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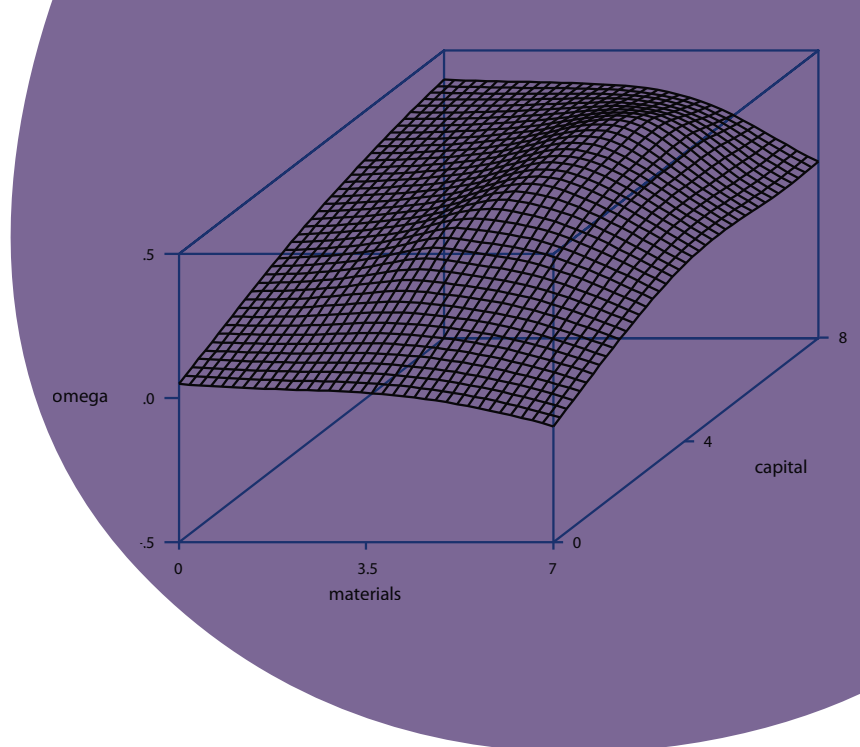
Leibniz Institute of Agricultural Development
in Transition Economies

The productivity of family and hired labour in EU arable farming

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ABSTRACT

This paper investigates the impact of labour force composition on productivity in EU arable farming. We test for heterogeneous effects of family and hired labour for a set of five EU member states. To this end, we estimate augmented production functions using FADN data for the years 2001–2008. The results reject the notion that hired labour is generally less productive than family workers. In fact, farms with a higher share of hired workers are more productive than pure family farms in countries traditionally characterised by family labour, namely France and West Germany. Here, an increase in reliance on hired labour or the shift of family labour to more productive tasks could raise productivity. This finding calls into question a main pillar of the received family farm theory. In about half the countries, there are no statistically different effects of both types of labour. For the United Kingdom, we find the classical case with family farms being more productive than those relying on hired labour. As a side result, we find little evidence of non-constant technical returns to scale.

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1 \ **Introduction**

According to a widely accepted view, large-scale farming operations involving many workers under a centralised management authority are economically inferior to smaller family-run businesses, at least in the temperate zones. The two maintained hypotheses of the underlying "family farm theory" are that (1) technological scale economies are typically exhausted before farm size exceeds the labour capacity of a family and that (2) growth of the labour force beyond family members is inhibited by rising supervision costs. These hypotheses used to be supported by a large body of empirical literature from developed and developing countries (Brewster, 1950; Schmitt, 1991; Hayami and Otsuka, 1993; Allen and Lueck, 1998; Eastwood et al., 2010). For many decades after World War II, the economic and social superiority of family farms over agriculture based on hired labour was a widely held notion among researchers, governments and international organisations.

However, even in agricultural regions traditionally dominated by small to medium family farm operations, such as Western Europe or the US, farm sizes have been growing and, more importantly, the share of hired workers in total labour force has been slowly but steadily increasing (Blanc et al., 2008; Darpeix et al., 2014). According to figures by Eurostat (2016), regularly employed non-family members on average contributed 15.4 per cent of the total agricultural workload in the EU-28 in 2013, whereas irregularly employed non-family members contributed another 8.1 per cent. This share has been on the rise for years, especially with regards to regularly employed hired labour. These workers replace family members on a year-round basis rather than complementing them during harvest time – a fact that calls into question the validity of hypothesis (2) outlined before (Figure 1).
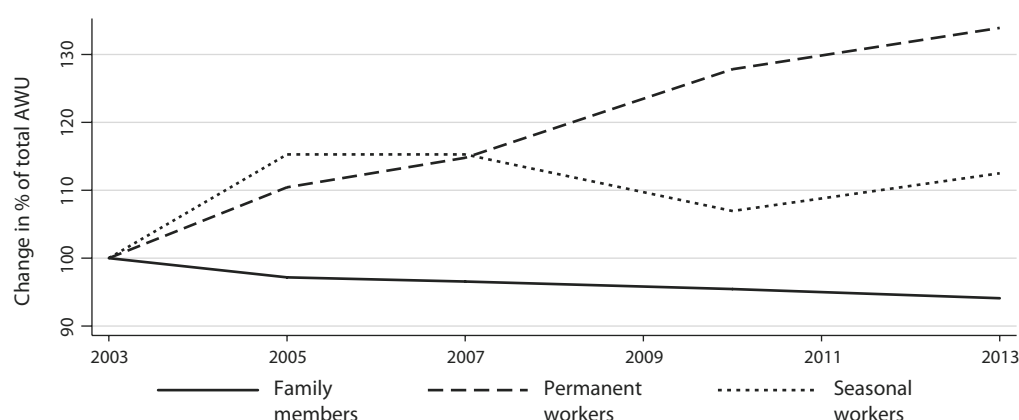
Figure 1   Change in the composition of the agricultural labour force in EU-28

Notes: 2003=100. AWU, Annual Working Units. Family consists of permanent family labour including holders and members of the sole holders family. Permanent workers consist of regularly employed non-family members. Seasonal workers are comprised of irregularly employed non-family members

Source: Authors compilation based on European Commission (2012, 2013) and Eurostat (2016)

The typical argument for different productivities of hired and family labour is based on the idea that both have diverging incentives. Hired labour is usually no residual claimant and their effort cannot commonly be observed because of the idiosyncrasy of agricultural production (e.g. seasonality, weather effects). Therefore, hired labourers have incentives to "shirk", resulting in effort levels that are only a fraction of those achieved by family labour. As a result, both kinds of labour are not easily substituted. This perceived problem can be mitigated by hired labour supervision. Hence, transaction costs in the form of supervision costs arise, making farm production based on hired labour more expensive. On the other hand, the following argument in favour of hired labour is often overlooked: growing farms with a larger stock of workers may allow more specialisation and the division of labour into distinct tasks (Allen and Lueck, 1998; Kimhi, 2009). For example, family members might concentrate on management and/or supervision tasks, while hired labourers specialise in non-managerial tasks. To the extent that modern farming technologies allow such specialisation benefits, the productivity of hired labour may well exceed that of a family member who is a "jack of all trades but the master of none".[1]

Given these conflicting views, the present study aims to revisit the relative superiority of family over hired labour by confronting the accepted wisdom with new empirical evidence. In exploring the relative productivity of family versus hired labour, we follow Bardhan (1973), Deolalikar and Vijverberg (1983, 1987) and Frisvold (1994) who investigated this question for the developing country context of India. Whereas these authors found evidence in favour of both arguments presented in the preceding paragraph, supervision versus specialisation effects, we are primarily interested in their methodological approach. We follow these authors in using a parametric production function specification that accounts for heterogeneous labour impacts. This approach focuses on a single parameter of relative labour productivity and thus allows straightforward interpretation. Yet, our estimation technique goes beyond the received estimators used by the previous authors in tackling potential endogeneity problems. Deolalikar and Vijverberg as well as Frisvold resorted to traditional household/farm fixed effects approaches. In this paper, we focus on a state of the art estimation procedure introduced by Wooldridge (2009). Our database is a panel originating from the Farm Accountancy Data Network (FADN) of five EU member states: Denmark, France, Germany (West), Italy and the United Kingdom. Data is available for the years 2001–2008. The sample of countries includes full-time arable farms and reflects the diverse farm structures prevalent in different member states. It comprises mostly countries with traditional family-type farming (e.g., France and Italy) as well as those with a relatively high share of hired labour (e.g., the United Kingdom). The variability in reliance on family labour across countries provides the necessary variation to study the influence of hired workers, while we limit the analysis to arable farms to justify the assumption of a homogenous production technology. We compare our results with the received ordinary least squares (OLS) approach. To our knowledge, and in which clearly differ from Latruffe et al. (2017), there exist no comparable studies for EU arable farming in the area of labor force heterogeneity to date.

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[1] Productivity differences may also be due to family members and workers possessing different levels of education and technical expertise. While the positive effects of farmers' human capital on production decisions have been analysed, we know relatively little about the effects of workers' education.

Our results reject the notion that farms with a higher share of hired labour are generally less productive than those with more (or only) family workers, everything else equal. As a most striking outcome, farms with more hired labour are more productive than farms with less hired workers in countries traditionally characterised by family farms, namely France and West Germany. The classical case in favour of labour supervision is observed for the United Kingdom. In the rest of the countries, there are no statistically different effects of the composition of labour. As a side result, we find little evidence of non-constant technical returns to scale. Farm growth in Europe may thus indeed be increasingly driven by scale neutral technologies which allow the realisation of gains from labour specialisation.

The study proceeds as follows. In section 2 we introduce the model specification to measure labour heterogeneity. In this section, we outline our specification decisions with regards to production technology and its statistical identification. In section 3 we describe the data. Section 4 presents the results. Section 5 concludes.

2 \ **Model specification**

In the remainder of the article, we explore the core hypothesis that the composition of the labour force (family versus hired) affects the productivity of agricultural labour input in European field crop farming. Testing this hypothesis empirically involves a number of specification decisions. First, we want our empirical model to be consistent with microeconomic production theory, which requires the specification of a production technology. Moreover, our empirical strategy has to make sure it identifies the parameters we are interested in for testing our hypothesis while being empirically tractable given the farm-level panel data we have available. As we discuss in the following, our preferred choice is a semi-parametric production function model that combines a parametrically specified technology with a robust, moment-based estimator controlling for unobserved heterogeneity.

2.1. | **Production technology**

A key dilemma in modelling production concerns the choice between functional flexibility and empirical tractability. On the one hand, researchers want to impose as little a-priori structure on the data as possible. On the other, less structure typically implies less precise estimates, less meaningful statistical tests and potential inconsistencies with theoretical assumptions such as concavity or monotonicity. At one extreme, technology could be estimated in an entirely non-parametric fashion. However, a disadvantage of such methods is that estimation with real-world data sets is rarely possible if the number of covariates is higher than two or three (the "curse of dimensionality", Ichimura and Todd, 2007). Another shortcoming is that fully non-parametric methods that can handle complex identifying assumptions are not well developed. We therefore resort to a parametric technology specification that allows a straightforward implementation of our core hypothesis. We start with the conventional Cobb-Douglas technology as a workhorse

model, which we then extend in various directions to accommodate our assumptions concerning labour force heterogeneity and identification.

Suppose the production technology can be described by the following expression:

$$y_{it} = \alpha^A a_{it} + \alpha^E e_{it} + \alpha^K k_{it} + \alpha^M m_{it} + \omega_{it} + \varepsilon_{it},$$
(1)

where y_{it} is the natural logarithm of output Y, A is land use, E is the effective labour effort, K fixed capital, M materials (working capital), lower case letters denote the natural logarithms of these variables, the α's are parameters to be estimated and i and t are farm and time indices. ω_{it} are farm- and time-specific factors known by the farmer but unobserved by the analyst (unobserved productivity). ε_{it} are the remaining independent and identically distributed errors.

A key idea in our strategy to test the influence of labour force heterogeneity is to substitute E by an effective labour function determined by the share of family labour in total labour input of the farm. We suggest a specification introduced by Frisvold (1994):

$$E = L \left(\frac{F + 1}{L} \right)^{\gamma},$$
(2)

where E is the effective labour input in efficiency units, L is total labour time, i.e. the sum of hired and family labour time, F is family labour time, and γ is a parameter measuring effective labour effort, which is to be estimated. Deolalikar and Vijverberg (1983, 1987) experimented with CES, general linear and generalised quadratic effective labour functions, while Bardhan (1973) also employed an exponential specification.
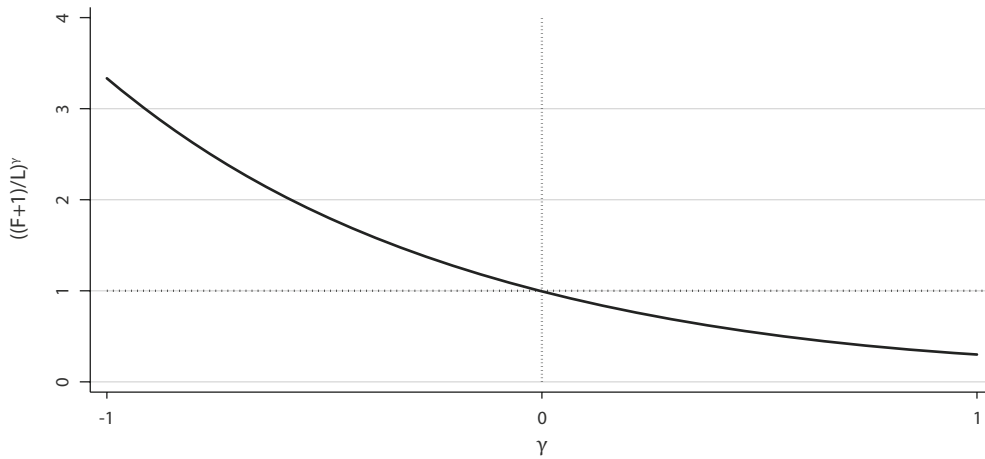

Figure 2   Effective labour as a function of γ
Notes: The ratio $((F + 1)/L) \in [0,1]$ has been set to 0.3
Source: Authors

As equation (2) shows, the exponential expression $((F+1)/L)^{\gamma}$ acts as a scaling factor for total labour time input. Following this model, the productivity of each hour of labour supplied to the farm depends on the share of family labour in total labour input and the parameter γ. The latter measures how a farm's labour force composition affects total farm productivity. If $\gamma > 0$, a higher share of family labour increases total farm productivity. If $\gamma < 0$, total farm productivity is decreased by a higher share of family labour. A given ratio of family to hired labour can decrease or increase total farm productivity, depending on whether γ is positive or negative (Figure 2). If $\gamma = 0$, there are no effects of labour force composition. An advantage is that this specification of E allows for farms entirely run by family or hired labour because a "1" is added in the numerator. Furthermore, the exponential form of (2) allows for direct estimation of γ in the framework of a Cobb-Douglas function. Applying basic logarithm rules to (2) and inserting it into (1) gives:

$$y_{it} = \alpha^A a_{it} + \alpha^E l_{it} + \theta r_{it} + \alpha^K k_{it} + \alpha^M m_{it} + \omega_{it} + \varepsilon_{it}, \tag{3}$$

where r and l are the natural logarithm of $R = ((F+1)/L)$ and L, respectively, and $\theta = \alpha^E \gamma$. Given this formulation, γ is equal to $\theta = \alpha^E$. We thus arrive at an empirically tractable technology specification that allows a direct test of the effect of labour force composition.

A further refined model could try to directly estimate even more specific aspects of labour composition, such as time spent on supervision or relative education or technological skills of the different groups of workers (see Frisvold (1994) for some steps in the former direction). In our application, these could not be implemented due to data limitations. Even so, our estimates of γ might indeed reflect different qualifications of family and hired labour.

The Cobb-Douglas technology has maintained its status as the workhorse of applied production function analysis up until the present day (see Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Petrin and Levinsohn, 2012 for some recent examples). However, it imposes a lot of structure on the production technology, including strong separability, constant output elasticities, a constant scale elasticity and substitution elasticities between all input pairs which are always constant ($=1$) as well (Chambers, 1988). This rigidity can be overcome by adding quadratic and interaction terms of inputs, leading to the more flexible Translog formulation. We test this extension below (section 4). To support the assumption of a homogeneous production technology, we restrict our empirical analysis to full-time farmers specialising in crop production (see section 3).

2.2. | **Identification**

Factor use across firms is usually under control of the farmer and decided simultaneously with unobserved events or may depend on such events. Therefore, the inputs in (3) are subject to an endogeneity problem. For instance, the farmer's and workers' reactions to environmental shocks are clearly endogenous as they may depend on omitted variables such as technological skills or the experience with past comparable shocks. In return, adjustment to these shocks also affects the other input choices. The unobserved heterogeneity (ω_{it}) might further represent factors such as natural resource endowments of the farm, e.g. soil quality. As a result, the ω_{it} will likely be correlated with the observed inputs. The standard OLS estimator will produce biased estimates

of output elasticities as it neglects the presence of ω_{it}. This endogeneity problem typically leads to upward biased elasticities for variable inputs (e.g. labour and materials; Levinsohn and Petrin, 2003). As Ackerberg et al. (2007) pointed out, the standard OLS approach also lacks the necessary information that allows separate identification of the production elasticities, leading to a collinearity problem. Factor use across farms varies only with the unobserved ω_{it}, so that the different production elasticities are not identified.[2]

To tackle these problems, we need to control for ω_{it} and provide identifying information for the inputs. We do this by inserting a non-parametric control function ω_{it} into (3), ending up with a partially linear, semi-parametric model first proposed by Olley and Pakes (1996: 1275). Moreover, we use the identification approach suggested by Wooldridge (2009), who uses orthogonality assumptions about past and present levels of input use in the framework of an instrumental variables estimator. This latter approach is consistent with the idea of adjustment costs in input provision that vary across inputs. With regard to our core hypothesis, it assumes that today's labour composition of a farm is affected by past endowments with factors. For example, contemporary labour composition may be driven by past decisions on land purchases. Adjustment costs play an important role in EU agriculture as a recent analysis by Rungsuriyawiboon and Hockmann (2015) using Polish FADN data suggests.

The rationale behind this approach may be best understood by comparing it with the traditional way to control ω_{it}, the 'within' or fixed effects approach (Mundlak, 1961). Suppose we can decompose ω_{it} further in:

$$\omega_{it} = \lambda_t + \eta_i + v_{it}$$

where λ_t is a time-specific shock identical for all farms in t, η_i is a farm-specific fixed effect that is constant over time, and v_{it} is the remaining farm- and time-specific productivity shock unanticipated by the farmer and unobserved by the analyst. The usual approach then is to purge the fixed effects (η_i) by the so called within transformation. To do so, farm-specific means are subtracted from all the variables. The λ_t are usually controlled for by incorporating time dummies into the model. However, the question remains whether the assumption of time constant fixed effects is plausible. If η_i represents factors such as management or soil quality they can be considered as time-varying over a sufficiently long period. Therefore, this assumption is likely to hold only for panels that cover rather short periods of time. Furthermore, the within transformation is known for removing too much variance from variables that exhibit little variation over time, such as land, labour and fixed capital, resulting in downward biased estimates for these factors (Griliches and Mairesse, 1998: 180–185). Especially with the effective labour function in mind, this can potentially lead to wrong conclusions.

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2   See Petrick and Kloss (2018) for a general discussion of these endogeneity and collinearity issues in the context of agricultural production function estimation.

In contrast, our approach controls for ω_{it} by a function of observed firm characteristics (Olley and Pakes, 1996). Levinsohn and Petrin (2003) proposed the level of materials input to be used as a proxy. Therefore, we assume ω_{it} evolves according to:

$$\omega_{it} = h(m_{it}, k_{it}),$$

where h is a non-parametric function. Furthermore, it is assumed that unobserved productivity follows a first-order Markov process:

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}] + \xi_{it}, \tag{4}$$

where ξ_{it} is an innovation uncorrelated with k_{it}, but possibly correlated with the other factors in the production function. Following Wooldridge (2009), we additionally assume that:

$$E[\omega_{it}|k_{it}, a_{it-1}l_{it-1}, r_{it-1}, k_{it-1}, m_{it-1}, \ldots, a_{i1}, l_{i1}, r_{i1}, k_{i1}, m_{i1}]$$

$$= E[\omega_{it}|\omega_{it-1}] = g(\omega_{it-1}) \equiv g[h(m_{it-1}, k_{it-1})], \tag{5}$$

where g is an unknown productivity function. Equation (4) together with (5) provide some deeper insight in the innovation ξ_{it}. It asserts that this innovation is uncorrelated with current and past realisations of k and past realisations of a, l, r and m. These assumptions are necessary to obtain a consistent estimate of α^K and α^M.

For the ε_{it}, Wooldridge proposes:

$$E[\varepsilon_{it}|a_{it}, l_{it}, r_{it}, k_{it}, m_{it}, a_{it-1}, l_{it-1}, r_{it-1}, k_{it-1}, m_{i,t-1}, \ldots$$

$$a_{i1}, l_{i1}, r_{i1}, k_{i1}, m_{i1}] = 0 \tag{6}$$

Therefore, the residuals are assumed to be orthogonal not only to current but also all past values of a, l, r, k and m.

Now, starting from (3), the problem can be formulated in terms of two equations. The first is given by:

$$y_{it} = \alpha^A a_{it} + \alpha^E l_{it} + \theta r_{it} + \alpha^K k_{it} + \alpha^M m_{it} + h(m_{it}, k_{it}) + \varepsilon_{it}, \tag{7}$$

where (6) provides the moment conditions holding for this equation. The second can be obtained by plugging $\omega_{it} = g[h(m_{it-1}, k_{it-1})] + \xi_{it}$ into the production function:

$$y_{it} = \alpha^A a_{it} + \alpha^E l_{it} + \theta r_{it} + \alpha^K k_{it} + \alpha^M m_{it} + g[h(m_{it-1}, k_{it-1})] + \epsilon_{it}, \tag{8}$$

where $\epsilon_{it} = \xi_{it} + \varepsilon_{it}$. The moment conditions holding for this equation are:

$$E[\epsilon_{it}|k_{it},a_{it-1},l_{it-1},r_{it-1},k_{it-1},m_{it-1},...,a_{i1},l_{i1},r_{i1},k_{i1},m_{i1}] = 0. \tag{9}$$

Hence, in (7) and (8) current and past values of k, past values of a, l, r and m as well as functions of these can be used as instruments. Additionally, in (7), contemporaneous proxy variables and current realisations of a, l and r are valid instruments.

The two equations (7) and (8) together with the moment conditions in (6) and (9) can be estimated within a Generalised Methods of Moments (GMM) framework. In empirical practice, these orthogonality conditions are usually weakened in that only lags up to order one are included. In our application, we identify the production function parameters by estimating (8) using instrumental variable estimation with instruments for a, l, r and m (Wooldridge, 2009: 113). The function h is approximated by low-order polynomials of first-order lags of m and k which act as their own instruments. According to the theoretical setup so far, m needs to be instrumented by its second order lag while a, l and r are instrumented by their first-order lags. The function g is assumed to follow a random walk with drift (Wooldridge, 2009: 114).

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.

Given this theoretical framework, the Wooldridge (2009) estimation procedure does not only control for endogeneity problems but also solves the collinearity issue raised by Ackerberg et al. (2007). This is in contrast to former versions of these so called control function approaches (cf. Bond and Söderbom, 2005; Ackerberg et al., 2007). Petrick and Kloss (2018) demonstrate that such approaches behave robustly in empirical practice, making them interesting alternatives to the traditional 'within' approach. In the following, we present results for a set of estimators that involves OLS as a baseline as well as our preferred semi-parametric estimator due to Wooldridge (2009).

3 \ **Data**

The EU's Farm Accountancy Data Network (FADN) provides a stratified farm level data set that holds accountancy data for 25 of the 27 EU member states. The stratification criteria are region, economic size and type of farming – full-time field crop farms (TF1) in the present study. This

means that the farm's operation is the core activity for the farmer with at least 40 operating hours per week (European Commission, 2014; FADN data). Output is measured as the total farm output in euros. The total utilised agricultural area is our land input in ha. It includes owned and rented land, and land in sharecropping. 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. The former consists of costs for seeds and seedlings, crop protection and other crop specific costs. Overheads are comprised of "supply costs linked to production activity" and are usually the single largest position in the materials input (European Commission, 2011). They include, amongst others, costs for energy such as fuel and electricity. We do not include the costs for fertiliser in our materials input. Land and fertiliser are highly correlated, suggesting that land and fertiliser inputs are utilised by farmers in an (almost) fixed ratio. We capture this "package" by including land input in hectares. Fixed capital is approximated by using the opening valuation of assets which is 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). In this case, we took the asset value of machinery and buildings from the FADN data. This measure accounts for different depreciation rates of machinery and buildings which are estimated at replacement value of these inputs (European Commission, 2011). In order to estimate the effective labour function (2) within a production function framework, i.e. estimating (3), we need information on hired and family labour working time separately in addition to the total labour hours which is readily available in the FADN data. Having this data available we can construct the additional covariate r. To this end, we calculate $R = ((F+1)/L)$ and take its natural logarithm. Table 1 gives definitions of the variables needed as well as their FADN codes. The sample of countries is selected to reflect the diverse farm sizes and structures in EU arable farming. The range is from small-scale family farms in Italy and West Germany to medium-sized commercial farms in Denmark, France and the UK (European Commission, 2012). The focus on countries that rely more or less heavily on family labour reflects our interest in investigating the dominant effect of supervision costs on hired labour productivity. Moreover, it is the variability of farm structures across countries that makes comparisons of labour force heterogeneity particularly insightful.

Table 1   Description of variables

FADN code	Variable description
Left-hand side	
SE131	Total output (EUR)
Right-hand side	
Inputs	
SE025	Total utilised 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) = capital
Effective labour effort	
SE011	Total labour input (hours)
SE016	Unpaid labour input, generally family (hours)
SE021	Paid labour input (hours)

Source: Authors, European Commission (2011)

For every country, we constructed a panel data set covering the years from 2001 up to 2008. The effective panel length is reduced by one year as we use the opening valuation of fixed assets which is taken from the previous year of observations as our capital proxy. In order to be included in the estimating sample, farms had to be present for at least four years in a row. Similar to Petrick and Kloss (2018), outlier analysis was performed on the basis of the fixed capital productivity per farm. Observations were excluded from the estimation if their value exceeded the interval given by $[Q_1 - 1.5 \cdot IQR; Q_3 + 1.5 \cdot IQR]$, where Q_1/Q_3 is the lower/upper quartile and IQR the interquartile range.

Monetary values were deflated to real values in 2005 prices using appropriate price indices. These 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.

Table 2 summarises the number of farms for every country in our sample, the labour force composition (average percentage of family labour), and the other variable means. Our data sample covers a total of 3,314 farms. The numbers on output reflect the different forms of agricultural organisation outlined before. A full set of descriptive statistics is given in Table A1. Further confirming the picture conveyed in Figure 1, according to the table, the dominant type of labour in EU arable farming is family labour. In addition, there are farms in the sample entirely run on hired or family labour (e.g. in Germany and Italy). This fact further warrants the use of the effective labour effort function given in (2). To get a more dynamic view of these figures, we graph their evolution over the sample period (Figure A1). In the majority of countries, the percentage of family labour is declining between 2001 and 2008. Exceptions to the general tendency are France and Italy, where the numbers remained more or less constant.

Table 2   Sample size and variable means

Country	Farms	Family labour in % of total labour	Total labour (thsd hours)	Output (thsd EUR)	Land (ha)	Materials (thsd EUR)	Capital (thsd EUR)
Denmark	208	84.52	2.8	180.4	122.7	98.0	840.0
France	1030	84.11	3.2	155.8	143.5	85.1	160.1
Germany (West)	566	84.70	4.2	150.9	92.3	84.7	153.9
Italy	1322	88.55	3.6	60.6	44.7	23.8	125.2
United Kingdom	188	64.76	6.3	278.1	248.7	157.2	239.3

Source: Authors based on FADN data

4 \ **Results**

4.1. | **Main findings**

To infer about the effective labour effort parameter γ, we estimate (3) employing two estimators per country. These are 1) OLS as a baseline and 2) Wooldridge (2009), hereafter Wooldridge/Levinsohn/Petrin (WLP). All estimations were performed with Stata 12. To implement the WLP estimator we employed the 'ivreg2' routine by Baum et al. (2007) as shown in Petrin and Levinsohn (2012).

As we mentioned in the identification subsection, the WLP estimation procedure incorporates lags of inputs up to the second order, which reduces the panel length for every country by two years. We also use the resulting estimation sample for the OLS estimates in order to ensure comparability. To recover the standard error of γ, we use the 'delta method' (Greene, 2011: 1123–1124). Returns to scale was measured as the sum of the direct production elasticities of labour, land, materials and capital. Given sufficiently developed factor markets for these four inputs in the countries studied, it seems reasonable to assume that all factors can be adjusted at some cost and with some delay (see section 2.2).

In Table A2 and Table A3 we report detailed results of the production function estimation per estimator and country. Our preferred one is the WLP estimator. On theoretical grounds, it corrects the biases induced by the endogeneity and collinearity problems present in production function estimation. Empirically, the results look very plausible. In contrast to the OLS estimates, which reject the assumption of constant technical returns to scale for every country but West Germany at the 5 per cent significance level, the WLP estimates never reject this hypothesis.

Table 3 gives the sample size, the point estimate as well as the standard error of γ per country and estimator. Regarding its significance in the different member states and regions, the following picture unfolds. In Denmark and Italy the coefficient of γ is not significantly different from zero, meaning that the null hypothesis of perfect substitution between hired and family labour cannot be rejected. The small- and medium scale agricultural structures of West Germany and France exhibit negative γ's that are significantly different from zero. This result implies that effective labour effort is a monotonically decreasing function of the share of family labour (Figure 3). Hence, farms relying on hired labour are more productive than family farms, and farms relying almost completely on hired labour are particularly productive. Moreover, the productivity loss created by a higher share of family labour declines as the ratio of family to total labour expressed in (2) increases (cf. Bardhan, 1973: 1381). It is probably in these instances where hired labour specialises on high productivity tasks and/or family labour focuses on low productivity tasks. Finally, the classical case of family members being more productive than hired labour ($\gamma > 0$) is only observed for the United Kingdom – the extent being moderate. In this case, there is an argument for labour supervision that might increase the productivity of hired workers.
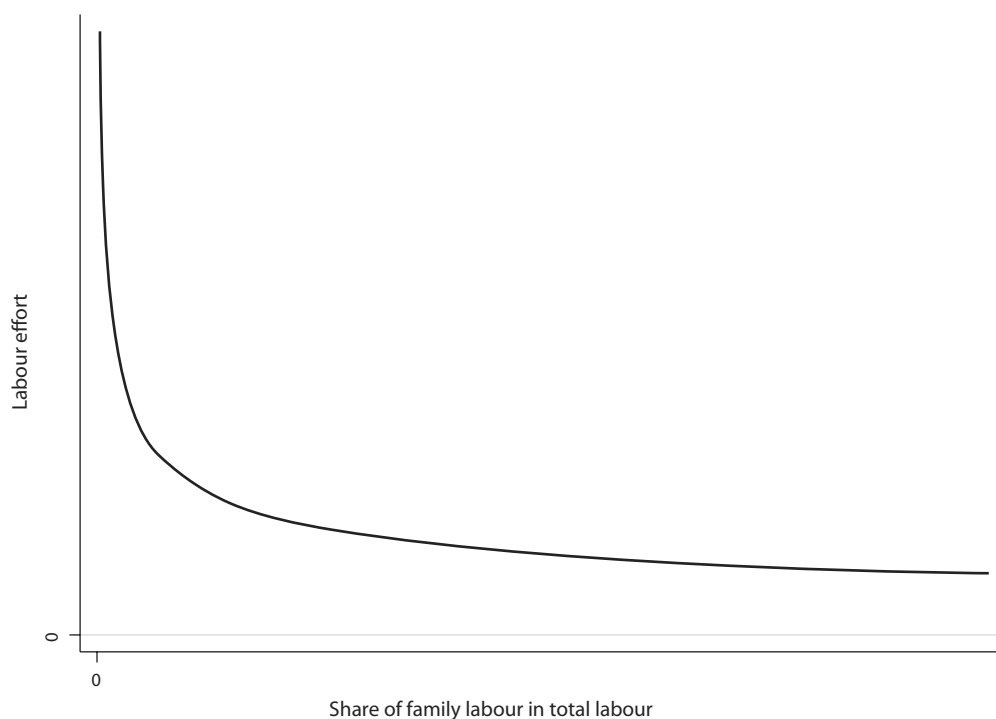
The image shows a graph with "Labour effort" on the y-axis and "Share of family labour in total labour" on the x-axis. A decreasing curve starts high on the left and flattens out toward the right. The y-axis is marked at 0 and the x-axis at 0.

Figure 3	Effective labour as a function of family labour share in total labour if $\gamma < 0$
	Notes: Graphical representation for hired labour being more productive than family labour ($\gamma < 0$) and constant total labour input
	Source: Authors' elaboration

Regarding the size of γ, West Germany exhibits the largest productivity differential between family and hired labour. An example calculation illustrates the effects. In West Germany, an increase in the share of hired labour time from 20 per cent to 30 per cent in total labour time amounts to an average increase in labour productivity by 0.56 EUR/hour or about 2.4 per cent – up to 23.50 EUR/hour.[3]

The direct output effects of the land input is with the exception of Denmark and the United Kingdom small in most countries, often not significantly different from zero. Italy displays a negative parameter estimate, though close to zero and not statistically significantly different from zero Table A3. Therefore, it is assumed to be zero. This finding is consistent with the plausible view that, while holding all other factors constant, expanding land does not raise output. The rationale behind this observation is as follows. Most farms utilise inputs, particularly materials, in abundance so that an additional hectare of land does not have a positive output effect. This result holds even more in the WLP model, i.e. when unobserved productivity differences are controlled for.

Levinsohn and Petrin (2003) argue that the bias direction in OLS estimates of the capital input depends on the degree of correlation between this input and the unobserved productivity (ω_{it}). It tends to be upward biased in our application, thus contributing to an upward bias in returns

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3   Calculation based on the sample means of the different inputs and the WLP production function estimates.

to scale. The OLS estimates of the materials output elasticity are also often larger than their WLP counterparts, which is consistent with prior theoretical predictions and empirical observations.

Compared to the WLP estimates, the OLS estimator detects labour force heterogeneity in one more case – Denmark. The reason for this result is probably an upward biased OLS estimate of the ratio r leading to an upward biased estimate of γ. Such a result is commonly observed for the OLS estimator in presence of endogeneity. Therefore, this estimate is most likely biased.

For the case of Denmark, there is one noteworthy finding. In this instance, the WLP estimator was not able to identify a parameter estimate for the materials input. The reason for this result is two-fold. First, there is probably not enough identifying information (variance) left in this input after the exclusion of fertiliser inputs. Second, the non-parametric control function that also houses the materials inputs most likely captures huge parts of the explaining variation that is left. This second argument explains why the WLP estimation procedure is affected, at least in this particular case.

Table 3   Effective labour effort parameter (γ) in comparison

Country	OLS			'Wooldridge/Levinsohn/Petrin'		
	N	γ	SE	N	γ	SE
Denmark	605	0.290***	0.108	605	0.117	0.090
France	4289	-0.554**	0.217	4289	-0.481**	0.214
Germany (West)	2408	-1.641**	0.698	2408	-1.517**	0.615
Italy	3545	-0.274	0.221	3545	-0.165	0.198
United Kingdom	612	0.190**	0.090	612	0.215**	0.095

Notes: Year dummies included in all models. *** (**, *) significant at the 1% (5%, 10%) level, based on standard errors robust to clustering in groups
Source: Authors

4.2. | **Robustness Checks**

To understand in how far the assumption of a Cobb-Douglas technology restrict our findings, we also experimented with a Translog production function.[4] This specification produced unreasonable results that exhibited (at sample means) at the same time negative production elasticities for some factors and elasticities bigger than one for others. In addition, the null hypothesis of joint insignificance of the interaction terms was never rejected for any country. Hence, interaction terms do not add any meaningful insights to the Cobb-Douglas specification. We do not consider the Translog functional form to be a suitable approximation to the data. Our findings are in line with other recent studies based on FADN data (cf. Zhengfei et al., 2006; Latruffe and Nauges, 2013).

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4   We estimated the Translog using total labour input (Table A4). A Translog specification incorporating the effective labour input could only be implemented insofar that interaction terms incorporating E were excluded.

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 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 $\widehat{\omega}_{it}$. Hence, we can only perform an ex-post analysis. To this end, we calculate $\widehat{\omega}_{it}$ as residuals from the predictions 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 (Duchon, 1976). This is 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 Figure A2 – Figure A6, we display the three-dimensional surface plots. In general, the monotonicity condition holds throughout the sample of countries. That is, in Denmark, West Germany, Italy and the United Kingdom materials increases in omega for a given level of capital. France, on the other hand, is an exception. In this case, the monotonicity condition only holds in regions with up to medium levels of materials usage and medium to high levels of capital. However, this region has 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 falling into that particularly area is large, too. In case of France, this amounts to about 60 per cent of observations. This 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.

5 \ **Conclusions**

In this study, we assessed the heterogeneity of family and hired labour in European field crop farming. To this end, we took a sample of five EU countries and estimated augmented production functions that allow testing for labour force heterogeneity using farm-level FADN data. The results unveil a diverse picture.

Contrary to the received wisdom, we find that farms with a higher share of hired labour are more productive than family farms in the small- and medium-scale agrarian structures of France and West Germany. According to our estimates, hired labour performs the high productivity tasks in these countries. In such a situation, an increase in reliance on hired labour or the shift of family labour to more productive tasks raises productivity. Hence, labour market reforms should aim at providing incentives to hire specialised labour. For instance, programs to train and hire skilled labour could improve their inflow into agricultural labour markets. In Denmark and Italy we found no evidence for labour force heterogeneity. We regard it an interesting question for future research to find out why hired labour in arable farming is so productive in France and West Germany, two countries traditionally characterised by family farms. One possible explanation is that farm technology, e.g. modern tractors and other field machinery using precision farming methods, has reached such levels of sophistication that benefits from labour specialisation can

be reaped. Farming in the UK, on the other hand, traditionally displays higher levels of hired labour. This pool of workers may to a larger extent consist of lower qualified personnel subject to the classical incentive problems. Our data did not allow to explicitly address the effects of skills and technical expertise of family versus hired workers. We regard this as an important area for future research, too.

The results have implications for future theoretical and empirical work. Most importantly, our results call into question the general validity of one of the received family farm theory's main pillars, i.e. the dominant effect of supervision costs on hired labour productivity. Countries regarded as traditional strongholds of the family farm have apparently crossed a technological threshold where specialisation of hired labour overcompensates the negative effects of workers' moral hazard. Factors such as the increasing importance of non-traditional and non-agricultural sources of farm household income are likely reinforcing this trend. On the other hand, the assumption of constant technical returns to scale is confirmed.

In classical production function estimation, labour input is measured as the sum of both, hired and family workers. Given the evidence on labour force heterogeneity in some countries, their heterogeneity should not be ignored. Such a treatment will improve model fit and avoid misspecification.

Finally, this work is also a plea for refined methods that control for the problems in production function estimation. Endogeneity and collinearity problems potentially lead to misleading results. The OLS estimator neglecting the presence of endogeneity does not always seem to detect labour force heterogeneity correctly. A possible alternative which has been extensively used in prior empirical work is the fixed effects regression. However, it is notorious for removing too much variance from variables that exhibit little variation over time. Hence, not enough variation is left in the data for estimation purposes (Petrick and Kloss, 2018). This shifted our attention to the control function framework introduced by Olley/Pakes and then further refined by Levinsohn/Petrin and Wooldridge. Especially the latter is a promising alternative to traditional OLS and 'within' approaches. The results obtained from the Wooldridge/Levinsohn/Petrin approach seem to strengthen their validity on empirical grounds, besides being plausible in the theoretical domain.

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APPENDIX: RESULTS TABLES AND FIGURES

Table A1 — Descriptive statistics

Country	Number of farms	Output (ths EUR)				Total labour (ths hours)				Land (ha)				Materials (ths EUR)				Capital (ths EUR)			
		Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Denmark	208	180.4	277.1	3.1	2733.4	2.8	4.0	0.1	49.0	122.7	172.2	3.3	1760.0	98.0	158.6	5.5	1824.4	840.0	1402.7	42.3	21381.0
France	1030	155.8	114.5	5.2	1574.7	3.2	2.4	1.2	38.2	143.5	82.6	3.6	647.4	85.1	56.2	4.7	618.6	160.1	127.7	2.8	1379.8
Germany (West)	566	150.9	137.1	12.8	2114.7	4.2	3.3	1.1	93.9	92.3	60.1	0.5	429.5	84.7	67.6	11.9	737.5	153.9	125.5	11.1	1013.3
Italy	1322	60.6	125.2	0.8	2165.2	3.6	4.5	0.0	98.7	44.7	75.5	0.6	723.3	23.8	53.8	0.5	1204.2	125.2	232.6	2.7	4692.2
United Kingdom	188	278.1	330.3	8.7	3548.6	6.3	5.1	0.3	51.8	248.7	182.4	17.8	1178.5	157.2	150.0	10.4	1475.8	239.3	216.5	8.4	1555.2

Notes: SD: standard deviation. Min: Minimum value. Max: Maximum value
Source: Authors' calculations

Table A2 — Results of production function estimations for the Ordinary Least Squares estimator per country

Country	Denmark		France		Germany (West)		Italy		United Kingdom	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.535***	0.067	0.125***	0.019	0.106***	0.031	0.279***	0.022	0.219***	0.041
Ratio (r)	0.155**	0.062	-0.069***	0.019	-0.173***	0.030	-0.077	0.058	0.041**	0.021
Land	0.229***	0.062	0.073***	0.018	0.045**	0.019	0.009	0.015	0.196***	0.046
Materials	0.523***	0.052	0.744***	0.019	0.777***	0.024	0.664***	0.020	0.726***	0.048
Capital	0.155***	0.040	0.159***	0.013	0.119***	0.019	0.093***	0.013	0.073**	0.032
N	605		4289		2408		3545		612	
Elasticity of scale	1.442	0.031	1.101***	0.018	1.046***	0.031	1.045***	0.016	1.214***	0.033
p-value const. ret. to scale	<0.001		<0.001		0.137		0.035		<0.001	
R²	0.949		0.864		0.859		0.847		0.907	
p-value coeff. jointly zero	<0.001		<0.001		<0.001		<0.001		<0.001	

Notes: Year dummies included in all models. ***; (**; *) significantly different from zero at the 1% (5%, 10%) level, based on standard errors robust to clustering in groups
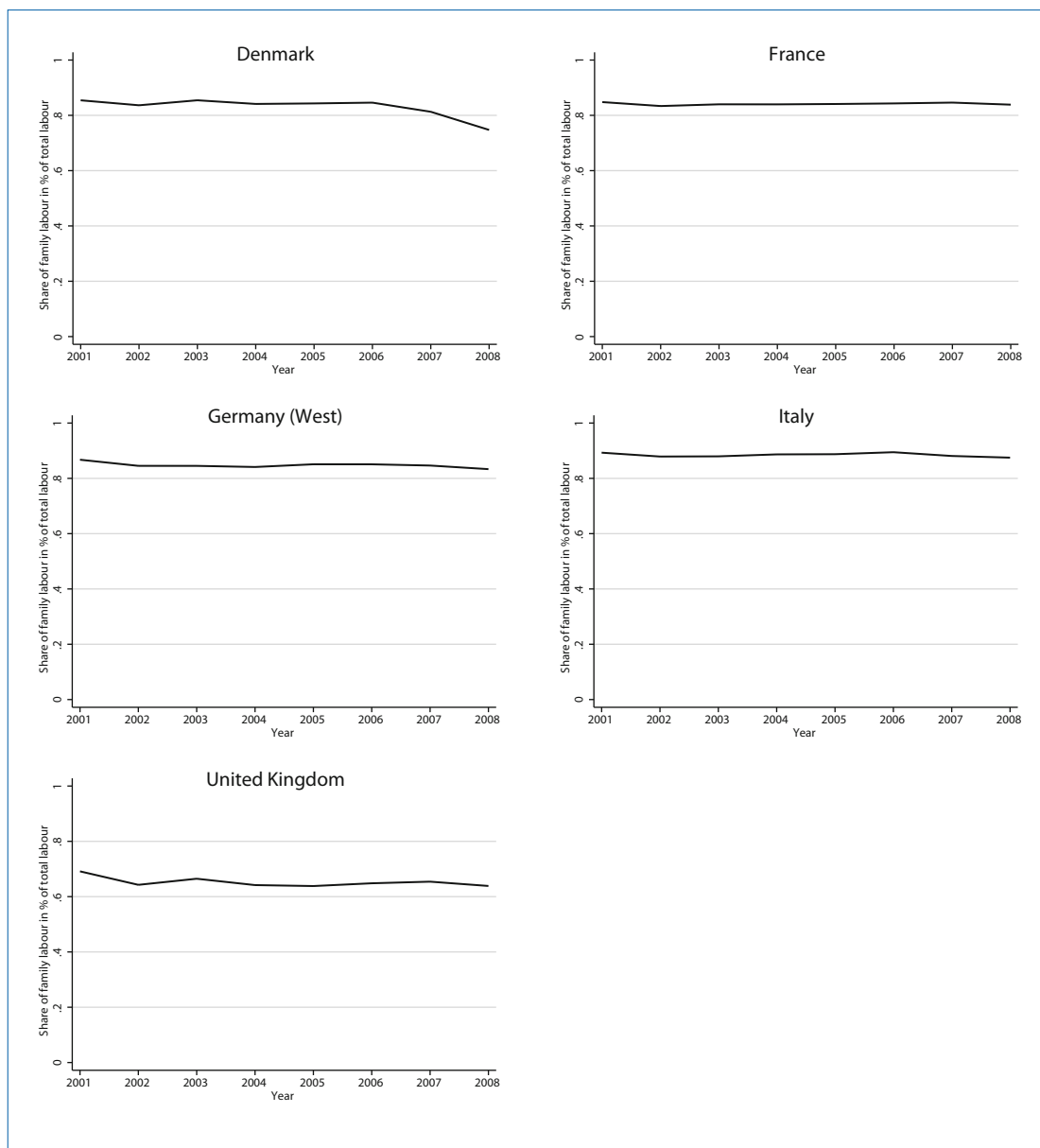Source: Authors' calculations

Table A3 Results of production function estimations for the Wooldridge/Levinsohn/Petrin estimator per country

Country	Denmark		France		Germany (West)		Italy		United Kingdom	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.653***	0.098	0.136***	0.022	0.120***	0.032	0.308***	0.027	0.203***	0.050
Ratio (r)	0.076	0.062	-0.065***	0.021	-0.182***	0.032	-0.051	0.059	0.044***	0.020
Land	0.220***	0.080	0.046***	0.018	0.013	0.019	-0.009	0.021	0.182***	0.060
Materials	-0.012	0.268	0.799***	0.083	0.729***	0.086	0.501***	0.107	0.722***	0.379
Capital	0.100	0.075	0.118***	0.015	0.085***	0.024	0.018	0.031	0.107***	0.063
N	605		4289		2408		3545		612	
Elasticity of scale	0.962***	0.230	1.099***	0.076	0.947***	0.082	0.818***	0.094	1.213***	0.364
p-value const. ret. to scale	0.868		0.193		0.517		0.054		0.557	
p-value coeff. jointly zero	<0.001		<0.001		<0.001		<0.001		<0.001	

Notes: Year dummies included in all models. *** (**, *) significantly different from zero at the 1% (5%, 10%) level, based on standard errors robust to clustering in groups
Source: Authors' calculations

Table A4 Results of Translog production function estimations for the Wooldridge/Levinsohn/Petrin estimator per country

Country	Denmark		France		Germany (West)		Italy		United Kingdom	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Labour	0.548	1.440	-0.325	0.494	-1.066**	0.491	-0.300	0.424	1.230	1.138
Land	0.163	0.988	0.250	0.267	1.046***	0.329	-0.031	0.294	2.383*	1.388
Materials	0.132	2.208	0.794	0.894	1.848**	0.810	1.033	0.637	-0.230	5.644
Capital	0.610	1.282	-0.632	0.612	-0.007	0.438	-0.407	0.376	-1.261	2.035
N	605		4289		2408		3545		612	
p-value coeff. jointly zero	<0.001		<0.001		<0.001		<0.001		<0.001	
p-value interact. terms jtly.zero	0.824		0.397		0.171		0.138		0.921	

Notes: Estimates at sample means. Year dummies included in all models. *** (**, *) significantly different from zero at the 1% (5%, 10%) level, based on standard errors robust to clustering in groups
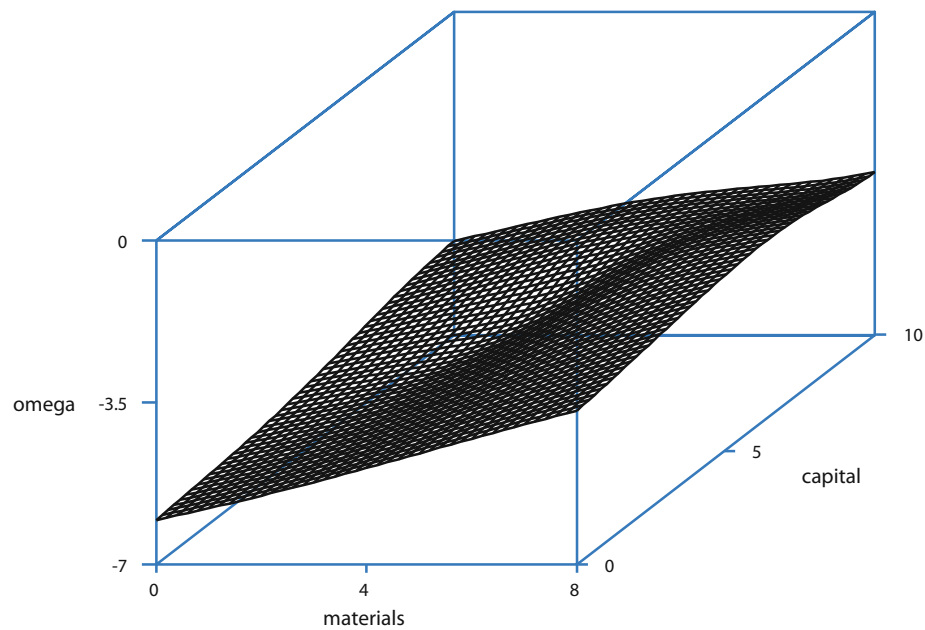Source: Authors' calculations

Figure A2   Prediction of omega as a function of materials and capital, Denmark
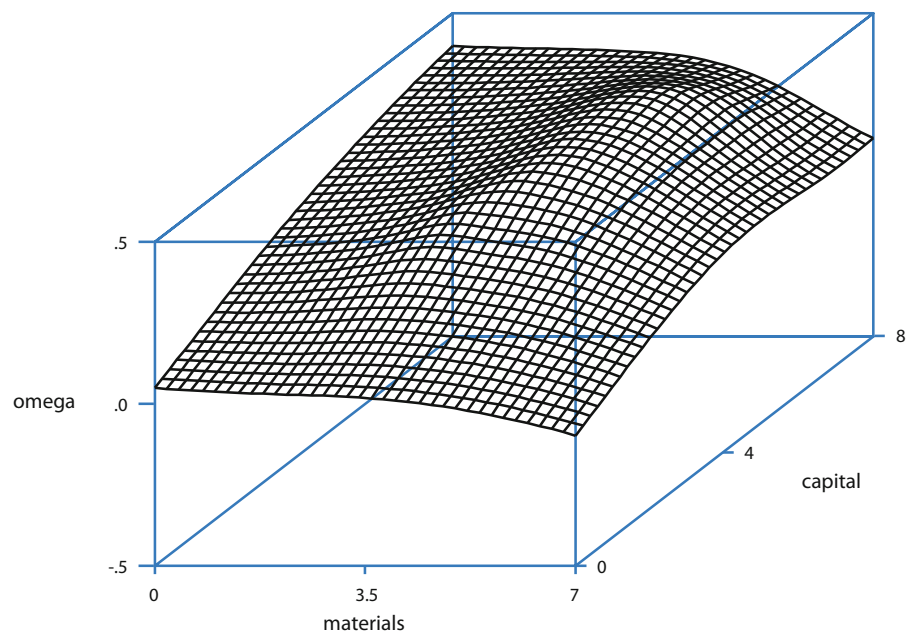Source: Authors

Figure A3   Prediction of omega as a function of materials and capital, France
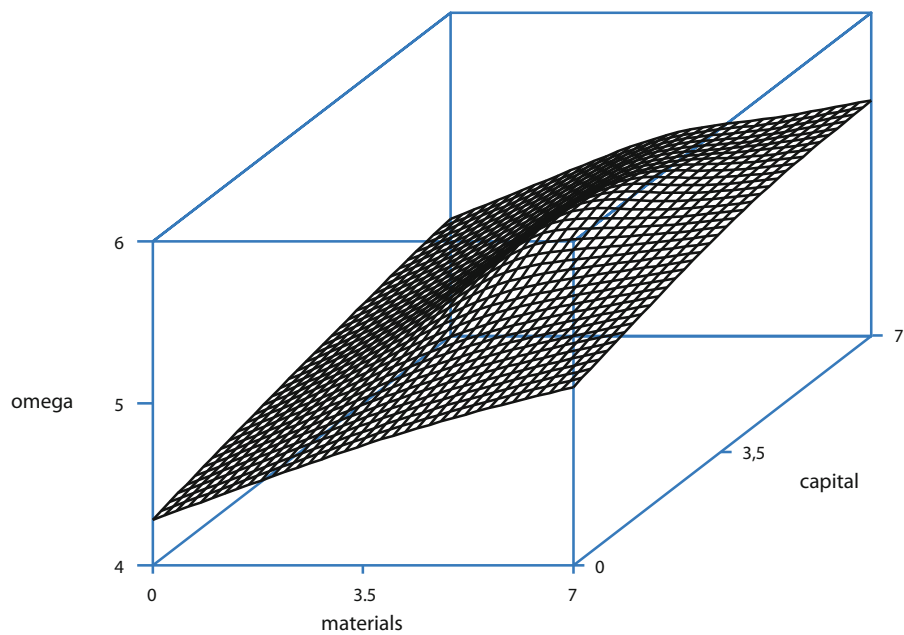Source: Authors

Figure A4   Prediction of omega as a function of materials and capital, Germany (West)
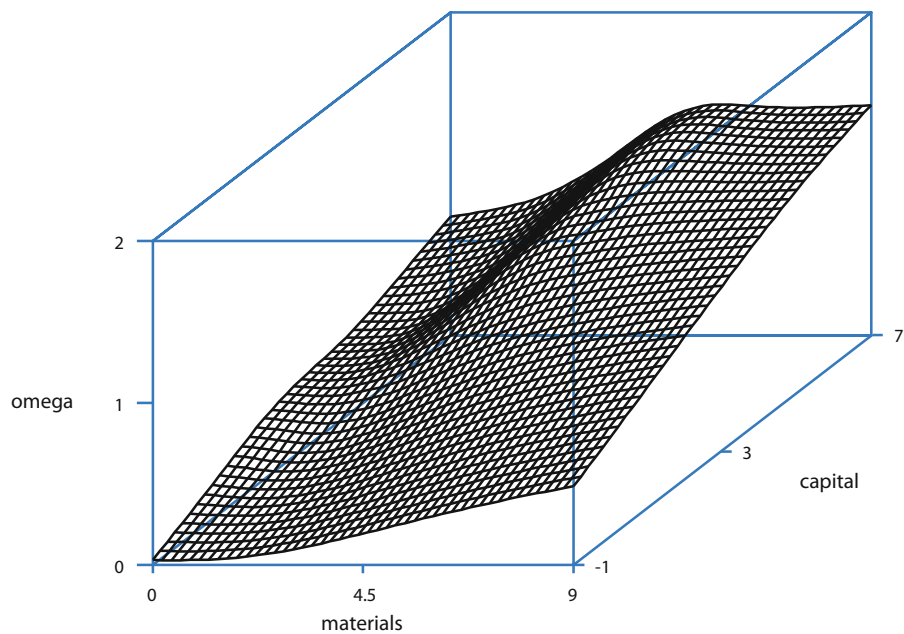Source: Authors

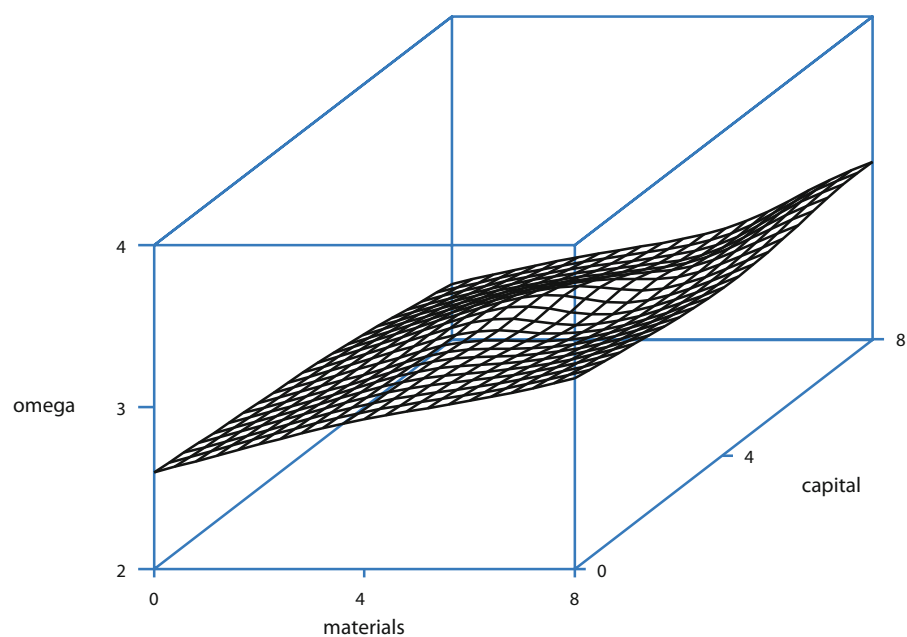Figure A5   Prediction of omega as a function of materials and capital, Italy
Source: Authors

Figure A6   Prediction of omega as a function of materials and capital, United Kingdom
Source: Authors

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