \sum_l^{-1} \left[J^b_{wp_l} \left(J^b_{lp_l} \right)^{-1} J^b_{ll} \right] \end{aligned} \right] l^o + \varepsilon \end{aligned} \tag{13}$$

Footnote 10 continued
land input increased by 4.5 % per year, while farm capital input increased by more than 7.5 %. These differences in the growth rates provide some support for our conjecture.

where ε is a linear disturbance vector with mean vector $\mathbf{0}$ and variance–covariance matrix Σ .

Equations (11)–(13) form the system equations of the dynamic efficiency model in the presence of inefficiencies. To estimate this model, it is necessary to specify the functional form of the behavioral value function. In addition, all inefficiencies must be specified to implement the estimation of all coefficient parameters of the behavioral value function. A quadratic behavioral value function assuming symmetry of the parameters can be expressed as¹¹:

$$J^b(\cdot) = \beta_0 + \mathbf{w}' \boldsymbol{\beta} + \frac{1}{2} \mathbf{w}' \mathbf{B} \mathbf{w}, \tag{14}$$

where $\mathbf{w}' = (\mathbf{w}^b p_k p_l k l y t)$; $\boldsymbol{\beta}$ denotes a vector of parameters and \mathbf{B} a symmetric matrix of parameters, each of appropriate dimension.

The system (11)–(13) is recursive and solved in two stages with net investment and land as endogenous variables of the first stage and second stage explanatory variables in the variable input demand equations. In the first stage, the optimized actual investment demands in capital and land are estimated by using the maximum likelihood estimation (MLE). Given that the optimized actual variable input demand equations are over-identified, the system of variable input demand equations is estimated in the second stage by using a generalized method of moments (GMM) estimation with all parameter values as determined in the first stage. All predetermined variables, including exogenous and dummy variables of each equation in the variable input demand equations, are defined as the instrumental variables of the system equation in the second stage. One function of GMM estimation is to find instrumental variable, \mathbf{z} , that are correlated with exogenous variables in the model but uncorrelated with the residual, ε , implying the orthogonality conditions, $E(\mathbf{z}' \varepsilon) = 0$. If the disturbances are heteroscedastic and serially correlated, the estimation in the presence of heteroscedasticity and autocorrelation can be corrected by applying a flexible approach developed by Newey and West (1987). The consistency of the system GMM estimator relies upon the assumption of no serial correlation in the idiosyncratic error terms. Following the Newey and West (1994) procedure, a lag of two periods (one period) in the autocorrelation terms is used to compute the covariance matrix of the orthogonality conditions for the GMM estimation in the Northwest (Southeast) model. Another essential assumption to ensure consistency of the system GMM estimator crucially depends on the assumption of exogeneity of the instruments. The validity of the

¹¹ The behavioral value function in Eq. (25) must satisfy the following regularity conditions: $J^b(\bullet)$ is non-increasing in (k, l) ; non-decreasing in $(\mathbf{w}^b, p_k, p_l, y)$; convex in (k, l) ; concave in (\mathbf{w}^b, p_k, p_l) ; and linearly homogenous in (\mathbf{w}^b, p_k, p_l) .

instrument variables is tested with Hansen's J -test of over-identifying restrictions (Hansen 1982). Under the null hypothesis of orthogonality of the instruments, the test statistic is asymptotically distributed as Chi square, with as many degrees of freedom as over-identifying restrictions. The null hypothesis fails to reject the assumption that the additional instrumental variables are valid, given that a subset of the instrument variables is valid and exactly identifies the coefficient.

5 Empirical results

In this section, the empirical results of the estimations are described. However, before proceeding with the details, some technical explanations are necessary. The analysis begins by estimating two models subject to specific assumptions in order to decide whether or not efficiency is achieved. (a) A full model is based on the assumption that firms are perfectly inefficient in dynamic and variable factor demands in order to capture all inefficiency parameters in the dynamic efficiency model. Technical and allocative efficiencies of dynamic and variable factors are assumed to vary across regions, among specializations and over time (Cornwell et al. 1990), and (b) a restricted model is based on the assumption that firms are perfectly efficient in dynamic and variable factor demands. The restricted model is estimated by setting all inefficiency parameters of the full model as equal to one.

A hypothesis test regarding the presence of perfect efficiency in production is conducted using the likelihood ratio (LR) test. The LR test is approximately Chi square distributed with degrees of freedom equal to the number of restrictions. Table 3 presents the estimated coefficients and standard errors for the structural parameters of the dynamic efficiency model in both specifications.¹² The estimation results from both models are similar and provide the same sign for all parameter estimates, apart from the estimated parameters β_{w3w3} , β_{w2w4} , β_{w2l} , β_{w4l} and β_{ll} . Most coefficient estimates, particularly the first-order coefficients, are significant at the 95 % confidence interval using a two-tailed test, apart from the estimated parameters β_{w2} and β_{w3} in the restricted model. The LR test of the null hypothesis that firms are perfectly efficient in dynamic and variable factor demands is rejected at the 95 % confidence level, thus implying that the firms in this study produced inefficiently.

¹² In the estimation, dummy variables are incorporated to account for firm's allocative and technical inefficiency parameters dynamic and variable factors demands. The inclusion of these dummy variables requires the implementation of a restricted version of the fixed effects panel data technique. The full sets of estimated coefficients including these dummy variables are not reported.

Furthermore, we conduct another hypothesis test to investigate whether farms operating in different regions have identical production technologies. Therefore, the estimation of the full model using the data of all farms (Table 3) is compared with estimates generated by separate estimations on regional data. The estimated coefficients for each model using the data in the Northwest and Southeast regions are presented in Table 4.

The estimation results of each model and all first-order coefficients have the same sign, apart from the estimated parameters, β_{w2w4} , β_{w2pk} , β_{w2k} , β_{w2y} , β_{w3k} , β_{w3l} , β_{pkt} , β_{plr} , β_{kt} , β_{ll} and β_{yl} . Most coefficient estimates, in particular the first-order coefficients, are significant at the 99 % confidence interval, apart from the estimated parameters β_{w2} and β_{pl} . The LR test of the null hypothesis that the group-specific technologies are identical is rejected at the 95 % confidence level, thus implying that the group-specific technologies are not the same. In the light of this denied "equality" hypothesis, the following empirical results can be discussed under the aspect of difference, thereby providing useful information to calculate inefficiency components. Table 5 reports the corresponding results.

Table 5 presents the average values of farm-level technical and allocative efficiencies of dynamic and variable factors by regions and across all farms during 2004–2007. Given that an estimate of the technical efficiency (TE) of dynamic and variable factors is bounded between zero and unity, a score of technical efficiency of one implies that the associated farm indeed is able to minimize both dynamic and variable factors to produce a given level of output. The estimated technical efficiencies of net investment in quasi-fixed factors range from 0.480 to 0.631 with an average of 0.536, whereas those of variable inputs range from 0.505 to 0.660 with an average of 0.576. According to these findings, the Polish farmers of this study on average failed to operate their farms fully efficient, thus, implying that they had potential for efficiency gains. More precisely, they could have reduced the input of dynamic and variable factors by 46 and 42 %, respectively, without reducing their existing output level at that point in time. The average Northwest farm producing an (average) value of 56.7 % for dynamic factors and 58.5 % for variable inputs achieved higher technical efficiencies than the average Southeast farm producing values, which were approximately 12 % lower in dynamic factors and 3.5 % lower in variable inputs.

In general, as with technical efficiency, allocative efficiency (AE) scores are bounded between zero and unity. Thus, a value of one indicates that the farms can use their dynamic factors in optimal ratios given respective prices and production technology. Average farm-level allocative efficiencies of net investments in capital and land amount to 0.529 and 0.753, respectively. Expressed in terms of

Table 3 Estimated parameters of dynamic efficiency for the full and restricted models

Parameter ^a	Full model		Restricted model		Parameter ^a	Full model		Restricted model	
	Estimate	Std Err	Estimate	Std Err		Estimate	Std Err	Estimate	Std Err
β_o	-0.152***	0.022	-0.614***	0.082	β_{w2l}	0.748	1.116	1.663***	0.475
β_{w2}	0.320**	0.212	0.248	0.209	β_{w3w4}	1.013*	0.599	4.772	6.817
β_{w3}	0.289***	0.025	0.197*	0.142	β_{w3pk}	-1.936	1.826	-0.989	1.337
β_{w4}	0.086***	0.021	0.187***	0.023	β_{w3pl}	7.213	4.624	0.683	2.846
β_{pk}	0.209***	0.002	0.381***	0.002	β_{w3k}	-8.368***	1.769	-4.940***	1.214
β_{pl}	0.011***	0.004	0.081***	0.014	β_{w3l}	4.776***	1.502	1.503	1.009
β_k	-0.800***	0.002	-0.180***	0.002	β_{w3y}	1.072	1.702	1.755	1.125
β_l	-0.027***	0.001	-0.267***	0.015	β_{w3t}	-1.151	3.835	-2.399	3.528
β_y	0.128***	0.002	0.430***	0.017	β_{w4pk}	-0.961***	0.185	-1.188***	0.171
β_t	0.015***	0.005	0.009**	0.003	β_{w4pl}	-0.888*	0.528	-1.094**	0.534
β_{w2w2}	23.002***	3.296	13.905***	3.236	β_{w4k}	-1.347***	0.218	-1.312***	0.22
β_{w3w3}	1.28	14.762	-7.647	10.102	β_{w4l}	0.139	0.201	0.091	0.202
β_{w4w4}	0.764***	0.185	0.728***	0.186	β_{w4y}	0.709***	0.223	0.642***	0.224
β_{pkpk}	0.153***	0.004	0.152***	0.003	β_{w4t}	-0.346	0.262	0.086	0.219
β_{plpl}	0.047	0.032	0.04	0.032	β_{pkk}	83.897***	2.011	43.628***	0.313
β_{kk}	-0.131***	0.005	-0.129***	0.005	β_{pky}	-9.681***	0.319	-9.714***	0.292
β_{ll}	-0.021***	0.003	-0.022***	0.003	β_{pkt}	0.335	0.493	0.514	0.443
β_{yy}	0.120***	0.004	0.120***	0.004	β_{pll}	36.798***	7.115	20.036***	0.78
β_{tt}	0.018	0.04	0.055	0.033	β_{ply}	-1.499*	0.866	-2.050**	0.858
β_{w2w3}	5.757**	2.864	2.883	1.78	β_{plt}	1.895*	1.149	0.997	0.932
β_{w2w4}	-3.059	2.615	3.361**	1.449	β_{ky}	-9.524***	0.379	-9.475***	0.379
β_{w2pk}	0.056	0.403	0.464**	0.236	β_{kt}	0.642	0.49	1.322***	0.402
β_{w2pl}	1.993*	1.107	0.48	0.539	β_{ly}	-1.791***	0.249	-1.908***	0.247
β_{w2k}	0.131	0.436	0.789***	0.234	β_{lt}	0.605	0.406	-0.02	0.331
β_{w2l}	0.187	0.375	-0.704***	0.2	β_{yt}	-0.852*	0.453	-0.733**	0.368
β_{w2y}	-0.294	0.427	-0.169	0.222					

The full model refers to the dynamic model in the presence of the perfect inefficiency, while the restricted model refers to the dynamic model assuming all inefficiency parameters equal to one

Source own calculations

Significance levels: * significant at 10 %; ** significant at 5 %; *** significant at 1 %. Estimates of dummy variables (used to calculate all efficiency parameters of dynamic and variable inputs) are not reported

^a Price of labor (w_l) was normalized. Subscripts of β_{wn} coefficients refer to the corresponding price of the n th input (w_n): 2 = crop; 3 = livestock; 4 = overheads; price of q th quasi-fixed factor p_k = capital; p_l = land. Under the assumption of independence of the quasi-fixed factors k and l , the estimated parameters, β_{kl} , β_{kpb} , β_{lpk} and β_{pkpl} are zero

savings potential in net investment and land in relation to the cost-minimizing level of factors, these results suggest that Polish farms could have reduced their inputs in net investment by 47 % and land area by 25 % during the investigation period. Turning to region-specific results, the Northwest region scores higher on average than the Southeast: the average value of the Northwest farm-level allocative efficiencies of net investments in capital is 0.625 and in land 0.802, compare to 0.414 and 0.625, respectively, in the Southeast.

Following the shadow price approach, the price of labor input is arbitrarily specified as the numeraire. The value of allocative efficiency of variable input demands reflects

price distortions of the n th variable input relative to labor input. Therefore, an estimate of allocative efficiency of variable input demands that is not equal to one means that the ratio of the shadow price of the n th variable input to labor input is not proportionally mirrored in the corresponding ratio of actual prices, but disproportionately so that the ratios of actual prices and shadow prices are distorted by a factor of greater or less to one (less or greater). Translated into terms of factor use, this means that the firms are overusing (underusing) the n th variable input relative to labor input. Table 5 also reports that average farm-level allocative efficiencies of crop, livestock and overhead input demands are 0.810, 0.629 and 1.848,

Table 4 Estimated parameters of the dynamic efficiency for the Northwest and Southeast models

Parameter ^a	Northwest Model		Southeast Model		Parameter ^a	Northwest Model		Southeast Model	
	Estimate	Std Err	Estimate	Std Err		Estimate	Std Err	Estimate	Std Err
β_o	-0.202***	0.034	-0.103***	0.032	β_{w2t}	0.099	0.168	0.026	0.174
β_{w2}	0.154	0.329	0.243	0.319	β_{w3w4}	2.891*	1.58	0.601	1.714
β_{w3}	0.521***	0.213	0.410***	0.224	β_{w3pk}	-0.027	0.228	-0.789***	0.274
β_{w4}	0.069***	0.017	0.085***	0.017	β_{w3pl}	0.331	0.703	1.063	0.738
β_{pk}	0.179***	0.003	0.201***	0.003	β_{w3k}	-0.597***	0.261	1.137***	0.268
β_{pl}	0.103	0.224	0.016**	0.007	β_{w3l}	0.710***	0.251	-0.066	0.213
β_k	-0.579***	0.002	-0.789***	0.003	β_{w3y}	0.120**	0.024	0.673***	0.241
β_l	-0.125***	0.011	-0.326***	0.028	β_{w3t}	-0.069	0.572	-0.099	0.584
β_y	0.136***	0.003	0.137***	0.002	β_{w4pk}	-0.087***	0.026	-0.149***	0.031
β_t	0.065	0.726	0.011	0.008	β_{w4pl}	-0.153**	0.076	-0.110	0.093
β_{w2w2}	31.428***	5.152	10.493**	5.143	β_{w4k}	-0.146***	0.032	-0.112***	0.036
β_{w3w3}	4.591	4.136	5.259	7.622	β_{w4l}	-0.013	0.030	-0.008	0.031
β_{w4w4}	0.808***	0.275	1.284***	0.301	β_{w4y}	0.093***	0.033	0.046	0.036
β_{pkpk}	0.163***	0.004	0.170***	0.005	β_{w4t}	-0.056	0.039	-0.011	0.043
β_{plpl}	0.080*	0.047	0.033	0.053	β_{pkk}	97.651***	2.256	75.465***	2.137
β_{kk}	-0.137***	0.007	-0.159***	0.006	β_{pky}	-0.114***	0.004	-0.128***	0.004
β_{ll}	-0.039***	0.005	-0.020***	0.004	β_{pkt}	0.001	0.007	-0.002	0.008
β_{yy}	0.138***	0.006	0.157***	0.006	β_{pll}	71.542**	17.382	61.018**	13.256
β_{tt}	0.052	0.062	-0.03	0.060	β_{ply}	-0.031**	0.013	-0.038***	0.014
β_{w2w3}	0.444*	0.143	9.059**	4.398	β_{plt}	0.034**	0.017	-0.013	0.019
β_{w2w4}	-0.682*	0.385	0.477	0.422	β_{ky}	-0.098***	0.005	-0.123***	0.005
β_{w2pk}	0.074	0.058	-0.113*	0.063	β_{kt}	0.009	0.007	-0.010	0.008
β_{w2pl}	0.269	0.165	0.098	0.177	β_{ly}	-0.030***	0.004	-0.025***	0.003
β_{w2k}	0.068	0.066	-0.134*	0.069	β_{lt}	0.021***	0.006	-0.009	0.006
β_{w2l}	0.195***	0.062	0.189***	0.053	β_{yt}	-0.021***	0.006	0.021***	0.007
β_{w2y}	-0.172***	0.064	0.234***	0.061					

The Northwest model refers to the full dynamic efficiency model using the regional data set of the Northwest region (Pomorze and Mazury), while the Southeast model refers to the full dynamic efficiency model using the regional data set of the Southeast region (Malopolska and Pogórze)

Source own calculations

Significance level: * significant at 10 %; ** significant at 5 %; *** significant at 1 %. The regressions that also include dummy variables used to calculate all efficiency parameters of dynamic and variable inputs are not reported

^a Price of labor (w_l) was normalized. Subscripts of β_{wn} coefficients refer to the corresponding price of the n th input (w_n): 2 = crop; 3 = livestock; 4 = overheads; price of q th quasi-fixed factor p_k = capital; p_l = land. Under the assumption of independence of the quasi-fixed factors k and l , the estimated parameters, β_{kl} , β_{kpl} , β_{lpk} and β_{pkpl} are assumed to be zero

respectively. Against the background of shadow and actual price ratios, these results reveal that Polish farms are over-using crops and livestock relative to labor input, while they are under-using overhead relative to labor input. The average value of the Northwest farm-level allocative efficiencies of crop, livestock and overhead input demands is 0.739, 0.587 and 1.328, respectively. Given that the corresponding values (0.896, 0.679, and 2.474, respectively) of Southeast farms lie above these values, the Northwest farms show a higher degree of overutilization in crops and livestock relative to labor, as well as a lower degree of underuse in overheads relative to labor.

Table 6 presents the average annual technical and allocative efficiency scores of dynamic and variable factor demands for each region over the period 2004–2007. These findings provide valuable information for examining the performance of Polish farms by region after accession to the EU in 2004. Accordingly, the Northwest farms score an average annual technical efficiency of dynamic and variable factors higher than that of the Southeast farms throughout the study period, apart from 2005, when the corresponding value of variable inputs (TE(x)) remained below the Southeast score. After the EU accession, technical efficiency scores in both regions decreased for

Table 5 Average farm technical and allocative efficiency scores of dynamic and variable factor demands, 2004–2007

Efficiency scores ^a	Northwest region (Pomorze and Mazury)	Southeast region (Malopolska and Pogórze)	All regions
TE(q)	0.567	0.497	0.536
TE(x)	0.585	0.565	0.576
AE(k)	0.625	0.414	0.529
AE(l)	0.802	0.695	0.753
AE(w ₂)	0.739	0.896	0.810
AE(w ₃)	0.587	0.679	0.629
AE(w ₄)	1.328	2.474	1.848

Source own calculations

^a TE(q) = technical efficiency of dynamic factors; TE(x) = technical efficiency of variable inputs; AE(k) = allocative efficiency of net investment in capital; AE(l) = allocative efficiency of net investment in land; AE(w₂) = allocative efficiency of crop input; AE(w₃) = allocative efficiency of livestock input; AE(w₄) = allocative efficiency of overhead input

Table 6 Average annual technical and allocative efficiency scores of dynamic and variable factor demands for each region, 2004–2007

Efficiency scores	Northwest region (Pomorze and Mazury)				Southeast region (Malopolska and Pogórze)			
	2004	2005	2006	2007	2004	2005	2006	2007
TE(q)	0.582	0.534	0.532	0.622	0.491	0.468	0.491	0.540
TE(x)	0.601	0.571	0.552	0.615	0.623	0.590	0.475	0.573
AE(k)	0.627	0.654	0.640	0.581	0.393	0.409	0.422	0.433
AE(l)	0.785	0.811	0.813	0.797	0.676	0.695	0.703	0.706
AE(w ₂)	0.752	0.746	0.736	0.723	0.900	0.895	0.895	0.892
AE(w ₃)	0.600	0.599	0.587	0.563	0.691	0.695	0.675	0.655
AE(w ₄)	1.398	1.322	1.292	1.300	3.156	2.513	2.074	2.151

Source own calculations

3 years, before subsequently rising again. Turning to average annual allocative efficiency of dynamic factors for both capital (AE(k)) and land (AE(l)), the results indicate that the Northwest farms were more efficient than the Southeast farms throughout the study period. In term of adjustment, this result suggests that the Northwest farms were able to adjust their dynamic factors to the cost-minimizing level of factors more easily than their Southeast counterparts. A more detailed look at the numbers reveals that allocative efficiency scores of the dynamic factors of the Southeast farms are increasing over time. However, the Northwest farms show a slightly different picture. While allocative efficiency of net investment in land (AE(l)) is also increasing over time, the allocative efficiency score of net investment in capital (AE(k)) varies considerably over the period. The post-accession estimates of allocative efficiency of variable inputs (AE(w₂), AE(w₃), AE(w₄)) indicate that farms in both regions tended to increase overuse in crops and livestock relative to labor, as well as decreasing underuse in overheads relative to labor. Figure 3 illustrates plots of technical and allocative efficiency scores of dynamic and variable factor demands by region over the

period 2004 to 2007. The plots show that the change in efficiency scores of the Southeast farms is relatively more constant than that of the Northwest farms, after the accession, apart from the technical efficiency of variable inputs (TE(x)) (Fig. 3a, b) and allocative efficiency of overhead input (AE(w₄)) (Fig. 3c).

This is the first study to investigate the allocative and technical efficiency of Polish agriculture using a dynamic shadow cost approach. Other analyses of Polish agriculture have relied on conventional approaches and employed models of static DEA (Latruffe et al. 2005) or SFA (Hockmann and Pieniadz 2009; Hockmann et al. 2007). In addition, given that these studies mostly investigated the performance of Polish farms based upon different data sets and time periods, it goes without saying that a cross-study comparison is precluded by lack of basis. For instance, Hockmann and Pieniadz (2009) and Hockmann et al. (2007) considered various causes for farm heterogeneity (management, differences in input quality), finding firms were on average more than 90 % technically efficient, in a value that is significantly higher than found in this present study. On the other hand, the DEA model employed by

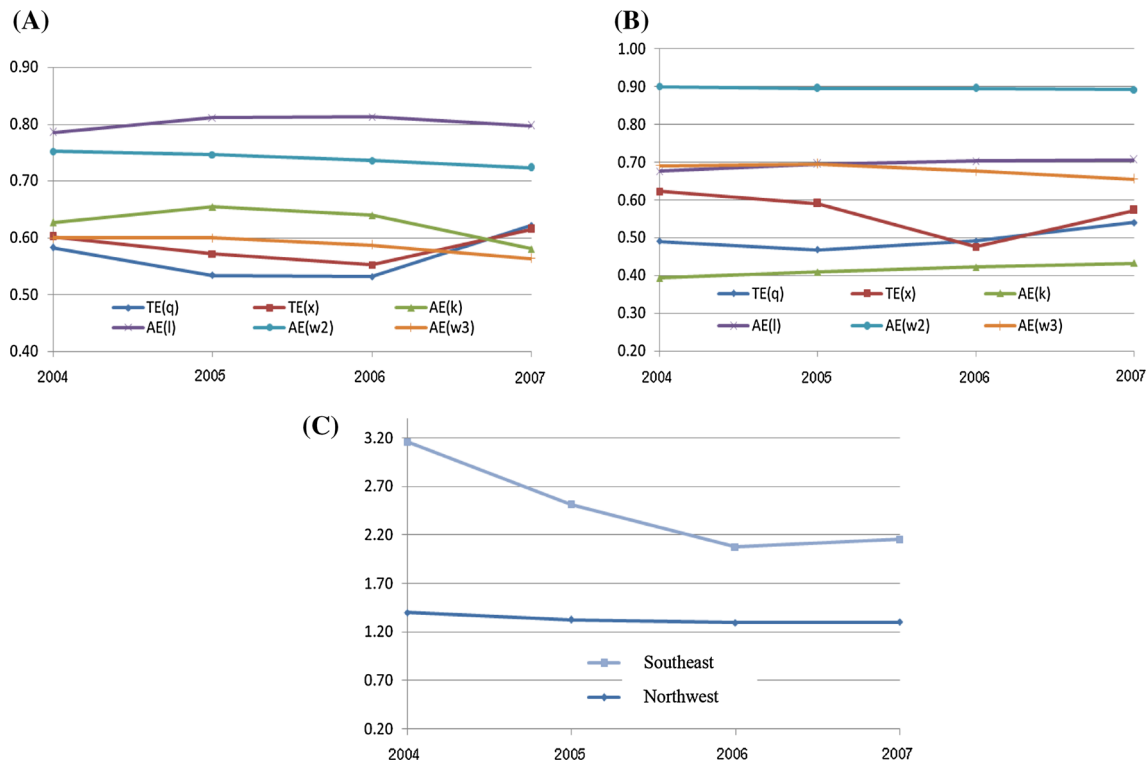


Fig. 3 Plot of technical and allocative efficiency scores of dynamic and variable factor demands by region over the period 2004 to 2007. **a** Northwest region. **b** Southeast region. **c** Allocative efficiency of overhead input [AE(w₄)]. *Source* own calculations

Latruffe et al. (2005) only yielded slightly higher efficiency scores than “our” approach.¹³

Turning to the role of adjustment costs in Polish farms, the partial adjustment coefficient of quasi-fixed factors M_u is defined as $M_u = (r - (\beta_{qpq})^{-1})$ where $q = \{k, l\}$ (Epstein and Denny 1983). Assuming a discount rate of 5 %, the findings of Table 4 indicate that the estimated partial adjustment rate of the quasi-fixed factor to its long-run equilibrium level is relatively low in both regions. In the Northwest region, the estimated adjustment rates of capital and land are 4.0 % per annum and 3.6 % per annum, respectively, or translated into the length of time necessary to fully adjust, it might take approximately 25 years for capital to fully adjust to its long-run equilibrium level, and even approximately 28 years for labor. Given the estimated rates, the Southeast farms might take an even longer time period to reach their optimal long-term equilibrium level. Accordingly, based upon the estimated adjustment rates of capital and land of 3.7 and 3.4 % per annum, respectively, it might

take approximately 27 years for capital and 30 years for labor to fully adjust to their optimal level. From these results, it naturally follows that the adjustment processes in Polish agriculture has only made sluggish progress; a finding consistent with a previous analysis of structural change and farm size development in Poland (Goraj and Hockmann 2010).

We further examined the performance of Polish farms associated with farm production specialization. Table 7 reports the average farm-level technical and allocative efficiency scores of dynamic and variable factor demands (TE(•), AE(•)) by types of farm production specializations from 2004 to 2007. The estimated TE(•) values across all types of production do not differ significantly between dynamic and variable factors, ranging from 0.527 (TE(q), mixed farming) to 0.628 (TE(x), granivores). Thus, in descending numerical order of the scores, granivores reveal the highest average technical efficiency score, followed by grazing livestock farms, dairy cattle, field crops and mixed farms. In terms of the average allocative efficiency of net investment in capital demand (AE(k)), the order of scores from lowest to highest efficiency starts with 0.504 for mixed farms, followed by 0.538 for granivores, 0.589 for dairy cattle, 0.592 for field crops and the highest value of 0.611 for grazing livestock. On the other hand, average the allocative efficiency of net investment in land demand (AE(l)) by production specialization ranges from 0.741 to

¹³ As explained in Sect. 2 (Fig. 1), this dissimilarity mainly results from both the different conceptual approaches in the conventional and shadow cost approach as well as the different assumption made in SFA and DEA analysis. Usually DEA efficiency scores are much lower than SFA scores since in DEA there is no two-sided error term to buffer some of the structural differences among farms.

Table 7 Average farm technical and allocative efficiency scores of dynamic and variable factor demands by farm production specialization, 2004–2007

Efficiency scores	Field crops	Dairy cattle	Grazing livestock	Granivores	Mixed farming
TE(q)	0.540	0.545	0.565	0.585	0.527
TE(x)	0.577	0.586	0.614	0.628	0.568
AE(k)	0.592	0.589	0.611	0.538	0.504
AE(l)	0.794	0.778	0.756	0.757	0.741
AE(w2)	0.754	0.788	0.771	0.759	0.831
AE(w3)	0.641	0.615	0.638	0.553	0.636
AE(w4)	2.132	1.535	1.602	1.596	1.881

Source own calculations

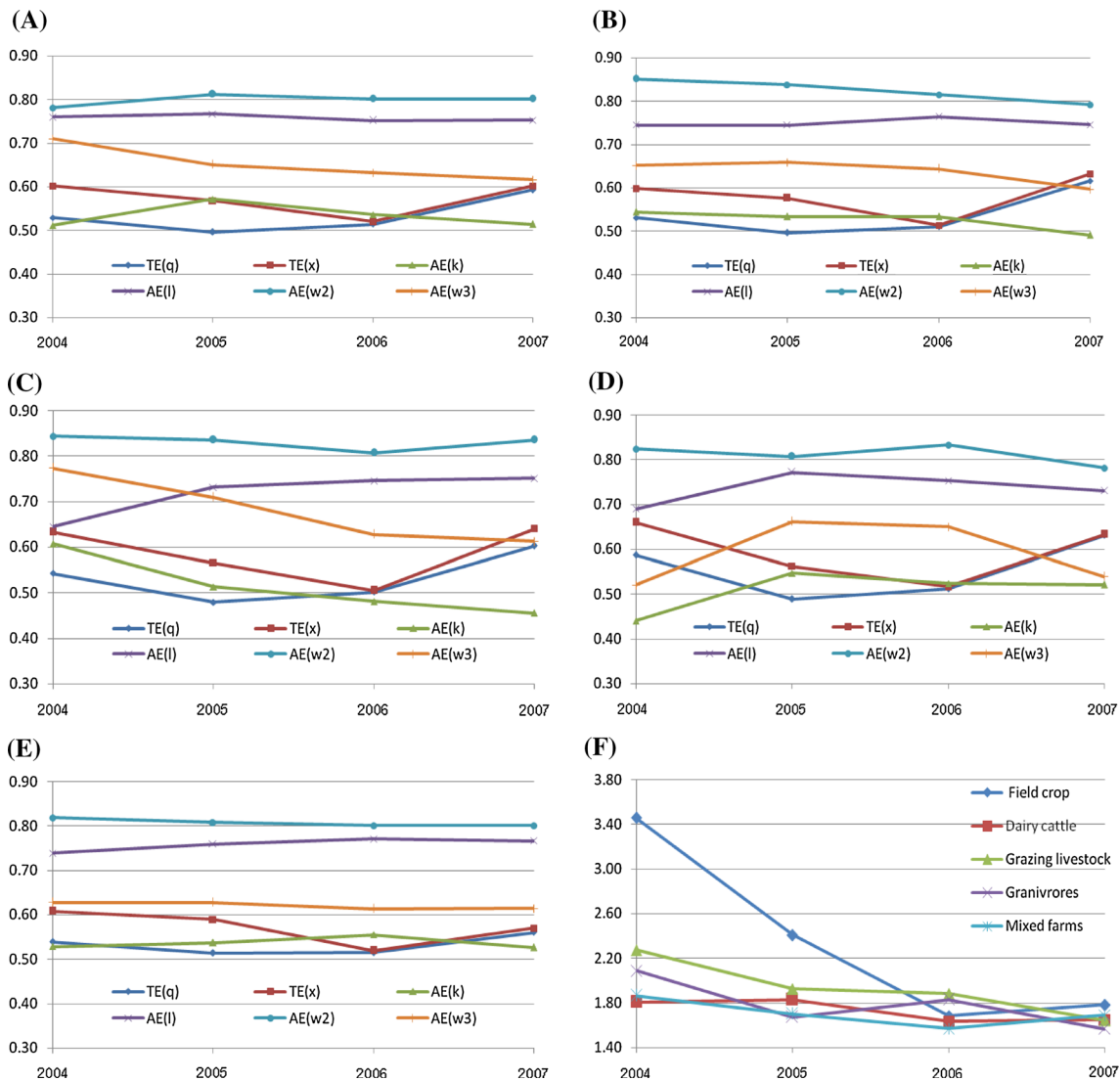


Fig. 4 Plot of technical and allocative efficiency scores of dynamic and variable factor demands by farm production specialization over the period 2004–2007. **a** Field crops. **b** Dairy cattle. **c** Other grazing

d Granivores. **e** Mixed farms. **f** Allocative efficiency of overhead input. Source own calculations

0.794, with mixed farms again scoring the lowest efficiency and farms with field crops generating the highest average allocative efficiency, followed (in descending order) by dairy cattle, granivores and grazing livestock.

Turning to the allocative efficiency scores of variable inputs (AE(w2), AE(w3), AE(w4)), the estimates indicate that field cropping farms operated with the highest degree of overuse in crops relative to labor, followed by

Table 8 Average farm technical and allocative efficiency scores of dynamic and variable factor demands by production specialization for each region, 2004–2007

Efficiency scores	Field crops	Dairy cattle	Other grazing livestock	Granivores	Mixed farms
Northwest region (Pomorze and Mazury)					
TE(q)	0.555	0.563	0.568	0.616	0.564
TE(x)	0.572	0.583	0.603	0.636	0.580
AE(k)	0.633	0.636	0.649	0.576	0.626
AE(l)	0.817	0.803	0.778	0.781	0.801
AE(w2)	0.721	0.761	0.755	0.723	0.741
AE(w3)	0.624	0.602	0.623	0.512	0.581
AE(w4)	1.306	1.344	1.405	1.26	1.339
Southeast region (Malopolska and Pogórze)					
TE(q)	0.470	0.459	0.447	0.443	0.508
TE(x)	0.606	0.578	0.563	0.548	0.540
AE(k)	0.392	0.401	0.394	0.413	0.423
AE(l)	0.684	0.684	0.685	0.700	0.703
AE(w2)	0.908	0.908	0.905	0.922	0.891
AE(w3)	0.723	0.735	0.766	0.714	0.667
AE(w4)	3.103	2.328	2.399	2.192	2.125

Source own calculations

granivores, grazing livestock, dairy cattle and mixed farms. The average allocative efficiency of livestock demand (AE(w3)) ranges from 0.553 to 0.641, thus revealing that granivores have the highest degree of overutilization in livestock relative to labor, followed by dairy cattle, mixed farms, grazing livestock and field crops. The average allocative efficiency of overhead demand (AE(w4)) amounts to 2.132 for field cropping, 1.881 for mixed farming, 1.602 for grazing livestock, 1.596 for granivores and 1.535 for dairy cattle, suggesting that farms with field cropping have the highest degree of under-utilization in overheads relative to labor, followed by mixed farming, grazing livestock, granivores and dairy cattle. Figure 4 illustrates plots of the technical and allocative efficiency scores of dynamic and variable factor demands by types of farm production specializations over the period 2004–2007. Plots of grazing livestock and granivores (Fig. 4c, d) show that efficiency scores vary considerably over time, while efficiency scores of mixed farming (Fig. 4e) are relatively constant across the entire post-accession period. The findings also show that the allocative efficiency of overhead input (Plot F) decreased for all types of production specialization throughout the entire period.

Table 8 reports the average farm technical and allocative efficiency scores of dynamic and variable factor demands by types of farm production specialization for each region. Compared to the other specializations in the Northwest, field cropping farms not only yield the highest allocative efficiency of net investment in land, but also the lowest technical efficiency of dynamic and variable factors. They have the highest degree of overuse in crop input relative to labor. Grazing livestock farms emerge with the

highest allocative efficiency of net investment in capital, but also the lowest allocative efficiency of net investment in land. They have the highest degree of underutilization in overheads relative to labor. Finally, granivore farms exhibit the highest technical efficiency of dynamic and variable factors, but the lowest allocative efficiency of net investment in capital. Moreover, they also have the highest degree of overuse in livestock input relative to labor. Turning to the Southeast farms, mixed farming creates the highest technical efficiency of dynamic factors and the highest allocative efficiency of net investment in capital and land. In addition, they also exhibit the highest degree of over-utilization in crop and livestock input relative to labor, while field cropping farms have the highest degree of underutilization in overheads relative to labor.

The estimates partly confirm the results regarding specialization in Latruffe et al. (2005). Without differentiating among regions, they found that livestock farms are more technically efficient than cropping farms. Indeed, our model produces the same results for the Northwest region for both dynamic and variable inputs. However, the results for the Southwest region prove to be opposite, as do allocative efficiency scores, which reveal a similar divergence pattern between specializations.

While the discussion of the results so far has focused separately on technical and allocative efficiency, an overall efficiency measure regarding individual input use is given by the relation of technical and allocative efficiencies. Consider Fig. 1 and define overall efficiency (OE) as the relation of cost contribution of quasi-fixed inputs at actual quantity levels and prices (Point A) and technically efficient levels at shadow prices (Point B), i.e.

Table 9 Overall efficiency scores of dynamic demands for each region, 2004–2007

Total efficiency scores	Field crops	Dairy cattle	Other grazing livestock	Granivores	Mixed farms				
Northwest region									
By specialization	Capital	0.877	0.885		0.875	1.069	0.901		
	Land	0.679	0.701		0.730	0.789	0.704		
Southeast region									
	Capital	1.416	1.404		1.442	1.492	1.333		
	Land	0.811		0.823	0.829	0.880	0.802		
By year									
Northwest region									
		2004	2005	2006	2007	Southeast region			
		2004	2005	2006	2007	2004	2005	2006	2007
	Capital	0.928	0.817	0.831	1.071	1.249	1.144	1.164	1.247
	Land	0.741		0.654	0.780	0.726	0.673		0.765
			0.658					0.698	

Source own calculations

$OE = \mathbf{p}^A \dot{\mathbf{q}}^A / \mathbf{p}^B \dot{\mathbf{q}}^B$.¹⁴ Given that technical and allocative efficiencies of dynamic factors are $\dot{\mathbf{q}}^B = \tau_q^{-1} \dot{\mathbf{q}}^A$ and $\mathbf{p}^B = \Sigma_q \mathbf{p}^A$, respectively (see Sect. 2.2), the overall efficiency of dynamic factors is given by:

$$OE = \tau_q \Sigma_q^{-1}.$$

Thus, overall efficiency is the ratio of technical to allocative efficiency: for $OE > 1$, the input is overused; whereas for $OE < 1$, the input is underused. Overall efficiency for variable inputs can be defined analogously. However, allocative efficiency of these inputs was estimated solely in relation to labor, only the discussion of overall efficiency regarding the quasi-fixed factors bears relevance.

From the arguments provided in the introduction, it follows that agriculture in Poland is supposed to operate too small in size, i.e. land is underused. The same is expected to hold for capital, with many Polish farmers facing credit constraints, i.e. they are unable to mobilize sufficient funds for investment (Petrick 2004).

Overall efficiency scores for capital and land are given in Table 9. The results confirm the conjecture that land is underused, for both regions and all specializations. The result for capital is not so unique but mixed. Generally, we observe an underuse of capital in the Northwest region, while Southeast farmers tend to overuse capital both for different specializations as well as over time. This counterintuitive view is also reported by Latruffe et al. (2005), who conducted their analysis with regionally pooled data. They argued that farmers still pursue strategies inherited from the socialist times, when they sought to be as independent from the state as possible and thus maintained high

levels of machinery and equipment, keeping high levels of equipment in stock to be prepared in case of shortages. The credit programs available EU accession might even have supported this behavior and increased capital input; in fact, so much so that these determinates might have overcompensated the investment-reducing effect of capital market constraints. Consequently, Polish farms still have high stocks of capital that impede efficiency gains. Provided this result holds for the Southeast region, where no land reform has yet taken place after World War II, the institutional argument for overinvestment is easily supported. By contrast, the Northwest experienced two land reforms: the first after World War II and the second after the breakdown of the Polish socialist government. Given that most of the farms were newly established in the wake of these historical events, the credit constraint can be regarded as one of the most critical determinants for input use.

6 Conclusions

Polish agriculture has faced a strong need for structural change over the past two decades. This paper deals with the astonishing observation that the process of farm restructuring in Poland has been rather sluggish and that there no current indication that this process will be set in motion in the next few years. In fact, quite the contrary seems to be true, given that farm size appears to remain rather small, even though the agricultural sector has faced significant internal and external threats, such as increasing intra-Community competition in agriculture or increasing demand for labor from other sectors of the overall economy.

This paper analyzes this phenomenon by developing and estimating a dynamic frontier model using the shadow cost approach in the framework of the dynamic duality model of intertemporal decision making. The dynamic cost

¹⁴ The letter \mathbf{p} is used to denote the shadow cost of the quasi-fixed factors ($\nabla_q J$).

efficiency model allows for considering the impact of allocative and technical efficiency, as well as adjustment costs resulting from the change of quasi-fixed input use. This model adopts a parametric structural approach to dynamic efficiency measurement when it is not possible to directly specify or estimate production technology. The model presented in this paper extends the theoretical literature in that it is not limited to the one quasi-fixed factor case but rather provides a solution to consider multiple quasi-fixed factors. The analysis is conducted using two quasi-fixed inputs (i.e. land and capital). Although the shadow cost approach fails to provide information for individual farms, it allows generating detailed information on average technical and allocative efficiencies of the variable and quasi-fixed inputs.

The data set used for the estimation was provided by the Polish FADN agency, and included detailed information on production and input use. Nonetheless, given that this information was not sufficient, the data had to be supplemented with information on product and factors prices from records of national statistics and EUROSTAT. We estimated the dynamic cost efficiency model for two rather distinct FADN regions (i.e. called Northwest and Southeast) from the perspective of Polish agriculture, whereby the first is characterized by larger farms and the second is dominated by smaller farms.

The results of the analysis not only show that adjustment costs held relevance for Polish agriculture, but also confirm what could be conjectured from a first, descriptive look at the data, namely that adjustment processes have been and remain very sluggish. Based upon the previous pace of adjustment, it will take up to 30 years until Polish farms reach the optimal level of capital and land input. The fact that this process is happening in slow motion with almost no noticeable structural adjustment taking place arises from the almost insurmountable burden that the associated adjustment costs place upon agriculture. Given that the factor supply equation and the market for final products are not explicitly considered, the model suggests that the sluggish adjustment results from technology-induced adjustment costs alone. By contrast, it might be objected that this reflects too restrictive an approach due to neglecting crucial conditions on the product and factor market; conditions that undeniably account for the hampered or even blocked adjustment. In this context, it should be mentioned that not only do credit rationing or the low degree of product market integration (Hockmann and Pieniadz 2009) produce adverse effects, but also that the land market is very likely to face substantial restrictions, resulting in a poor functioning. Farm growth can only occur when some farmers exit agriculture. However, the propensity to exit can easily be foiled by risk considerations that advise farmers to remain in agriculture to ensure the only available source of income in

times of high unemployment or economic depression, for instance. Indeed, the observed migration of industrial labor to the agricultural sector during the economic crises at the turn of the century supports this view. Moreover, the pensions that farmers obtain are subsidized pensions that are subject to owned landed property; concretely, they are paid as long as they own more than one hectare of land (Latruffe et al. 2005).

The estimates provide that technical efficiency is relevant for both regions and all inputs. Moreover, the efficiency scores for both variable and quasi-fixed inputs produced similar values, albeit with slightly higher figures in the Northwest. In general, what follows from these scores is that, with respect to both inputs, it would have been possible to reduce the input level by about 50 % without reducing the given output level, which could have been kept constant. Moreover, there is neither any significant indication that technical efficiency varies over time nor any evidence for large differences among farm specializations, with these two conclusions also holding for allocative efficiency. However, allocative efficiencies for land and capital are higher in the Northwest than the Southeast, thus implying that the larger farms in the Northwest respond more quickly than the smaller farms in the Southeast. Furthermore, the estimates provide that labor is overused in relation to overheads, but underutilized in relation to crop and animal inputs. Although this holds for both regions, there are some inter-regional differences: in the Northwest, overuse relative to overheads that is more pronounced, as opposed to overuse relative to the second input category, which is predominant in the Southeast. Furthermore, the estimates are generally consistent with the expectation that the quasi-fixed factors are underutilized. Overinvestment was only found in the Southeast region; certainly a region with agricultural structures that survived the socialist times and that had basically been inherited from the time before World War II (Zientara 2000).

Altogether, the estimates not only confirm but also fine-tune the well-known policy recommendation for the removal of obstacles in the way of adjustment, as proposed by other studies (e.g. Latruffe et al. 2005). Accordingly, in order to increase farm size, subsidies on retirement payment have to be reformed; in particular, the restriction regarding minimal amount of land has to be removed. Regarding farm structure, only if a sufficient number of farmers exit agricultural production can enough land can be provided to the “remaining farmers to increase farm sizes. This step would also foster investment incentives, although it must be conceded that such stimuli would only translate into gaining momentum to take full effect if the constraints on the capital market were relaxed. However, this relaxation will not be achieved without strong support from investment programs, such as those available in the second

pillar of EU agricultural policy, through which the government is entitled to provide the guaranteed payment of a loan. The pronounced allocative efficiencies also indicate that institutions that govern and monitor the functioning of markets do not work efficiently. This calls for the improvement of market infrastructure, e.g. increasing market transparency by establishing information systems and securing access to factor markets. Moreover, the results also support the notion that there is a strong need for better education and training of farmers. Accordingly, it is widely acknowledged that one prerequisite for the reduction of allocative and technical inefficiencies is that farmers receive appropriate training in production techniques and the application of modern management systems. This call particularly applies to Poland especially, given that its farmers are relatively young compared to other European countries. Moreover, the need to both adopt new production techniques as well as improving existing management regimes is rapidly growing, providing an apparent sign that educational programs are expected to yield higher rates of return.

Acknowledgments The authors gratefully acknowledge financial support from the Thailand Research Fund (TRF), the Commission on Higher Education (CHE), Ministry of Education (Thailand) [TRF-CHE Research Grant for Mid-Career University Faculty], the German Academic Exchange Service (DAAD) and the Leibniz Institute of Agricultural Development in Central and Eastern Europe (IAMO). Usual disclaimer applies.

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