

FACTOR MARKETS

Comparative Analysis of Factor Markets for Agriculture across the Member States

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Identifying Factor Productivity from Micro-data

The case of EU agriculture

ABSTRACT

The classical problem of agricultural productivity measurement has regained interest owing to recent price hikes in world food markets. At the same time, there is a new methodological debate on the appropriate identification strategies for addressing endogeneity and collinearity problems in production function estimation. We examine the plausibility of four established and innovative identification strategies for the case of agriculture and test a set of related estimators using farm-level panel datasets from seven EU countries. The newly suggested control function and dynamic panel approaches provide attractive conceptual improvements over the received 'within' and duality models. Even so, empirical implementation of the conceptual sophistications built into these estimators does not always live up to expectations. This is particularly true for the dynamic panel estimator, which mostly failed to identify reasonable elasticities for the (quasi-) fixed factors. Less demanding proxy approaches represent an interesting alternative for agricultural applications. In our EU sample, we find very low shadow prices for labour, land and fixed capital across countries. The production elasticity of materials is high, so improving the availability of working capital is the most promising way to increase agricultural productivity.

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1. Introduction

The analysis of factor productivity has been a recurrent theme in economics since its early days. Agricultural applications have driven many methodological innovations in this field – including the first formulations of marginal productivity theory by Johann Heinrich von Thünen in 19th century Germany, early empirical estimations of agricultural technology by Tolley et al. (1924) in the United States and the invention of fixed effects regression principles by Hoch (1955) and Mundlak (1961). One reason agriculture became such a breeding ground for new methodologies was no doubt the availability of microeconomic data, which motivated and enabled testing of the new approaches. After World War I, statistical agencies started to systematically collect farm data because there was a perceived societal need to learn more about a farming sector that was stuck in a deep economic crisis. In addition, as Chambers (1988) notes, many economists felt that agricultural technologies approximate the key assumptions of production theory – such as diminishing returns to factor use and the substitutability of inputs – particularly well. After all, many children's books show vividly how the farmer combines land, labour, seed and fertiliser to obtain a good harvest.

In recent years, exploding food prices on world markets have conspicuously signalled that global resources for agricultural production are indeed scarce (FAO, 2009). How farm productivity could be raised has recaptured the attention of the global media (e.g. Parker, 2011) and food riots have been reported in several developing countries. Interestingly, at about the same time, a new debate among econometricians about very basic methodological issues in measuring productivity at the firm level has gained new momentum. The debate departs from a fundamental idea that has been prominent since the days of Cobb and Douglas (1928), namely that there is a *continuous relationship* between inputs and output – the production function. Taking this idea for granted, the old question has been raised about whether statistical methods exist that can identify how much the various factors actually contribute to the joint product. As was recognised early by Marschak and Andrews (1944), real world production does not occur in an experimental setting, and unobserved factors – e.g. managerial abilities or unexpected weather shocks – do affect its outcomes. How their influence could be separated from the more tangible inputs, such as land, labour or capital is at the heart of the current debate. It is of key importance for understanding how agricultural productivity could be increased.

Basically two issues have been raised in the recent debate. The first takes input use as a control variable that is potentially decided upon simultaneously with other unobserved events or may depend on unobserved, omitted variables. This *endogeneity problem*, albeit a classical one, has again moved to centre stage after Olley and Pakes (1996) suggested a non-parametric control function to proxy these unobserved factors. Bond and Söderbom (2005) as well as Ackerberg et al. (2007) raised the question of whether the typical identifying

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assumptions underlying production function estimation are rich enough to isolate the productivities of different variable inputs at all. By addressing this *collinearity problem*, the authors claim that some sort of adjustment cost is necessary to induce an independent variation of factors in the first place. Among the most recent contributions to this debate is a paper by Gandhi et al. (2011), who try to solve both problems simultaneously – interestingly by referring to an empirical strategy that has been around for many decades, the share regression.

In the present paper, we apply the various methodological approaches to an extensive panel dataset on European agriculture and scrutinise their arguments in this classical field of application. We review the central identifying assumptions maintained by six traditional and recent approaches to the estimation of production functions, apply them to our data and ask how plausible they are in an agricultural context. These approaches are 1) the calculation of factor shares in farm revenue, 2) ordinary least squares (OLS) as the 'naïve' estimation standard, 3) fixed effects regression, 4) the dynamic panel data estimator by Blundell and Bond (2000) as well as the control function approaches by 5) Olley and Pakes (1996) and 6) Levinsohn and Petrin (2003). All models are estimated under the assumption of a Cobb Douglas technology. For models (2) and (3), we also explore a Translog technology, so that in total eight models are estimated. Our study thus attempts to make methodological and empirical contributions to the literature. Our methodological contribution is that we provide the first comparative evaluation of a number of recently proposed production function estimators for agricultural data. Our empirical contribution is a unique and current set of estimated production elasticities for eight firm-level datasets at the EU country level.

While there has been quite some research activity on new approaches to tackle the classical challenges of production function estimation, few researchers have engaged in comparative evaluation using real world data. Most developers have confined practical application of their estimators to datasets from highly specific contexts, if they provide applications at all. For example, Blundell and Bond (2000) work with a dataset on US manufacturing firms covering the 1980s, which had been the basis of other methodological investigations before. Levinsohn and Petrin (2003) use data from Chilean firms that were later also utilised by Ackerberg et al. (2006). Kasahara and Rodrigue (2008) take these Chilean data as the basis for various panel data estimators including dynamic panel and proxy approaches. There are certainly good reasons to control variation that is due to the dataset when evaluating innovative estimators. Even so, the ultimate test of their value added can be assessed only after application to datasets that are not only of methodological but also topical or policy interest. The present study is among the first to apply a whole set of recently discussed estimators to a dataset that is politically highly relevant.

Our European database covers firm-level data from all EU member states that were collected following a harmonised procedure in all countries. This is one of the first micro studies of agricultural productivity that simultaneously uses firm-level data from several countries for comparative purposes. These extensive data allow us to come up with new, country-specific estimates of production elasticities and factor shadow prices in agriculture that are potentially robust to endogeneity and collinearity issues. We thus extend the results on capital productivity presented in a companion study focusing on the credit constraints of EU farms (Petrick and Kloss, 2012). While agriculture is a classical field of productivity estimation, there has been surprisingly little systematic analysis using the production function approach recently. Mundlak (2001) attributes this to the emergence and widespread acceptance of duality theory in agricultural economics from the 1970s onwards. This approach typically recovers the price elasticity of factor demand but not the production elasticities. As Mundlak (2001) notes and as we discuss below, the dual approach is based on restrictive theoretical assumptions and is far from being without methodological problems. One key expectation from duality was that it would allow a more flexible representation of technology, such as that based on the Translog functional form (Shumway, 1995). Interestingly, our results show that making the Cobb Douglas production function more flexible by adding quadratic and interaction terms does not add much insight. In the OLS case, the results were highly implausible, whereas they differed little from the Cobb Douglas for the 'within' panel estimator.

Our empirical estimates suggest that returns to labour, land and fixed capital are low throughout our European subsamples. This finding is in contrast to recent estimates by Mundlak et al. (2012), according to whom there are significant returns to land and fixed capital in a cross-country sample of developing and developed countries. On the other hand, our materials elasticity is quite high, above 0.7. This outcome is particularly prominent in the Levinsohn/Petrin and Blundell/Bond estimators. In the conceptual part, we argue that both estimators provide more plausible identification strategies than the established 'within' or duality approaches. While the one-period control function model of Levinsohn/Petrin is easier to implement empirically, the multiperiod adjustment process implied by the Blundell/Bond model is more compelling in an agricultural context. But Blundell/Bond failed to produce reasonable results for the fixed variables in most of our country subsamples. There is hence a trade-off between the theoretical plausibility and empirical robustness of the different identification strategies.

In the following section 2, we discuss the key identification problems that have provoked much of the methodological debate in production function estimation as well as the four main assumptions invoked in the literature to address them. Section 3 describes the dataset. Section 4 presents the empirical results. Section 5 concludes.

2. Identification problems in production function estimation and approaches to their solution

2.1 A typology of production factors

The process of agricultural production serves as a useful illustration of the differing nature of production factors. For the ensuing discussion, two characteristics of these factors are of particular importance:

a) their variability or the ease with which they can be adjusted, and
b) whether they are observed by the econometrician.

Table 1 differentiates three categories of variability. Among the highly variable factors are intermediate inputs, such as seed, fertiliser or concentrate fodder. These factors are typically included in farm-level datasets and thus observed by the econometrician (type I factors). In economic parlance, they are also called 'control variables' because the decision-maker (the farmer) can manipulate their level to achieve his/her objectives. Other highly variable control variables may be hard to observe from the outside, such as work effort (type IV factors).

Other important factors are much less variable and are subject to adjustment costs (type II and V factors, depending on whether they are observed). For example, land is often available in limited quantities only and subject to long-term rental agreements. Agriculture in Europe is typically organised in family farms on which labour is often highly immobile (Tocco et al., 2012) and may be influenced significantly by life-cycle considerations of the farm family (Glauben et al., 2009). Agricultural credit markets suffer from informational asymmetries and may be characterised by rationing and high transaction costs (see e.g. Benjamin and Phimister, 2002; Petrick and Latruffe, 2006). Management has long been recognised as an important factor of production that is nevertheless difficult to measure (Mundlak, 1961).

A final group includes factors that are completely fixed in the long run, such as the geographical location of the farm or the quality of its soils (type III and VI factors).

All the less variable factors – types II, III, V and VI – are called 'state variables', as their value cannot be modified within a short-term planning horizon.

As indicated in Table 1, there is an important distinction between the highly variable and unobserved factors, types IV and VII. Some of these also come as a surprise to the farmer.

They represent exogenous states (shocks) of the environment (type VII factors). How the farmer reacts to these shocks, however, will be endogenous (type IV factors).

Table 1. A typology of production factors in agriculture

	Highly variable	Subject to adjustment costs	Fixed
Observed by the econometrician & farmer	**Type I** Seed, fertiliser, chemicals, concentrate, livestock numbers	**Type II** Land, labour, machinery, buildings	**Type III** Geographical location
Typically unobserved by the econometrician but known to the farmer	**Type IV** Farmer's effort, reaction to environmental shocks	**Type V** Management abilities, human capital of the labour force, availability of a farm successor	**Type VI** Soil quality, climatic conditions
Unobserved by the econometrician & unanticipated by the farmer	**Type VII** Weather events, rainfall, diseases, legal requirements	–	–

Source: Authors.

2.2 Two problems of identification

To illustrate the problems involved, we start with a simple model of a farmer wishing to produce an aggregate output. Denote y_{it} the natural logarithm of farm *i*'s output Y at time t, A_{it} land use of this farm, L_{it} labour, K_{it} fixed capital and M_{it} materials or working capital. These four factors of production are observed by the econometrician. ω_{it} is an aggregate, farm-specific, time-varying factor that is anticipated by the farmer at the time of decision-making about current production, but unobserved by the econometrician. Without further specification, it compounds the effects of factors categorised as types IV to VI in Table 1. ε_{it} is a productivity shock not anticipated by the farmer (and not observed, thus type VII), or simply measurement error. Assuming a linear structure of the model and the availability of panel data containing the observed output and inputs, the econometrician's problem is to recover farm productivity determined by the following equation:

$$y_{it} = f(A_{it}, L_{it}, K_{it}, M_{it}) + \omega_{it} + \varepsilon_{it}, \tag{1}$$

where $f(.)$ is the production function.

Because ω_{it} will likely be correlated with the other input choices, estimation of (1) is subject to an *endogeneity problem* (Marschak and Andrews, 1944). The production elasticities of the observed factors are not identified because the compound error term $\omega_{it} + \varepsilon_{it}$ is not identically and independently distributed (i.i.d.). Regressing output on observed input levels using OLS and choosing an appropriate functional form for $f(.)$ will produce biased estimates. In particular, input coefficients will be upward biased if there is serial correlation in ω_{it}. This effect will be stronger the easier it is to adjust input use (Levinsohn and Petrin, 2003, p. 332). A typical OLS result may be that the coefficients of labour and materials are upward biased, while those of land and capital are downward biased. Much of the methodological literature on production function estimation is concerned with precisely this issue (see the instructive review in Griliches and Mairesse, 1998).

According to the implicit theoretical setup so far, all observed factors are assumed to be control variables and are treated as being fully flexible (as if they all belong to type I). The typical assumption in the literature (e.g. Chambers, 1988) is then that output and all factors are traded on perfectly competitive markets, such that on each of the markets all farmers face the same price for the traded good. If farmers maximise profits, defined as revenues from the sale of output minus the costs of all inputs, and $f(.)$ is a monotonous and concave function, the canonical decision rule for allocating inputs is identical for all inputs and says that the marginal revenue product of each factor should equal its factor price. For example, for materials this decision rule is as follows:

$$p^Y \frac{\partial f}{\partial M} = p^M, \tag{2}$$

with p^Y denoting the price of output and p^M that of materials, respectively. Estimation of (1) requires the assumption that the technology represented by $f(.)$is identical for all farmers included in the estimating sample. If all farmers also face the same price on each of the output and input markets, there is nothing in the model that induces heterogeneous factor use across farms except for the unobserved ω_{it}. This is the *collinearity problem* pointed out by Bond and Söderbom (2005) and Ackerberg et al. (2007).[1] Factor use across firms varies only with the unobserved ω_{it}, so that again the different production elasticities are not identified.

We now review the main approaches found in the literature to deal with either of these identification problems. The discussion is guided by Table 2, which summarises the four approaches we distinguish. After introducing each approach, we ask how plausible the specific identifying assumption is in the context of agriculture. We then evaluate to what extent the two key identification problems presented before are addressed and how the resulting estimator can be applied in practice.

Table 2. Identifying assumptions in production function estimation

	(A) ω_{it} is additively separable & time invariant	**(B) Profit maximisation & perfect competition on product & factor markets**	**(C) Heterogeneous frictions in factor adjustments**	**(D) ω_{it} evolves monotonously with an observed characteristic of the firm**
If correct, does the assumption solve the endogeneity problem?	Yes.	Yes if prices can be used as instruments.	Yes if adjustment costs are sufficiently heterogeneous across inputs.	Yes.
Does it solve the collinearity problem?	Not without further assumptions.	Yes if there is only one free input (Gandhi et al., 2011).	Yes if adjustment costs are sufficiently heterogeneous across inputs.	Not without further assumptions (Ackerberg et al., 2006).
Practical implementation	'Within' regression to sweep out the fixed effect.	Share regression, approaches based on duality.	Typically combined with assumption (A) in a dynamic, panel data regression model using first differences.	Semiparametric control function approaches using investment or intermediate inputs as proxies.

[1] A very detailed exposition is given by Ackerberg et al. (2006).

Table 2. cont'd

Remaining problems	Remaining variance may be too small to allow precise parameter estimation.	Prices with sufficient variation may not be observed. Heterogeneous firm-specific prices may not be exogenous.	Weak instruments, small variance of differenced variables.	Zero observations for proxies (e.g. investment). Slowly changing unobserved effects are not captured.
Plausibility in agriculture	Limited plausibility, as farm- & time-specific effects are likely, e.g. reactions to weather shocks.	Limited plausibility, as market imperfections on labour, land & capital markets are widespread in agriculture.	Plausible for land, labour, fixed capital, but less so for seed, fertiliser, plant protection, concentrate, energy.	Plausible for annually fluctuating shocks, but less so for slowly changing unobservables, such as soil or management quality.
Examples in the literature	Widely used. See Mundlak (1961) and the overview in Griliches & Mairesse (1998).	Widely used. See the overview in Mundlak (2001) and Bonnieux (1989) on French agriculture.	Blundell & Bond (2000); Hempell (2005). No agricultural applications so far.	Olley & Pakes (1996); Levinsohn & Petrin (2003); Kazukauskas et al. (2010) on Irish dairy farms.

Source: Authors.

2.3 Additively separable, time-invariant firm characteristics

The key idea of this approach is that ω_{it} can be further decomposed into the following equation:

$$\omega_{it} = \gamma_t + \eta_i + v_{it}, \tag{3}$$

where γ_t is a time-specific shock that is identical for all farms in t (likely a type VII event), η_i is a farm-specific fixed effect that does not vary over time (a type VI factor), and v_{it} is the remaining farm- and time-specific productivity shock (type VII). Think of γ_t representing common weather or policy shocks and η_i capturing soil quality or time-invariant preferences of the manager. In a farming context, v_{it} may represent local weather conditions that vary between farms and years. If they are not anticipated by the manager, v_{it} is subsumed into ε_{it}. If the production function is linearly separable in the logs of observed and unobserved factors, a commonly used functional form is Cobb Douglas, so that the function can be written as $y_{it} = \alpha^A a_{it} + \alpha^L l_{it} + \alpha^K k_{it} + \alpha^M m_{it} + \gamma_t + \eta_i + \varepsilon_{it}$, with lower case letters denoting logs, α^X the coefficients to be estimated, and X a shorthand for the observed production factors $X \in \{A, L, K, M\}$. Using panel data, a *'within' transformation* expresses all values as deviations from farm-specific means and thus eliminates η_i and all levels from this equation:

$$y_{it} - \bar{y}_i = \sum_X \alpha^X (x_{it} - \bar{x}_i) + \gamma_t + (\varepsilon_{it} - \bar{\varepsilon}_i), \tag{4}$$

where $\bar{x}_i$ denotes farm-specific log means over time. The fixed effect is hence 'swept out' of the equation. Introduced by Hoch (1955) and Mundlak (1961) in a farming context to eliminate "management bias" from the equation, this model has found widespread application at different levels of aggregation. The effect of γ_t is typically taken into account by including time dummies into the model. An alternative to 'within' is to estimate the model in first differences, as discussed by Wooldridge (2010, pp. 321-6).

Mundlak et al. (2012) present a recent application to agricultural productivity at the country level where the fixed and year effects alone explained 98.5% of output variation (p. 146). Even so, the question remains of whether it is legitimate to assume that v_{it} is an innovation that is orthogonal to observed factor use, such that all unobserved factors are indeed either time invariant or the same for all farms. Table 1 suggests that farm- and time-specific unobserved effects *which the farmer still takes into account when making input decisions* (type IV and V) are very likely to be relevant. Examples include annual fluctuations in rainfall or pest occurrence as well as patterns of livestock health. Furthermore, applications in practice have found that the within transformation removes (too) much variance from some of the variables, particularly those which display little variation over time (Griliches and Mairesse, 1998, pp. 180-5). In agriculture, input levels of the type II production factors of land, labour and fixed capital often vary only a little in time. As a consequence, the signal-to-noise ratio with regard to these factors is reduced and the estimated coefficients are biased downwards (Griliches and Hausman, 1986). Finally, without further assumptions, the collinearity problem is not addressed at all by this approach.

2.4 Profit maximisation and perfect competition

This approach imposes further microeconomic theory upon the data, including its main assumptions of profit maximisation and perfect competition on product and input markets. A key result of this theory is the first-order condition (2), which multiplied through with $\frac{M}{p^Y Y}$ yields the following (for the case of materials):

$$\frac{\partial f}{\partial M}\frac{M}{Y} = \frac{p^M M}{p^Y Y}. \tag{5}$$

If one further assumes constant returns to scale, (5) says that the production elasticity of each input (left-hand side) is equal to its value share in revenue (right-hand side). All value shares add up to one. Given these assumptions, revenue shares of inputs are valid estimators of production elasticities. For the simple Cobb Douglas technology, the problem of estimating production elasticities has thus been 'solved' by the imposition of strong theoretical assumptions. Yet, production function estimates of elasticities in agriculture have often been found to differ from observed revenue shares (Mundlak, 2001). These differences may even be an object of investigation, for example in studies of credit rationing (Petrick, 2005; Petrick and Kloss, 2012). Such studies thus require productivity estimation independent of the revenue share.

For more flexible functional forms, (5) has led to the widely applied share regression model. For example, if the production function is assumed to be Translog, thus also including quadratic and cross terms of the variable inputs in logs, the first order condition yields the following *share regression* (again for the case of materials):

$$s_{it}^M = \alpha^M + \alpha^{MM} m_{it} + \alpha^{MA} a_{it} + \alpha^{ML} l_{it} + \alpha^{MK} k_{it} + \omega_{it}^M + \varepsilon_{it}^M, \tag{6}$$

with $s_{it}^M = \frac{p_{it}^M M_{it}}{p_{it}^Y Y_{it}}$ the revenue share of materials of firm i at time t, α^X the direct and cross-elasticities of the inputs involved, ω_{it}^M the part of the unobserved productivity characteristic that affects s_{it}^M, and ε_{it}^M an i.i.d. error term. Such an equation can be derived for all production factors, thus constituting a system of equations amenable to estimation by imposing the parameter restrictions derived from theory (Berndt and Christensen, 1973; see Bonnieux, 1989 for an application to French agriculture).

Note that (6) is still subject to the endogeneity and collinearity of factors. The way out of these problems typical of this approach is finding appropriate instruments for the input levels. The role of the instruments would be to distil that part out of m, a, l and k that is not correlated with ω_{it}^M. In the given theoretical framework, the most natural candidates are factor prices, which were used to estimate systems of share equations like (6) by two- and three-stage least squares (Antle and Capalbo, 1988). Given the possibility to recover technology parameters also from profit and cost functions by means of duality theory (Chambers, 1988), there is now a large body of empirical literature with agricultural applications of this approach (see the critical review in Mundlak, 2001).

Despite the applications in the literature, the use of prices to solve the two identification problems must be questioned on both theoretical and empirical grounds. To qualify as instruments, prices must not be endogenous to the decision problem of the farmer. This condition is usually ensured by the assumption of perfectly competitive markets on which atomistic agents have no price-setting power. In agriculture, it may hold for a number of output markets, but is very unlikely to prevail on most factor markets. For example, farmland markets are known to be characterised by spatial oligopolies and strong government regulation in many European countries (Huettel and Margarian, 2009; Ciaian et al., 2012). As noted before, agricultural labour is usually very immobile owing to life-cycle considerations and specific human capital. Agricultural credit may be rooted in a rationing regime that depends on the credit history of the farmer. Hence, factor prices may not be exogenous and may depend on the past and current decisions of the farmer. Under such conditions, the theoretical model underlying this approach is clearly too simplistic to allow straightforward identification of the production function.[2]

On the other hand, if factor markets worked at least approximately as postulated by the theoretical ideal, there should be little price variation across farms, and thus the value of prices for solving the endogeneity and collinearity problems is doubtful. In the first place, this is a theoretical argument – on perfect markets, there is no price variation across firms and so the different flexible factors are not identified by the data generation process. In fact, empirical applications have shown that price variation is indeed often small and may be due to quality differentials (Griliches and Mairesse, 1998, p. 189). With regard to agricultural labour or land, it may be hard to find appropriate price series at all.

2.5 Heterogeneous frictions in factor adjustment

If prices are problematic instruments, another option is to look for a different source of exogenous variation that has explanatory power for productivity analysis. One such source now routinely employed in the literature on dynamic panel data modelling entails past decisions on factor use (Arellano and Bond, 1991; Blundell and Bond, 1998). This literature argues that the current variation in input use is caused by lagged adjustment to past productivity shocks. It thus introduces the history of input use as a source of identification. Such identification is plausible if modifications of input levels are subject to adjustment costs (Bond and Söderbom, 2005). This approach effectively turns observed input levels into state variables (type II) and makes them subject to an intertemporal optimisation problem. One way to account for costly adjustment is to allow serial correlation of the unobserved productivity characteristic of the firm, so that it could be written as follows:

$$v_{it} = \rho v_{it-1} + e_{it}, \text{ with } |\rho| < 1, \tag{7}$$

where ρ denotes the autoregressive parameter and e_{it} an independent mean zero innovation. Substituting (7) and (3) into (1), Blundell and Bond (2000) suggest a dynamic production function specification that can be estimated with a *dynamic panel data estimator*:

$$y_{it} = \sum_X (\alpha^X x_{it} - \alpha^X \rho x_{it-1}) + \rho y_{it-1} + (\gamma_t - \rho\gamma_{t-1}) + (1-\rho)\eta_i + \varepsilon_{it}^*. \tag{8}$$

[2] An important step to relax the rigid assumptions of this approach was the introduction of dynamic duality in studies of agricultural production (e.g. Thijssen, 1994; Sckokai and Moro, 2009). Conceptually, these studies build a bridge to the approaches described in subsequent sections. The empirical interest was often no longer on recovering factor productivities, however.

Alternatively, this model can be written as follows:

$$y_{it} = \sum_X \pi^{1X} x_{it} + \sum_X \pi^{2X} x_{it-1} + \pi^3 y_{it-1} + \gamma_t^* + \eta_i^* + \varepsilon_{it}^*, \quad (9)$$

subject to the common factor restrictions that $\pi^{2X} = -\pi^{1X}\pi^3$ for all X.

Blundell and Bond (2000) use lagged levels and differences of inputs as instruments in a general methods of moments (GMM) framework to estimate (8). If the η_i are removed by first differencing (FD), this estimator allows the consistent recovery of all input elasticities in (1) as well as ρ. Blundell and Bond (2000) suggest the method of minimum distance (Wooldridge, 2010, pp. 545-7) to test whether the parameters estimated by the unrestricted model (8) conform with the restrictions imposed by (9).

Note that the within transformation (section 2.3) assumes *strict* exogeneity of inputs, which means that ω_{it} must not be transmitted to any future period (contrary to what is assumed in (7)). First differencing to eliminate fixed effects only assumes that input levels are *sequentially* exogenous, i.e. transmission of ω_{it} to the next but one and subsequent periods is allowed (Chamberlain, 1982; Wooldridge, 2010, pp. 321-6). FD is thus the typical approach to eliminate time-invariant heterogeneity in GMM applications, as it allows input levels lagged more than two periods to be used as instruments for contemporaneous differences (Arellano and Bond, 1991). Of course, these instruments will only have power if there actually *is* such a transmission (e.g. motivated by adjustment costs). To increase the power of the GMM approach, Blundell and Bond (1998) have shown that in addition to past levels, also lagged differences of inputs can be used as instruments if their variance is assumed to be stationary. This leads to the systems GMM estimator for production functions presented in Blundell and Bond (2000) and applied by Hempell (2005). Hempell uses data on German service firms from 1994 to 1999. In the empirical application of Blundell and Bond (2000), their preferred systems estimator produces a lower employment coefficient and a higher capital coefficient than OLS or ‘within’ estimators, thus correcting the expected bias.

If factor levels can suitably be instrumented by this approach, it addresses both the endogeneity and the collinearity problems. Contrary to the duality approach presented in section 2.4, it is much more plausible that the instruments proposed here are actually valid in an agricultural context. There are important production factors in agriculture that are subject to adjustment costs (or ‘transaction costs’; type II variables in Table 1) and such costs should be an element in any plausible theory of agricultural factor markets. As the nature of these costs is likely to differ among factors (see section 2.1), it is also plausible that different factors of production display different dynamic paths of adjustment. This is a favourable condition for identification (Bond and Söderbom, 2005). It is only with regard to some intermediate inputs (e.g. seed, fertiliser, plant protection, concentrate or energy) that factor use appears to be more flexible, such that the assumption of adjustment costs may be harder to justify (type I factors). In sum, this estimator is a promising candidate for agricultural applications.

2.6 Monotonous coevolution of unobserved productivity shocks with observed firm characteristics

The final method to be discussed here avoids the main disadvantage of any fixed effects approach to unobserved heterogeneity, which is the typically low variance of the transformed variables. At the same time, it does not rely on the strong *a priori* assumptions about the market structure of duality theory to identify the productivity parameters of interest. It rather attempts to proxy ω_{it} (as a compound type IV-to-VI production factor) by a *non-parametric control function*, which itself contains only observed firm characteristics. Olley and Pakes (1996) were the first to suggest log investment (i_{it}) as an observed characteristic driven by ω_{it}:

$$i_{it} = i_t(\omega_{it}, k_{it}), \quad (10)$$

where k_{it} is the pre-determined level of capital use at time t. The latter is assumed to evolve according to $k_{it+1} = (1-\delta)k_{it} + i_{it}$, with δ the depreciation rate.

The function $i_t(.)$ can vary over time and is not parametrically restricted except that it needs to be monotonous in ω_{it}. This latter trait allows inversion of this function, so that

$$\omega_{it} = \hbar_t(i_{it}, k_{it}),$$

where $\hbar_t$ is now potentially observable and acts as a proxy for ω_{it}. Furthermore, it is assumed that unobserved productivity follows a first-order Markov process:

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}] + \xi_{it},$$

where ξ_{it} is an innovation (a type VII factor) uncorrelated with k_{it}, but possibly correlated with the type I factors in the production function. Because k_{it} is a type II factor, the moment condition $E[\, k_{it}\xi_{it}] = 0$ can be used to identify α^K.

Given this setup, estimation proceeds in two stages. The basic idea is to jointly control for the influence of k and ω in the first stage and to recover the true coefficient of k as well as ω in the second. Referring again to our Cobb Douglas example, all observed factors except capital are assumed to be fully variable type I factors. Their elasticities are determined in the *first stage* by substituting $\hbar(.)$ into the production function and estimating the following:

$$y_{it} = \alpha^A a_{it} + \alpha^L l_{it} + \alpha^M m_{it} + \phi_t(i_{it}, k_{it}) + \varepsilon_{it}, \tag{11}$$

where $\phi_t = \alpha^K k_{it} + \hbar_t(i_{it}, k_{it})$. In practice, ϕ_t is approximated by a higher order polynomial of i and k, which controls for ω_{it}. As shown in (11), ϕ_t is assumed to be additively separable from the remaining variable inputs. Flexible functional forms involving interactions of all variable and fixed inputs (such as the Translog) thus cannot be implemented with this procedure.

In the *second stage*, α^K is determined in a series of steps (see e.g. Petrin et al., 2004). First, using the parameters of ϕ_t and a candidate value for α^K, a prediction $\widehat{\omega}_{it}$ is computed for all periods. Next, $\widehat{\omega}_{it}$ is regressed on its lagged values to obtain a consistent predictor of that part of ω that is free of the innovation ξ. Finally, using the parameters of the variable factors from the first stage together with the prediction of the 'clean' ω_{it} and the moment condition $E[\, k_{it}\xi_{it}] = 0$, a consistent estimate of α^K can be obtained by minimum distance.[3] In their original application to the US telecommunications equipment industry, Olley and Pakes (1996) show how this procedure yields lower labour coefficients than OLS and higher capital coefficients than 'within'. In the only application to agriculture known to us, Kazukauskas et al. (2010) found for Irish dairy farms that the materials coefficient estimated with an Olley/Pakes procedure was lower than the OLS result.

One problem that arises from using investment as a proxy is zero observations for certain years and firms. Levinsohn and Petrin (2003) therefore suggested materials instead of investment as a proxy of ω_{it} in the previous algorithm. Again, the assumption is that materials evolve monotonously with the unobserved productivity characteristic, so that the effect of the latter can be inverted out. Materials is assumedly a type I factor and thus part of the production function. In the Levinsohn/Petrin approach, however, its elasticity cannot be estimated in the first stage, as it is now part of $\hbar(.)$. Therefore, the additional moment condition $E[\, m_{it-1}\xi_{it}] = 0$ is postulated to obtain α^M in the second stage.

If the control function fully captures the influence of ω_{it}, it solves the endogeneity problem and provides a useful alternative to the fixed effects approaches described before. Yet in agriculture, the assumptions on monotonicity and dynamic evolution of the productivity shock must be considered with caution. A key question is *what exactly ω_{it} is representing and whether investment or material use are good proxies for it*. If ω_{it} stands for annually fluctuating, unobserved factors (type IV), such as management effort or reaction to

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3 This is the algorithm used in the literature subsequent to Olley and Pakes (1996). In the original paper, it was combined with an exit and entry mechanism for firms, which we ignore to simplify the exposition.

environmental conditions, there may be cases where the 'right behaviour' of the farmer (i.e. positive ω_{it}) does not lead to more investment. The same is true for materials. The productivity-enhancing reaction to environmental shocks in crop production may sometimes be less input use (fertiliser, chemicals) rather than more. In all these cases, neither investment nor materials will be good proxies of ω_{it}. Furthermore, the 'memory-less' first-order Markov process appears unconvincing if ω_{it} actually represents unobserved type V factors that are subject to adjustment costs. They evolve slowly and will typically have implications for the intertemporal optimisation problem, so that also k_{it} is affected by them and (10) is misspecified. Investment may not be a good proxy for ω_{it} if there are other important determinants of it beyond k_{it}. In a farming context, this is likely to be the case, because investment decisions are usually influenced by long-term business strategies or the availability of a farm successor (or both).

Another problem with the procedure suggested by Olley/Pakes and Levinsohn/Petrin is that it does not solve the collinearity problem. As discussed at length by Ackerberg et al. (2006), unless one is willing to make very unintuitive assumptions on measurement error or timing, there is no data generation process that separately identifies the coefficients of the type I factors in either of the two approaches. Ackerberg et al. therefore suggest giving up estimation of these coefficients in the first stage altogether, and invoke additional timing assumptions that justify moment conditions for estimating these coefficients in the second stage. In the framework of a Translog specification, Gandhi et al. (2011) propose to estimate the coefficient for one free input from a share regression akin to equation (6) and then to proceed in a similar way as described in this section to recover the other elasticities.

Notice that the assumption of costly factor adjustment is a cornerstone of both the dynamic panel data approach described in section 2.5 and the present one. In both cases, this assumption provides moment conditions necessary for consistent estimation of the parameters. The main difference is that the former approach allows time-invariant fixed effects, whereas the latter does not. The former imposes a linear structure on the dynamic process, while it can be arbitrary in the latter. Even so, factor adjustment is assumed to occur in a single period in Olley/Pakes and followers, whereas the process covers many periods in the dynamic panel data models. In the context of agricultural applications, this may be one key advantage of the dynamic panel data approach.[4]

2.7 Interim evaluation of estimation approaches

The previous discussion has displayed the variety of assumptions invoked for addressing the endogeneity and collinearity problems inherent to production function estimation. In our opinion, the assumptions underlying 'within' regression and the duality approach are fairly strong and implausible for the case of agriculture. Perhaps not surprisingly, they have often not performed well in estimation practice. This insight shifts our attention to the promising new approaches using heterogeneous frictions in factor adjustment. We regard the presence of adjustment costs as particularly relevant for the production factors that are of key interest in agricultural applications. They also provide an interesting link to more sophisticated theories of business structures in agriculture, which usually embody some form of adjustment frictions in agricultural factor use (such as Allen and Lueck, 2002 or Pollak, 1985). So far, there are almost no applications to agricultural data of these new estimators. The following sections seek to fill this void.

3. Data

The data used in this study are mostly identical to those used in Petrick and Kloss (2012). The EU's Farm Accountancy Data Network (FADN) provides a stratified farm-level dataset that holds accountancy data for 25 of the 27 EU member states. The stratification criteria are

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[4] Other subtle differences between the two approaches are discussed in Ackerberg et al. (2006).

region, economic size and type of farming. The farm universe consists of all farms with more than one hectare or those with less than one hectare that provide the market with a specified amount of output. From this universe all non-commercial farms are excluded in order to arrive at the field of observation. To be classified as a commercial farm, a farm must exceed a certain economic size. It is measured in economic size units (ESUs). One ESU represents a certain amount in euros and is periodically adjusted for inflation. To determine the economic size of farms, the concept of standard gross margin is used. In addition, farms are classified by type of farming.

In the present study, we only use field crop farms (TF1), to justify the assumption of a homogenous state of technology across farms. As in Petrick and Kloss (2012), we produce separate results for the following countries:

- Denmark (DK),
- France (FR),
- Germany East (DEE),
- Germany West (DEW),
- Italy (IT),
- Poland (PL),
- Slovakia (SK), and the
- United Kingdom (UK).

The raw data provided by FADN were arranged in a way that panel data estimators can be applied. For every country and sector in the study, we created a panel dataset covering the years from 2001 up to 2008. For Poland and Slovakia, FADN data were collected for the first time in 2004. Therefore, these panels only cover five years. As we use the opening valuation of capital and this is taken from the previous year of observation, the panel size for Poland and Slovakia is effectively reduced to four years. A small number of duplicates in the data were dropped. In total, 19,722 observations were included in the EU-wide sample.

The variables and their measurement are readily available in the codebooks provided by FADN. Output is measured as the total farm output in euros. Labour is measured by the time worked in hours by total labour input on the farm, including both hired and family labour. The total utilised agricultural area is our land input in ha. It includes owned and rented land, and land in sharecropping.

A persistent issue in estimating production functions has been the specification of the capital variable. Typically, some simple measures of input quantities (such as fertilisers or pesticides) and machinery use (such as fuel expenses or tractor hours) are used in cross-sectional studies. In this study, the material or working capital input is proxied by total intermediate consumption in euros. It consists of total specific costs and overheads arising from production in the accounting year. Among others, it includes feed, fuel, lubricants, water, electricity and seed. Other than in Petrick and Kloss (2012), where we used annual depreciation as a capital proxy, but consistent with most of the recent literature on production function estimation with firm-level data (such as Olley and Pakes, 1996; Blundell and Bond, 2000; Levinsohn and Petrin, 2003), we approximate fixed capital inputs by using the opening valuation of assets. In this case, we took the asset value of machinery and buildings from the FADN data.

To calculate revenue shares, we needed factor prices for labour, land and capital. These were taken from the actually paid wage to hired farm workers, the actually paid rent per hectare of rented land and the actually paid interest per debt capital. As there were many missing values, we calculated median factor prices per region (variable A1) and imputed these to all farms in that region. Table 3 summarises the variable definitions and gives the actual FADN codes.

Table 3. Selection of variables

FADN code	Variable description
Outputs	
SE131	Total output (€)
Inputs	
SE011	Labour input (hours)
SE025	Total utilised agricultural area (ha) = land
SE275	Total intermediate consumption (€) = materials
L.SE450 + L.SE455	Opening valuation of machinery and buildings (€) = fixed capital
SE516	Gross investment (€)
Factor prices	
SE370/SE021	Wage per hour (€)
SE375/SE030	Land rent per ha (€)
SE380/SE485*100	Interest on capital (%)

Note: L. denotes the one-year lag.
Source: Authors, FADN data.

All monetary values are deflated to real values in 2005 prices using respective price indices. Price indices were extracted from the Eurostat online database and merged with the panels. Output was deflated by the agricultural output price index. Fixed capital and investment were deflated by the agricultural input price index for goods and services contributing to agricultural investment, and materials by the agricultural input price index for goods and services currently consumed in agriculture. Revenue shares were all calculated in nominal terms.

Outliers were identified on the basis of the fixed capital productivity per farm (real SE131/(real (L.SE450 + L.SE455))). Observations were dropped for the production function estimation if their value was beyond the median ± 1.5 of the interquartile range (IQR). Furthermore, we only included farms that had some minimum panel representation in the data. Farms had to be present in the data for at least four years in a row; in the case of Slovakia, they had to be present for at least three years. Descriptive statistics, including the data patterns of the panels, are given in the appendix.

4. Results

For this study, we estimated eight models per country as summarised inTable 4. For Poland and Slovakia, the dynamic panel data model could not be estimated due to a lack of data. The ‘within’ Translog was obtained by interacting the group-wise demeaned logs of factors and using an appropriate degree of freedom correction. Other than by simply calling a panel estimation command with the interacted variables in logs, this procedure ensures that levels are effectively eliminated from the regression.

Table 4. Models estimated

	DK	FR	DEE	DEW	IT	PL	SK	UK
Output shares	X	X	X	X	X	X	X	X
OLS Cobb Douglas	X	X	X	X	X	X	X	X
OLS Translog	X	X	X	X	X	X	X	X
'Within' Cobb Douglas	X	X	X	X	X	X	X	X
'Within' Translog	X	X	X	X	X	X	X	X
Olley/Pakes Cobb Douglas	X	X	X	X	X	X	X	X
Levinsohn/Petrin Cobb Douglas	X	X	X	X	X	X	X	X
Blundell/Bond Cobb Douglas	X	X	X	X	X	-	-	X

Source: Authors.

Table 5 in the next section displays a summary evaluation of the estimators with regard to the estimated production elasticities and returns to scale. The performance of the Translog specifications and the dynamic panel data model is given particular attention. Generally, the interest was to detect systematic differences across estimators and countries, and to assess their practical implementation. Detailed results tables are presented in the appendix, which includes an overview table for each country containing the results for the first seven models, plus an additional table for each country that includes more in-depth diagnostic results for the Blundell/Bond model.

All estimations were performed with Stata 12. For the Olley/Pakes and Levinsohn/Petrin estimators we employed the user-written routine `levpet` (Petrin et al., 2004). The Blundell/Bond estimator was implemented with `xtabond2` by Roodman (2009) using the `h(2)` option, and combined with Söderbom's (2009) `md_ar1` minimum distance estimator.

4.1 Evaluation of estimators

As a general tendency, factor elasticities were found to be low for labour, land and capital, and high for materials (Table 5 and Table 6). Estimates for the first three of these factors are in the range of 0.2 and lower, sometimes not significantly different from zero or even significantly negative. The production elasticity of materials is typically between 0.7 and 1.0.

The estimates support the conventional wisdom that OLS tends to be upward biased for particularly variable factors. In the present data, this primarily applies to materials, the OLS estimate of which is (except for Denmark) higher than its revenue share. It may be taken as evidence for the existence of serially correlated, unobservable factors (Olley and Pakes, 1996, p. 1274).

The opposite bias is found for capital in the 'within' estimator, which is typically below the revenue share. This tendency is also in line with previous studies and can be attributed to the low variance of capital over time (Griliches and Hausman, 1986).

The Olley/Pakes estimator does not commonly produce a lower elasticity for materials than OLS. Levinsohn/Petrin does this in some cases (West Germany, Italy and Poland). Olley/Pakes and OLS estimates are typically very similar. Estimating the Olley/Pakes model always led to a loss of observations due to missing investment data. This was particularly severe in the cases of Italy and Poland. These tendencies are basically in line with the findings of Kasahara and Rodrigue (2008) for a Chilean plant-level dataset. The Levinsohn/Petrin model may thus be taken as a plausible alternative to the received estimators if one is willing to accept the theoretical problems in identification of labour and land (which the other estimators except for the Blundell/Bond share).

Estimated elasticities of scale fluctuate around 1.0, with higher values for Denmark and the UK. Given the previous findings on production elasticities, OLS estimates tend to be higher than 1.0 while 'within' tend to be lower. Overall, the scale elasticity in European crop farming appears to be close to one.

We report the production elasticities estimated by the Levinsohn/Petrin procedure for all subsamples in Table 6 and compare them with two rather distinct benchmark studies. Heady and Dillon (1961) is an early collection of OLS Cobb Douglas production function estimates. It is based on farm-level data from 32 countries all over the world, with a focus on North America, Australia and India, and represents one of the most comprehensive collections of production elasticity estimates ever published (p. 630). Table 6 simply reports the overall mean elasticities of all 32 studies. It should be noted that these studies display considerable variation among themselves (see the extensive discussion in Heady and Dillon, 1961, pp. 585-643). Mundlak et al. (2012) is a recent cross-country regression of a Cobb Douglas production function based on the 'within' estimator. The authors use data from 30 developing and developed countries for 1972–2000. Without aiming at a substantial interpretation of the differences between these varying studies, Table 6 nevertheless serves to illustrate a number of interesting tendencies:

- A comparatively low production elasticity of labour prevails throughout the EU samples and was also found by Heady and Dillon as well as Mundlak et al.
- The production elasticity of land is much lower in the EU than in the benchmark studies.
- The production elasticity of materials is much higher in the EU than in the benchmark studies.
- The production elasticity of fixed capital is much lower in the EU than in Mundlak et al. (2012).
- Returns-to-scale estimates fluctuate at around 1.0 throughout.
- The Mundlak et al. study reveals remarkably low elasticities for labour and materials. The low materials coefficient can be explained by the fact that the dependent variable in their model is value added. Despite the use of the 'within' approach, the capital elasticity is surprisingly high.

Returning to the comparison of estimators for the EU samples, the results based on the Translog specification display remarkably uniform features across countries. The OLS Translog produced unreasonable results throughout, e.g. reflected in the coexistence of negative production elasticities for some factors and elasticities bigger than one for others (at sample means). The 'within' Translog elasticities, on the other hand, were at sample means typically close to the 'within' Cobb Douglas, and the interaction terms of the Translog were often not jointly different from zero.

The performance of the Blundell/Bond estimator was examined in some detail for the six longer samples. We present the results for the unrestricted and the restricted models along with Arellano-Bond tests for serial correlation of error terms. If the model is correctly specified, the test should reject autocorrelation of order one but not of order two (Arellano and Bond, 1991). We also apply Hansen's over-identification (OID) test for instrument validity (Hansen, 1982). While serial correlation of the error terms was never a problem for the models and the common factor restriction was never rejected, the Hansen OID test of instrument validity was not passed in three cases.

Table 5. Summary evaluation of estimator performance

	DK	FR	DEE	DEW	IT	PL	SK	UK
Factor elasticities	All OLS below shares; materials below shares throughout CD; capital=0 in 'within' & OP	Land<0 in OLS, OP, LP, BB; materials above shares in OLS, OP, LP, BB; capital<0.1 in shares, 'within', OP, BB	Labour=0 throughout; land<0 in OLS, OP, LP; materials≥1.0 in OLS, OP, LP; capital≈0 in 'within', OP, LP, BB	Materials above shares in OLS & OP, lower in 'within' & BB; capital≈0 in 'within', OP, LP, higher in BB	Land≤0 in OLS, OP, LP, BB; materials above shares in OLS, OP, BB; capital<0.1 in OLS, =0 in all other CD	Land=0 in OLS, OP, LP; materials above shares in OLS, OP, LP, lower in 'within'; capital<0.1 in shares, 'within', OP.	Labour≤0 throughout; land varying; materials above shares in OLS, OP, LP, lower in 'within'; capital=0 in 'within', OP, LP	Land<0.1 in OLS, OP, LP; materials above shares in OLS, OP, LP; capital≤0.1 throughout
Returns to scale	Shares add up to 2.18; OLS, OP, LP lower but still>1; 'within' close to 1; 1.2 in BB	Close to 1.0 throughout	Close to 1.0 in OLS, 'within', OP, LP; 0.9 in BB	1.1 in OLS, <1 in 'within', OP, LP, BB	Shares add up to 1.71; OLS, OP ≈1.1; 'within', LP <0.9; BB=0.5	OLS & LP >1; 'within', OP <1	OLS, LP <1; 'within', OP<0.8	OLS, 'within', OP, LP≈1.2; BB=0.5
Performance of Translog	OLS unreasonable; 'within' close to CD	OLS unreasonable; 'within' close to CD	OLS unreasonable; 'within' close to CD	OLS unreasonable; 'within' close to CD; interactions not sig.	OLS unreasonable; 'within' close to CD	OLS unreasonable; 'within' close to CD; interactions not sig.	OLS unreasonable; 'within' close to CD; interactions not sig.	OLS unreasonable; 'within' close to CD; interactions not sig.
Blundell/ Bond estimator	Specification tests ok; output highly persistent; levels better instrumented than diff.	OID not passed; land, mat., capital, output highly persistent; levels better instrumented than diff.	Specification tests ok; land, mat., output highly persistent; levels better instrumented than diff.	OID not passed; labour, land, mat. highly persistent; capital, output explosive; levels better instrumented than diff.	OID not passed; labour, capital highly persistent; land & output explosive; poor instrumentation	-	-	Specification tests ok; labour, land, capital highly persistent; mat. & output explosive; poor instrumentation
Data issues	-	-	-	-	Few observations for investment	Few observations for investment	Small sample	-

Notes: BB: Blundell/Bond, CD: Cobb Douglas, LP: Levinsohn/Petrin, OID: over-identification test, OLS: ordinary least squares, OP: Olley/Pakes.
Source: Authors.

Table 6. Production elasticities in comparison

	DK	FR	DEE	DEW	IT	PL	SK	UK	Heady Dillon (1961)	Mundlak et al. (2012)
Labour	0.45	0.18	0.04#	0.23	0.30	0.21	-0.10#	0.18	0.21	0.01#
Land	0.18	-0.05	-0.13	-0.06	-0.05	0.01#	-0.15#	0.08#	0.38	0.44
Materials	0.63	0.83	1.00	0.64	0.55	0.70	1.00	0.83	0.39	0.10
Capital	0.12	0.11	0.15#	0.13	0.02#	0.13	0.17#	0.11	-	0.46
Ret. to scale	1.38	1.06	1.06	0.94	0.82	1.05	0.91	1.20	0.98	1.00*

* Imposed on the model

Not significantly different from zero at conventional confidence levels

Notes: Results are for field crop farms in EU countries are based on the Levinsohn/Petrin estimator. Heady and Dillon (1961) represents the mean elasticities from a sample of 32 cross-sectional Cobb Douglas estimates originating from various countries (their table 17.15). Mundlak et al. (2012) is based on a cross-country regression of 30 countries for 1972–2000, using value added as a dependent variable and the 'within' estimator (their table 2, first column).

Source: Authors.

To allow further diagnosis, simple autoregressive models of order one (AR(1)) were estimated separately for all factors and output, following Blundell and Bond (2000). Labour and land were found to be highly persistent, which makes dynamic panel data estimation a natural option. Moreover, we regressed the differences of the latest available year on the lagged levels of all available previous years and the latest available levels on all available lagged differences of previous years. The reported *p*-values and coefficients of determination allow an insight into the explanatory power of the instrument sets. Generally, the instrument performance was better for levels (instrumented by differences) than for differences (instrumented by levels). System GMM approaches that use not only differences but also levels for instrumentation (Blundell and Bond, 1998) are thus warranted. Even so, the elasticities of the persistent factors of labour, land and capital often could not be identified. Parameters were very sensitive to the selection of the sample and the precise specification of the estimator. Occasionally, dynamic factor evolution apparently followed an explosive process, as the AR(1) coefficient was estimated to be bigger than one. On the other hand, the estimates for materials appear very reasonable throughout, as they were typically lying somewhere between the OLS and 'within' results. It is here where the Blundell/Bond estimator can likely claim some superiority.

There are some noteworthy findings for Denmark compared with the other countries. Denmark was the only country where materials elasticity was lower than the materials' revenue share. Shares add up to the extremely high value of 2.18 (which is actually inconsistent with the interpretation as shares). This outcome may be an artefact of imputed factor prices that are systematically higher than those for other countries. The unbalanced panel pattern of Denmark made it difficult to perform the diagnostic regressions on the explanatory power of the lagged instruments in the Blundell/Bond approach. Even so, estimation of the persistent factors of labour, land and capital produced more satisfying results for Denmark than for the other countries.

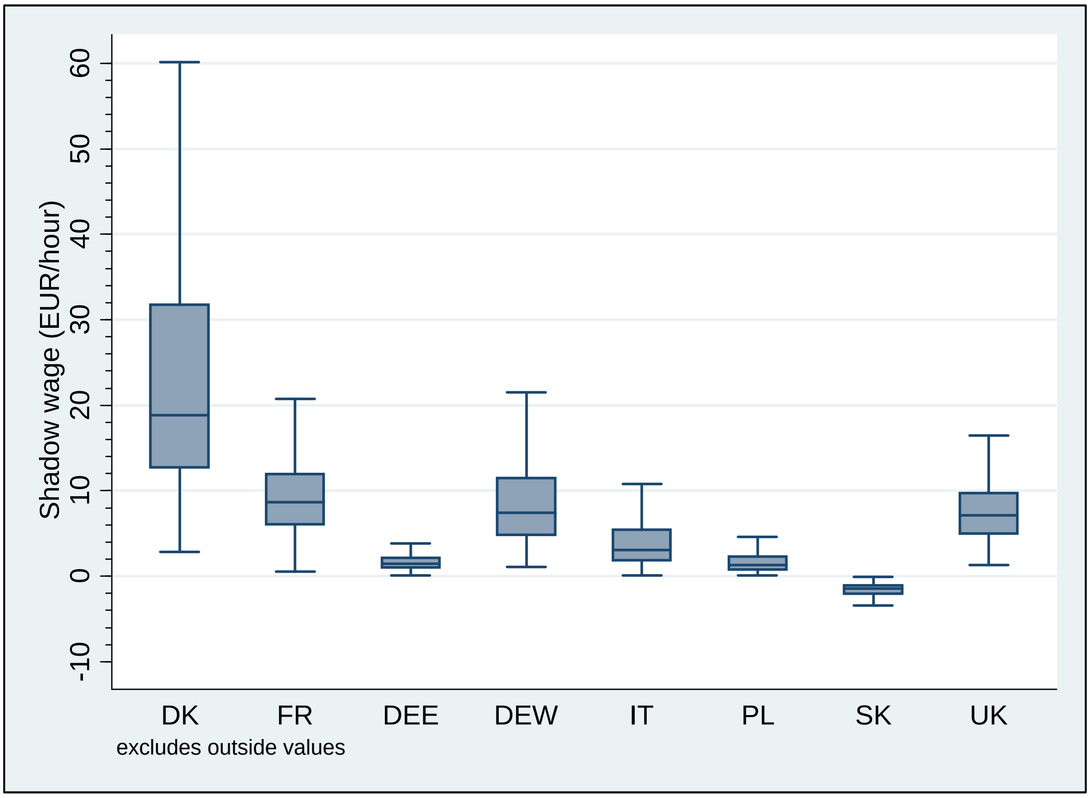
4.2 Distribution of shadow prices

To ease the economic interpretation of the findings, we computed farm-individual shadow prices for all the farms used in the estimations. To this end, we multiplied the production elasticities obtained from the Levinsohn/Petrin estimator (Table 6) with the farm-specific (average) factor productivities. For the two capital variables, net returns equal to the marginal value product minus one were calculated (Petrick and Kloss, 2012, p. 2). The distribution of the shadow prices for the four factors and the eight subsamples is illustrated in Figures 1-4 by using box plots. In a box plot, the line dividing the box into two equal parts represents the median, while the first and third quartiles of the distribution define the lower and upper limits of the box. The lower and upper whiskers are limited by the adjacent values defined as first (third) quartiles minus (plus) 1.5 times the IQR.

The findings from the box plots are not too surprising given the results presented in the previous section. The shadow prices of the factors of labour, land and fixed capital tend to be quite low. The median shadow wage in agriculture is below €9/hour in France, West Germany and the UK; in East Germany, Italy and Poland it is below €2/hour and in Slovakia even negative. Denmark stands out with a value of almost €20/ha. Shadow land rents are only minimally different from zero throughout. Shadow prices of fixed capital are negative in all subsamples, with medians per country in the range of -85 to -100%. There is considerable variation for some of the subsamples, and outside values beyond the adjacent values were not displayed.

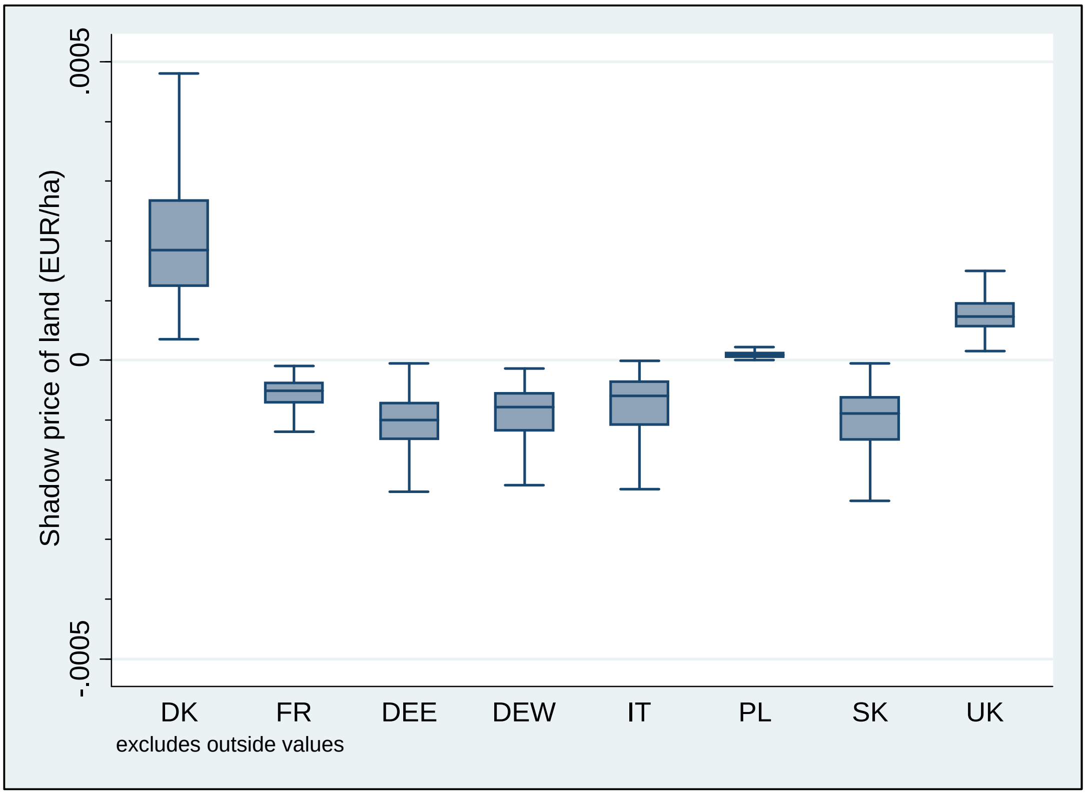
The box plots on the shadow interest rate of materials deserve a closer look. It is here where median rates are in a range above typical interest rates for external capital, notably in France, East Germany, Italy, Slovakia and the UK. Given the wide variation of outcomes, there are many farms displaying shadow rates well above typical market interest rates in all countries. This finding hints at the existence of funding constraints with regard to working capital. It qualifies our conclusion in Petrick and Kloss (2012), according to which there was little evidence of credit rationing with regard to working capital in EU agriculture. A closer inspection of the reasons for the different findings reveals that our earlier study used the 'within' estimator, whereas the results here are based on Levinsohn/Petrin. As shown in the results tables in the appendix, the production elasticity from the 'within' estimator is lower than the Levinsohn/Petrin model in all subsamples, which is likely to be the immediate cause of the lower shadow prices reported in Petrick and Kloss (2012). Higher materials coefficients are also supported by the Blundell/Bond estimates, as far as they are available.

Figure 1. Shadow wage: Distributions per country



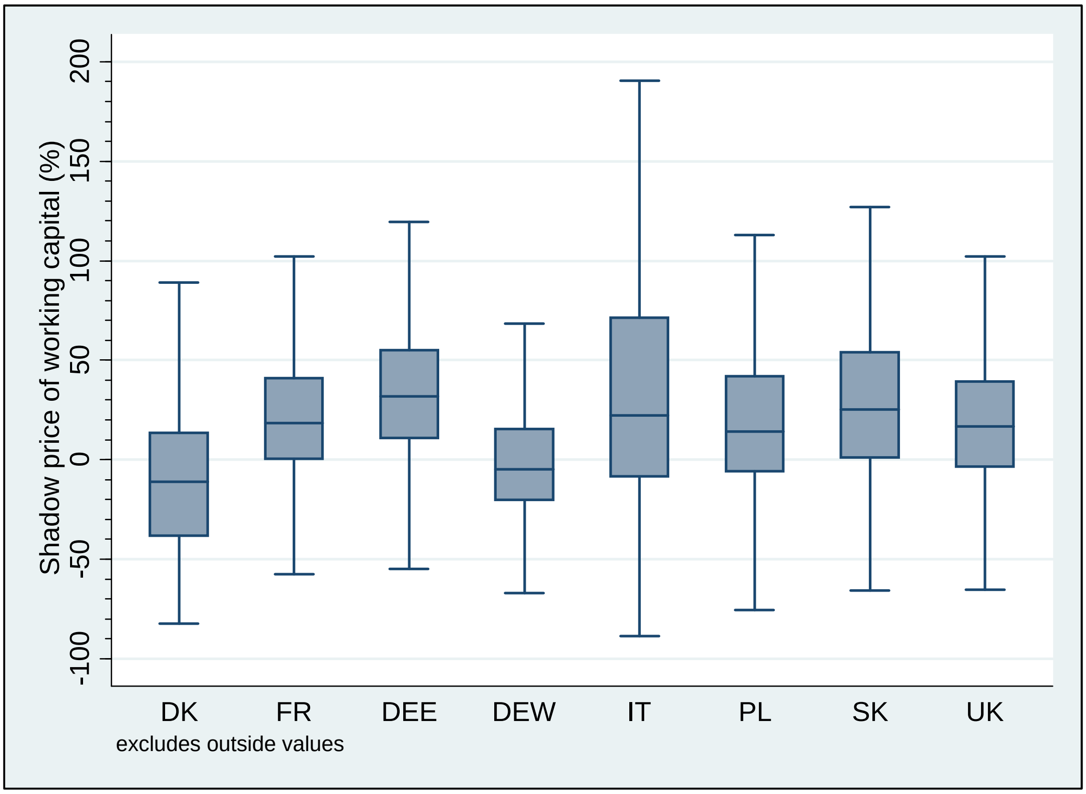
Note: Farm-specific predictions based on the Levinsohn/Petrin Cobb Douglas model.
Source: Authors based on FADN data.

Figure 2. Shadow land rent: Distributions per country



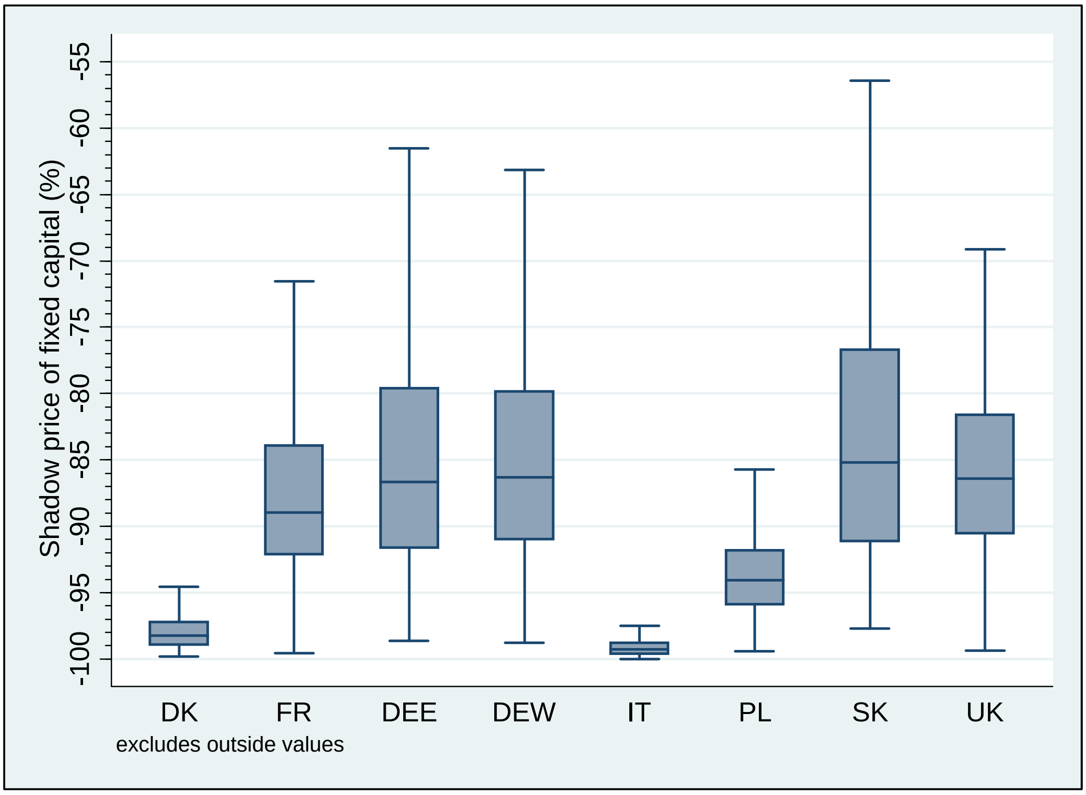
Note: Farm-specific predictions based on the Levinsohn/Petrin Cobb Douglas model.
Source: Authors based on FADN data.

Figure 3. Shadow interest rate of materials: Distributions per country



Note: Farm-specific predictions based on the Levinsohn/Petrin Cobb Douglas model.
Source: Authors based on FADN data.

Figure 4. Shadow interest rate of fixed capital: Distributions per country



Note: Farm-specific predictions based on the Levinsohn/Petrin Cobb Douglas model.
Source: Authors based on FADN data.

5. Conclusions

The aim of this study has been to provide a comparison of innovative production function estimators and to apply them to a recent firm-level dataset representing the agricultural sector of seven EU countries. The starting point of our analysis has been the recently revived debate in the literature on how the classical identification problems of endogeneity and collinearity could be addressed. By introducing a typology of production factors in agriculture, we argue that their adjustment flexibility over time and whether the econometrician observes them are of crucial importance for the choice of an appropriate estimator.

On theoretical grounds, we show that the assumptions underlying 'within' (fixed effects) regression and the duality approach are fairly strong and implausible for the case of agriculture. 'Within' approaches neglect the potentially important unobserved factors that vary over time. Duality relies on the short-term profit maximisation of agents and perfect competition on output and factor markets. In agriculture, these conditions are unlikely to be met. Perhaps not surprisingly, these approaches often have not performed well in estimation practice.

This insight shifted our attention to more innovative approaches using heterogeneous frictions in factor adjustment for identification. In light of the comprehensive literature on adjustment frictions on rural land, labour and capital markets, we regard the presence of adjustment costs as particularly relevant for the production factors that are of key interest in agricultural applications. Olley and Pakes (1996), Blundell and Bond (2000) and Levinsohn and Petrin (2003) all base their identification strategy on adjustment frictions in factor allocation, which seems to be an *a priori* plausible approach. The main difference is that Blundell/Bond allow time-invariant fixed effects, whereas Olley/Pakes and Levinsohn/Petrin do not. The former impose a linear structure on the dynamic process, while it can be arbitrary in the latter. Even so, factor adjustment is assumed to occur in a single period in the proxy approaches, whereas the process potentially covers many periods in the dynamic panel data models. In agricultural applications, this is a conceptual advantage of the Blundell/Bond approach. Adjustments of land, labour and capital are typically of an intertemporal nature, which is not appropriately covered by a one-year lag. Furthermore, Olley/Pakes and Levinsohn/Petrin do not satisfactorily address the problem of collinearity in production function estimation. These approaches regard labour and land as fully flexible production factors for which there is no source of identifying variance across observations (Ackerberg et al., 2006).

In the empirical section, we provide results for revenue shares, OLS Cobb Douglas and Translog, 'within' Cobb Douglas and Translog, as well as Olley/Pakes, Levinsohn/Petrin and Blundell/Bond Cobb Douglas models. Each model was estimated separately for panels of field crop farms in Denmark, France, East and West Germany, Italy, Poland, Slovakia and the UK. Owing to a lack of data, the Blundell/Bond model could not be implemented for Poland or Slovakia. We also provide shadow price calculations for all four factors per country, based on the Levinsohn/Petrin estimates.

Compared with the revenue shares, OLS and 'within' display the biases expected from the literature. OLS typically overestimated the variable factor materials, while 'within' underestimated the relatively fixed factor of capital. Extending the received Cobb Douglas specification to a Translog generally did not provide illuminating insights. Either the results were obviously implausible or little different from Cobb Douglas.

Olley/Pakes tended to be close to OLS and thus did not address the biases. Moreover, it suffered from missing investment data. Levinsohn/Petrin produced more plausible results and may be taken as an easy-to-implement alternative to the received estimators. Given the conceptual problems in identifying the supposedly flexible inputs of labour and land, which the other estimators except for Blundell/Bond share, this is certainly only a second-best choice.

The Blundell/Bond estimator could be implemented with sufficiently long panels, but did not always perform satisfactorily. The combined first-difference and instrumental variable approach of this estimator goes a long way in trying to get rid of all the factors perturbing an unbiased estimation of productivity. Its assumptions on adjustment costs are theoretically very plausible and could be empirically supported for labour, land and capital. Yet, there is evidence that in agriculture this approach overshoots the mark. This is because adjustment costs are so high and factor evolution is so persistent that, despite using the systems GMM approach of Blundell and Bond (1998), there is often too little variance left for identification. It is only with regard to materials that this estimator appeared to produce reasonable estimates.

Our estimates show a consistent picture of very low production elasticities for labour, land and fixed capital, whereas the elasticity of materials is above 0.7 throughout. As a consequence, shadow prices for the three fixed factors are also very low. The median shadow wage in agriculture is below €9/hour in France, West Germany and the UK; in East Germany, Italy and Poland it is below €2/hour and in Slovakia even negative. Shadow land rents are typically close to zero. The net return on fixed capital is in the range of -80 to -100%. This finding suggests an excess capacity of fixed production factors in EU agriculture. A further outflow of factors may be necessary to bring returns up to factor remuneration in other sectors.

The Levinsohn/Petrin estimates used to calculate these figures shed a different light on the shadow price of working capital (materials). Other than in the computations based on a 'within' estimator presented in Petrick and Kloss (2012), the shadow return on working capital is often above typical market interest rates for capital. The higher elasticity for materials is also supported by the Blundell/Bond estimates. This finding suggests that credit rationing is an issue on agricultural finance markets in the EU, particularly with regard to short-term lending. In other words, improving the availability of working capital is the most promising way to increase agricultural productivity, whereas land, labour and fixed capital are not among the bottleneck factors of EU arable farming.

Summing up the methodological insights of this analysis, the recently suggested approaches to the estimation of production functions provide attractive conceptual improvements over the received 'within' and duality models. Using adjustment costs for the identification of factor use seems particularly plausible in a sector like agriculture, in which long-lasting adjustment frictions in land, labour and capital have been recognised for a long time. Even so, empirical implementation of the conceptual sophistications built into these estimators does not always live up to expectations. This is particularly true for the dynamic panel estimator suggested by Blundell and Bond (2000), which mostly failed to identify reasonable elasticities for the (quasi-) fixed factors. Less demanding proxy approaches, such those related to Levinsohn and Petrin (2003), represent an interesting alternative for agricultural applications.

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Appendix: Data & results tables

Table A1. Descriptive statistics

	Denmark				France				Germany (East)			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Output (ths €)	183.3	278.2	3.1	2733.4	158.4	115.9	5.2	1574.7	550.2	1020.0	5.5	9242.1
Labour (ths hours)	2.8	3.9	0.1	49.0	3.1	2.3	1.2	38.2	15.4	29.6	2.2	268.1
Land (ha)	123.4	174.0	3.3	1760.0	144.9	83.2	3.6	647.4	540.9	648.3	2.3	5155.9
Materials (ths €)	109.4	167.2	6.9	1844.0	104.8	64.5	5.7	698.9	385.6	686.5	15.8	6534.7
Capital (ths €)	868.1	1431.4	42.3	21381.0	158.8	127.3	2.8	1379.8	509.6	725.4	14.7	6591.7
Investment (ths €)	62.9	372.6	-4840.9	5688.0	36.0	58.6	-697.3	903.9	98.4	175.5	-945.8	1615.4
Wage (€/hour)	17.4	0.0	17.4	17.4	10.6	0.6	9.3	14.1	9.3	0.9	8.1	10.4
Land rent (€/ha)	370.7	0.0	370.7	370.7	137.4	36.7	99.9	949.7	144.5	35.0	89.2	179.3
Interest on capital (%)	5.8	0.0	5.8	5.8	3.6	0.4	2.9	4.5	3.8	0.3	3.4	4.5
No. of observations*	818				5330				1448			
No. of farms	209				1031				292			

Denmark Pattern	Denmark Frequency	France Pattern	France Frequency	Germany (East) Pattern	Germany (East) Frequency
...1111.	6	1111	237	1111	48
...11111	8	...1111.	36	...1111.	18
..1111..	93	...11111	176	...11111	16
.1111...	39	..1111..	69	..1111..	39
.11111..	108	..11111.	76	..11111.	140
.1111111	6	..111111	370	..111111	90
1111....	120	.1111...	48	.1111...	33
11111...	112	.11111..	68	.11111..	12
111111..	320	.111111.	40	.111111.	25
1111111.	6	.1111111	384	.1111111	84
		1111....	321	1111....	18
		11111...	360	11111...	172
		111111..	370	111111..	45
		1111111.	318	1111111.	330
		11111111	2457	11111111	378

* Except for investment

Source: Authors based on FADN data.

Table A1. Descriptive statistics cont'd

	Germany (West)				Italy				Poland			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Output (ths €)	152.7	140.0	12.8	2114.7	61.4	124.8	0.8	2165.2	40.1	50.5	0.9	904.6
Labour (ths hours)	4.1	3.4	1.1	93.9	3.6	4.5	0.0	98.7	4.5	3.1	0.6	43.2
Land (ha)	93.6	61.1	0.5	429.5	44.6	74.9	0.6	723.3	49.0	62.7	1.6	666.1
Materials (ths €)	97.4	74.5	11.4	789.5	28.3	59.9	0.5	1102.5	23.5	29.8	1.4	500.5
Capital (ths €)	152.5	125.6	11.1	1008.0	121.4	227.3	2.7	4360.4	81.3	81.9	4.5	999.6
Investment (ths €)	33.4	90.9	-369.1	2806.1	35.0	122.2	-1725.7	1687.6	12.6	30.2	-393.9	234.7
Wage (€ per hour)	7.6	0.9	6.3	10.5	7.4	1.5	5.0	11.5	1.4	0.1	1.3	1.5
Land rent (€ per ha)	254.3	57.6	63.4	314.3	184.9	96.1	61.1	500.0	37.0	7.7	21.2	44.0
Interest on capital (%)	4.2	0.4	3.4	4.9	6.2	2.2	3.0	13.3	2.5	0.0	2.4	2.5
No. of observations*		3030				5053				3090		
No. of farms		573				1362				1030		

Germany (West) Pattern	Frequency	Italy Pattern	Frequency	Poland Pattern	Frequency
....1111	165	1111	282	1111	3090
...1111.	15	...1111.	1,230		
...11111	112	...11111	2,668		
..1111..	18	..1111..	33		
..11111.	16	..11111.	40		
..111111	215	..111111	80		
.1111...	48	.1111...	15		
.11111..	68	.11111..	20		
.111111.	40	.111111.	20		
.1111111	462	.1111111	42		
1111....	96	1111....	111		
11111...	152	11111...	108		
111111..	145	111111..	150		
1111111.	162	1111111.	114		
11111111	1316	11111111	140		

* Except for investment

Source: Authors based on FADN data.

Table A1. Descriptive statistics cont'd

	Slovakia				United Kingdom			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Output (ths €)	531.4	538.2	11.5	2228.1	281.0	342.3	8.7	3548.6
Labour (ths hours)	37.6	39.0	1.3	176.7	6.2	5.2	0.3	51.8
Land (ha)	776.3	735.7	30.2	3299.6	249.3	182.2	17.8	1178.5
Materials (ths €)	403.0	378.3	9.6	1709.7	183.1	169.3	12.6	1606.1
Capital (ths €)	836.0	1129.2	8.1	5869.2	236.6	214.7	10.0	1522.9
Investment (ths €)	97.0	196.8	-689.9	1743.0	69.1	165.9	-513.8	2496.2
Wage (€ per hour)	3.1	0.0	3.1	3.1	10.9	0.3	9.1	11.2
Land rent (€ per ha)	32.6	0.0	32.6	32.6	197.4	13.7	172.9	206.9
Interest on capital (%)	9.9	0.0	9.9	9.9	4.7	0.3	4.2	5.2
No. of observations*	146				807			
No. of farms	56				189			

Pattern (Slovakia)	Frequency	Pattern (United Kingdom)	Frequency
.111	24	1111	102
111.	20	...1111.	24
1111	102	...11111	116
		..1111..	30
		..11111.	28
		..111111	85
		.1111...	42
		.11111..	56
		.111111.	45
		.1111111	138
		1111....	9
		11111...	16
		111111..	5
		1111111.	6
		11111111	105

* Except for investment

Source: Authors based on FADN data.

Table A2. Results of production function estimations, Denmark

	Output shares		**OLS** Cobb Douglas		**OLS** Translog		**'Within'** Cobb Douglas		**'Within'** Translog		**Olley/Pakes** Cobb Douglas		**Levinsohn/Petrin** Cobb Douglas	
	Mean	SD	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.479***	0.318	0.461***	0.035	0.958***	0.265	0.205***	0.048	0.203***	0.029	0.472***	0.033	0.453***	0.042
Land	0.411***	0.230	0.191***	0.033	0.802**	0.369	0.254***	0.073	0.252***	0.045	0.132**	0.064	0.184***	0.060
Materials	0.820***	0.438	0.587***	0.033	0.237	0.346	0.582***	0.054	0.580***	0.031	0.586***	0.049	0.626***	0.115
Capital	0.470***	0.368	0.136***	0.025	1.120***	0.301	-0.033	0.040	0.001	0.023	-0.001	0.065	0.118**	0.056
N	818		818		818		818		818		659		818	
Elasticity of scale			1.375***	0.015			1.008***	0.078			1.189***	0.062	1.381***	0.279
p-value const. ret. to scale			<0.001				0.919				0.036		0.051	
R^2			0.950		0.957		0.598		0.599					
p-value coeff. jointly zero			<0.001		<0.001		<0.001		<0.001		<0.001		<0.001	
p-value interact. terms jtly zero					<0.001				0.037					

Table A3. Results of production function estimations, France

	Output shares		**OLS** Cobb Douglas		**OLS** Translog		**'Within'** Cobb Douglas		**'Within'** Translog		**Olley/Pakes** Cobb Douglas		**Levinsohn/Petrin** Cobb Douglas	
	Mean	SD	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.245***	0.002	0.161***	0.008	-0.206	0.210	0.105***	0.030	0.101***	0.014	0.166***	0.014	0.175***	0.010
Land	0.134***	0.064	-0.040***	0.009	0.145	0.129	0.265***	0.064	0.274***	0.029	-0.051***	0.013	-0.052***	0.013
Materials	0.695***	0.211	0.874***	0.013	1.477***	0.226	0.629***	0.042	0.585***	0.018	0.852***	0.018	0.827***	0.057
Capital	0.037***	0.025	0.142***	0.007	0.109	0.143	0.037***	0.012	0.032***	0.006	0.062***	0.016	0.106***	0.013
N	5330		5330		5330		5330		5330		4696		5330	
Elasticity of scale			1.137***	0.008			1.036***	0.054			1.030***	0.029	1.055***	0.0642
p-value const. ret. to scale			<0.001				0.508				0.245		0.367	
R^2			0.877		0.882		0.507		0.494					
p-value coeff. jointly zero			<0.001		<0.001		<0.001		<0.001		<0.001		<0.001	
p-val. interact. terms jtly zero					0.016				0.003					

*** (**, *) significant at the 1% (5%, 10%) level, based on standard errors robust to clustering in groups

Notes: Year dummies are included in all models. Standard errors in Olley/Pakes and Levinsohn/Petrin are based on bootstrapping with 20 replications.

Source: Authors.

Table A4. Results of production function estimations, Germany (East)

	Output shares		**OLS** Cobb Douglas		**OLS** Translog		**'Within'** Cobb Douglas		**'Within'** Translog		**Olley/Pakes** Cobb Douglas		**Levinsohn/Petrin** Cobb Douglas	
	Mean	SD	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.337***	0.305	-0.009	0.021	-0.039	0.194	0.030	0.031	0.023	0.015	0.043	0.045	0.043	0.042
Land	0.209***	0.130	-0.111***	0.029	1.38***	0.189	0.378***	0.063	0.433***	0.031	-0.125***	0.045	-0.131***	0.045
Materials	0.796***	0.297	1.088***	0.028	0.260	0.301	0.596***	0.054	0.607***	0.028	1.077***	0.038	1.000***	0.087
Capital	0.054***	0.042	0.109***	0.017	0.403	0.285	0.008	0.024	-0.031***	0.011	-0.052	0.047	0.152	0.139
N	1448		1448		1448		1448		1448		1300		1448	
Elasticity of scale			1.076***	0.008			1.011***	0.067			0.943***	0.075	1.06***	0.186
p-value const. ret. to scale			<0.001				0.868				0.186		0.738	
R^2			0.950		0.956		0.525		0.509					
p-value coeff. jointly zero			<0.001		<0.001		<0.001		<0.001		<0.001		<0.001	
p-val. interact. terms jtly zero					<0.001				<0.001					

Table A5. Results of production function estimations, Germany (West)

	Output shares		**OLS** Cobb Douglas		**OLS** Translog		**'Within'** Cobb Douglas		**'Within'** Translog		**Olley/Pakes** Cobb Douglas		**Levinsohn/Petrin** Cobb Douglas	
	Mean	SD	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.259***	0.167	0.210***	0.012	-0.755**	0.331	0.093***	0.027	0.090***	0.013	0.207***	0.021	0.226***	0.021
Land	0.178***	0.103	-0.052***	0.010	1.106***	0.198	0.252***	0.051	0.265***	0.023	-0.053***	0.021	-0.055***	0.020
Materials	0.681***	0.199	0.871***	0.014	1.266***	0.253	0.499***	0.029	0.499***	0.014	0.864***	0.024	0.643***	0.076
Capital	0.046***	0.031	0.120***	0.010	0.154	0.243	0.044***	0.015	0.039***	0.007	-0.041	0.034	0.130*	0.068
N	3030		3030		3030		3030		3030		2426		3030	
Elasticity of scale			1.148***	0.012			0.889***	0.061			0.977***	0.029	0.944***	0.063
p-value const. ret. to scale			<0.001				3.3, 0.070				0.446		0.619	
R^2			0.861		0.869		0.327		0.329					
p-value coeff. jointly zero			<0.001		<0.001		<0.001		<0.001		<0.001		<0.001	
p-val. interact. terms jtly zero					<0.001				0.269					

*** (**, *) significant at the 1% (5%, 10%) level, based on standard errors robust to clustering in groups

Notes: Year dummies are included in all models. Standard errors in Olley/Pakes and Levinsohn/Petrin are based on bootstrapping with 20 replications.

Source: Authors.

Table A6. Results of production function estimations, Italy

	Output shares		**OLS** Cobb Douglas		**OLS** Translog		**'Within'** Cobb Douglas		**'Within'** Translog		**Olley/Pakes** Cobb Douglas		**Levinsohn/Petrin** Cobb Douglas	
	Mean	SD	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.874***	0.930	0.318***	0.012	-0.307**	0.151	0.097***	0.019	0.103***	0.012	0.283***	0.025	0.296***	0.016
Land	0.155***	0.184	-0.036***	0.009	0.127	0.119	0.314***	0.052	0.299***	0.028	-0.025	0.024	-0.046***	0.013
Materials	0.494***	0.271	0.712***	0.012	1.130***	0.154	0.497***	0.027	0.499***	0.016	0.778***	0.021	0.551***	0.080
Capital	0.190***	0.252	0.093***	0.009	-0.098	0.146	-0.024	0.027	-0.047***	0.016	0.062	0.053	0.015	0.037
N	5053		5053		5053		5053		5053		1413		5053	
Elasticity of scale			1.087***	0.009			.884***	0.056			1.098***	0.067	0.816***	0.073
p-value const. ret. to scale			<0.001				0.038				0.066		0.072	
R^2			0.846		0.857		0.348		0.350					
p-value coeff. jointly zero			<0.001		<0.001		<0.001		<0.001		<0.001		<0.001	
p-val. interact. terms jtly zero					<0.001				0.036					

Table A7. Results of production function estimations, Poland

	Output shares		**OLS** Cobb Douglas		**OLS** Translog		**'Within'** Cobb Douglas		**'Within'** Translog		**Olley/Pakes** Cobb Douglas		**Levinsohn/Petrin** Cobb Douglas	
	Mean	SD	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.252***	0.217	0.208***	0.014	-1.026***	0.332	0.151***	0.041	0.150***	0.029	0.229***	0.017	0.212***	0.019
Land	0.044***	0.028	0.008	0.012	0.590**	0.282	0.345***	0.062	0.348***	0.046	0.016	0.011	0.011	0.014
Materials	0.585***	0.199	0.740***	0.017	1.842***	0.375	0.378***	0.030	0.378***	0.021	0.680***	0.020	0.695***	0.045
Capital	0.058***	0.036	0.214***	0.012	-0.900***	0.344	-0.007	0.036	-0.007***	0.026	-0.123**	0.053	0.127**	0.056
N	3090		3090		3090		3090		3090		1916		3090	
Elasticity of scale			1.171***	0.012			0.867***	0.078			0.803***	0.103	1.045***	0.058
p-value const. ret. to scale			<0.001				0.087				0.001		0.580	
R^2			0.901		0.905		0.237		0.239					
p-value coeff. jointly zero			<0.001		<0.001		<0.001		0.001		<0.001		<0.001	
p-val. interact. terms jtly zero					0.227				0.368					

*** (**, *) significant at the 1% (5%, 10%) level, based on standard errors robust to clustering in groups

Notes: Year dummies are included in all models. Standard errors in Olley/Pakes and Levinsohn/Petrin are based on bootstrapping with 20 replications.

Source: Authors.

Table A8. Results of production function estimations, Slovakia

	Output shares		**OLS** Cobb Douglas		**OLS** Translog		**'Within'** Cobb Douglas		**'Within'** Translog		**Olley/Pakes** Cobb Douglas		**Levinsohn/Petrin** Cobb Douglas	
	Mean	SD	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.277***	0.346	-0.032	0.056	-0.525	0.527	-0.230*	0.127	-0.170*	0.097	-0.111	0.143	-0.104	0.076
Land	0.069***	0.084	-0.165**	0.081	0.550	0.800	0.537***	0.101	0.472***	0.102	-0.164	0.174	-0.150	0.133
Materials	0.892***	0.390	1.009***	0.086	0.639	0.850	0.439***	0.118	0.447***	0.116	1.067***	0.154	1.000***	0.150
Capital	0.141***	0.115	0.149***	0.041	0.955	1.006	0.025	0.064	0.006	0.055	-0.017	0.135	0.166	0.115
N	146		146		146		146		146		123		146	
Elasticity of scale			0.961***	0.028			0.771***	0.173			0.775***	0.137	0.911***	0.125
p-value const. ret. to scale			0.168				0.193				0.092		0.652	
R^2			0.939		0.951		0.594		0.601					
p-value coeff. jointly zero			<0.001		<0.001		<0.001		<0.001		<0.001		<0.001	
p-val. interact. terms jtly zero					0.530				0.458					

Table A9. Results of production function estimations, UK

	Output shares		**OLS** Cobb Douglas		**OLS** Translog		**'Within'** Cobb Douglas		**'Within'** Translog		**Olley/Pakes** Cobb Douglas		**Levinsohn/Petrin** Cobb Douglas	
	Mean	SD	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.297***	0.187	0.196***	0.021	0.169	0.211	0.237***	0.055	0.203***	0.028	0.211***	0.035	0.179***	0.036
Land	0.204***	0.097	0.082***	0.028	1.647***	0.319	0.347***	0.096	0.363***	0.050	0.085	0.064	0.076	0.046
Materials	0.741***	0.251	0.827***	0.030	-0.182	0.363	0.629***	0.072	0.562***	0.040	0.797***	0.063	0.828*	0.139
Capital	0.043***	0.030	0.065***	0.020	0.042	0.281	0.014***	0.029	-0.019	0.016	0.065	0.042	0.113***	0.064
N	807		807		807		807		807		703		807	
Elasticity of scale			1.170***	0.015			1.226***	0.085			1.158***	0.060	1.197***	0.101
p-value const. ret. to scale			<0.001				0.008				0.006		0.167	
R^2			0.910		0.915		0.589		0.579					
p-value coeff. jointly zero			<0.001		<0.001		<0.001		<0.001		<0.001		<0.001	
p-val. interact. terms jtly zero					0.397				<0.001					

*** (**, *) significant at the 1% (5%, 10%) level, based on standard errors robust to clustering in groups

Notes: Year dummies are included in all models. Standard errors in Olley/Pakes and Levinsohn/Petrin are based on bootstrapping with 20 replications.

Source: Authors.

Table A10. Results of the Blundell/Bond Cobb Douglas estimator, Denmark

	Production function estimates	
Unrestricted model	Coeff	SE
Labour	0.331*	0.198
- lagged	-0.120	0.161
Land	0.252*	0.153
- lagged	0.023	0.144
Materials	0.538***	0.153
- lagged	-0.151	0.179
Capital	0.118	0.143
- lagged	0.173**	0.084
Output lagged	0.071	0.124
p-val. coeff. jointly zero	<0.001	
Arellano-Bond test (1)	<0.001	
Arellano-Bond test (2)	0.620	
Hansen OID test	0.135	
Restricted model		
Labour	0.353**	0.151
Land	0.234*	0.134
Materials	0.536***	0.151
Capital	0.112**	0.053
ρ	0.137***	0.023
Elasticity of scale	1.239***	0.176
Common factors	0.988	

Diagnosis of model specification	**Labour**		**Land**		**Materials**		**Capital**		**Output**	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
AR(1) model	0.454*	0.25	0.532	0.32	0.476	0.52	0.36	0.5	0.884***	0.28
Instruments differences										
p-value coeff. jointly zero	<0.001		0.987		0.376		0.172		0.601	
R^2	0.305		<0.001		0.022		0.038		0.011	
Instruments levels										
p-value coeff. jointly zero	0.005		0.738		0.283		0.039		0.06	
R^2	0.111		0.007		0.028		0.069		0.061	

*** (**, *) significant at the 1% (5%, 10%) level

Notes: Year dummies are included in the production function and AR(1) models. In production function and AR(1) models, lags of order two back to the maximum possible are used as GMM-type instruments for the lagged dependent variable in the differenced equation using the two-step procedure. Lagged differences are used as GMM-type instruments for the lagged dependent variable in the level equation. First differences of year dummies are used as standard instruments in the production function. Standard errors are adjusted using the Windmeijer (2005) procedure. The minimum distance estimation stems from Söderbom (2009). 'Instruments differences' based on regression of the first difference for year=2006 on lagged levels three and four years back. 'Instruments levels' based on regression of the lagged level for year=2006 on lagged first differences two and three years back, using OLS.

Source: Authors.

Table A11. Results of the Blundell/Bond Cobb Douglas estimator, France

Production function estimates		
Unrestricted model	Coeff	SE
Labour	0.056	0.120
- lagged	-0.025	0.099
Land	-0.025	0.167
- lagged	-0.144	0.157
Materials	0.984***	0.151
- lagged	0.049	0.147
Capital	-0.031	0.073
- lagged	0.116**	0.056
Output lagged	0.098	0.081
p-val. coeff. jointly zero	<0.001	
Arellano-Bond test (1)	<0.001	
Arellano-Bond test (2)	0.226	
Hansen OID test	<0.001	
Restricted model		
Labour	0.083	0.064
Land	-0.007	0.106
Materials	0.940***	0.106
Capital	-0.049	0.066
ρ	0.193***	0.037
Elasticity of scale	0.983***	0.131
Common factors	0.766	

Diagnosis of model specification	Labour		Land		Materials		Capital		Output	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
AR(1) model	-0.062	0.34	0.887***	0.25	0.955***	0.2	0.859***	0.11	0.964***	0.25
Instruments differences										
p-value coeff. jointly zero	0.640		0.399		0.582		0.035		0.108	
R^2	0.010		0.015		0.011		0.034		0.026	
Instruments levels										
p-value coeff. jointly zero	<0.001		0.272		0.007		<0.001		<0.001	
R^2	0.119		0.018		0.045		0.176		0.096	

*** (**, *) significant at the 1% (5%, 10%) level

Notes: Year dummies are included in the production function and AR(1) models. In production function and AR(1) models, lags of order two back to the maximum possible are used as GMM-type instruments for the lagged dependent variable in the differenced equation using the two-step procedure. Lagged differences are used as GMM-type instruments for the lagged dependent variable in the level equation. First differences of year dummies are used as standard instruments in the production function. Standard errors are adjusted using the Windmeijer (2005) procedure. The minimum distance estimation stems from Söderbom (2009). 'Instruments differences' based on regression of the first difference for year=2008 on lagged levels three to seven years back. 'Instruments levels' based on regression of the lagged level for year=2008 on lagged first differences two to six years back, using OLS.

Source: Authors.

Table A12. Results of the Blundell/Bond Cobb Douglas estimator, Germany (East)

	Production function estimates	
Unrestricted model	Coeff	SE
Labour	-0.006	0.095
- lagged	0.027	0.087
Land	0.141	0.174
- lagged	-0.225	0.150
Materials	0.711***	0.110
- lagged	0.181	0.137
Capital	0.027	0.104
- lagged	-0.038	0.079
Output lagged	0.169**	0.069
p-val. coeff. jointly zero	<0.001	
Arellano-Bond test (1)	<0.001	
Arellano-Bond test (2)	0.232	
Hansen OID test	0.143	
Restricted model		
Labour	0.001	0.079
Land	0.123	0.110
Materials	0.738***	0.101
Capital	0.054	0.084
ρ	0.269***	0.034
Elasticity of scale	0.873***	0.227
Common factors	0.571	

Diagnosis of model specification	Labour		Land		Materials		Capital		Output	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
AR(1) model	0.978***	0.025	0.934***	0.079	0.937***	0.212	0.290	0.560	1.282***	0.357
Instruments differences										
p-value coeff. jointly zero	0.111		0.350		0.544		0.076		0.207	
R^2	0.165		0.107		0.078		0.183		0.135	
Instruments levels										
p-value coeff. jointly zero	<0.001		0.412		0.966		0.645		0.001	
R^2	0.567		0.097		0.019		0.066		0.358	

*** (**, *) significant at the 1% (5%, 10%) level

Notes: Year dummies are included in the production function and AR(1) models. In production function and AR(1) models, lags of order two back to the maximum possible are used as GMM-type instruments for the lagged dependent variable in the differenced equation using the two-step procedure. Lagged differences are used as GMM-type instruments for the lagged dependent variable in the level equation. First differences of year dummies are used as standard instruments in the production function. Standard errors are adjusted using the Windmeijer (2005) procedure. The minimum distance estimation stems from Söderbom (2009). 'Instruments differences' based on regression of the first difference for year=2008 on lagged levels three to seven years back. 'Instruments levels' based on regression of the lagged level for year=2008 on lagged first differences two to six years back, using OLS.

Source: Authors.

Table A13. Results of the Blundell/Bond Cobb Douglas estimator, Germany (West)

	Production function estimates	
Unrestricted model	Coeff	SE
Labour	0.119	0.123
- lagged	0.026	0.112
Land	-0.025	0.210
- lagged	-0.032	0.179
Materials	0.617***	0.091
- lagged	0.275**	0.125
Capital	0.121	0.106
- lagged	-0.002	0.100
Output lagged	0.053	0.097
p-val. coeff. jointly zero	<0.001	
Arellano-Bond test (1)	<0.001	
Arellano-Bond test (2)	0.068	
Hansen OID test	<0.001	
Restricted model		
Labour	0.115	0.095
Land	-0.022	0.079
Materials	0.605***	0.082
Capital	0.130*	0.050
ρ	0.101***	0.013
Elasticity of scale	0.831***	0.243
Common factors	0.989	

Diagnosis of model specification	Labour		Land		Materials		Capital		Output	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
AR(1) model	0.860***	0.117	0.929***	0.042	0.886***	0.091	1.042***	0.058	1.213***	0.109
Instruments differences										
p-value coeff. jointly zero	0.171		0.386		0.513		0.556		0.760	
R^2	0.041		0.028		0.023		0.021		0.014	
Instruments levels										
p-value coeff. jointly zero	<0.001		<0.001		<0.001		<0.001		<0.001	
R^2	0.281		0.179		0.1835		0.232		0.171	

*** (**, *) significant at the 1% (5%, 10%) level

Notes: Year dummies are included in the production function and AR(1) models. In production function and AR(1) models, lags of order two back to the maximum possible are used as GMM-type instruments for the lagged dependent variable in the differenced equation using the two-step procedure. Lagged differences are used as GMM-type instruments for the lagged dependent variable in the level equation. First differences of year dummies are used as standard instruments in the production function. Standard errors are adjusted using the Windmeijer (2005) procedure. The minimum distance estimation stems from Söderbom (2009). 'Instruments differences' based on regression of the first difference for year=2008 on lagged levels three to seven years back. 'Instruments levels' based on regression of the lagged level for year=2008 on lagged first differences two to six years back, using OLS.

Source: Authors.

Table A14. Results of the Blundell/Bond Cobb Douglas estimator, Italy

	Production function estimates	
Unrestricted model	Coeff	SE
Labour	-0.086	0.059
- lagged	0.308***	0.086
Land	-0.237	0.182
- lagged	0.035	0.176
Materials	0.727***	0.105
- lagged	0.000	0.092
Capital	0.077	0.107
- lagged	-0.015	0.084
Output lagged	0.134***	0.059
p-val. coeff. jointly zero	<0.001	
Arellano-Bond test (1)	<0.001	
Arellano-Bond test (2)	0.599	
Hansen OID test	<0.001	
Restricted model		
Labour	-0.069	0.058
Land	-0.211***	0.076
Materials	0.664***	0.081
Capital	0.116	0.075
ρ	0.235***	0.027
Elasticity of scale	0.482**	0.198
Common factors	0.428	

Diagnosis of model specification	Labour		Land		Materials		Capital		Output	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
AR(1) model	0.726***	0.202	1.007***	0.053	0.525	0.330	0.985***	0.023	1.242**	0.50
Instruments differences										
p-value coeff. jointly zero	0.086		0.839		0.206		0.617		0.873	
R^2	0.466		0.126		0.374		0.205		0.111	
Instruments levels										
p-value coeff. jointly zero	0.1753		0.275		0.546		0.007		0.712	
R^2	0.393		0.337		0.230		0.651		0.173	

*** (**, *) significant at the 1% (5%, 10%) level

Notes: Year dummies are included in the production function and AR(1) models. In production function and AR(1) models, lags of order two back to the maximum possible are used as GMM-type instruments for the lagged dependent variable in the differenced equation using the two-step procedure. Lagged differences are used as GMM-type instruments for the lagged dependent variable in the level equation. First differences of year dummies are used as standard instruments in the production function. Standard errors are adjusted using the Windmeijer (2005) procedure. The minimum distance estimation stems from Söderbom (2009). 'Instruments differences' based on regression of the first difference for year=2008 on lagged levels three to seven years back. 'Instruments levels' based on regression of the lagged level for year=2008 on lagged first differences two to six years back, using OLS.

Source: Authors.

Table A15. Results of the Blundell/Bond Cobb Douglas estimator, UK

	Production function estimates	
Unrestricted model	Coeff	SE
Labour	0.318***	0.074
- lagged	-0.193**	0.085
Land	0.483**	0.233
- lagged	-0.247	0.217
Materials	0.727***	0.117
- lagged	-0.025	0.161
Capital	0.059	0.062
- lagged	-0.037	0.060
Output lagged	0.107	0.093
p-val. coeff. jointly zero	<0.001	
Arellano-Bond test (1)	<0.001	
Arellano-Bond test (2)	0.648	
Hansen OID test	0.916	
Restricted model		
Labour	0.313***	0.070
Land	0.471***	0.109
Materials	0.684***	0.081
Capital	0.049	0.050
ρ	0.187***	0.029
Elasticity of scale	1.586	0.196
Common factors	0.920	

Diagnosis of model specification	Labour		Land		Materials		Capital		Output	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
AR(1) model	0.812***	0.255	0.929***	0.062	1.344***	0.328	0.902***	0.130	1.194***	0.232
Instruments differences										
p-value coeff. jointly zero	0.379		0.646		0.015		0.653		0.355	
R^2	0.402		0.276		0.747		0.273		0.414	
Instruments levels										
p-value coeff. jointly zero	0.186		0.206		0.719		0.194		0.152	
R^2	0.516		0.502		0.241		0.511		0.543	

*** (**, *) significant at the 1% (5%, 10%) level

Notes: Year dummies are included in the production function and AR(1) models. In production function and AR(1) models, lags of order two back to the maximum possible are used as GMM-type instruments for the lagged dependent variable in the differenced equation using the two-step procedure. Lagged differences are used as GMM-type instruments for the lagged dependent variable in the level equation. First differences of year dummies are used as standard instruments in the production function. Standard errors are adjusted using the Windmeijer (2005) procedure. The minimum distance estimation stems from Söderbom (2009). 'Instruments differences' based on regression of the first difference for year=2008 on lagged levels three to seven years back. 'Instruments levels' based on regression of the lagged level for year=2008 on lagged first differences two to six years back, using OLS.

Source: Authors.

Comparative Analysis of Factor Markets for Agriculture across the Member States

245123-FP7-KBBE-2009-3

The Factor Markets project in a nutshell

Title	Comparative Analysis of Factor Markets for Agriculture across the Member States
Funding scheme	Collaborative Project (CP) / Small or medium scale focused research project
Coordinator	CEPS, Prof. Johan F.M. Swinnen
Duration	01/09/2010 – 31/08/2013 (36 months)
Short description	Well functioning factor markets are a crucial condition for the competitiveness and growth of agriculture and for rural development. At the same time, the functioning of the factor markets themselves are influenced by changes in agriculture and the rural economy, and in EU policies. Member state regulations and institutions affecting land, labour, and capital markets may cause important heterogeneity in the factor markets, which may have important effects on the functioning of the factor markets and on the interactions between factor markets and EU policies. The general objective of the FACTOR MARKETS project is to analyse the functioning of factor markets for agriculture in the EU-27, including the Candidate Countries. The FACTOR MARKETS project will compare the different markets, their institutional framework and their impact on agricultural development and structural change, as well as their impact on rural economies, for the Member States, Candidate Countries and the EU as a whole. The FACTOR MARKETS project will focus on capital, labour and land markets. The results of this study will contribute to a better understanding of the fundamental economic factors affecting EU agriculture, thus allowing better targeting of policies to improve the competitiveness of the sector.
Contact e-mail	info@factormarkets.eu
Website	www.factormarkets.eu
Partners	17 (13 countries)
EU funding	1,979,023 €
EC Scientific officer	Dr. Hans-Jörg Lutzeyer