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Identifying factor productivity from micro-data: the case of EU agriculture

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ABSTRACT

We examine the plausibility of four established and innovative identification strategies for agricultural production functions using farm-level panel datasets from five EU countries. Newly suggested proxy and dynamic panel approaches provide attractive conceptual improvements over received Within and duality models. Even so, empirical implementation of such advancements 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, high production elasticities for materials prevail. Hence, improving the availability of working capital is the most promising way to increase agricultural productivity.

JEL codes: C13, C23, D24, Q12

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

ZUSAMMENFASSUNG

Die Identifizierung von Faktorproduktivitäten auf der Basis von Mikrodaten: das Beispiel des EU Agrarsektors

Auf der Grundlage von einzelbetrieblichen Paneldatensätzen aus fünf EU Ländern untersuchen wir die Plausibilität von vier etablierten und innovativen Identifikationsstrategien für landwirtschaftliche Produktionsfunktionen. Die in jüngerer Zeit vorgeschlagenen Proxy- und dynamischen Panel-Ansätze bieten aussichtsreiche konzeptionelle Verbesserungen gegenüber herkömmlichen „Within“ und Dualitätsmodellen. Die empirische Umsetzung dieser Weiterentwicklungen erfüllt jedoch nicht immer die Erwartungen. Dies trifft besonders auf den dynamischen Panel-Schätzer zu, dem es überwiegend nicht gelang, glaubwürdige Elastizitäten für die (quasi-) fixen Faktoren zu identifizieren. Weniger anspruchsvolle Proxy-Ansätze stellen eine interessante Alternative für landwirtschaftliche Anwendungen dar. In unserer EU Stichprobe fanden wir überwiegend hohe Produktionselastizitäten für Betriebsmittel. Die Verbesserung der Verfügbarkeit von Betriebsmittelkrediten erscheint daher als vielversprechender Weg, um die landwirtschaftliche Produktivität zu erhöhen.

JEL Codes: C13, C23, D24, Q12

Schlüsselwörter: Landwirtschaftliche Faktorproduktivität, Schätzung von Produktionsfunktionen, EU, Testbetriebsnetz

TABLE OF CONTENT

LIST OF TABLES

LIST OF TABLES IN APPENDIX

LIST OF FIGURES IN APPENDIX

1 Introduction[1]

In recent years, 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. Taken this idea for granted, the old question has been raised whether statistical methods exist that can identify how much the various factors actually contribute to the joint product. As was recognized early by MARSCHAK and ANDREWS (1944), real world production does not occur in an experimental setting, and unobserved factors such as managerial abilities or unexpected weather shocks do affect its outcomes. How their influence could be separated from the more tangible inputs such as land, labor 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 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 *endogeneity problem*, albeit a classical one, has again moved centre stage after OLLEY and PAKES (1996) (OP) 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 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 independent variation of factors in the first place. WOOLDRIDGE (2009) tried to solve both problems simultaneously by adopting and refining the OLLEY and PAKES (1996) identification strategy.

In the present paper, we take the various methodological approaches to an extensive panel dataset on European agriculture and scrutinize 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 (Within) regression, (4) the dynamic panel data estimator by BLUNDELL and BOND (2000) (BB) as well as the control function approach by (5) LEVINSOHN and PETRIN (2003) (LP) and (6) its WOOLDRIDGE (2009) extension (WLP). All models were estimated under the assumption of a Cobb Douglas technology. For models (2), (3) and (6), we also explore a Translog technology, so that in total nine 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 five firm-level datasets at the EU country level.

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[1] This Discussion Paper serves as an extended background paper to PETRICK and KLOSS (forthcoming). Financial support under the EU’s 7th Research Framework Programme within the project "Factor Markets" Grant agreement N°: 245123-FP7-KBBE-2009-3 (www.factormarkets.eu) is gratefully acknowledged. We also thank two anonymous referees for their helpful comments during the review process. An earlier version was published as a Factor Markets working paper in January 2013.

Recently, there has been considerable research activity on new approaches in production function estimation and there have been comparative evaluations on such approaches using simulated data (cf. Van Biesebroeck, 2007). If estimator developers provide empirical applications at all, they do so from highly specific contexts. 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 was later also utilized by Ackerberg et al. (2006). Kasahara and Rodrigue (2008) take this Chilean data as a basis for various panel data estimators including dynamic panel and proxy approaches.[2] 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 politically highly relevant dataset.

Our European database covers firm-level data from all EU member states that was collected following a harmonized 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. This extensive data allows us to come up with new, country-specific estimates of production elasticities in agriculture that are potentially robust to endogeneity and collinearity issues. 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 far from being without methodological problems. One key expectation from duality was that it would allow a more flexible representation of technology, such as 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 and Wooldridge (2009) case, the results were highly implausible, whereas they differed little from the Cobb Douglas for the Within panel estimator.

Our empirical estimates suggest that output elasticities of labor, 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, around 0.7. This outcome is particularly prominent in the LP, WLP and BB estimators. In the conceptual part, we argue that these estimators provide more plausible identification strategies than established Within or duality approaches. While the one-period control function models of LP and WLP are easier to implement empirically, the multiperiod adjustment process implied by the BB model is more compelling in an agricultural context. But BB failed to produce reasonable results for the fixed variables in most of our country subsamples.

[2] Other authors explore subsets of models that interest us here. Hempell (2005) investigates German service firms and focuses on dynamic panel data models. Van Biesebroeck (2008) compares the OP approach with envelope and frontier models, using data on manufacturing firms from Colombia and Zimbabwe. The distinct literature studying frontier models has just recently begun to address endogeneity concerns (Amsler et al., 2016), including an application to dairy farms in the EU (Latruffe et al. 2017).

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 that have motivated 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 for the different 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, fertilizer 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 organized in family farms on which labor 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 characterized by rationing and high transaction costs (see e.g. Benjamin and Phimister, 2002; Petrick and Latruffe, 2006). Management has long been recognized 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 geographic location of the farm or the quality of its soils (type III and VI factors). All the less variable factors type 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 type 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). However, how the farmer reacts to these shocks will be endogenous (type IV factors).

Table 1. A typology of production factors in agriculture

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

Source: Authors.

2.2 Two problems of identification

To illustrate the involved 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} labor, 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 categorized as type 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 $f(\cdot)$ 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 $f(\cdot)$ 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: 332). A typical OLS result may be that the coefficients of labor and materials are upward biased, while those of land and capital are downward biased, although the opposite may occur as well (Geylani and Stefanou, 2013: 168). 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 belonged 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 so that on each of the markets all farmers face the same one price for the traded good. If farmers maximize profits defined as revenues from the sale of output minus costs of all inputs and (·) 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 $f(\cdot)$ 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.

Table 2. Identifying assumptions in production function estimation

	(A) ω_{it} **is additively separable & time invariant**	**(B) Profit maximization & 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.	Yes if adjustment costs are sufficiently heterogeneous across inputs.	Not without further assumptions (ACKERBERG et al. 2015; WOOLDRIDGE 2009).
Practical implementation	"Within" regression to sweep out 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.
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 labor, land & capital markets are widespread in agriculture.	Plausible for land, labor, fixed capital, less for seed, fertilizer, plant protection, concentrate, energy.	Plausible for annually fluctuating shocks, less for slowly changing unobservables such as soil or management quality.
Examples in the literature	Widely used. See MUNDLAK (1961); overview in GRILICHES & MAIRESSE (1998).	Widely used. See 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, PETRIN and LEVINSOHN (2012); RIZOV et al. (2013) on EU-15.

Source: Authors.

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 summarizes 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.

2.3 Additively separable, time-invariant firm characteristics

The key idea of this approach is that can be further decomposed into:

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

where y_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 y_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 as $y_{it} = \alpha^A a_{it} + \alpha^L L_{it} + \alpha^K k_{it} + \alpha^M m_{it} + y_t + \eta_i + \varepsilon_{it}$, 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 the 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 y_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: 321-326).

Mundlak et al. (2012: 146) present a recent application to agricultural productivity at the country level where the fixed and year effects alone explained 98.5% of output variation. Even so, the question remains whether it is legitimate 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. 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, particular those which display little variation over time. In agriculture, input levels of the type II production factors land, labor and fixed capital often vary only 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 Mairesse, 1998: 180-185). Finally, without further assumptions, the collinearity problem is not addressed at all by this approach.

2.4 Profit maximization and perfect competition

This approach imposes further microeconomic theory upon the data, including its main assumptions of profit maximization 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):

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

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. 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). 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 $s_{it}^M = \dfrac{p_{it}^M M_{it}}{p_{it}^Y Y_{it}}$ 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 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 to 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 characterized by spatial oligopolies and strong government regulation in many European countries (Huettel and Margarian, 2009; Ciaian, et al. 2012). As noted before, agricultural labor is usually very immobile due to life-cycle considerations and specific human capital. Agricultural credit may be due to a rationing regime that depends on the credit history of the farmer. Hence, factor prices may not be exogenous and may depend on 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.[3]

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. 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 generating 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: 189). With regard to agricultural labor 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, which is based on the literature on dynamic panel data modeling, are past decisions on factor use (Arellano and Bond, 1991; Blundell and Bond, 1998). This literature suggests 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 (type II) and makes them subject to an intertemporal optimization 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:

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

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

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

Alternatively, this model can be written as:

$$y_{it} = \sum_X \pi^{1X} x_{it} + \sum_X \pi^{2X} x_{it-1} + \pi^3 y_{it-1} + \gamma^*_t + \eta^*_i + \varepsilon^*_{it}, \tag{9}$$

[3] 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.

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: 545-547) 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* exogeneous, i.e. transmission of ω_{it} to the next but one and subsequent periods is allowed (Chamberlain, 1982; Wooldridge, 2010: 321-326). 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 they are orthogonal to the fixed effects (η_i) – an assumption which will hold if their variance is assumed to be, in the broadest sense, stationary (Roodman, 2009: 114-115). 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 which 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 favorable condition for identification (Bond and Söderbom; 2005). It is only with regard to some intermediate inputs such as seed, fertilizer, 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 (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. 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} (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}:

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

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 – δ) k_{it} + i_{it}, with δ the depreciation rate.

The function $i_t(\cdot)$ 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:

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}] + \xi_{it}, \tag{11}$$

where ξ_{it} is an innovation (a type VII factor) uncorrelated with k_{it}, but possibly correlated with the other 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 $h(\cdot)$ into the production function and estimating:

$$y_{it} = \alpha^A a_{it} + \alpha^L l_{it} + \alpha^M m_{it} + \phi_t(i_{it}, k_{it}) + \varepsilon_{it}, \tag{12}$$

where $\phi_t = \alpha^k k_{it} + h_t\,(i_{it}, k_{it})$. In practice, ϕ_t is approximated by a low-order polynomial of *i* and *k* which controls for ω_{it}. (12) shows that 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 $\widehat{\omega}_{it}$ 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.[4] In their original application to the US telecommunications equipment industry, OLLEY and PAKES (1996) show how this procedure yields lower labor coefficients than OLS and higher capital coefficients than Within. In an agricultural application, KAZUKAUSKAS et al. (2010) found for Irish dairy farms that the materials coefficient estimated with an OP procedure was lower than the OLS result.

4 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.

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. However, in the LP approach, its elasticity cannot be estimated in the first stage, as it is now part of $h(\cdot)$. Therefore, the additional moment condition $E[m_{-it1}\xi_{it}] = 0$ is postulated to obtain α^k 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 (type IV) 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 (fertilizer, 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 type V factors which are subject to adjustment costs. They evolve slowly and will typically have implications for the intertemporal optimization 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 and/or the availability of a farm successor.

Another problem with the procedure suggested by OP and LP is that it does not solve the collinearity problem. As discussed at length by ACKERBERG et al. (2015), 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. (2015) 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. WOOLDRIDGE (2009) suggests a simple procedure that borrows the identification strategy from OP and LP and modifies as well as extends the moment conditions to resolve the collinearity problem. Hence, this approach is referred to as the WOOLDRIDGE/LEVINSOHN/PETRIN (WLP) estimator (PETRIN and LEVINSOHN, 2012). Unlike LP, WOOLDRIDGE (2009) assumes that ε_{it} is orthogonal not only to current but also all past values of a, l, k and m. In practical implementation, only current realizations and one lag of the inputs are assumed to be uncorrelated with the ε_{it}. Moreover, the innovation ξ_{it} is assumed to be uncorrelated with current and past realizations of k and past realizations of a, l and m. Now, the problem can be formulated in terms of two equations. The first is given by:

$$y_{it} = \alpha^A a_{it} + \alpha^L l_{it} + \alpha^K k_{it} + \alpha^M m_{it} + h(m_{it}, k_{it}) + \varepsilon_{it}. \tag{13}$$

The second can be obtained by plugging $\omega_{it} = g[h(m_{it-1}, k_{it-1})] + \xi_{it}$, into the production function, with $g(\cdot)$ a an unknown productivity function:

$$y_{it} = \alpha^A a_{it} + \alpha^L l_{it} + \alpha^K k_{it} + \alpha^M m_{it} + g[h(m_{it-1}, k_{it-1})] + e_{it}, \tag{14}$$

where $e_{it} = \xi_{it} + \varepsilon_{it}$. Given the above orthogonality conditions, in (13) and (14), current and past values of k, past values of a, l, and m as well as functions of these can be used as instruments. Additionally, in (13), contemporaneous proxy variables and current realizations of a and l are valid instruments. Given this setup, the two equations (13) and (14) can be estimated within a GMM framework. Alternatively, we can identify the production function parameters by estimating (14) using IV estimation with instruments for a, l, and m (Wooldridge, 2009: 113). Petrin and Levinsohn (2012) employ this second approach. h is approximated by low-order polynomials of first-order lags of m and k.

In our agricultural application, the intuition of this approach may be as follows (cf. Levinsohn and Petrin, 2003: 322). Consider ω_{it} to represent a farm-specific stock of management knowledge. Any positive shift of ω_{it} assumedly increases the marginal productivity of m_{it} and possibly all other production factors. As m can be readily adjusted, a profit-maximising farmer increases the level of m_{it} in response to the shift, thus motivating our use of m as a proxy for ω_{it}. The same process may also work in the other direction, so that farms with negative shocks reduce material inputs. If ω is persistent, the farm-specific over- or under-application of material inputs is likely to be correlated over time, so that past levels can be used as proxies for current productivity shifts. Consistent with primarily positive shifts is the empirical observation that, on average, both farm output and materials input increase over the years. This is precisely what our data confirms.

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 OP 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.[5]

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 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.

5 Other subtle differences between the two approaches are discussed in Ackerberg et al. (2015).

3 Data

The data used in this study comes from the EU's Farm Accountancy Data Network (FADN), which provides a stratified farm level data set that holds accountancy data for all 28 EU member states. The stratification criteria are 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 (ESU). 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 (TF).

In the present study, we only use field crop farms (TF1), to justify the assumption of a homogenous state of technology across farms. The sample of countries is selected to reflect the diverse farm sizes and structures in EU agriculture. The range is from small-scale family farms in Italy and West Germany up to medium-sized commercial farms in Denmark, France and the UK (European Commission, 2012). West Germany contains the nine federal states Baden-Württemberg, Bavaria, Hamburg, Hesse, Lower Saxony, North Rhine-Westphalia, Rhineland-Palatinate, Saarland and Schleswig-Holstein. It does not include Berlin and Bremen, which are not represented in the FADN data. Therefore, we produce separate results for the following countries:

- Denmark (DK),
- France (FR),
- Germany West (DEW),
- Italy (IT), and the
- United Kingdom (UK).

The raw data provided by FADN was arranged in a way that panel data estimators can be applied. For every country in the study, we created a panel data set covering the years from 2001 up to 2008. A small number of duplicates in the data were dropped. In total, 14,801 observations were included in the EU-wide sample.

The variables and their measurement are readily available in the codebooks provided by FADN (European Commission, 2007, 2008). Output is measured as the total farm output in euros. Labor is measured by the time worked in hours by total labor input on the farm, including both hired and family labor. The total utilized 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 fertilizers 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. We do not include fertilizer in our materials specification. As land and fertilizer are highly correlated in the data sample, they are applied in more or less fixed ratios on the average farm, which, in return, might induce a multicollinearity problem in the estimations.[6] Nevertheless, the nature of this co-movement between land and fertilizer implies that the effect of fertilizer might also be captured by the land input. By applying this strategy, we mitigate the potential multicollinearity problem and maintain the correct model specification. 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 labor, 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 summarizes the variable definitions and gives the actual FADN codes.

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 was 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.

Table 3. Selection of variables

FADN code	Variable description
Outputs	
SE131	Total output (EUR)
Inputs	
SE011	Labor input (hours)
SE025	Total utilized agricultural area (ha) = land
F72 + SE300 +	
SE305 + SE336	Costs for seed and seedlings + crop protection + other crop specific costs + overheads (EUR) = materials
L.SE450 + L.SE455	Opening valuation of machinery and buildings (EUR) = fixed capital
Factor prices	
SE370/SE021	Wage per hour (EUR)
SE375/SE030	Land rent per ha (EUR)
SE380/SE485*100	Interest on capital (%)

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

[6] The inclusion of fertilizer leads to results that display negative estimates of land coefficients in conjunction with relatively high materials coefficients for several countries in the sample. See KLOSS (2017: 50 – 53) for an in depth analysis on the role of materials and land in EU agriculture.

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 upper or lower quartile ± 1.5 times the interquartile range (IQR). Furthermore, we only included farms which had some minimum panel representation in the data. Farms had to be present in the data for at least four years in a row. Descriptive statistics including the data patterns of the panels are given in the appendix (Table A1).

4 Results

4.1 Overview

For this study, we estimated nine models per country: Output shares, OLS Cobb Douglas, OLS Translog, Within Cobb-Douglas, Within Translog, LP Cobb Douglas, WLP Cobb Douglas, WLP Translog, BB Cobb Douglas. The Within Translog was obtained by interacting the groupwise demeaned logs of factors and using an appropriate degree of freedom correction. Other than by simply calling a built-in fixed effects panel estimation command with the interacted variables in logs, this procedure ensures that levels are effectively eliminated from the regression.

Table 4 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 eight models, plus an additional table for each country including more in-depth diagnostic results for the BB model.

All estimations were performed with Stata 12. For the LP estimator we employed the user-written routine `levpet` (Petrin et al. 2004). To implement the WLP estimator the `ivreg2` routine by Baum et al. (2007) was utilized as demonstrated in Petrin and Levinsohn (2012). This procedure includes lags of inputs up to the second order. Therefore, the panel length is reduced by two years. The BB estimator was implemented with `xtabond2` by Roodman (2009) using the `h(2)` option, and combined with Söderbom's (2009) `md _ ar1` minimum distance estimator. To maintain a maximum of comparability and homogeneity of the estimation samples as well as utilizing the highest amount of data as possible for estimation, we proceeded as follows. Estimations for all estimators, except for the WLP estimator, are based on the BB estimation sample. Since this estimator implies a dynamic specification with first order lags of inputs and the dependent variable, the effective panel length is reduced by one year. We did not impose this 'restriction' for the WLP procedure, which includes lags of inputs up to the second order. Hence, the difference between the WLP estimation sample and the sample employed for all other estimators is one round of observations as depicted by the tables in the appendix. In the WLP model (14) we proxy for h with lags rather than contemporaneous values of m and k, as it is done in the traditional control function setup. This treatment allows for easy implementation of the Translog functional form (Petrin and Levinsohn, 2012: 718).

As a general tendency, factor elasticities were found to be low for land and capital, high for materials and somewhere in between for labor (Table 4 and Table 5). Estimates for the first two of these factors are in the range of 0.2 and lower, sometimes not significantly different from zero. The production elasticity of materials is typically between 0.5 and 0.8. Labour elasticities usually fluctuate at around 0.2.

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: 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 LP estimator commonly produces a lower elasticity for materials than OLS, the only exception being the United Kingdom. In case of the WLP estimator the only exception is France. LP and WLP estimates are typically very similar which makes us feel confident of the proxy variable identification strategy. These models may thus be taken as plausible alternatives to the received estimators. However, on theoretical grounds the WLP model further corrects for collinearity which gives this estimator an edge over the LP model. In addition, empirically the former is occasionally more successful in identifying the capital coefficient, i.e. with a higher precision as indicated by the standard errors.

Estimated elasticities of scale fluctuate around 1.0. Given the previous findings on production elasticities, OLS estimates tend to be higher than Within estimates. Overall, the scale elasticity in European crop farming appears to be close to one.

We report the production elasticities estimated by the WLP procedure for all subsamples in Table 5 and compare them with two rather distinct agricultural 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 collection of production elasticity estimates ever published. Table 5 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: 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. While the choice of sample countries is different to our study, the sectoral integrity is maintained. Hence, it is meaningful to make comparisons on methodological grounds. Against these benchmarks from the literature, Table 5 illustrates a number of interesting tendencies:

- A comparatively low production elasticity of labor 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 Mundlak et al. study reveals remarkably low elasticities for labor and materials. Despite the use of the Within approach, the capital elasticity is surprisingly high. The low materials coefficient can be explained by the fact that the dependent variable in their model is value added.

4.2 Validity of the proxy variable

According to the theoretical set-up of the control function approaches the materials proxy should be increasing in unobserved productivity (ω_{it}). Otherwise it is not ensured that materials usage is an appropriate proxy for ω_{it}. To elaborate on this so-called monotonicity condition, we proceed in a similar fashion as LEVINSOHN and PETRIN (2003) by producing three-dimensional productivity surfaces of $\omega_{it} = f(m_{it}, k_{it})$. As ω_{it} is by definition unobserved, we need to come up with an estimate $\widehat{\omega}_{it}$. To this end, we predict $\widehat{\omega}_{it}$ by using the parameter estimates of the production function. Now, having data for the three dimensions – omega, materials and capital – we interpolate and smooth the original data using thin plate splines due to DUCHON (1976), a widely used data interpolation method for multidimensional data (see HASTIE et al., (2009: 162-167) for an overview). The processed data can then be used to draw three-dimensional surface plots and to visually inspect the monotonicity condition.

In Table 5, we summarize the results of this analysis. In general, the monotonicity condition holds throughout the sample of countries (Figures A1 – A5 in the appendix). In Denmark, West Germany, Italy and the United Kingdom materials increases in omega for every given level of capital. In France, the monotonicity condition only holds for up to medium levels of materials usage and medium to high levels of capital. Supposedly, a possible explanation is that the regions where the monotonicity condition holds are the ones with particularly good data support, i.e. in regions where increasing levels of materials (for a given level of capital) are observed the number of sample observations is large, too. Indeed, this is the case in France for about 60% of the observations. This finding is in line with OLLEY and PAKES (1996: 1265) who state that the monotonicity condition should be fulfilled for at least a subset of the data.

4.3 Functional form: Cobb Douglas vs. Translog

The results on the Translog specification display remarkably uniform features across countries. The Within Translog elasticities 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 OLS Translog, on the other hand, produced unreasonable results throughout, e.g. reflected in the co-existence of negative production elasticities for some factors and elasticities bigger than one for others (at sample means). Similarly unreasonable results are observed for the WLP Translog. In this model not a single country displayed interaction terms that were jointly significantly different from zero. Additionally, we applied the KLEIBERGEN and PAAP (2006) under-identification test to the WLP Translog model. This tests whether the model equation is identified, i.e. the excluded instruments are correlated with the endogenous regressors.[7] Failing to reject the null hypothesis that the equation is unidentified implies an increased bias in the estimated coefficients. The bias is in the same direction as in the OLS estimator (BAUM et al. 2007). While we always rejected the null at the 5% and even the 1% significance level in the Cobb Douglas model, we could not do so in the cases of Denmark ($p = 0.41$) and the United Kingdom ($p = 0.62$) in the Translog model.

To sum up, the Translog specification does not perform well. Our findings are in line with other recent studies utilizing FADN data with this functional form (cf. ZHENGFEI et al., 2006; LATRUFFE and NAUGES, 2013). The prime reason for these difficulties is multicollinearity, which is supposedly even more severe in the Translog than in the Cobb Douglas, as many more parameters have to be estimated. While we cannot ultimately decide whether the true data generation process followed a Translog technology, we can say that farm-level data typically does not allow estimating its parameters. This makes the Translog a less credible functional form for applied work.

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7 "Excluded" means that these instruments are not part of the model equation. Tests for over-identification restrictions could not be performed because the model is just identified.

Table 4. Summary evaluation of estimator performance

	DK	FR	DEW	IT	UK
Factor elasticities	All OLS below shares; Materials below shares throughout CD, insignificant in LP and WLP (=0); Capital=0 in Within	Land & labour =0 in BB; Materials above shares in OLS, LP, WLP, BB; Capital<0.1 in shares, Within, BB	Materials above shares in OLS, LP WLP, BB, lower in Within; Capital≈0 in Within&WLP, higher in LP&BB	Land=0 in OLS, LP, WLP, <0 in BB; Materials above shares throughout CD; Capital<0.1 in OLS, >0.1 BB, =0 in all other CD	Materials above shares in OLS, LP, BB; Capital≤0.1 throughout
Returns to scale	Shares add up to 2.07; OLS, LP, lower but still >1; Within, WLP, BB close to 1	OLS >1; Close to 1.0 for the other estimators	1.1 in OLS, <1 in Within, BB; Close to 1.0 in LP, WLP	Shares add up to 1.61; OLS ≈1.1; Within, LP, WLP <0.9; BB=0.5	OLS, Within, LP≈1.2; WLP≈1.1; BB≈1.5
Performance of Translog	OLS unreasonable; Within close to CD; WLP unreasonable; Interactions not sig. in Within & WLP	OLS unreasonable; Within close to CD; WLP unreasonable; Interactions not sig. in WLP	OLS unreasonable; Within close to CD; WLP unreasonable; Interactions not sig. in Within & WLP	OLS unreasonable; Within in part close to CD; WLP unreasonable; Interactions not sig. in WLP	OLS unreasonable; Within close to CD; WLP unreasonable; Interactions not sig. in OLS & WLP
Blundell/ Bond estimator	Specification tests ok; levels better instrumented than diff.; relatively poor instrumentation	OID not passed; Land, mat, capital, 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; Materials & output explosive; poor instrumentation

Notes: BB: Blundell/Bond, CD: Cobb Douglas, LP: Levinsohn/Petrin, OID: Over-identification test, OLS: Ordinary Least Squares, WLP: Wooldridge/Levinsohn/Petrin.
Source: Authors.

Table 5. Agricultural production elasticities in comparison

	DK	FR	DEW	IT	UK	Heady Dillon (1961)	Mundlak et al. (2012)
Labor	0.62	0.17	0.22	0.32	0.19	0.21	0.01#
Land	0.23	0.04	-0.01#	-0.01#	0.17	0.38	0.44
Materials	0.00#	0.80	0.77	0.51	0.62#	0.39	0.10
Capital	0.10#	0.12	0.09	0.02#	0.10#	--	0.46
Ret. to Scale	0.95	1.13	1.08	0.84	1.09	0.98	1.00*
Monotonicity	+	o	+	+	+	--	--

Notes: Results for field crop farms in EU countries based on Wooldridge/Levinsohn/Petrin (WLP) estimator. Heady and Dillon (1961) represents mean elasticities from a sample of 32 cross-sectional Cobb Douglas estimates originating from various countries (their table 17.15). Mundlak et al. (2012) based on a cross country regression of 30 countries for 1972-2000, using value added as dependent variable and the Within estimator (their table 2, first column). * imposed on model. # not significantly different from zero at conventional confidence levels. Montonicity: + holds throughout, o holds partially.
Source: Authors.

4.4 Dynamic panel data estimation

The performance of the BB estimator was examined in some detail. We present results for the unrestricted and the restricted model 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 for the models was never a problem and the common factor restriction was also never rejected, the Hansen OID test of instrument validity was not passed in three instances.

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). Labor 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 which do not only use differences but also levels for instrumentation (Blundell and Bond, 1998) are thus warranted. Even so, the elasticities of the persistent factors labor, land and capital could often 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 somewhere between the OLS and Within results. It is here where the BB estimator can likely claim some superiority.

There are some noteworthy findings for Denmark compared to 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 2.07 (which is actually inconsistent with the interpretation as shares). This outcome may be an artefact of systematically higher imputed factor prices than in 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 BB approach. Admittedly, the capital coefficient in such regressions is rather low (0.52). Even so, compared to the control function estimation approaches the BB estimator is able to identify a materials output elasticity. The reason LP and WLP estimators leaving the materials elasticity unidentified might be explained by the non-parametric control function utilized in these estimators. In this function higher order and interaction terms of materials enter so that the same captures a lot of the explaining variance. Hence, there is not enough variation left for the sole materials input. Furthermore, there is also an extreme materials coefficient decrease in size from LP to WLP which might be explained by the lower sample size of the latter and consequently reinforces the problem. Given specification tests do not fail and the materials coefficient is close to the Within regression, the BB coefficient for this parameter is a more plausible candidate.

5 Conclusions

The aim of this study was to provide a comparison of innovative production function estimators and to apply them to a recent firm-level dataset representing the agricultural sector of six EU countries. The starting point of our analysis was 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 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 short-term profit maximization of agents and perfect competition on output and factor markets. In agriculture, these conditions are unlikely to be met, which may be a reason why these approaches 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, labor 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), Levinsohn and Petrin (2003) and Wooldridge (2009) 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 BB allow time-invariant fixed effects, whereas OP, LP and WLP 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 or control function approaches, while the process potentially covers many periods in the dynamic panel data models. In agricultural applications, this is a conceptual advantage of the BB approach. Adjustments of land, labor and capital are typically of an intertemporal nature, which is not appropriately covered by a one-year lag. Furthermore, OP and LP do not satisfactorily address the problem of collinearity in production function estimation. These approaches regard labor and land as fully flexible production factors for which there is no source of identifying variance across observations (Ackerberg et al., 2015).

However, Wooldridge (2009) proposes a solution to this issue by modifying and extending the central identifying assumptions of OP and LP.

In the empirical section, we provide results for revenue shares, OLS Cobb Douglas and Translog, Within Cobb Douglas and Translog, WLP Cobb Douglas and Translog as well as OP, LP and BB Cobb Douglas models. Each model was estimated separately for panels of field crop farms in Denmark, France, West Germany, Italy, and the United Kingdom. Compared to 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 capital.

LP produced 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 labor and land, which the other estimators except for BB and WLP share, this is only a second-best choice. Generally, LP and WLP produced very similar results which strengthens our confidence in the proxy approach on the whole. However, the theoretical advantage in identifying the land and labor coefficients gives the latter an edge over the former.

The BB estimator 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 labor, land and capital. However, 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.

Extending the received Cobb Douglas specification to a Translog generally did not add meaningful insights. Either the results were obviously implausible (OLS and WLP) or little different from Cobb Douglas (Within). These results are supposedly a direct consequence of multicollinearity. Hence, the more parsimonious parameterization of the Cobb Douglas remains a pragmatic, empirically well-supported alternative. We regard the analysis of alternative functional forms in conjunction with FADN data as an interesting starting point for future research. For instance, Zhengfei et al. (2006) proposed augmented Translog specifications that incorporate agronomic principles. However, so far, in applied empirical work there has been a trade-off between more flexible functional forms for production functions and methodological sophistication with regards to estimation methods.

Our estimates show a consistent picture of very low production elasticities for labor, land and fixed capital, whereas the elasticity of materials is around 0.7 throughout indicating that improving the availability of working capital is the most promising way to increasing agricultural productivity. This finding is in contrast to recent estimates by Mundlak et al. (2012), which report significant returns to land and fixed capital in a cross-country sample of developing and developed countries. Compared to other world regions, field crop technologies in the EU are characterized by a strong responsiveness to variable inputs such as fuel, fertilizer and chemicals. In a policy perspective, attempts to increase agricultural productivity in the EU in the short run, i.e. with given technology, should focus on this factor. Whether farmers actually exhaust the returns to such inputs should be analyzed in subsequent work, for example by calculating shadow prices of production factors based on the estimates provided in this article.

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, labor and capital have been recognized 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) and Wooldridge (2009) represent an interesting alternative for agricultural applications.

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Appendix: Data & results tables

Table A1. Descriptive statistics

	Denmark					France				Germany (West)			
	Mean	SD	Min	Max		Mean	SD	Min	Max	Mean	SD	Min	Max
Output (ths EUR)	184.2	278.7	3.1	2733.4		158.6	115.9	5.2	1574.7	153.9	140.6	14.8	2114.7
Labour (ths hours)	2.8	3.9	0.1	49.0		3.1	2.3	1.2	38.2	4.2	3.4	1.1	93.9
Land (ha)	124.0	174.3	10.1	1760.0		145.0	83.2	3.6	647.4	93.9	61.1	0.5	429.5
Materials (ths EUR)	97.7	153.4	5.5	1683.4		85.2	56.1	4.7	618.6	85.1	68.3	11.9	737.5
Capital (ths EUR)	872.2	1434.8	42.3	21381.0		158.9	127.4	2.8	1379.8	152.8	126.2	11.1	1008.0
Wage (EUR / hour)	17.4	0.0	17.4	17.4		10.6	0.6	9.3	14.1	7.6	0.9	6.3	10.5
Land rent (EUR / ha)	370.7	0.0	370.7	370.7		137.4	36.7	99.9	949.7	254.8	57.5	63.4	314.3
Interest on capital (%)	5.8	0.0	5.8	5.8		3.6	0.4	2.9	4.5	4.2	0.4	3.4	4.9
No. of observations	813				5321	2977				1334			
No. of farms	209				1031	573				292			

Denmark Pattern	Frequency	France Pattern	Frequency	Germany (West) Pattern	Frequency
...1111.	2	1111	79	1111	55
...11111	2	...1111.	12	...1111.	5
..1111..	31	...11111	44	...11111	28
.1111...	13	..1111..	23	..1111..	6
.11111..	27	..11111.	19	..11111.	4
.1111111	1	..111111	74	..111111	43
1111....	40	.1111...	16	.1111...	16
11111...	28	.11111..	17	.11111..	17
111111..	64	.111111.	8	.111111.	8
1111111.	1	.1111111	64	.1111111	77
		1111....	107	1111....	32
		11111...	90	11111...	38
		111111..	74	111111..	29
		1111111.	53	1111111.	27
		11111111	351	11111111	188

Source: Authors based on FADN data.

Descriptive statistics continued

	Italy				United Kingdom			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Output (ths EUR)	62.4	126.5	1.1	2165.2	282.9	343.2	8.7	3548.6
Labour (ths hours)	3.6	4.6	0.0	98.7	6.2	5.2	0.3	51.8
Land (ha)	44.4	75.3	0.6	723.3	250.5	182.4	17.8	1178.5
Materials (ths EUR)	23.9	52.3	0.5	938.4	155.8	151.7	10.4	1475.8
Capital (ths EUR)	122.6	230.6	2.7	4360.4	237.7	215.2	10.0	1522.9
Wage (EUR / hour)	7.4	1.5	5.0	11.5	10.9	0.3	9.1	11.2
Land rent (EUR / ha)	187.0	95.7	61.1	500.0	197.4	13.6	172.9	206.9
Interest on capital (%)	6.3	2.2	3.0	13.3	4.7	0.3	4.2	5.2
No. of observations	4890				800			
No. of farms	1362				189			

Pattern	Frequency	Pattern	Frequency
....1111	94	1111	34
...1111.	410	...1111.	8
...11111	667	...11111	29
..1111..	11	..1111..	10
..11111.	10	..11111.	7
..111111	16	..111111	17
.1111...	5	.1111...	14
.11111..	5	.11111..	14
.111111.	4	.111111.	9
.1111111	7	.1111111	23
1111....	37	1111....	3
11111...	27	11111...	4
111111..	30	111111..	1
1111111.	19	1111111.	1
11111111	20	11111111	15

Source: Authors based on FADN data.

Table A2. Results production function estimations, Denmark

	Output shares		OLS Cobb Douglas		OLS Translog		Within Cobb Douglas		Within Translog		Levinsohn/Petrin Cobb Douglas		Wooldridge/ Levinsohn/Petrin Cobb Douglas		Wooldridge/ Levinsohn/Petrin Translog	
	Mean	SD	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.476***	0.313	0.482***	0.053	0.888**	0.376	0.207***	0.047	0.196***	0.029	0.472***	0.053	0.617***	0.091	0.548	1.440
Land	0.412***	0.230	0.273***	0.060	0.606	0.491	0.287***	0.066	0.282***	0.041	0.267***	0.054	0.232***	0.080	0.163	0.988
Materials	0.716***	0.402	0.495***	0.047	0.332	0.509	0.481***	0.047	0.477***	0.027	0.365	0.226	-0.001	0.269	0.132	2.208
Capital	0.469***	0.367	0.134***	0.041	0.722*	0.413	-0.023	0.042	-0.001	0.026	0.106	0.068	0.096	0.075	0.610	1.282
N	813		813		813		813		813		813		605		605	
Elasticity of scale			1.384***	0.026			0.952***	0.072			1.209***	0.234	0.945***	0.229		
p-value const. ret. to scale			<0.001				0.504				<0.001		0.809			
R²			0.948		0.957		0.564		0.562							
p-value coeff. jointly zero			<0.001		<0.001		<0.001		<0.001		<0.001		<0.001		<0.001	
p-value interact. terms jtly. zero					<0.001				0.315						0.824	

Table A3. Results production function estimations, France

	Output shares		OLS Cobb Douglas		OLS Translog		Within Cobb Douglas		Within Translog		Levinsohn/Petrin Cobb Douglas		Wooldridge/ Levinsohn/Petrin Cobb Douglas		Wooldridge/ Levinsohn/Petrin Translog	
	Mean	SD	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.243***	0.171	0.169***	0.015	-0.232	0.336	0.109***	0.031	0.106***	0.015	0.181***	0.020	0.168***	0.018	-0.325	0.494
Land	0.134***	0.063	0.060***	0.017	0.284	0.209	0.341**	0.066	0.345***	0.030	0.048***	0.015	0.041**	0.017	0.250	0.267
Materials	0.559***	0.181	0.749***	0.018	1.323***	0.290	0.547***	0.038	0.500***	0.017	0.716***	0.057	0.804***	0.084	0.794	0.894
Capital	0.037***	0.025	0.158***	0.012	0.066	0.167	0.038***	0.012	0.033***	0.006	0.114***	0.014	0.119***	0.015	-0.632	0.612
N	5321		5321		5321		5321		5321		5321		4289		4289	
Elasticity of scale			1.136***	0.014			1.035***	0.058			1.059***	0.058	1.132***	0.077		
p-value const. ret. to scale			<0.001				0.549				0.309		0.086			
R²			0.865		0.873		0.500		0.485							
p-value coeff. jointly zero			<0.001		<0.001		<0.001		<0.001		<0.001		<0.001		<0.001	
p-value interact. terms jtly. zero					0.132				0.004				0.086		0.397	

Notes: Year dummies included in all models. *** (**, *) significant at the 1% (5%, 10%) level, based on standard errors robust to clustering in groups. Standard errors in LEVINSOHN/PETRIN based on bootstrapping with 20 replications.

Source: Author.

Table A4. Results production function estimations, Germany (West)

	Output shares		**OLS** Cobb Douglas		**OLS** Translog		**Within** Cobb Douglas		**Within** Translog		**Levinsohn/Petrin** Cobb Douglas		**Wooldridge/ Levinsohn/Petrin** Cobb Douglas		**Wooldridge/ Levinsohn/Petrin** Translog	
	Mean	SD	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.256***	0.162	0.208***	0.023	-0.667*	0.379	0.082***	0.026	0.080***	0.013	0.222***	0.022	0.222***	0.026	-1.066**	0.491
Land	0.177***	0.102	0.025	0.017	1.360***	0.315	0.273***	0.050	0.293***	0.023	0.022*	0.012	-0.005	0.019	1.046***	0.329
Materials	0.583***	0.173	0.799***	0.023	0.904**	0.363	0.476***	0.026	0.469***	0.013	0.652***	0.048	0.770***	0.086	1.848**	0.810
Capital	0.045***	0.031	0.120***	0.018	0.203	0.323	0.044***	0.015	0.038***	0.007	0.155***	0.029	0.088***	0.024	-0.007	0.438
N	2977		2977		2977		2977		2977		2977		2408		2408	
Elasticity of scale			1.152***	0.023			0.875***	0.060			1.051***	0.048	1.075***	0.080		
p-value const. ret. to scale			<0.001				0.038				0.283		0.344			
R^2			0.854		0.865		0.332		0.331							
p-value coeff. jointly zero			<0.001		<0.001		<0.001		<0.001		<0.001		<0.001		<0.001	
p-value interact. terms jtly. zero					0.008				0.350						0.171	

Table A5. Results production function estimations, Italy

	Output shares		**OLS** Cobb Douglas		**OLS** Translog		**Within** Cobb Douglas		**Within** Translog		**Levinsohn/Petrin** Cobb Douglas		**Wooldridge/ Levinsohn/Petrin** Cobb Douglas		**Wooldridge/ Levinsohn/Petrin** Translog	
	Mean	SD	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.243***	0.171	0.169***	0.015	-0.232	0.336	0.109***	0.031	0.106***	0.015	0.181***	0.020	0.168***	0.018	-0.325	0.494
Land	0.134***	0.063	0.060***	0.017	0.284	0.209	0.341**	0.066	0.345***	0.030	0.048***	0.015	0.041**	0.017	0.250	0.267
Materials	0.559***	0.181	0.749***	0.018	1.323***	0.290	0.547***	0.038	0.500***	0.017	0.716***	0.057	0.804***	0.084	0.794	0.894
Capital	0.037***	0.025	0.158***	0.012	0.066	0.167	0.038***	0.012	0.033***	0.006	0.114***	0.014	0.119***	0.015	-0.632	0.612
N	5321		5321		5321		5321		5321		5321		4289		4289	
Elasticity of scale			1.136***	0.014			1.035***	0.058			1.059***	0.058	1.132***	0.077		
p-value const. ret. to scale			<0.001				0.037				0.012		0.081			
R^2			0.843		0.855		0.327		0.328							
p-value coeff. jointly zero			<0.001		<0.001		<0.001		<0.001		<0.001		<0.001		<0.001	
p-value interact. terms jtly. zero					<0.001				0.012						0.138	

Notes: Year dummies included in all models. *** (**, *) significant at the 1% (5%, 10%) level, based on standard errors robust to clustering in groups. Standard errors in LEVINSOHN/PETRIN based on bootstrapping with 20 replications.

Source: Author.

Table A6. Results production function estimations, United Kingdom

	Output shares		**OLS** Cobb Douglas		**OLS** Translog		**Within** Cobb Douglas		**Within** Translog		**Levinsohn/Petrin** Cobb Douglas		**Wooldridge/ Levinsohn/Petrin** Cobb Douglas		**Wooldridge/ Levinsohn/Petrin** Translog	
	Mean	SD	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.293***	0.179	0.203***	0.039	0.158	0.320	0.242***	0.055	0.209***	0.029	0.187***	0.048	0.191***	0.050	1.230	1.138
Land	0.204***	0.097	0.165***	0.046	1.575***	0.403	0.387***	0.105	0.392***	0.053	0.158***	0.031	0.174***	0.061	2.383*	1.388
Materials	0.623***	0.227	0.729***	0.046	-0.096	0.442	0.594***	0.072	0.524***	0.041	0.731***	0.123	0.622	0.399	-0.230	5.644
Capital	0.043***	0.030	0.077**	0.032	-0.361	0.253	0.017	0.030	-0.017	0.016	0.106	0.066	0.099	0.065	-1.261	2.035
N	800		800		800		800		800		800		612		612	
Elasticity of scale			1.174***	0.027			1.240***	0.093			1.182***	0.156	1.086***	0.380		
p-value const. ret. to scale			<0.001				0.010				0.244		0.820			
R^2			0.903		0.909		0.578		0.567							
p-value coeff. jointly zero			<0.001		<0.001		<0.001		<0.001		<0.001		<0.001		<0.001	
p-value interact. terms jtly. zero					0.732				0.003						0.921	

Notes: Year dummies included in all models. *** (**, *) significant at the 1% (5%, 10%) level, based on standard errors robust to clustering in groups. Standard errors in LEVINSOHN/PETRIN based on bootstrapping with 20 replications.

Source: Author.

Table A7. Results Blundell/Bond Cobb Douglas estimator Denmark

	Production function estimates	
Unrestricted model	Coeff	SE
Labour	0.241	0.248
- lagged	-0.064	0.186
Land	0.334*	0.193
- lagged	-0.018	0.172
Materials	0.460***	0.171
- lagged	0.015	0.188
Capital	-0.014	0.150
- lagged	0.196	0.190
Output lagged	0.093	0.128
p-val. coeff. jointly zero	<0.001	
Arellano-Bond test (1)	<0.001	
Arellano-Bond test (2)	0.494	
Hansen OID test	0.070	
Restricted model		
Labour	0.260	0.225
Land	0.309*	0.162
Materials	0.464***	0.166
Capital	0.031	0.129
ρ	0.160***	0.056
Elasticity of scale	1.020***	0.211
Common factors	0.986	

Diagnosis of model specification	Labour		Land		Materials		Capital		Output	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
AR(1) model	0.161	0.31	0.737	0.58	0.634*	0.35	0.515	0.60	0.168	0.52
Instruments differences										
p-value coeff. jointly zero	<0.001		0.987		0.309		0.172		0.601	
R^2	0.305		<0.001		0.026		0.038		0.011	
Instruments levels										
p-value coeff. jointly zero	0.005		0.738		0.356		0.039		0.060	
R^2	0.111		0.007		0.023		0.069		0.061	

Notes: N=818. *** (**, *) significant at the 1% (5%, 10%) level. Year dummies included in 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 used as GMM-type instruments for the lagged dependent variable in the level equation. First differences of year dummies used as standard instruments in the production function. Standard errors adjusted using WINDMEIJER (2005) procedure. Minimum distance estimation due to SÖDERBOM (2009). "Instruments differences" based on regression of first difference for year=2006 on lagged levels three and four years back. "Instruments levels" based on regression of lagged level for year=2006 on lagged first differences two and three years back, using OLS.

Source: Author.

Table A8. Results Blundell/Bond Cobb Douglas estimator France

	Production function estimates	
Unrestricted model	Coeff	SE
Labour	0.241	0.248
- lagged	-0.064	0.186
Land	0.334*	0.193
- lagged	-0.018	0.172
Materials	0.460***	0.171
- lagged	0.015	0.188
Capital	-0.014	0.150
- lagged	0.196	0.190
Output lagged	0.093	0.128
p-val. coeff. jointly zero	<0.001	
Arellano-Bond test (1)	<0.001	
Arellano-Bond test (2)	0.494	
Hansen OID test	0.070	
Restricted model		
Labour	0.260	0.225
Land	0.309*	0.162
Materials	0.464***	0.166
Capital	0.031	0.129
ρ	0.160***	0.056
Elasticity of scale	1.020***	0.211
Common factors	0.986	

	Diagnosis of model specification									
	Labour		Land		Materials		Capital		Output	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
AR(1) model	0.161	0.31	0.737	0.58	0.634*	0.35	0.515	0.60	0.168	0.52
Instruments differences										
p-value coeff. jointly zero	<0.001		0.987		0.309		0.172		0.601	
R^2	0.305		<0.001		0.026		0.038		0.011	
Instruments levels										
p-value coeff. jointly zero	0.005		0.738		0.356		0.039		0.060	
R^2	0.111		0.007		0.023		0.069		0.061	

Notes: N=5330. *** (**, *) significant at the 1% (5%, 10%) level. Year dummies included in 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 used as GMM-type instruments for the lagged dependent variable in the level equation. First differences of year dummies used as standard instruments in the production function. Standard errors adjusted using Windmeijer (2005) procedure. Minimum distance estimation due to Söderbom (2009). "Instruments differences" based on regression of first difference for year=2008 on lagged levels three to seven years back. "Instruments levels" based on regression of lagged level for year=2008 on lagged first differences two to six years back, using OLS.

Source: Author.

Table A9. Results Blundell/Bond Cobb Douglas estimator Germany (West)

Production function estimates	Coeff	SE
Unrestricted model		
Labour	-0.006	0.118
- lagged	0.083	0.103
Land	-0.042	0.202
- lagged	0.015	0.183
Materials	0.681***	0.087
- lagged	0.209*	0.115
Capital	0.094	0.103
- lagged	0.026	0.095
Output lagged	0.047	0.091
p-val. coeff. jointly zero	<0.001	
Arellano-Bond test (1)	<0.001	
Arellano-Bond test (2)	0.104	
Hansen OID test	<0.001	
Restricted model		
Labour	-0.007	0.103
Land	-0.045	0.072
Materials	0.671***	0.079
Capital	0.103**	0.049
ρ	0.092***	0.013
Elasticity of scale	0.727***	0.234
Common factors	0.991	

Diagnosis of model specification	Labour		Land		Materials		Capital		Output	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
AR(1) model	0.860***	0.12	0.929***	0.04	0.865***	0.13	1.042***	0.06	1.213***	0.11
Instruments differences										
p-value coeff. jointly zero	0.171		0.388		0.315		0.556		0.760	
R^2	0.041		0.028		0.032		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		0.154		0.232		0.171	

Notes: N=3030. *** (**, *) significant at the 1% (5%, 10%) level. Year dummies included in 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 used as GMM-type instruments for the lagged dependent variable in the level equation. First differences of year dummies used as standard instruments in the production function. Standard errors adjusted using Windmeijer (2005) procedure. Minimum distance estimation due to Söderbom (2009). “Instruments differences” based on regression of first difference for year=2008 on lagged levels three to seven years back. “Instruments levels” based on regression of lagged level for year=2008 on lagged first differences two to six years back, using OLS.

Source: Author.

Table A10. Results Blundell/Bond Cobb Douglas estimator Italy

	Production function estimates	
Unrestricted model	Coeff	SE
Labour	-0.072	0.060
- lagged	0.263***	0.078
Land	-0.218	0.189
- lagged	0.033	0.176
Materials	0.665***	0.089
- lagged	0.010	0.082
Capital	0.148	0.122
- lagged	-0.037	0.105
Output lagged	0.156**	0.062
p-val. coeff. jointly zero	<0.001	
Arellano-Bond test (1)	<0.001	
Arellano-Bond test (2)	0.401	
Hansen OID test	<0.001	
Restricted model		
Labour	-0.066	0.056
Land	-0.199**	0.080
Materials	0.621***	0.077
Capital	0.186***	0.071
ρ	0.257***	0.030
Elasticity of scale	0.522***	0.229
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***	0.20	1.007***	0.05	0.770	0.32	0.985***	0.02	1.242**	0.50
Instruments differences										
p-value coeff. jointly zero	0.086		0.839		0.180		0.617		0.873	
R^2	0.466		0.126		0.433		0.205		0.111	
Instruments levels										
p-value coeff. jointly zero	0.175		0.275		0.561		0.007		0.712	
R^2	0.393		0.337		0.254		0.651		0.173	

Notes: N=5053. *** (**, *) significant at the 1% (5%, 10%) level. Year dummies included in 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 used as GMM-type instruments for the lagged dependent variable in the level equation. First differences of year dummies used as standard instruments in the production function. Standard errors adjusted using Windmeijer (2005) procedure. Minimum distance estimation due to Söderbom (2009). "Instruments differences" based on regression of first difference for year=2008 on lagged levels three to seven years back. "Instruments levels" based on regression of lagged level for year=2008 on lagged first differences two to six years back, using OLS.

Source: Author.

Table A11. Results Blundell/Bond Cobb Douglas estimator United Kingdom

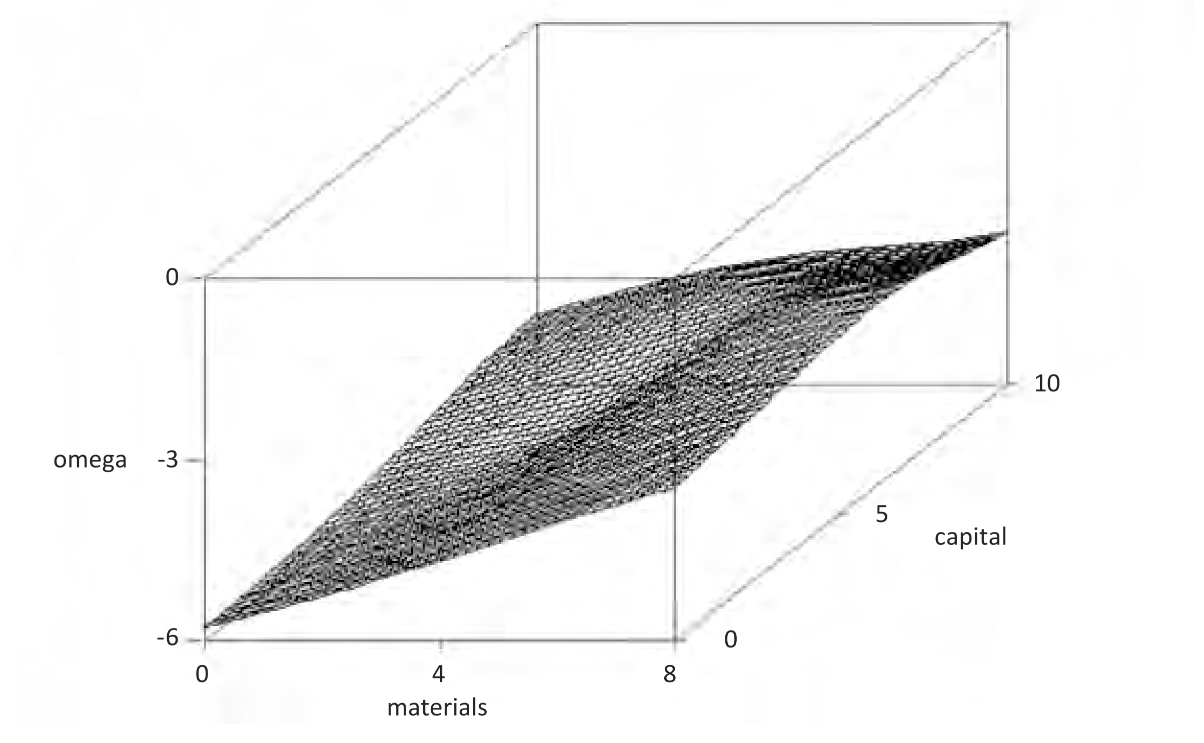
	Production function estimates	
Unrestricted model	Coeff	SE
Labour	0.269**	0.123
- lagged	-0.123	0.127
Land	0.498*	0.282
- lagged	-0.243	0.269
Materials	0.664***	0.136
- lagged	-0.176	0.181
Capital	0.016	0.070
- lagged	-0.002	0.064
Output lagged	0.225**	0.116
p-val. coeff. jointly zero	<0.001	
Arellano-Bond test (1)	<0.001	
Arellano-Bond test (2)	0.943	
Hansen OID test	0.708	
Restricted model		
Labour	0.241**	0.095
Land	0.389***	0.120
Materials	0.640***	0.093
Capital	0.020	0.059
ρ	0.297***	0.080
Elasticity of scale	1.448***	0.217
Common factors	0.929	

Diagnosis of model specification	Labour		Land		Materials		Capital		Output	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
AR(1) model	0.812***	0.26	0.929***	0.06	1.166***	0.22	0.902***	0.13	1.194***	0.23
Instruments differences										
p-value coeff. jointly zero	0.379		0.646		0.274		0.653		0.355	
R^2	0.402		0.276		0.494		0.273		0.414	
Instruments levels										
p-value coeff. jointly zero	0.186		0.206		0.447		0.194		0.152	
R^2	0.516		0.502		0.399		0.511		0.543	

Notes: N=807. *** (**, *) significant at the 1% (5%, 10%) level. Year dummies included in 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 used as GMM-type instruments for the lagged dependent variable in the level equation. First differences of year dummies used as standard instruments in the production function. Standard errors adjusted using WINDMEIJER (2005) procedure. Minimum distance estimation due to SÖDERBOM (2009). "Instruments differences" based on regression of first difference for year=2008 on lagged levels three to seven years back. "Instruments levels" based on regression of lagged level for year=2008 on lagged first differences two to six years back, using OLS.

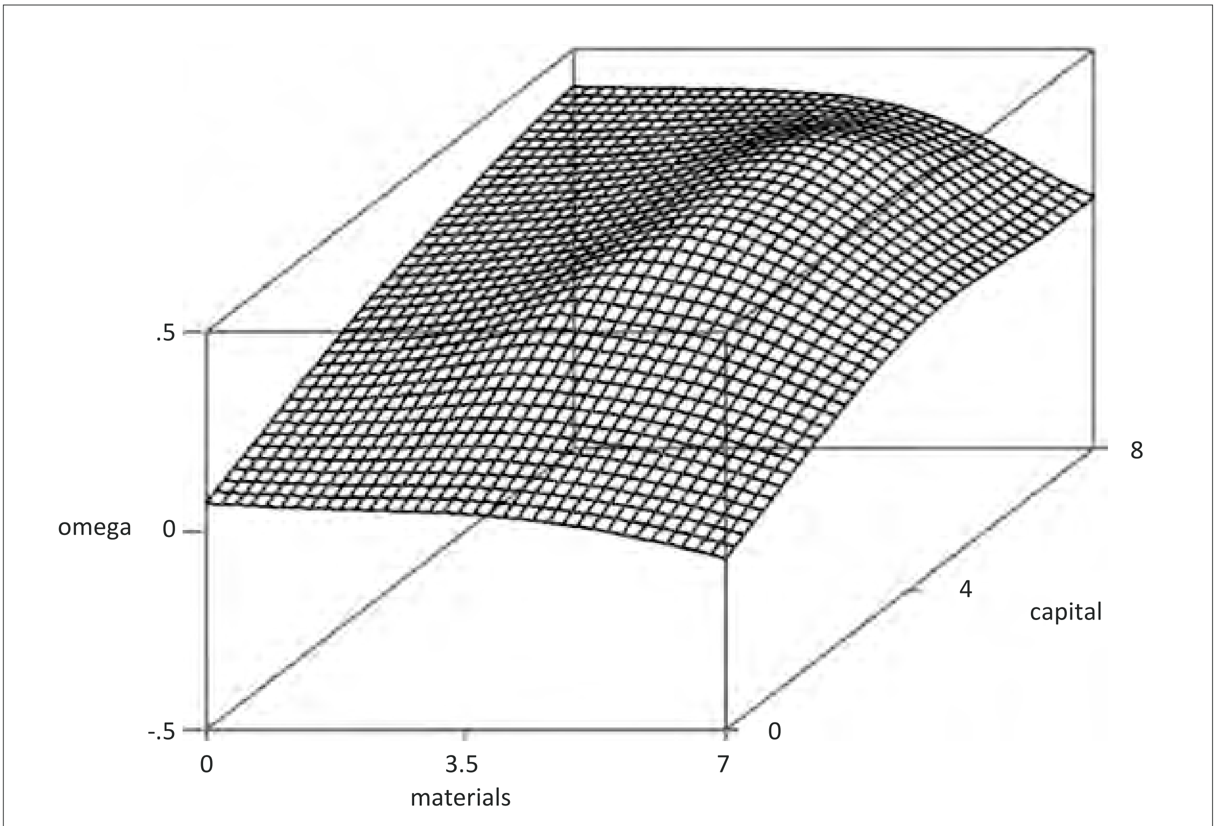
Source: Author.

Figure A1. Prediction of omega as a function of materials and capital, Denmark



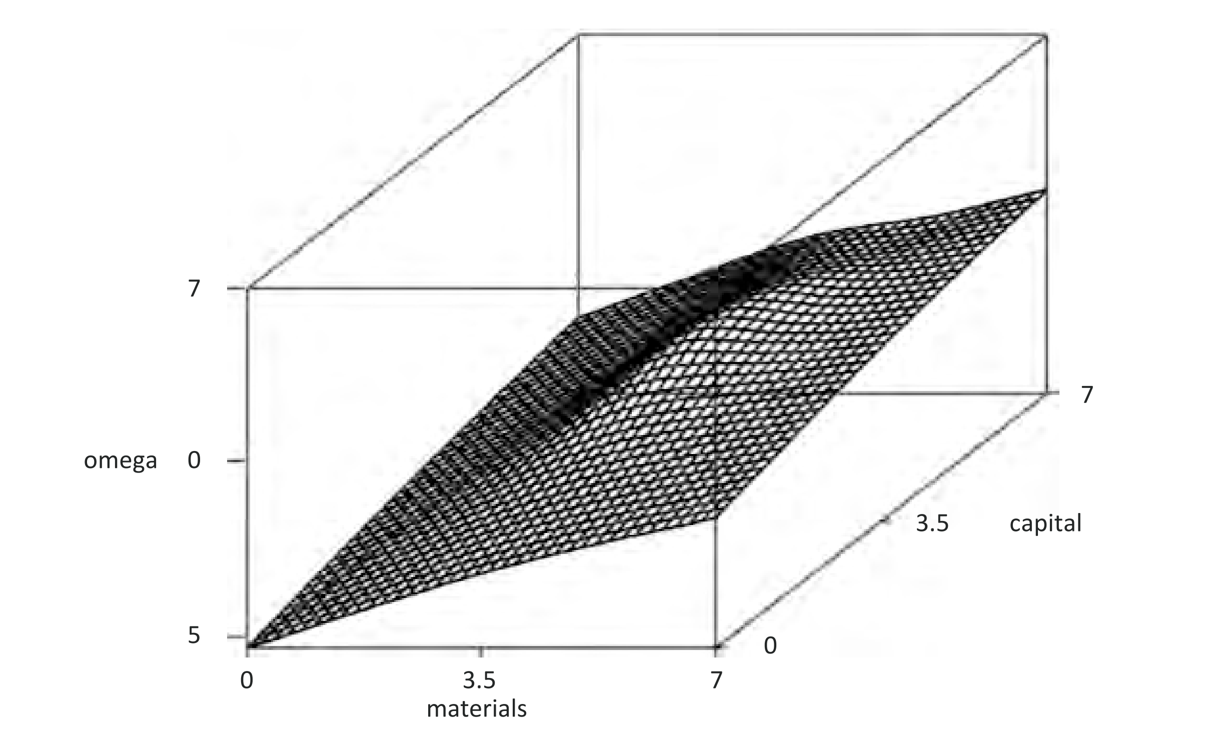
Source: Authors.

Figure A2. Prediction of omega as a function of materials and capital, France



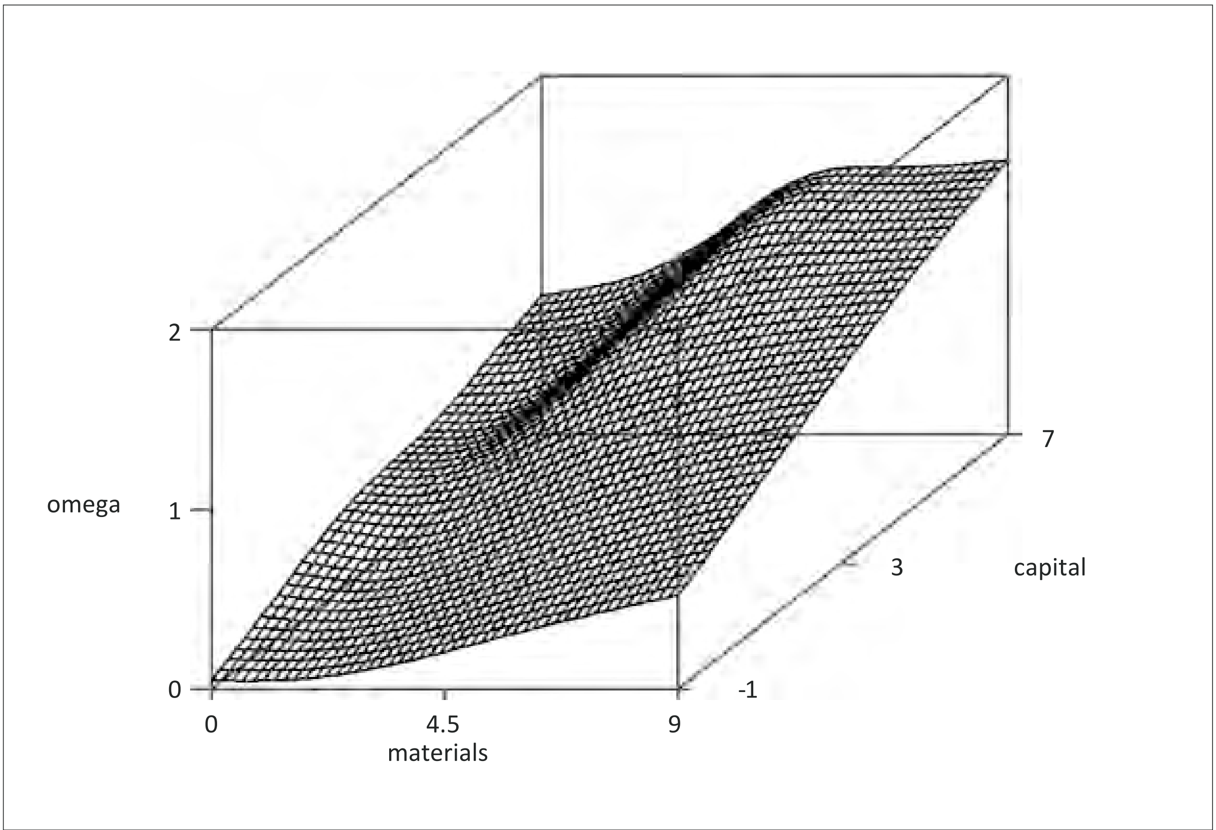
Source: Authors.

Figure A3. Prediction of omega as a function of materials and capital, Germany (West)



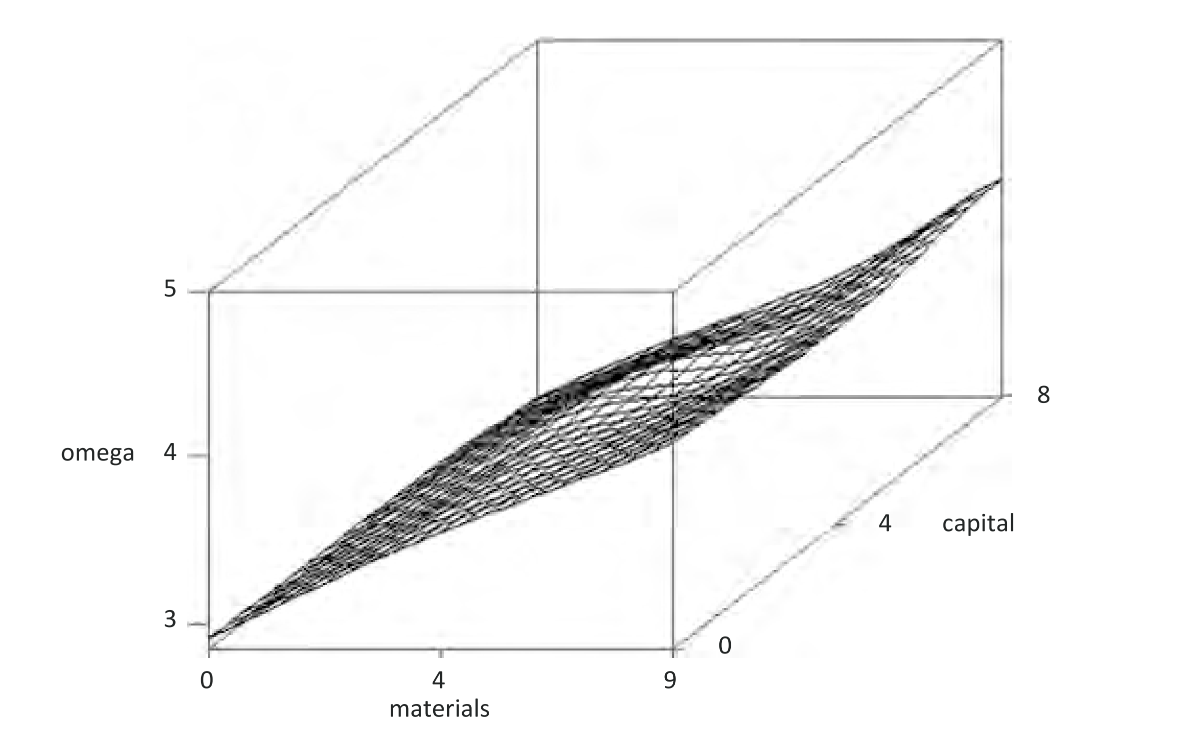
Source: Authors.

Figure A4. Prediction of omega as a function of materials and capital, Italy



Source: Authors.

Figure A5. Prediction of omega as a function of materials and capital, United Kingdom



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