IDENTIFYING FACTOR PRODUCTIVITY BY DYNAMIC PANEL DATA AND CONTROL FUNCTION APPROACHES: A COMPARATIVE EVALUATION FOR EU AGRICULTURE

Martin Petrick and Mathias Kloss

Leibniz Institute of Agricultural Development in Central and Eastern Europe (IAMO),

Halle (Saale)

petrick@iamo.de

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Summary

The classical problem of agricultural productivity measurement has regained interest due 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 alternative identification strategies for the case of agriculture and test two related, innovative estimators using farm-level panel datasets from seven EU countries. The 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 in 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 that improving the availability of working capital is the most promising way to increase agricultural productivity.

Keywords

Agricultural factor productivity, production function estimation, EU, Farm Accountancy Data Network.

1 Introduction

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 attention of the global media (e.g. PARKER 2011). 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 there is a *continuous relationship* between inputs and output – the production function (COBB and DOUGLAS 1928). Taken this idea for granted, the old question has been raised whether statistical methods exist that can identify each factors' contribution 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 do affect its outcomes. How their influence could be separated from the more tangible inputs is the core of the current debate. It is of key importance for understanding how agricultural productivity could be increased.

Two issues were 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 classic *endogeneity problem* has again moved 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 whether the typical identifying assumptions underlying production function estimation are sufficient 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 independent variation of factors in the first place.

In the present paper, we review the central identifying assumptions maintained by traditional and recent approaches to the estimation of production functions, apply them to an extensive dataset from the EU Farm Accountancy Data Network (FADN) and ask how plausible they are in an agricultural context. The focus here is on the recently proposed dynamic panel data estimator by BLUNDELL and BOND (2000) as well as the control function approaches by OLLEY and PAKES (1996) and LEVINSOHN and PETRIN (2003). All models were estimated assuming a Cobb Douglas technology. We also explore a Translog technology. Our methodological contribution is that we provide the first comparative evaluation of two 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.

Our results 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), who find 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. In the conceptual part, we argue that both the BLUNDELL/BOND and LEVINSOHN/PETRIN estimators provide more plausible identification strategies than 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 the latter failed to produce reasonable results for the fixed inputs in most of our subsamples. There is hence a trade-off among theoretical plausibility and empirical robustness of the different identification strategies.

In the following section 2, we discuss the key identification problems in production function estimation as well as the four main assumptions invoked in the literature to address them. Section 3 briefly 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 Two problems of identification

To illustrate the involved methodological problems, 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. ε_{it} is a productivity shock not anticipated by the farmer, or simply measurement error. Assuming a linear structure of the model and the availability of panel data, the econometrician's problem is to recover farm productivity determined by the following equation:

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

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, as 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. 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. The typical assumption in the literature (e.g. CHAMBERS 1988) is then that output and all factors are traded on perfectly competitive markets so that on each of the markets all farmers face the same one price for the traded good. If farmers maximise profits defined as revenues from the sale of output minus 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 recently by BOND and SÖDERBOM (2005) and ACKERBERG et al. (2007). Factor use across firms varies only with the unobserved ω_{it}, so that again the different production elasticities are not identified.

We now review four main approaches found in the literature to deal with either of these identification problems. 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.

2.2 Additively separable, time-invariant firm characteristics

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

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

where γ_t is a time-specific shock that is identical for all farms in t, η_i is a farm-specific fixed effect that does not vary over time, and v_{it} is the remaining farm- and time-specific productivity shock. 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 $X \in \{A, L, K, M\}$. Applying the usual 'within' transformation, the fixed effect η_i is "swept out" of the equation. Introduced by MUNDLAK (1961) in a farming context to eliminate "management bias", 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.

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 whether it is feasible to assume that v_{it} is an innovation that is orthogonal to observed factor use so that all unobserved factors are indeed either time invariant or the same for all farms. Furthermore, empirical applications have found that the within transformation removes (too) much variance from some of the variables, particular those which exhibit little variation over time (GRILICHES and MAIRESSE 1998, 180-185). As a consequence, the signal-to-noise ratio of 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.

2.3 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 (for the case of materials):

$$\frac{\partial f}{\partial M}\frac{M}{Y} = \frac{p^M M}{p^Y Y}. \tag{4}$$

If one further assumes constant returns to scale, (4) 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. However, production function estimates of elasticities in agriculture were often 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, (4) has led to the widely applied share regression model. For example, if the production function is assumed to be Translog, the first order condition yields the following *share regression* (again for the case of materials):

$$s_{it}^M = \alpha^M + \alpha^{MM} m_{it} + \alpha^{MA} a_{it} + \alpha^{ML} l_{it} + \alpha^{MK} k_{it} + \omega_{it}^M + \varepsilon_{it}^M, \tag{5}$$

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 involved inputs, 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.

Note that (5) is still subject to the endogeneity and collinearity of factors. The way out of these problems typical to this approach is finding appropriate instruments for the input levels. The most natural candidates are factor prices, which were used to estimate systems of share equations like (5) by instrumental variable methods. 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 be exogenous to the decision problem of the farmer. This condition is usually ensured by the assumption of perfectly competitive markets on which atomistic agents are price takers. In agriculture, it may hold for a number of output markets, but is very unlikely to prevail on most factor markets. For example, land 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). Under such conditions, the theoretical model underlying this approach is clearly too simplistic to allow straightforward identification of the production function. This criticism also tends to apply to the large body of literature on stochastic frontier modeling (COELLI et al. 2005), which by and large neglects the identification issues raised here.[1]

On the other hand, if factor markets were at least approximately working as postulated by the theoretical ideal, there should be little price variation across farms so that the value of prices for solving the endogeneity and collinearity problems is doubtful; empirical findings support this view (GRILICHES and MAIRESSE 1998, 189). With regard to agricultural labour or land, it may be hard to find appropriate price series at all.

2.4 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 are past decisions on factor use (ARELLANO and BOND 1991; BLUNDELL and BOND 1998). This literature argues that 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 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:

$$v_{it} = \rho v_{it-1} + e_{it}, \text{ with } |\rho| < 1, \tag{6}$$

where ρ denotes the autoregressive parameter and e_{it} an independent mean zero innovation. Substituting (6) and (3) into (1), BLUNDELL and BOND (2000) suggest a dynamic production function specification that can be estimated with a *dynamic panel data estimator*:

$$y_{it} = \sum_X (\alpha^X x_{it} - \alpha^X \rho x_{it-1}) + \rho y_{it-1} + (\gamma_t - \rho\gamma_{t-1}) + (1-\rho)\eta_i + \varepsilon_{it}^*. \tag{7}$$

Alternatively, this model can be written as:

$$y_{it} = \sum_X \pi^{1X} x_{it} + \sum_X \pi^{2X} x_{it-1} + \pi^3 y_{it-1} + \gamma_t^* + \eta_i^* + \varepsilon_{it}^*, \tag{8}$$

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 (7). 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, 545-547) to test whether the parameters estimated by the unrestricted model (7) conform with the restrictions imposed by (8).

Note that the within transformation (section 2.2) assumes *strict* exogeneity of inputs which means that ω_{it} must not be transmitted to any future period (contrary to what is assumed in (6)). First differencing to eliminate fixed effects only assumes that input levels are *sequentially* exogeneous, i.e. transmission of ω_{it} to the next but one and subsequent periods is allowed (CHAMBERLAIN 1982; WOOLDRIDGE 2010, 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.

[1] 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 desribed in subsequent sections. The empirical interest was often no longer on recovering factor productivities, however.

This leads to the systems GMM estimator for production functions presented in BLUNDELL and BOND (2000).

Furthermore, in purging the fixed effects we rely on the assumption of linear addivity of the same (ANGRIST and PISCHKE 2009, 222). Hence, there is no straightforward implementation of flexible functional forms that involve interactions of the inputs.

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 2.3, it is much more plausible that the instruments proposed here are actually valid in an agricultural context. There are important production factors in agriculture which are subject to adjustment costs 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, 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 such as seed, fertiliser, plant protection, concentrate, or energy that factor use appears to be more flexible so that the assumption of adjustment costs may be harder to justify. In sum, this estimator is a promising candidate for agricultural applications.

2.5 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. However, it also does not rely on the strong a-priories about market structure of duality theory to identify the productivity parameters of interest. It rather attempts to proxy ω_{it} 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}:

$$i_{it} = i_t(\omega_{it}, k_{it}), \tag{9}$$

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:

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

where h_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 uncorrelated with k_{it}, but possibly correlated with highy variable factors (e.g. seed) in the production function. 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 factors. Their elasticities are determined in the *first stage* by substituting $h(.)$ into the production function and estimating:

$$y_{it} = \alpha^A a_{it} + \alpha^L l_{it} + \alpha^M m_{it} + \phi_t(i_{it}, k_{it}) + \varepsilon_{it}, \tag{10}$$

where $\phi_t = \alpha^K k_{it} + h_t(i_{it}, k_{it})$. In practice, ϕ_t is approximated by a higher order polynomial of *i* and *k* which controls for ω_{it}. (10) shows that ϕ_t is assumed to be additively separable from the remaining variable inputs. Flexible functional forms 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.[2] 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 fully variable factor and thus part of the production function. However, in the LEVINSOHN/PETRIN approach, its elasticity cannot be estimated in the first stage, as it is now part of $h(.)$. 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. However, 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 such as management effort or reaction to 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 "memoryless" first-order Markov process appears unconvincing if ω_{it} actually represents unobserved factors which 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 (9) 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 and/or the availability of a farm successor.

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 fully variable 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.

[2] This is the algorithm used in 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.

Notice that the assumption of costly factor adjustment is a cornerstone of both the dynamic panel data approach described in section 2.4 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 light of agricultural applications, this may be one key advantage of the dynamic panel data approach.[3]

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 often have also 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 particular 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 aim to fill this void.

3 Data

The data used in this study is from the EU’s FADN. It provides a stratified farm level data set that holds accountancy data for 25 of the 27 EU member states. The stratification criteria are region, economic size and 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. We produce separate results for the following countries: Denmark (DK), France (FR), East Germany (DEE), West Germany (DEW), Italy (IT), Poland (PL), Slovakia (SK) and the United Kingdom (UK). The member states selected for this study include major agricultural producers and reflect the diverse agricultural finance structures (PETRICK and KLOSS 2013a). We use a data panel for the years 2001-2008, for PL and SK from 2004. For a detailed description of the data see PETRICK AND KLOSS (2013b).

4 Results

Table 1 lists the estimated Cobb Douglas production elasticities for the BLUNDELL/BOND and LEVINSOHN/PETRIN estimators.[4] Extensive results for the performed estimates as well as for OLS and ‘within’ models and their economic interpretation are available in PETRICK AND KLOSS (2013b). For Poland and Slovakia, the dynamic panel data model could not be estimated due to a lack of data. As a general tendency, factor elasticities were found to be low for labour, land and capital, and high for materials. 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 0.6 and 1.0.

Elasticities of the persistent factors labour, land and capital could often not be identified by the BLUNDELL/BOND estimator. Parameters were very sensitive to the selection of the sample and the precise specification of the estimator. On the other hand, the estimates for materials appear very reasonable throughout, as they were typically lying somewhere between OLS and

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

[4] For details regarding the empirical implementation of these estimastors see PETRICK and KLOSS (2013b).

‘within’ results (not shown). It is here where the BLUNDELL/BOND estimator can likely claim some superiority.

Compared with the benchmark OLS, LEVINSOHN/PETRIN produces a lower elasticity for materials in some cases (West Germany, Italy, Poland). 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.

Estimated elasticities of scale fluctuate around 1.0, with higher values for Denmark and the United Kingdom. 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.

Table 1: Production Elasticities in comparison

		DK	**FR**	**DEE**	**DEW**	**IT**	**PL**	**SK**	**UK**
Labour	BB	0.35	0.08#	0.00#	0.12#	-0.07#	-	-	0.31
	LP	0.45	0.18	0.04#	0.23	0.30	0.21	-0.10#	0.18
Land	BB	0.23	-0.01#	0.12#	-0.02#	-0.21	-	-	0.47
	LP	0.18	-0.05	-0.13	-0.06	-0.05	0.01#	-0.15#	0.08#
Materials	BB	0.54	0.94	0.74	0.61	0.66	-	-	0.68
	LP	0.63	0.83	1.00	0.64	0.55	0.70	1.00	0.83
Capital	BB	0.11	-0.05#	0.05#	0.13	0.12#	-	-	0.05#
	LP	0.12	0.11	0.15#	0.13	0.02#	0.13	0.17#	0.11
Ret. to scale	BB	1.24	0.98	0.87	0.83	0.48	-	-	1.59#
	LP	1.38	1.06	1.06	0.94	0.82	1.05	0.91	1.20

Notes: Results for field crop farms in EU countries based on Blundell/Bond (BB) and Levinsohn/Petrin (LP) estimator. # not significantly different from zero at 10% confidence level.
Source: authors.

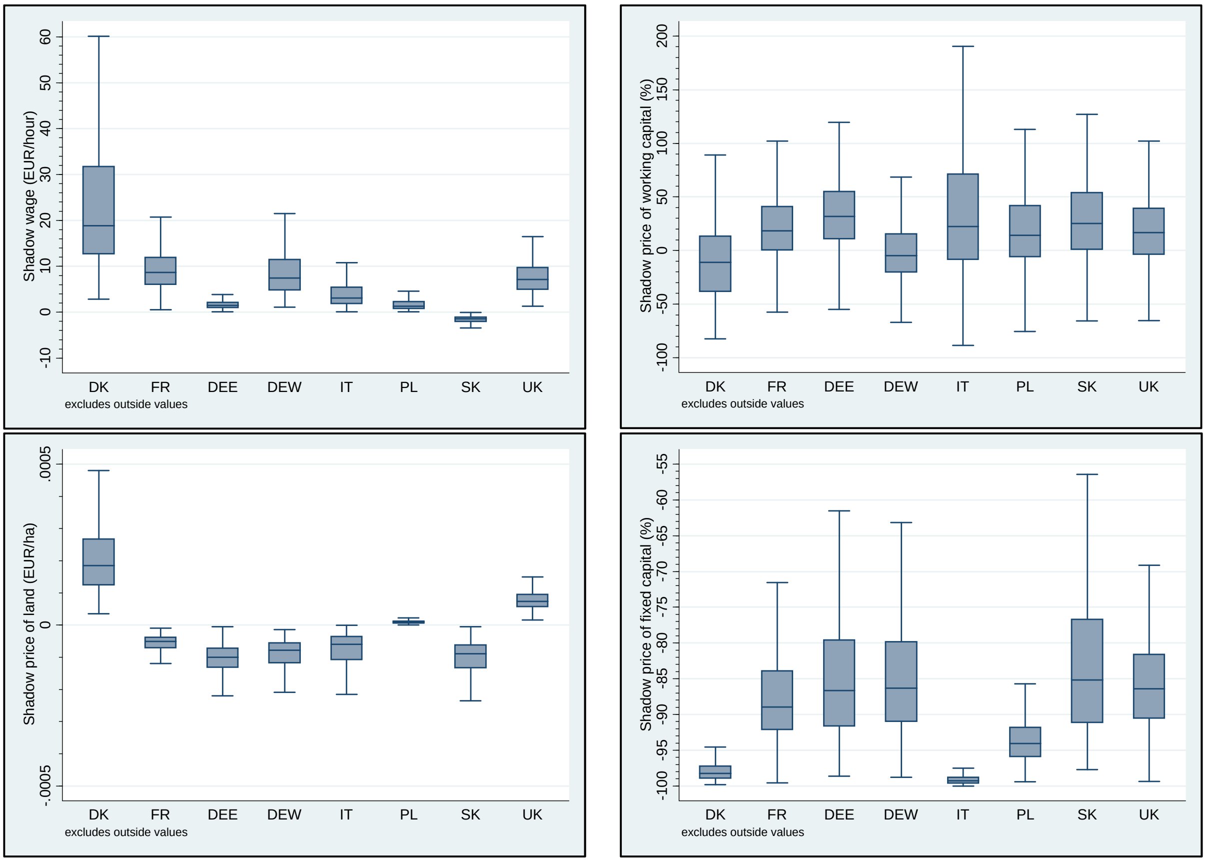
Estimates of Translog specifications (not shown) displayed remarkably uniform features across countries. The OLS Translog produced unreasonable results throughout, e.g. reflected in the coexistence of negative production elasticities for some factors and elasticities bigger than one for others (at sample 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.

To ease the economic interpretation of the findings, we computed farm-individual shadow prices for all farms used in the estimations. To this end, we multiplied the production elasticities obtained from the LEVINSOHN/PETRIN estimator (Table 1) 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, 2). The distribution of the shadow prices for the four factors and the eight subsamples is illustrated in Figure 1 by using box plots.

The shadow prices of the factors labour, land and fixed capital tend to be quite low. The median shadow wage in agriculture is below 9 EUR/hour in France, West Germany and the UK; in East Germany, Italy and Poland it is below 2 EUR/hour and in Slovakia even negative. Denmark stands out with a value of almost 20 EUR/ha. Shadow land rents are only minimally different from zero throughout. Shadow prices of fixed capital are negative in all subsamples. There is considerable variation for some of the subsamples and outside values beyond the adjacent values were not displayed.

Median shadow interest rates of materials 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. For further insights regarding the matter of credit constraints we refer to PETRICK and KLOSS (2013a).

Figure 1: Distribution of shadow prices per country



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

5 Conclusions

In light of the comprehensive literature on adjustment frictions on rural land, labour and capital markets, we regard the presence of adjustment costs as particular 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.

Our LEVINSOHN/PETRIN estimation appeared to correct the upward bias inherent in OLS regression of production functions and may be taken as an easy-to-implement alternative to the received estimators. However, given the conceptual problems in identifying the supposedly flexible inputs labour and land, this is only a second-best choice. The BLUNDELL/BOND estimator could be implemented with sufficiently long panels, but did not always perform satisfactorily. 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 mostly above 0.6. As a consequence, shadow prices for the three fixed factors are also very low. A further reduction in the use of fixed factors in EU crop farming may be necessary to bring returns up to factor remuneration in other sectors. However, the shadow return on working capital is often above typical market interest rates for capital. This finding suggests that credit rationing is an issue on agricultural finance markets in the EU, particularly with regard to short-term lending.

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 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 in 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 as due to LEVINSOHN and PETRIN (2003) represent an interesting alternative for agricultural applications.

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