



The impact of CAP subsidies on the productivity of cereal farms in six European countries: A historical perspective (2008–2018)

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ABSTRACT

Productivity is an always-hotly-debated issue within the EU agricultural policymaking, particularly concerning the effect of subsidies distributed via the Common Agricultural Policy (CAP). The cereal sector is under particular political scrutiny nowadays, with the Ukraine conflict and environmental issues menacing food security levels for both developing and developed countries.

Using individual farm data from 2008 to 2018 for France, Germany, Italy, Poland, Spain, and the United Kingdom, we investigate the effects of different subsidies on the cereal farms' productivity, accounting for the intrinsic farms' productivity levels (low, medium and high productive farms). The System-GMM estimator, combined with Inverse Mills Ratios, is applied within a three-step strategy to overcome endogeneity problems. Results highlight how CAP subsidies affect farms' Total Factor Productivity (TFP), and to what extent they differ according to the nature of the subsidy, the country, and, interestingly, the intrinsic farm's productivity level. The analysis reveals that TFP embeds an autoregressive behaviour that should always be accounted for when assessing the relationship with subsidies. Most of the CAP subsidies entail a negative-to-unsignificant effect on TFP, except for agri-environmental subsidies, which can increase farms' productivity. Interestingly, the negative role of direct payments seems more recurrent in the low productive farms, accelerating their exit from the market.

1. Introduction

Productivity is considered among the most critical drivers of economic growth and welfare (Basu et al., 2022). The argument gains particular strength when the agricultural sector is concerned, challenged by the increasingly competitive and globalized economy and battered by extreme changes in the climate pattern, besides the very recent COVID-19 pandemic and the war in Ukraine (FAO, 2022a, 2022b; Global Network Against Food Crises, 2022). Indeed, while highly productive farms may handle challenges efficiently, the opposite is true for those with low productivity levels (Olley & Pakes, 1996; Rizov et al., 2013). The European Union (EU) identifies productivity enhancement as one of the four pillars of its economic policy, guiding structural reforms, investments, and fiscal responsibility for the incoming years (EC, 2019,

2020). Remarkably, the Common Agricultural Policy (CAP) aims, among other goals, at the growth of EU farms' productivity (Article 39 of the EU Treaty - (EC, 2007))², destining around 40 billion euros per year to the EU farming sector (Massot, 2020). Therefore, investigating how the CAP affects farms' productivity gathers pivotal political and economic importance nowadays, feeding the debate on the upcoming CAP reform. Furthermore, the current conflict in Ukraine significantly affects the cereal, oilseeds, and energy markets, with skyrocketing prices of grains and supply disruptions threatening food security in low-income countries (The Economist, 2022a, 2022c, 2022b), as well as awakening warnings in the most developed ones. Indeed, the European Commission recently adopted a support package to boost grain production (EU, 2022) in an attempt to lose dependency from Eastern grains (FAO, 2022b).

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² <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=OJ:C:2007:306:TOC>.

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The strand of literature devoted to the understanding of how the CAP leverages farms' productivity is yet far from being conclusive, delivering controversial results, although concluding on a generally negative correlation between the two (Khafagy & Vigani, 2022a; Mary, 2013; Minviel & Latruffe, 2017; Rizov et al., 2013). As stated by Khafagy and Vigani (2022a) in their EU-wide analysis of CAP and productivity, subsidies differ in nature, having specific aims and hence diverse influence on productivity and farmers' behaviour, partially justifying such controversial results the literature delivers (see among others: Dudu & Kristkova, 2017; Garrone et al., 2019a; Latruffe & Desjeux, 2016; Pisulewski & Marzec, 2022).

The present study attempts to deepen the understanding of how CAP subsidies affect farms' productivity, providing a microeconomic multi-country analysis focused on field crop farms in six EU countries, namely France, Germany, Italy, Poland, Spain, and the UK, spanning ten years (2008 – 2018). We considered coupled direct payments (CDP), decoupled direct payments (DDP), agro-environmental scheme payments (AES), payments for less-favoured areas (LFA), and support to farm investments and other annual payments provided by the Rural Development Policies – RDP – (RDP inv and RDPa Other, respectively).

The econometric strategy follows the three-step technique as in Mary (2013), where: (i) in the first step, the production function is specified and estimated; (ii) in the second step, production function estimates are used for retrieving the Total Factor Productivity (TFP) via the System Generalize Method of Moments (SYS-GMM) dynamic panel estimator; (iii) in the third step, the relationship between CAP subsidies and TFP is assessed, either for the aggregated and sub-sampled dataset, the latter according to the intrinsic farm's productivity level - low, medium, and high productivity levels - unconditional on the CAP received.

Up to the authors knowledge, no other empirical application discerns the effect of the CAP on TFP, accounting for different farm-specific productivity levels and controlling for self-selection bias. Second, we provide a multi-country analysis exploring a sector, the field crop, that is currently under the policy spotlight for the implications of the Ukraine war, hence providing timely insights to the EU policymaking process. Finally, we stress the importance of considering productivity as a dynamic process, hence accounting for the persistence of past occurrences. All three of these aspects can help shed light on the literature controversial results over the relationship between CAP measures and TFP. This study highlights how opposite results may be due to intrinsic country characteristics, the nonlinear relationship between CAP measures and the level of agricultural productivity, unveiled by investigating different subsets of farms with different productivity levels, and, finally, the strong autoregressive component of TFP, which does not allow CAP to change productivity significantly. Depending on specific measures, the country, and the productivity level of the farm, the sign and the magnitude of CAP subsidies vary, supporting the idea that a one-CAP-fits-all policy may not be efficient and tailored subsidies may be needed.

The remainder of the paper proceeds as follows: section 2 summarizes the principal differences regarding how the CAP is applied in different countries, besides offering an extended literature review on the empirical relationship between productivity and CAP measures; section 3 presents the estimation strategy adopted and describes the data used; section 4 describes the results obtained in each of the three estimation steps; section 5 draws policy implications of the results obtained, and, finally, section 6 concludes the paper.

2. Background

2.1. The common agricultural policies among six countries analysed: A stylized analysis

The six analysed countries differ in how the CAP is implemented. The year 2018 will be the reference year for the following stylized analysis. Firstly, how CAP resources are allocated between the two Pillars differs:

Pillar 2 in Italy and Poland received significantly higher shares than the other four countries and Spain and Italy spent around 10% of the overall amount of CAP resources on market measures, against the 5% EU average (EC, 2023) – probably because of the relevance of the fruit and vegetable sector. Furthermore, within Pillar 2, resources are heterogeneously distributed between the different Priorities: Italy focuses on supporting food chain organization and risk management (Priority 3); Germany and Poland on social inclusion and economic development (Priority 6); while France on restoring, preserving, and enhancing ecosystems (Priority 4) (EC, 2023).

Within Pillar 1 payments, hence direct payments (DP), the Single Payment Scheme (SPS) is implemented in all countries but Poland, where the Single Area Payment Scheme is valid. Nevertheless, also within those applying SPS, Spain, France, Italy, and the UK - Wales and Scotland – rely on the historical SPS, while Germany on the regional flat rate (Henke et al., 2015). Another relevant difference concerns the relative importance of voluntary coupled support, accruing for more than 14% of the overall national ceiling for direct payments in 2018, although not applied in Germany, France, and Poland (EC, 2023).

2.2. The impact of subsidies on productivity: A literature review

Since increasing productivity is one of the objectives of the CAP, the empirical literature studying the relationship between subsidies and productivity is as vast as controversial. Nevertheless, one should bear in mind that CAP measures are of different nature and aim at different goals, and that the wide range of econometric models – with different statistical and economic assumptions - scholars applied, may prevent a comprehensive comparison of the bulk of these studies (Khafagy & Vigani, 2022a; Minviel & Latruffe, 2017).

2.2.1. TFP and direct payments

The major share of the CAP is absorbed by Pillar 1 direct payments, hence CDP and DDP. Both for this reason, as well as the CAP Reform of 2003 with the massive introduction of DDP, research efforts have been especially dedicated to these payments; Table 1 offers a summary of empirical applications devoted to studying DP and productivity. According to Kumbhakar & Lien (2010), DP should not affect farmers' short-term marginal production decisions in the case of perfectly competitive markets, absence of economies of scale, and assuming risk neutrality of farmer behaviour. However, since such an assumption is often, if not always, violated, both CDP and DDP affect production function and productivity; they influence prices of both inputs and outputs (Bezlepikina & Lansink, 2006), labour conditions (Hennessy, 1998; Serra et al., 2005), and farm growth and exit of the market (Goodwin & Mishra, 2006; Zhu & Oude Lansink, 2008). Indeed, DP tend to reduce farmers' efforts to produce efficiently (Martin & Page, 1983), especially when a significant part of their income is subsidized (Minviel & Latruffe, 2017). However, DP influences the farmer's risk attitude (Serra et al., 2008), hence may stimulate investments by reducing financial constraints (Khafagy & Vigani, 2022b; Lee & Chambers, 1986; Manaresi & Pierri, 2019; Warusawitharana & Levine, 2012).

Considering 2005 as the watershed when the CAP reform towards decoupling finally took place in all the EU. Before 2005, empirical results generally agreed on the positive effect of CDP on TFP (Bakucs et al., 2010; Quiroga et al., 2017; Weber & Key, 2012), while, conversely, post-2005, this turns negative (Garrone et al., 2019a; Pechrová, 2015; Rizov et al., 2013). Interestingly, different farming sectors feature different CAP influences on farms' productivity: Latruffe & Desjeux (2016) found an opposite effect for DP on the TFP of cereal, oilseed and protein farms with respect to dairy, positive and negative, respectively; for field crop farms, Coelli et al. (2006) and Zhu & Lansink (2010) find non-significant effects of CDP before the CAP decoupling period, while Mary (2013) concludes on the negative relationship during the transition period. For the dairy sector, results are controversial: while Kazukauskas et al. (2010), Latruffe et al. (2017), and Martinez Cillero et al. (2018) agree on

Table 1
Literature on the impact of Direct Payments on productivity.

| Authors | Period | Sector | Level | Method/model | CDP on TFP | DDP on TFP |
|---------------------------------|-------------------|----------------|-----------|---------------|------------|------------|
| (Ayouba et al., 2017) | 2005–2008 | Field Crop | Farms | DEA | | Positive |
| (Bakucs et al., 2010) | 2001–2005 | All | Farms | SFA | Positive | |
| (Banga, 2014) | 1995–2010 | All | Countries | DEA | | Positive |
| (Bonfiglio et al., 2020) | 2014–2020 | All | Farms | SFA | | Negative |
| (Boussemart et al., 2019) | 1992–2012 | All | Farms | DEA | | Negative |
| (Ciaian & Swinnen, 2006) | | | | PEA | | Negative |
| (Coelli et al., 2006) | 1987–2002 | Field Crop | Farms | DEA | Neutral | Neutral |
| (Emvalomatis et al., 2008). | 1996–2000 | Field Crop | Farms | SFA | | Negative |
| (Ferjani, 2009) | 1990–2001 | All | Farms | Tobit model | | Negative |
| (Garrone et al., 2019a) | 2004–2014 | All | Nuts 2 | DPD | Negative | Positive |
| (Gohin, 2006) | 1995–2008 | COP - Dairy | CGE | | Negative | |
| (Kazukauskas et al., 2013) | 2001–2007 | All | Farms | Probit and FE | | Negative |
| (Kazukauskas et al., 2010) | 2001–2007 | Dairy | Farms | CFE | Positive | |
| (Khafagy & Vigani, 2022a) | 2004–2015 | All | Farms | GMM - System | | Positive |
| (Kleinhanß et al., 2007). | 1999–2000 | All | Farms | DEA | | Positive |
| (Lambarraa & Kallas, 2009) | 1990–2007 | Dairy | Farms | SFA | | Negative |
| (Lambarraa et al., 2009) | 1995–2003 | COP | Farms | SFA | | Negative |
| (Latruffe & Desjeux, 2016) | 1990–2006 | COP - Dairy | Farms | DEA | Positive | |
| (Latruffe et al., 2012) | 1990–2007 | Dairy | Farms | SFA | | Negative |
| (Latruffe et al., 2017) | 1990–2007 | Dairy | Farms | SFA | Neutral | Negative |
| (Martinez Cillero et al., 2018) | 2000–2013 | Dairy | Farms | SFA | Positive | Positive |
| (Mary, 2013) | 1996–2003 | Field Crop | Farms | DPD | Negative | Negative |
| (Minviel & Latruffe, 2017) | Systematic review | Meta-analysis | Positive | Neutral | | |
| (Pechrová, 2015) | 2005–2012 | All | Farms | SFA | Negative | Negative |
| (Pisulewski & Marzec, 2022) | 2004–2011 | Dairy | Farms | SFA | Negative | Negative |
| (Quiroga et al., 2017). | 1996–2009 | All | Nuts 2 | SFA | Positive | Negative |
| (Rizov et al., 2013) | 1990–2007 | Six farm types | Farms | CFE | Negative | Negative |
| (Serra et al., 2008) | 1998–2001 | All | Farms | SFA | | Negative |
| (Weber & Key, 2012) | 2002–2007 | All | Farms | OLS-IV | Negative | Negative |
| (Zbranek, 2014) | 2012 | COP - Dairy | Farms | DEA | Negative | Neutral |
| (Zhu & Lansink, 2010) | 1995–2004 | Field Crop | Farms | SFA | Neutral | |

COP = Cereal, Oleaginoses, Protein Crops – DEA: Data Envelopment Analysis – SFA: Stochastic Frontier Analysis - CFE: Control Function Estimator - DPD dynamic panel data – OLV-IV: Ordinary least squared with Instrumental Variables – FE: Fixed Effect – CGE: computable general equilibrium – PEA: Partial Equilibrium Analysis – ATT: Average Treatment on Treated – DiD: Differences-in-Differences – PSM: Propensity Score Matching - GMM – System: System of multiple equations with GMM estimator – RE: Random effect.

the positive effect of CDP on TFP, Pisulewski & Marzec (2022) and Zbranek (2014) conclude on the opposite.

Regarding DDP, results generally agree on their detrimental effect on TFP (Bonfiglio et al., 2020; Boussemart et al., 2019; Kazukauskas et al., 2013; Pechrová, 2015; Quiroga & Iglesias, 2008; Rizov et al., 2013; Serra et al., 2008; Weber & Key, 2012). Nevertheless, exceptions exist, although characterized by unique approaches. Garrone et al. (2019b) find positive effects on labour productivity only; Khafagy & Vigani (2022a) rely on a system of equations using the GMM estimator and assuming a Constant elasticity of substitution (CES) production function; Kleinhanß et al. (2007) investigated a very specific one-year-period spanning 1999–2000; finally, Banga, (2016) analyzed the relationship between DDP and TFP using the country level found a positive impact. When specific farming sectors are analyzed, dairy farms are generally negatively affected by DDP (Gohin, 2006; Lambarraa & Kallas, 2009; Latruffe et al., 2017, 2012; Martinez Cillero et al., 2018; Pisulewski & Marzec, 2022), while for field crops and cereals, oilseeds, protein crops (COP), although the majority of applications point to the negative (Emvalomatis et al., 2008; Gohin, 2006; Lambarraa et al., 2009; Mary, 2013) or non-significant effect (Coelli et al., 2006; Zbranek, 2014) of decoupled payments on productivity, Ayouba et al., (2017) are the only concluding on their positive influence on TFP.

2.2.2. TFP and Rural Development Policies

Assessing the relationship between RDP and productivity is complex, as CAP measures diverge in goals, design, and country implementation (Table 2). According to the relevant literature, we adopt a similar disaggregation of Pillar 2 payments for the sake of comparison: AES, LFA, and RDP INV.

AES present quite heterogeneous result; while a negative effect is mainly due to the reduction of input to reach environmental goals (Arata

& Skokoi, 2016; Khafagy & Vigani, 2022a; Pechrová, 2015; Quiroga et al., 2017), even when specific sectors are investigated, namely COP and dairy farms (Boulanger & Philippidis, 2015; Lakner, 2009; Pisulewski & Marzec, 2022), Banga (2016), Dudu et al. (2017), and Pufahl & Weiss (2009) converge on the positive impact of AES on TFP. However, these latter researches are not conducted on individual farms but rather on different aggregate levels, that is, country (Banga, 2014) and NUTS2 levels (Dudu & Kristkova, 2017), besides different periods as in Pufahl & Weiss (2009). Furthermore, using the Data Envelopment Analysis (DEA) approach for COP and dairy, Latruffe & Desjeux (2016) found a positive effect. Non-significant effects are reported by Baráth et al. (2020) for Slovenia, and Garrone et al. (2019a) for labour productivity only, and Latruffe et al. (2017) for the dairy EU farmers.

Concerning LFA, both positive (Banga, 2014; Khafagy & Vigani, 2022a; Pechrová, 2015) and non-significant effects (Baráth et al., 2018, 2020; Dudu & Kristkova, 2017; Garrone et al., 2019b; Quiroga et al., 2017) are reported. However, such subsidies are designed for sustaining farmers' income, hence not to increase productivity. When specific farm sectors are investigated, Latruffe et al. (2017) find non-significant effects for EU dairies, Pisulewski and Marzec (2022) conclude on the positive effects on Czech farms, and Zbranek (2014) describes a negative one in Slovakia, the latter also investigating COP Slovak farms.

Finally, investment subsidies entail an expected generally-positive effect (Dudu & Kristkova, 2017; Khafagy & Vigani, 2022a; Latruffe et al., 2008; Nilsson, 2017; Nowak et al., 2015); indeed, investments are mainly undertaken to increase productivity levels. However, two studies report a non-significant effect on TFP: Baráth et al. (2018) in Slovenia and Garrone et al. (2019a) for labour productivity. This insignificant character reverberates to both COP and dairy farms (Latruffe et al., 2017; Latruffe & Desjeux, 2016; Zbranek, 2014), although Brümmer and Loy (2000) – investigating a different period (1987–1994) – find a

Table 2
Literature on the impact of Rural Development Payments on productivity.

| Authors | Period | Sector | Level | Method/ model | AES on TFP | LFA on TFP | RDP INV on TFP |
|---------------------------------|---------------------|---------------|-----------|----------------|------------|------------|----------------|
| (Arata & Schokai, 2016) | 2003–2006 | All | Farms | PSM DiD | Negative | | |
| (Banga, 2014) | 1995–2010 | All | Countries | DEA | Positive | Positive | |
| (Baráth et al., 2018) | 2007–2013 | All | Farms | ATT on SFA | | Neutral | |
| (Baráth et al., 2020) | 2006–2013 | All | Farms | SFA + ATT | Neutral | Neutral | Neutral |
| (Boulanger & Philippidis, 2015) | 1991–2008 | COP - Dairy | Farms | CGE | Negative | | |
| (Brümmer & Loy, 2000) | 1987–1994 | Dairy | Farms | SFA | | | Positive |
| (Dudu & Kristkova, 2017) | 2007–2013 | All | NUTS 2 | GMM | Positive | Neutral | Positive |
| (Garrone et al., 2019a) | 2004–2014 | All | Nuts 2 | SYS-GMM | Neutral | Neutral | Neutral |
| (Kazukauskas et al., 2010) | 2001–2007 | Dairy | Farms | CFE + SFA | | | Negative |
| (Khafagy & Vigani, 2022a) | 2004–2015 | All | All | GMM System | Negative | Positive | Positive |
| (Lakner, 2009) | 1994/1995–2005/2006 | Dairy | Farms | SFA | Negative | | |
| (Lambarraa & Kallas, 2009) | 2000–2004 | Olive | Farms | RE Tobit & SFA | | Negative | |
| (Lambarraa et al., 2009) | 1995–2003 | COP | | SFA | | Negative | |
| (Latruffe & Desjeux, 2016) | 1990–2006 | COP - Dairy | Farms | DEA | Positive | | Neutral |
| (Latruffe et al., 2008) | 2010 | All | Farms | DEA | | | Positive |
| (Latruffe et al., 2017) | 1990–2007 | Dairy | Farms | SFA | Neutral | Neutral | Neutral |
| (Mary, 2013) | 1996–2003 | Field Crop | Farms | DPD | Neutral | Negative | Negative |
| (Mennig & Sauer, 2020) | 2007–2011 | COP | Farms | DiD + SFA | Positive | | |
| (Minviel & Latruffe, 2017) | Systematic review | Meta-analysis | Neutral | Neutral | Positive | | |
| (Nilsson, 2017) | 2007–2012 | All | Farms | CFE | | | Positive |
| (Nowak et al., 2015) | 2010 | All | Country | DEA | | | Positive |
| (Pechrová, 2015) | 2005–2012 | All | Farms | SFA | Negative | Positive | |
| (Pisulewski & Marzec, 2022) | 2004–2011 | Dairy | Farms | SFA | Negative | Positive | Positive |
| (Pufahl & Weiss, 2009) | 2000–2005 | All | Farms | PSM DiD | Positive | | |
| (Quiroga et al., 2017) | 1996–2009 | All | NUTS2 | SFA | Negative | Neutral | |
| (Zbranek, 2014) | 2012 | COP - Dairy | Farms | DEA | | Negative | Neutral |

COP = Cereal, Oleaginoses, Protein Crops – DEA: Data Envelopment Analysis – SFA: Stochastic Frontier Analysis – CFE: Control Function Estimator- DPD dynamic panel data – OLV-IV: Ordinary least squared with Instrumental Variables – FE: Fixed Effect – CGE: computable general equilibrium – PEA: Partial Equilibrium Analysis – ATT: Average Treatment on Treated – DiD: Differences-in-Differences – PSM: Propensity Score Matching - GMM – System: System of multiple equations with GMM estimator – RE: Random effect.

positive effect, as well as [Pisulewski and Marzec, \(2022\)](#) for Czechia. [Kazukauskas et al. \(2010\)](#) derive that RDP INV has a negative influence on TFP for Irish farms.

Significantly, the implementation of the measure, particularly financial constraints, can condition the farmer to invest ([Khafagy & Vigani, 2022b](#)).

3. Estimation strategy and data

The econometric strategy we apply follows a three-step technique as in [Mary \(2013\)](#). In the first step, the production function is estimated; in the second step, estimates of the production function are used for retrieving the TFP via both the Control Function Estimator (CFE) and dynamic panel estimator. In the third and last step, the relationship between the CAP payments and farm-specific TFP is assessed.

To define productivity, we relied on [Solow \(1957\)](#) specification, that is, the part of production growth not attributable to the accumulation of factors of production – i.e. the Solow residual or TFP. Such a definition has been recently described as the most appropriate for policy analysis ([Helfand & Taylor, 2021](#)).

Literature offers different methods to estimate productivity, including indexes ([Baldoni & Esposti, 2021](#)), non-parametric methods such as the DEA ([Keizer & Emvalomatis, 2014](#); [T. Skevas & Lansink, 2014](#)), parametric methods, especially the Stochastic Frontier Analysis (SFA) ([Minviel & Latruffe, \(2017\)](#), CFE ([Akune & Hosoe, 2021](#))), and dynamic panel estimators ([Mary, \(2013\)](#)³. The dynamic panel estimator ([Blundell & Bond, 1998, 2000, 2023](#)) is the most efficient to account for simultaneity – via lagged variables -, measurement error and omitted variables bias using both first-differences and IVs ([Ackerberg et al., 2020](#)). Therefore, after specifying the production function and estimating it via the SYS-GMM, in the second step, we obtain TFP as the

residuals of the first step, using a Minimum Distance Estimator (MDE). However, to include time-invariant characteristics in the TFP estimates, we rely on the CFE; estimated values will be used to define the three productivity categories, relying on the farm-median value. TFP obtained via SYS-GMM defines the dependent variable in the third and final step, where the relationship between CAP subsidies and farms' TFP is assessed, both at the aggregated and productivity-related farm groups, within each country. [Fig. 1](#) offers a graphical representation of the methodological strategy applied.

3.1. Definition and estimation of the production function (step 1)

The recent contributions of [Khafagy & Vigani, \(2022a, 2022b\)](#) make use a CES production function with three inputs – land, capital, and labour – arguing that Cobb-Douglas production functions are limited by the restrictive assumption regarding the elasticity of substitution equal to one. Nevertheless, excellent contributions such as those of [Ackerberg et al. \(2020\)](#), [Henningesen & Henningesen \(2012\)](#), [Kim et al. \(2019\)](#), and [Miller \(2008\)](#), demonstrated that either the translog or CES functions might generate multiple spurious solutions, making the production function quite challenging to estimate. Estimating a translog production function would imply using interaction and squared terms, increasing the number of instruments necessary for identification. Furthermore, increasing the number of variables would favour the finding of a local minimum rather than a global one: the GMM criterion function is nearly flat around the true value of some parameters, driving point estimates far from the true values ([Ackerberg et al., 2020](#); [Henningesen & Henningesen, 2012](#); [Kim et al., 2019](#); [Miller, 2008](#))⁴. The recent contributions

³ For a more comprehensive review of TFP estimation procedures see van Beveren (2012).

⁴ For robustness-check, both the translog and CES production functions results are available in the Appendix (Table A.11) and in the online material, respectively. Overall, the translog production function performs poorly when compared to the CD, with lower goodness-of-fit values. Concerning CES production function, depending on the order of inputs as well as on the minimization algorithm, multiple results are obtained.

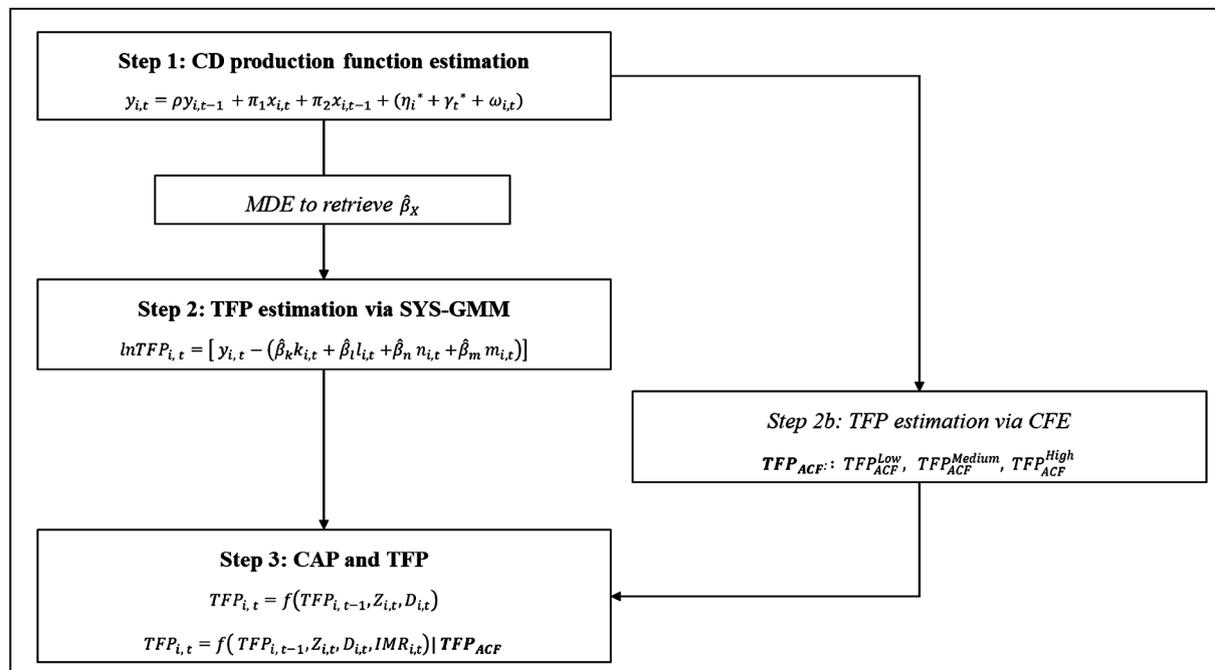


Fig. 1. Graphical representation of the methodological steps.

of Brummund & Merfeld (2022) and Merfeld & Brummund (2021) report on convergence problems in the CES production function, eventually agreeing on both translog and Cobb-Douglas production functions as reasonable choices for specifying any agricultural production function. Additionally, Akerberg et al. (2020) show that different functional forms do not significantly improve the TFP estimates.

Due to the fact that most of the empirical literature assessing productivity relies on the Cobb-Douglas production function specification (Akune & Hosoe, 2021; Frick & Sauer, 2018; Mary, 2013; Nilsson, 2017; Rizov et al., 2013; I. Skevas et al., 2022), and that deploying the System-GMM estimator overcomes the restriction regarding constant returns to scales, since $\sum \beta_x = 1$ “[...] is not necessarily imposed” (Blundell & Bond, 2000; p. 323), relying on the Cobb-Douglas (CD) would allow for a more thorough and comprehensive comparison of results with other empirical applications (Ulveling & Fletcher, 1970; Akune & Hosoe, 2021; Mary, 2013; Rizov et al., 2013).

In the first step, the production function for the i_{th} farm at time t is estimated using the CD production function specification as follows:

$$Y_{i,t} = \Omega_{i,t} K_{i,t}^{\beta_K} N_{i,t}^{\beta_N} L_{i,t}^{\beta_L} M_{i,t}^{\beta_M} e^{\epsilon_{i,t}} \quad i = 1, \dots, N; t = 1, \dots, T \tag{1}$$

where $Y_{i,t}$ is production output, $\Omega_{i,t}$ is the level of TFP, $K_{i,t}$ is capital stock, $N_{i,t}$ is the amount of labor, $L_{i,t}$ represents the amount of land, and $M_{i,t}$ refers to materials with input factor set defined as $X := \{K, L, N, M\}$ ⁵.

The estimation of (1) is made feasible through the logarithmic transformation, where small letters indicate the logarithmic transformation of the original variable with input factor set defined as $x := \{k, l, n, m\}$ and $\alpha_{i,t}$ is the constant term and $\omega_{i,t}$ is the logarithm of $\Omega_{i,t}$:

$$y_{i,t} = \alpha_{i,t} + \beta_x x_{i,t} + \omega_{i,t} + \epsilon_{i,t} \tag{2}$$

Using Ordinary Least Squares (OLS) to identify coefficients β_x would deliver biased results because of endogeneity: farmers know their TFP ($\omega_{i,t}$) when choosing inputs to maximize profits, while OLS assumes that $\epsilon_{i,t} = \omega_{i,t} + \epsilon_{i,t}$, in other words, that TFP is not known and embedded in

the error term (Akerberg et al., 2007; Marschak & Andrews, 1944). The seminal work of Mundlak (1963) solved the issue by using deviations from the firm-specific mean (also known as the within-estimator), distinguishing individual time-variant ($x_{i,t}$) and time-invariant (η_i) characteristics as well as and time intercepts (γ_t). Modelling all these element increases complexity, falling into the “curse of dimensionality” and biasing the result. Indeed, Mundlak (1963) relies on time-fixed effects only, assuming TFP includes individual time-invariant characteristics ($\eta_i + \omega_i$) within the error term in (2), i.e. $\epsilon_{i,t} = \gamma_t + (\eta_i + \omega_i) + \epsilon_{i,t}$:

$$y_{i,t} = \alpha_{i,t} + \beta_x x_{i,t} + \gamma_t + (\eta_i + \omega_i) + \epsilon_{i,t} \tag{3}$$

Nevertheless, Akerberg et al. (2007) and Olley & Pakes (1996) well explain how relying only on time-fixed effects fails to control for endogeneity; state variables k and l depend on past values not fully controlled by the farmer, hence weakly correlated with $\epsilon_{i,t}$. In contrast, free-state variables, n and m , are under the farmer control, are strongly correlated with residual errors, generating downward estimation bias. IVs emerged as the solution for the endogeneity issues, although the identification of IVs is complex and does not entirely solve the endogeneity problems (Akerberg et al., 2015). A further and essential aspect to consider is the dynamic nature of the process: the current production function is not independent of past results.

The literature offers two main approaches: CFE and the dynamic panel estimator SYS-GMM. CFE was first implemented by Olley & Pakes (1996), assuming TFP as a Markov process and using a two-step semi-parametric procedure. Nevertheless, criticisms arose for using investment as a proxy variable for TFP: their value is zero for long time intervals, and, by nature, they are multi-year processes, hence not an efficient instrument for TFP annual changes. Akerberg et al. (2007, 2015) and Levinsohn & Petrin (2003) overcome this problem by using materials as a proxy for TFP instead of investments.

The SYS-GMM developed Blundell & Bond, (2000) allows estimating a production function as⁶:

⁵ All variables are defined as in Rizov et al.,(2013). Details in the appendix A.1.

⁶ $\epsilon_{i,t}, \xi_{i,t} \sim MA(0)$ meaning that the error term follow a Moving Average of order 0 also referred to as constant or drift term. Considering that without omitted variables or measurement error $\omega_{i,t} = \xi_{i,t} \sim MA(0)$, while in the case of their presence, we have $\omega_{i,t} \sim MA(1)$.

$$y_{i,t} = \alpha_{i,t} + \beta_x x_{i,t} + \gamma_t + (\eta_i + \omega_i + \varepsilon_{i,t}) \omega_{i,t} = \rho \omega_{i,t-1} + \xi_{i,t} \text{ with } |\rho| < 1, \varepsilon_{i,t}, \xi_{i,t} \text{ MA}(0) \tag{4}$$

being $\xi_{i,t}$ the omitted variables of measurement errors. Double-differencing of (4) allows to introduce dynamic formulation and, at the same time, removing first-order autocorrelation (Cochrane & Orcutt, 1949). Considering $(\omega_{i,t} - \rho \omega_{i,t-1}) = \xi_{i,t}$ leads to the following representation:

$$y_{i,t} = \rho y_{i,t-1} + \beta_x x_{i,t} - \rho \beta_x x_{i,t-1} + (1 - \rho) \eta_i + (\gamma_t - \rho \gamma_{t-1}) + \xi_{i,t} \tag{5}$$

Considering a dynamic (common factor) representation $\pi_1 = \beta_x$ and $\pi_2 = \rho \beta_x$, $(1 - \rho) \eta_i = \eta_i^*$ and $\gamma_t^* = (\gamma_t - \rho \gamma_{t-1})$, (5) can be re-written as:

$$y_{i,t} = \rho y_{i,t-1} + \pi_1 x_{i,t} + \pi_2 x_{i,t-1} + (\eta_i^* + \gamma_t^* + \omega_{i,t}) \tag{6}$$

with the corresponding common factors restrictions

$$\pi_2 = -\rho \pi_1 \tag{7}$$

used for retrieving the true value of $\hat{\beta}_x$ via MDE - as explained in Blundell et al. (1996) and Chamberlain (1982) (see section 3.2 for details). SYS-GMM addresses simultaneity bias, deriving from the potential correlation between input factors and TFP, using both lagged levels and first differences as IVs, besides accounting for individual fixed effects η_i^* via first-differencing and time fixed effects γ_t^* to identifies $\omega_{i,t}$ (Bond, 2002)⁷. Using CFE would require the researcher to indicate the free and state input variables, as well as the right set of Instrumental Variables (IVs), while SYS-GMM do not, eliminating the risk of evaluation errors (Ackerberg, 2017, 2020; Ackerberg et al., 2020)⁸. Finally, the use of a GMM-type estimator does not require to specify the probability density function of $y_{i,t}$ (Hansen, 1982, 2010; Wooldridge, 2009). All in all, SYS-GMM faces omitted variable bias as well as measurement errors, besides accounting for selection bias (Kim et al., 2016; Lizal & Galuscar, 2012; Song, 2015). The battery of tests described in Arellano & Bond (1991) allows checking for the robustness of estimation, in particular for the autoregressive component of degree one (AR1) and of degree two (AR2) and the correct specification of the IV (i.e., the Sargan test).

3.2. Estimation of TFP (Step 2)

After specifying and estimating the CD production function, farm-level TFP is calculated as the Solow residual, hence that portion of production output not directly related to production factors (Ackerberg et al., 2007; Olley & Pakes, 1996):

$$\ln TFP_{i,t} = [y_{i,t} - (\hat{\beta}_k k_{i,t} + \hat{\beta}_l l_{i,t} + \hat{\beta}_n n_{i,t} + \hat{\beta}_m m_{i,t})] \tag{9}$$

Therefore, to obtain $\hat{\beta}_k, \hat{\beta}_l, \hat{\beta}_n, \hat{\beta}_m$, MDE is used to satisfy the common factors restrictions in (7)⁹.

Return to scale (RTS) are given by $RTS = (\hat{\beta}_k + \hat{\beta}_l + \hat{\beta}_n + \hat{\beta}_m)$, with standard errors calculated via the delta method (Dorfman, 1938; Ver Hoef, 2012). To test for constant RTS, the Wald test is used to verify the null hypothesis $H_0 : [(\hat{\beta}_k + \hat{\beta}_l + \hat{\beta}_n + \hat{\beta}_m) - 1] = 0$. Indeed, this is necessary to verify that the proportionality axiom (O'Donnell, 2016) is fulfilled; if RTS is not constant, proportionality needs to be restored. Following T. Skevas et al., (2022) (equation 8) and (Ding et al., 2016)

⁷ Roodman, (2009a, 2009b) and Windmeijer, (2005, 2021) propose a better instrumenting strategy, making estimated errors more robust by using a collapsed instrument variables matrix.

⁸ For instance, labor inputs are commonly assumed to be a free variable, while in agriculture, part of this production factor - i.e., unpaid family work - is fixed, leading to potential biased estimates.

⁹ Please, see section A.2 in the Appendix for a detailed explanation of the MDE and its application.

Table 3
Description of acronyms used.^a

| Variable | Description |
|------------------|--|
| Total Output (Y) | Value of total annual output |
| Capital (K) | Total fixed assets excluding land value |
| Land (L) | Land Value |
| Labour (N) | Hours worked annually |
| Material (M) | Total annual specific costs + total annual farming overheads |
| CDP | Coupled Direct Payments |
| DDP | Direct Decoupled Payments |
| AES | Rural Development Payments for Agri-Environmental Schemes |
| LFA | Rural Development Payments for Less Favourable Areas |
| RDP Other | Other Annual Rural Development Payments |
| RDP inv | Rural Development Subsidies on investments |
| Economic Size | Total economic farm size |
| Debt on asset | Total Liabilities/Total Assets |
| UAA Rented | Rented Utilized Agricultural Area |
| H Index | Diversification index using Herfindahl– Hirschman Index |
| Insurance | Payments for insurance premiums |

^a A complete description of the variables, the modality of calculation and the references with FADN code is reported in appendix.

(equation 2a), equation (9) is re-defined as a special case of the Färe & Primont, (1995) input index to satisfy proportionality¹⁰:

$$\ln TFP_{i,t} = y_{i,t} - \left[\frac{1}{\hat{\beta}_k + \hat{\beta}_l + \hat{\beta}_n + \hat{\beta}_m} (\hat{\beta}_k k_{i,t} + \hat{\beta}_l l_{i,t} + \hat{\beta}_n n_{i,t} + \hat{\beta}_m m_{i,t}) \right] \tag{10}$$

For building the three productivity-categories, we rely on the farm intrinsic level of TFP (TFP_{ACF}), hence the CD production function in (2) is estimated using a CFE approach as in Ackerberg et al. (2015). This as TFP_{ACF} embeds fixed effects, hence more appropriate for segmenting farms according to their intrinsic productivity level; according to the tertile in which the farm-specific TFP falls, low, medium and high TFP levels are defined for each country : TFP_{ACF}^{Low} , TFP_{ACF}^{Medium} , TFP_{ACF}^{High} . Considering that the $TFP_{ACF,i,t}$ can vary between years, the median value is used for categorization.

3.3. Assessing the relationship between TFP and different CAP measures (Step 3)

An extensive literature on the relationship between CAP and TFP analyses the aggregated amount of subsidies, neglecting measure-specific assessments (Mary, 2013). Much of the empirical attempt to disentangle the relationship between direct payments - CDP and DDP - on TFP, generally concluding on the negative role of DDP and the positive one of CDP, although results vary significantly among countries and the methodology applied (Mary, 2013; Minviel & Latruffe, 2017; Rizov et al., 2013).

The present study attempts to fill the gap in the literature by comparing six EU countries simultaneously and by using a homogeneous methodology, allowing for comparison between countries and CAP-specific measures.

The relationship between CAP measures and farms' TFP is expressed as follows:

$$TFP_{i,t} = f(TFP_{i,t-1}, Z_{i,t}, D_{i,t}) \tag{11}$$

where $TFP_{i,t}$ is retrieved from the CD production function estimates as described in the step 2; hence, it accounts for time-fixed effects, for instance policy changes within the period analyzed, as well as individual fixed effects. $TFP_{i,t-1}$ is the autoregressive term as TFP is assumed to follow a Markov process $TFP_{i,t} = \rho TFP_{i,t-1}$ as in Ackerberg et al., (2015), Levinsohn & Petrin, (2003), Mary, (2013), Olley & Pakes, (1996), and Wooldridge, (2009); $Z_{i,t}$ represents the vector of CAP-specific measures

¹⁰ We thank the anonymous reviewer for the suggestion.

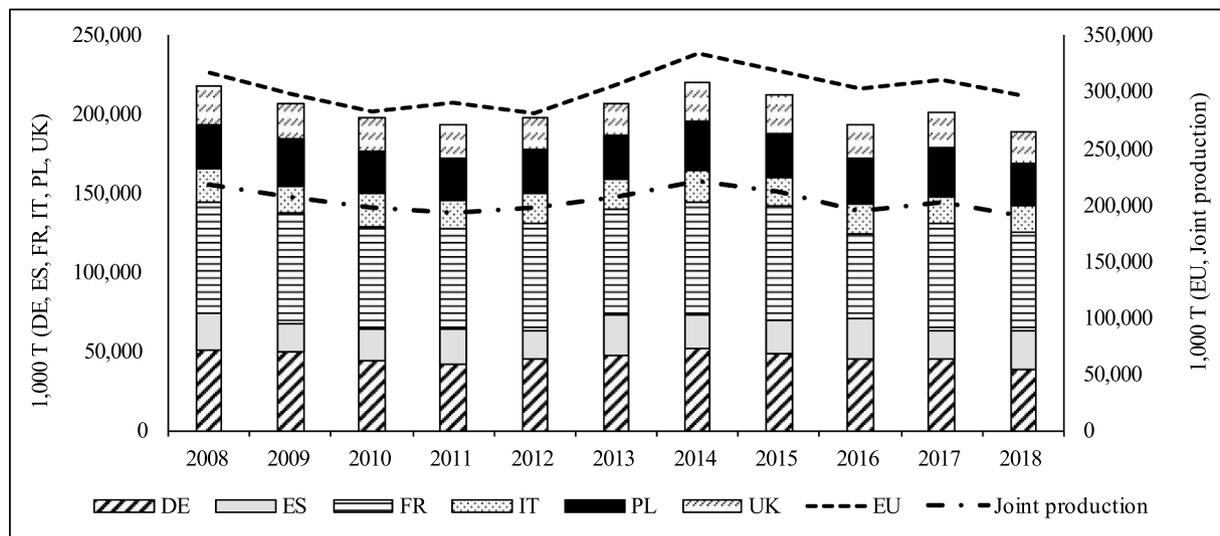


Fig. 2. Cereal production in some European countries and the EU, 2008–2018.

$Z_{i,t} : \{CDP_{i,t}, DDP_{i,t}, AES_{i,t}, LFA_{i,t}, RDPa\ others_{i,t}, RDP\ inv_{i,t}\}$; while $D_{i,t}$ is a vector of different elements that, according to the literature (Keizer & Emvalomatis, 2014; T. Skevas et al., 2012; T. Skevas & Lansink, 2014; Wossink & Denaux, 2006; Zhu & Lansink, 2010) may be correlated to TFP and introduced as control variables $D_{i,t} : \{Economic\ Size_{i,t}, Debit\ on\ asset\ ratio_{i,t}, UAA\ rented_{i,t}, H\ Index_{i,t}, Insurance\ expenses_{i,t}\}$.

Endogeneity issues may arise, especially concerning CAP subsidies: payments coupled with production volumes are assessed on regional-yield levels; aids for less-favoured areas require the farm to be located in a specific geographical location to receive the subsidy; some incentives belonging to Pillar 2, such as those intended to cover farmers' investments, require the economic ability to anticipate the investment. SYS-GMM offers an agile solution by instrumenting endogenous variables and considering the CAP subsidies' dynamic (multi-year) nature, apart from non-observable individual characteristics (e.g., farmer's managerial ability or the soil's quality) (Bokusheva et al., 2012; Mary, 2013).

The analysis is developed both on country's overall sample as well as accounting for the three productivity-categories within each country separately. Nevertheless, farms may not be randomly assigned to the TFP group to which they belong, thus selection bias may arise - farmers adapt, for instance, according to soil fertility, infrastructure and services, and climate characteristics, and, particularly, they decide to which CAP measures to adhere (Asmare et al., 2019, 2022).

In other words, unobservable (latent) variables are likely to influence farmers' belonging to a productivity-specific group, and, hence, the relationship between TFP and CAP measures. In order to account for selection-bias, Inverse Mills Ratios (IMR) (Heckman, 1979, 2010) have been introduced into the model. Since belonging to a specific productivity-category is a dynamic process, IMRs are observation-specific, as the same farm may belong to different categories within the time period analyzed. Nevertheless, the autoregressive component controls for extreme jumps from one category to the other. We follow the Double LASSO (Least Absolute Shrinkage And Selection Operator) approach as in Belloni et al. (2012) and Windmeijer et al. (2018) for selecting those variables that effectively explain the belonging of the farm to the specific productivity-category but that does not correlate to the TFP - our dependent variable in step 3. Observation-specific IMR are added to the model, allowing SYS-GMM to adopt linear autoregressive

characteristics (Arellano et al., 1999; Semykina & Wooldridge, 2013; Wooldridge, 1995)¹¹. Accordingly, equation (11) can now be specified as:

$$TFP_{i,t} = f(TFP_{i,t-1}, Z_{i,t}, D_{i,t}, IMR_{i,t}) | TFP_{ACF} \quad (12)$$

where $IMR_{i,t}$ refer to the observation-specific IMR to correct for self-selection and the bias it may produce.

3.4. Data

The Farm Accountancy Data Network (FADN)¹² for 2008 – 2018 serves as the basis for the analysis (see Table 3 for variables' acronyms details). Notably, as in Mary (2013) and Rizov et al.(2013), Zhu and Lansink, 2010, TFP is estimated using deflated production monetary values (prices), that is, implicit quantities, for those inputs for which quantities are not available, i.e. k , l , and¹³ m ; n is expressed as the amount of annual working hours¹⁴. Since a homogeneous type of farming is analysed, this excludes potential biases due to price shocks - that may be interpreted as productivity changes; indeed, shocks (if any) would be common to all sampled farms, hence controlled by the inclusion of time dummies. Moreover, homogeneity in both the production technology and the output is particularly relevant from a production function perspective (Mary, 2013; Rizov et al., 2013)¹⁵, besides reducing intra-sectoral heterogeneity effects (Baráth et al., 2020).

Since the econometric strategy requires a sufficiently large number of observations over time, field crop farms in France, Germany, Italy,

¹¹ The procedure to obtain IMR is reported in the appendix A.3.

¹² We thank the European Commission for allowing us to use the data. The authors are solely responsible for the content of the paper. The views expressed are purely those of the authors and may not in any circumstances be regarded as stating a position of the European Commission.

¹³ Please, see Section A.1 in the Appendix for more details on how monetary values have been deflated to calculate the implicit quantities.

¹⁴ Annual Working Units (AWU) is not used as how this is defined changes depending on the country.

¹⁵ General type of farming '1. Specialist field crops', principal type of farming'15. Specialist cereals, oilseeds and protein crops' and '16. General field cropping' according to the Commission Implementing Regulation (EU) 2015/220 (available at: <https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32015R0220&from=EN>) (see Annex XV).

Table 4
General Statistics of the considered farms by country.

| Variable | U.M. | Germany (DE) | Spain (ES) | France (FR) | Italy (IT) | Poland (PL) | United Kingdom (UK) |
|---------------|--------|--------------|-------------|-------------|--------------|-------------|---------------------|
| Observations | Number | 22,399 | 21,151 | 19,347 | 32,107 | 31,776 | 5282 |
| Total Output | Euro | 31,470.3.15 | 66455.75 | 207870.92 | 94630.14 | 83523.48 | 388885.22 |
| Capital | Euro | 716602.18 | 121853.62 | 234319.46 | 227394.03 | 247342.40 | 1633730.43 |
| Land | Euro | 346403.14 | 138434.88 | 42601.49 | 324778.32 | 122982.94 | 1441404.41 |
| Labour | Hours | 6092.72 | 2665.78 | 3056.16 | 3596.11 | 5265.96 | 7109.20 |
| Material | Euro | 299883.33 | 59264.95 | 197076.87 | 62887.73 | 74926.42 | 384546.50 |
| CDP | Euro | 522.93 | 3068.17 | 3896.20 | 2146.52 | 879.21 | 237.62 |
| DDP | Euro | 60092.01 | 15155.20 | 36986.56 | 16219.74 | 13778.29 | 67268.92 |
| AES | Euro | 4384.36 | 787.44 | 646.02 | 1493.28 | 1441.61 | 11064.05 |
| LFA | Euro | 722.52 | 3358.43 | 312.58 | 283.71 | 674.25 | 30.54 |
| RDP Other | Euro | 55.53 | 69.03 | 223.73 | 365.20 | 98.84 | 287.86 |
| RDP inv | Euro | 204.29 | 232.79 | 652.73 | 242.30 | 871.08 | 575.74 |
| Economic Size | Euro | 311290.24 | 67026.41 | 190625.20 | 11001.34 | 76366.71 | 384795.63 |
| Debt on asset | % | 0.25 | 0.04 | 0.44 | 0.01 | 0.08 | 0.14 |
| UAA Rented | Ha | 143.18 | 41.33 | 120.90 | 22.73 | 35.24 | 123.58 |
| H Index | % | 0.33 | 0.41 | 0.35 | 0.41 | 0.35 | 0.33 |
| Insurance | Euro | 1173.75 | 631.97 | 1708.99 | 187.02 | 402.54 | 3615.53 |
| | | (596608.89) | (114740.72) | (194689.15) | (244199.13) | (212374.81) | (600892.86) |
| | | (1147730.37) | (233840.51) | (226050.03) | (1529538.73) | (388713.06) | (3306189.68) |
| | | (737325.99) | (307695.18) | (92646.11) | (1170448.32) | (301543.53) | (2630023.16) |
| | | (12697.62) | (3451.57) | (3192.54) | (5121.31) | (8499.77) | (13860.97) |
| | | (555895.82) | (90598.86) | (162768.13) | (16080.17) | (223764.40) | (528729.64) |
| | | (5377.47) | (9635.62) | (7616.89) | (16599.88) | (4465.87) | (992.87) |
| | | (108860.05) | (19670.24) | (25155.95) | (35186.19) | (28373.61) | (77892.47) |
| | | (14619.87) | (3037.26) | (3080.71) | (8261.68) | (4822.58) | (23433.63) |
| | | (3358.43) | (820.02) | (1652.85) | (1416.88) | (1459.16) | (470.33) |
| | | (1078.50) | (1043.15) | (1836.48) | (3185.25) | (1098.27) | (1761.80) |
| | | (8747.38) | (3197.24) | (5696.40) | (4707.31) | (3901.69) | (6023.27) |
| | | (575008.44) | (91248.95) | (154845.33) | (265157.83) | (162189.93) | (550366.42) |
| | | (0.51) | (0.13) | (0.39) | (0.06) | (0.14) | (0.56) |
| | | (296.33) | (70.05) | (88.81) | (46.87) | (123.43) | (225.18) |
| | | (0.07) | (0.07) | (0.07) | (0.08) | (0.08) | (0.07) |
| | | (3456.23) | (2561.05) | (3640.22) | (1274.96) | (2658.86) | (6625.59) |

Poland, Spain, and the UK were analyzed as the most generous countries in these terms¹⁶.

According to Eurostat, averaging on 2008–2018, these six countries together account for around 65% and 67% of EU cereal crops' area and harvested production of the whole EU, respectively¹⁷ (Fig. 2).

Note that farms in these countries differ in their economic and structural characteristic: on average, farms in the UK are larger than in other countries, while the opposite is true for those in Spain; UK farms also rely on a more limited amount of labour, the output per unit of land is very high in France, and the relative importance of CAP is similar, on average, in the farms located in the six countries, with the UK showing slightly lower relative importance of CAP subsidies (i.e., in comparison with the generated total output) (Table 4).

Furthermore, the six countries also differ in how the CAP has been implemented (Fig. 3). Regarding the basic payment, for example, the UK opted for a regional flat-rate payment, Poland supported farmers through the Single Area Payment Scheme, while the other countries opted for a partial convergence approach (Henke et al., 2015). Likewise, the relative importance of the CDP differs: high shares of the overall financial ceiling devoted to direct support are registered in France, Poland, Spain, and Italy, while lower shares in UK and Germany (Henke et al., 2015).

4. Results

The following three sub-sections present and explain the results obtained in each step.

4.1. Production function estimates (Step 1)

Table 5 shows the result of production function estimation for the six countries. All model specifications successfully fulfil the usual battery of statistical tests: the autoregressive error component tests of orders 1 and 2 (m1 and m2) have the expected significance levels – i.e., highly significant for m1, thus ascertaining the presence of an autoregressive process of order one, and not significant for m2, excluding autoregressive processes of order more than one (Arellano & Bond, 1991; Blundell & Bond, 1998, 2023; Roodman, 2009a, 2009b). The Sargan test fails to reject the null of valid over-identifying restrictions, and the Wald test on estimated coefficients demonstrates that each model specification significantly differs if only the constant term is used as the regressor. Finally, Wald Test on time dummies highlights the presence of year-specific effects (Arellano & Bond, 1991; Blundell & Bond, 1998, 2023; Roodman, 2009a, 2009b; Windmeijer, 2005).

The lower panel of Table 5 shows the sets of IVs adopted, considering lags from t_{-1} to t_{-5} for all regressors. The nature of lagged IV varies as the endogeneity nature of factors changes among different economic environment (Latruffe & Desjeux, 2016; O'Donnell, 2016). Finally, the lags for IV are the minimum necessary for having robust instruments, as indicated in (Bond, 2002; Doornik et al., 2002; Zhengfei & Lansink, 2006).

The coefficients of y_{t-1} is statistically significant for all countries, signalling that total output variability is a Markov process; that is, part of past output explains the variation of the total outcome of the following period (y_t).

Table 6 presents input elasticities calculated via MDE. The assets' elasticity $\hat{\beta}_k$ presents a low value, in line with literature. Indeed, assets strictly depend on past occurrences, besides being limited by financial constraints and a weakly-adjusting production factor in the short run (Kazukauskas et al., 2010). Note that capital elasticity is higher in Poland, where a fixed capital increase creates a high outcome value,

¹⁶ This does not necessarily imply that the selected samples perfectly represent the whole population of the cereal farms of each country.

¹⁷ Crop production in EU standard humidity [apro_cpsh1].

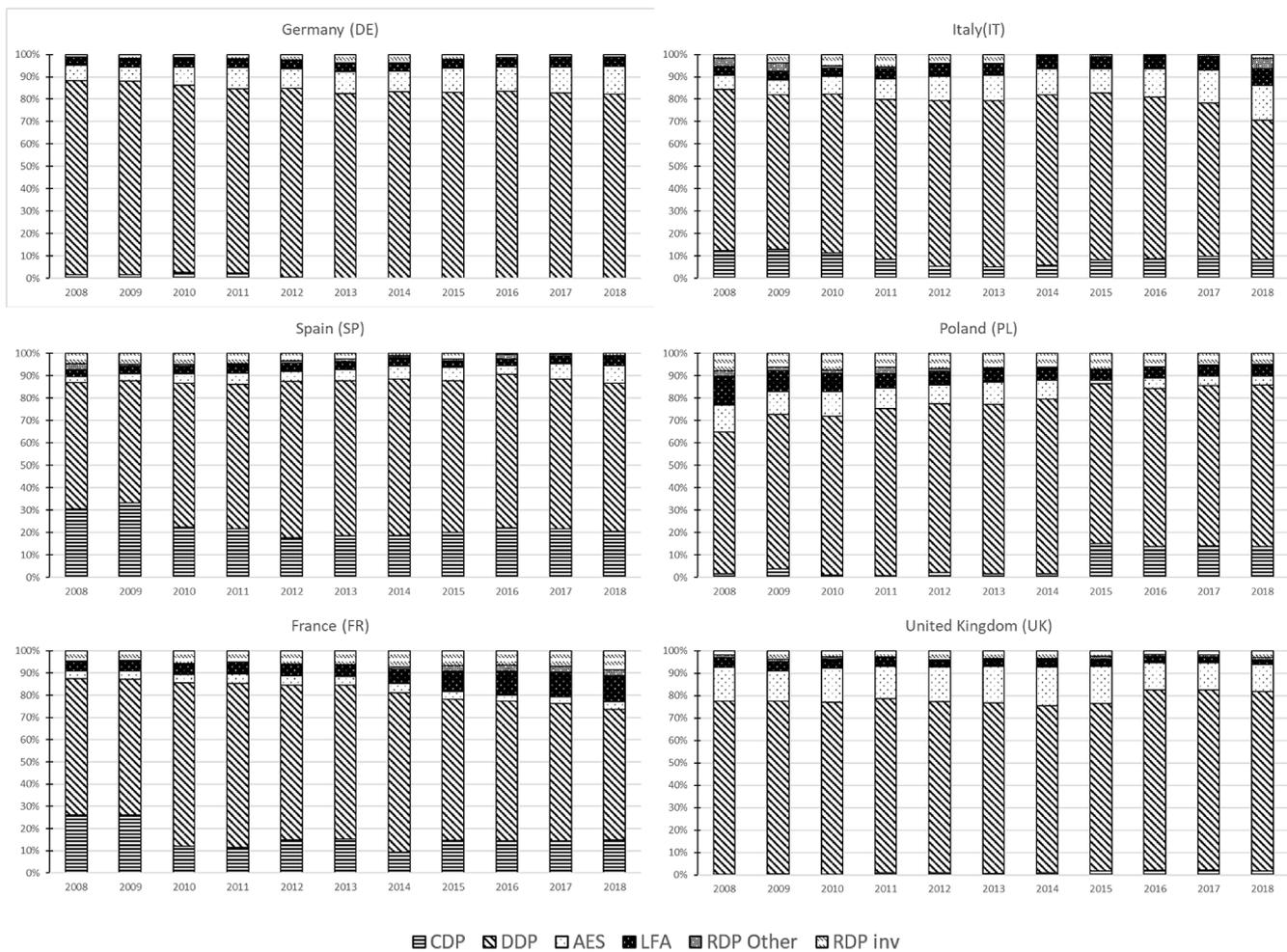


Fig. 3. Relative importance of CAP measures by country and year, 2008–2018 (Source: our elaboration on FADN data).

highlighting the pivotal role of assets (Ciaian et al., 2012; Fogaras and Latruffe, 2009).

As expected, land $\hat{\beta}_l$ results being quite inelastic. Italy and the UK register a non-significant elasticity, which can be due to the local conditions of the land market (Bokusheva et al., 2012a; Kazukauskas et al., 2010; Mary, 2013).

Labour elasticities $\hat{\beta}_n$ show high variability between countries, with Germany, France, and the United Kingdom representing the most labour-elastic countries, in line with the literature (Baráth et al., 2018; Brümmner & Loy, 2000). Conversely, Italy, Spain and Poland embed inelastic labour input, probably due to a generally-low degree of specialization of the agricultural workforce, which can be easily and quickly substituted (Kazukauskas et al., 2010). Moreover, the higher the presence of family (unpaid) workforce on the farm, the lesser the flexibility of the labour input - labour behaves as a state variable (Kazukauskas et al., 2010; Olley & Pakes, 1996; Rizov et al., 2013).

Finally, material inputs $\hat{\beta}_m$ show a generally elastic behaviour as expected (Baráth et al., 2018; Lakner, 2009), particularly for France and Germany, with the UK being the less-elastic. Country-specific production methods and far characteristics may explain such differences, although this goes beyond the scope of this research.

RTS for each country are estimated by the delta method, summing up the input estimated coefficients (Table 6) - that is the input elasticities. With respect to CD assumptions, RTS are not imposed to one: indeed, for Spain, Italy and Poland the null hypothesis of RTS equal to one is rejected (Table 7). The comparison of RTS shows lower values for Spain, Italy and Poland, while the highest are recorded for Germany, France

and the United Kingdom.

4.2. Total factor productivity estimates (Step 2)

Table 8 presents TFP estimated via SYS-GMM, with the highest values belonging to the UK and France - whose results are in line with (Mary, 2013) - Germany, Italy, Spain, and, finally, Poland. Fig. 4 depicts each country's TFP trend, which, interestingly, share a very similar path, and whose values align with Kijek et al. (2019) (see Table A. 2 in the Appendix for further details on the TFP trends). Interestingly, the very tiny standard deviation for all countries' TFP estimates point to an efficient allocation of resources (Bhattacharya et al., 2013; Daron Acemoglu & Zilibotti, 2001; Larrain & Stumpner, 2017; Pearce & Wu, 2022; Restuccia & Rogerson, 2013).

Within the period of analysis, the annual average of the change rate of TFP was 0.06% for Germany and France, 0.40 % for Spain and Italy, 0.22% for Poland and, finally, -0.09% for the UK. The cumulated TFP, obtained from the sum of productivity deltas throughout the period analyzed, points to a slight overall variation, pointing to a stable field crop agricultural sector (Table A. 2). Similar patterns were identified by Baráth et al. (2020), Bokusheva & Čechura, (2017), Dakpo et al., (2019), and Rizov et al., (2013), whereas the negative UK cumulated TFP may be because of negative change rates in certain years, although not representing a solid negative pattern. Nevertheless, such phenomenon has also been found by other scholars (Latruffe & Desjeux, 2016).

Table 5
Production function estimation results using the SYS-GMM approach (Step 1).

| | Germany (DE) | | Spain (ES) | | France (FR) | | Italy (IT) | | Poland (PL) | | United Kingdom (UK) | | | | | |
|-----------------------|--------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|---------------------|----------------|----------------|----------------|----------------|----------------|
| | Value | St.d | p-value | Value | St.d | Value | St.d | Value | St.d | Value | St.d | p-value | | | | |
| $y_{(t-1)}$ | -0.122 | (0.052) | 0.018 | 0.155 | (0.023) | < 0.001 | -0.300 | (0.040) | < 0.001 | 0.254 | (0.028) | < 0.001 | -0.214 | (0.071) | 0.003 | |
| $k_{(t)}$ | 1.048 | (0.310) | < 0.001 | -0.476 | (0.156) | 0.002 | -0.017 | (0.119) | 0.884 | -0.105 | (0.088) | 0.231 | -1.127 | (0.604) | 0.062 | 0.205 |
| $k_{(t-1)}$ | -0.842 | (0.265) | 0.001 | 0.398 | (0.147) | 0.007 | -0.006 | (0.095) | 0.954 | 0.129 | (0.082) | 0.113 | 0.868 | (0.574) | 0.131 | 0.485 |
| $l_{(t)}$ | 0.462 | (0.154) | 0.003 | 0.350 | (0.093) | < 0.001 | 0.266 | (0.111) | 0.017 | 0.047 | (0.076) | 0.537 | 0.239 | (0.214) | 0.265 | 0.514 |
| $l_{(t-1)}$ | -0.375 | (0.130) | 0.004 | -0.343 | (0.089) | < 0.001 | -0.257 | (0.101) | 0.011 | -0.070 | (0.075) | 0.355 | -0.323 | (0.190) | 0.089 | 0.956 |
| $n_{(t)}$ | -0.259 | (0.342) | 0.449 | -0.185 | (0.116) | 0.111 | 2.104 | (0.565) | < 0.001 | 0.992 | (0.344) | 0.004 | 2.150 | (1.045) | 0.040 | 0.004 |
| $n_{(t-1)}$ | 0.238 | (0.248) | 0.337 | 0.120 | (0.048) | 0.012 | -1.739 | (0.444) | < 0.001 | -0.317 | (0.140) | 0.024 | -1.381 | (0.628) | 0.028 | 0.015 |
| $m_{(t)}$ | 1.665 | (0.165) | < 0.001 | 0.782 | (0.069) | < 0.001 | 2.084 | (0.174) | < 0.001 | 0.496 | (0.122) | < 0.001 | 2.300 | (0.262) | < 0.001 | < 0.001 |
| $m_{(t-1)}$ | -0.390 | (0.073) | < 0.001 | -0.099 | (0.039) | 0.012 | -0.634 | (0.097) | < 0.001 | -0.073 | (0.047) | 0.122 | -0.538 | (0.075) | < 0.001 | < 0.001 |
| T | | 11 | | | 11 | | | 11 | | | 11 | | | 11 | | |
| Num. obs. | | 22,399 | | | 21,151 | | | 19,347 | | | 32,107 | | | 31,776 | | |
| Sargan test (p-value) | | 0.167 | | | 0.217 | | | 0.251 | | | 0.441 | | | 0.147 | | 0.901 |
| m1 (p-value) | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | 0.000 |
| m2 (p-value) | | 0.291 | | | 0.080 | | | 0.059 | | | 0.580 | | | 0.286 | | 0.237 |
| Wald coeff. (p-value) | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | 0.000 |
| Wald time (p-value) | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | 0.000 |
| R ² | | 0.778 | | | 0.604 | | | 0.667 | | | 0.836 | | | 0.782 | | 0.872 |
| Instruments | y | t ₁ | t ₅ | t ₂ | t ₂ | t ₆ | t ₁ | t ₁ | t ₅ | t ₂ | t ₂ | t ₅ | t ₁ | t ₁ | t ₃ | t ₅ |
| | k | t ₃ | t ₅ | t ₂ | t ₂ | t ₅ | t ₂ | t ₂ | t ₅ | t ₂ | t ₂ | t ₅ | t ₂ | t ₂ | t ₃ | t ₃ |
| | l | t ₃ | t ₅ | t ₂ | t ₂ | t ₄ | t ₂ | t ₂ | t ₅ | t ₂ | t ₂ | t ₅ | t ₂ | t ₂ | t ₃ | t ₃ |
| | n | t ₃ | t ₅ | t ₂ | t ₂ | t ₅ | t ₂ | t ₂ | t ₅ | t ₂ | t ₂ | t ₅ | t ₂ | t ₂ | t ₃ | t ₃ |
| | m | t ₃ | t ₅ | t ₂ | t ₂ | t ₃ | t ₂ | t ₂ | t ₅ | t ₂ | t ₂ | t ₅ | t ₂ | t ₂ | t ₃ | t ₃ |

The list of the GMM instruments contains all the regressors lagged at least 1 and maximum 5 periods.

Table 6
Elasticity of capital, land, labor, and material is represented with $\beta_k, \beta_l, \beta_n, \beta_m$ calculated using the MDE estimator from table 3.

| Regressor | Germany (DE) | | Spain (ES) | | France (FR) | | Italy (IT) | | Poland (PL) | | United Kingdom (UK) | | | | | | | |
|-----------|--------------|---------|------------|-------|-------------|-------|------------|---------|-------------|-------|---------------------|---------|--------|---------|-------|-------|---------|-------|
| | Value | St.d | p-value | Value | St.d | Value | St.d | Value | St.d | Value | St.d | p-value | | | | | | |
| β_k | 0.296 | (0.035) | 0.000 | 0.117 | (0.019) | 0.000 | 0.107 | (0.024) | 0.000 | 0.116 | (0.014) | 0.000 | 0.418 | (0.054) | 0.000 | 0.163 | (0.042) | 0.000 |
| β_l | 0.103 | (0.017) | 0.000 | 0.065 | (0.014) | 0.000 | 0.028 | (0.011) | 0.013 | 0.017 | (0.014) | 0.238 | 0.182 | (0.025) | 0.000 | 0.031 | (0.022) | 0.151 |
| β_n | 0.340 | (0.053) | 0.000 | 0.006 | (0.026) | 0.810 | 0.466 | (0.060) | 0.000 | 0.141 | (0.028) | 0.000 | -0.086 | (0.088) | 0.326 | 0.793 | (0.096) | 0.000 |
| β_m | 0.327 | (0.057) | 0.000 | 0.222 | (0.023) | 0.000 | 0.515 | (0.058) | 0.000 | 0.148 | (0.022) | 0.000 | 0.145 | (0.056) | 0.010 | 0.083 | (0.100) | 0.406 |

Table 7
Return to scale.

| | Germany (DE) | Spain (ES) | France (FR) | Italy (IT) | Poland (PL) | United Kingdom (UK) |
|-------------------------|------------------|------------------|------------------|------------------|------------------|---------------------|
| Return to scale | 1.065 (0.071) | 0.410 (0.047) | 1.116 (0.070) | 0.422 (0.043) | 0.659 (0.099) | 1.070 (0.124) |
| H0: Return-to-scale = 1 | Accepted | Rejected | Accepted | Rejected | Rejected | Accepted |
| Wald Test - pvalue | 0.357 | 0.000 | 0.098 | 0.000 | 0.001 | 0.570 |

Standard deviation calculated via delta method, in brackets.

Table 8
TFP Estimates using the SYS-GMM approach (Step 2).

| Year | Germany (DE) | | Spain (ES) | | France (FR) | | Italy (IT) | | Poland (PL) | | United Kingdom (UK) | |
|------|--------------|---------|------------|---------|-------------|---------|------------|---------|-------------|---------|---------------------|---------|
| | Mean | St.d. | Mean | St.d. | Mean | St.d. | Mean | St.d. | Mean | St.d. | Mean | St.d. |
| 2008 | 1.091 | (0.048) | 1.007 | (0.066) | 1.172 | (0.031) | 1.072 | (0.070) | 0.931 | (0.051) | 1.298 | (0.083) |
| 2009 | 1.118 | (0.051) | 1.002 | (0.064) | 1.188 | (0.030) | 1.104 | (0.069) | 0.919 | (0.056) | 1.314 | (0.098) |
| 2010 | 1.106 | (0.051) | 1.010 | (0.058) | 1.190 | (0.030) | 1.105 | (0.065) | 0.923 | (0.055) | 1.329 | (0.096) |
| 2011 | 1.088 | (0.051) | 1.005 | (0.055) | 1.171 | (0.030) | 1.077 | (0.062) | 0.898 | (0.069) | 1.299 | (0.103) |
| 2012 | 1.092 | (0.050) | 0.988 | (0.058) | 1.170 | (0.035) | 1.082 | (0.061) | 0.901 | (0.071) | 1.302 | (0.107) |
| 2013 | 1.097 | (0.052) | 1.004 | (0.053) | 1.163 | (0.034) | 1.083 | (0.064) | 0.898 | (0.060) | 1.284 | (0.097) |
| 2014 | 1.112 | (0.043) | 1.023 | (0.050) | 1.170 | (0.032) | 1.093 | (0.074) | 0.960 | (0.049) | 1.296 | (0.077) |
| 2015 | 1.109 | (0.045) | 1.032 | (0.049) | 1.180 | (0.031) | 1.099 | (0.069) | 0.959 | (0.052) | 1.312 | (0.079) |
| 2016 | 1.116 | (0.045) | 1.051 | (0.049) | 1.174 | (0.031) | 1.110 | (0.071) | 0.958 | (0.053) | 1.304 | (0.068) |
| 2017 | 1.112 | (0.044) | 1.037 | (0.050) | 1.186 | (0.030) | 1.112 | (0.071) | 0.957 | (0.051) | 1.286 | (0.070) |
| 2018 | 1.097 | (0.049) | 1.048 | (0.046) | 1.179 | (0.034) | 1.111 | (0.072) | 0.949 | (0.057) | 1.285 | (0.064) |

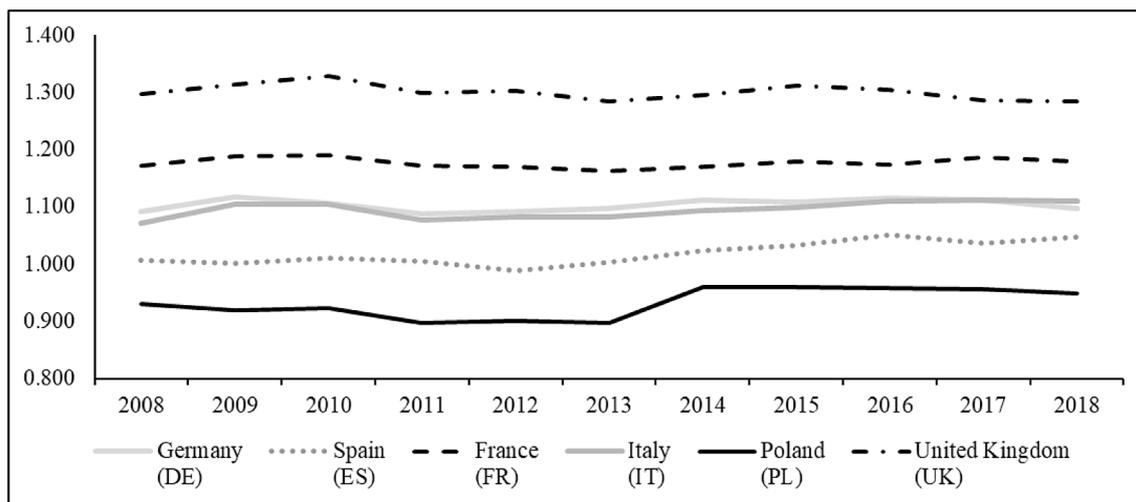


Fig. 4. TFP estimates by country, 2008–2018.

4.3. The relationship between factors and TFP, with a focus on CAP subsidies (Step 3)

The results of the third and last step of the empirical application unveil whether and how different CAP payments influence farms' TFP and whether such influence differs according to the productivity category; Table 9 reports estimations' results, while Table 10 provides a graphical synthesis¹⁸.

Results show that the lagged term of TFP has a positive correlation for most of the productivity categories in all countries. Conversely, the least-productive farms in Spain and the most-productive in the United Kingdom negatively correlate with the past productivity value. France shows the most controversial outputs, with only the highly-productive category being significant and positive. This may point to the maturity of the French field crop sector, with farms having reached a stable and efficient TFP level. Indeed, according to Basu (1996) and Esposti (2000),

the TFP can fluctuate according to three reasons: the irregular evolution of production technologies, the non-constant RTS that generates cyclical variations of TFP, and mismeasurement in the inputs used, obtaining biased TFP values, for instance, caused by the difficulty in correctly evaluating the quantity of labour or capital.

When productivity levels are not accounted for, only Spain and Poland entail some negative and significant influence of CDP on TFP; on the other hand, when farms' TFP levels are considered, CDP seems detrimental for TFP for at least one productivity category per country – particularly for medium-productive farms in Germany and France, least-productive farms in Spain and the UK, and highly-productive farms in France, Italy, and Poland. The latter countries are indeed characterized by a relatively high share of CDP. When subsidies are coupled to production, one may expect either non-significant (farms already exhausted their capacity to increase productivity) or positive effects; although negative effects may be controversial, the recent work of Khafagy & Vigani (2022a) also finds some general discouraging impacts of CDP on EU-27 farms' productivity, particularly for all but Northern EU farms. Besides, both Mary (2013) and Rizov et al. (2013) also find a negative

¹⁸ Detailed results are provided in Tables from A. 4 to A. 10 in the Appendix.

Table 9
Impacts of CAP subsidies and control variables on TFP (Step 3). Overall samples and sub-groups of farms' productivity levels (low, medium, and high levels) in each country. In bold are reported the coefficients with p. value < 0.10.

| | | Germany (DE) | | | | | Spain (ES) | | | | | France (FR) | | | | |
|-------------------|-----------------------|---------------------|-----------|---------------|---------------|---------------|---------------|-----------|---------------|---------------|---------------|---------------|-----------|--------|---------------|---------------|
| | | Overall | Sparkline | Low | Medium | High | Overall | Sparkline | Low | Medium | High | Overall | Sparkline | Low | Medium | High |
| Rho | TF P _{t-1} | 0.432 | | 0.153 | 0.377 | 0.440 | 0.197 | | -0.097 | 0.395 | 0.279 | 0.172 | | 0.161 | 0.086 | 0.186 |
| Regressors | CDP (x1000) | -0.002 | | -0.006 | -0.001 | -0.002 | -0.001 | | -0.002 | -0.001 | -0.000 | -0.000 | | -0.001 | -0.002 | -0.001 |
| | DDP (x1000) | -0.000 | | -0.001 | -0.003 | -0.000 | -0.000 | | -0.003 | -0.000 | -0.000 | -0.000 | | -0.001 | -0.001 | -0.001 |
| | AES (x1000) | -0.001 | | 0.002 | -0.003 | 0.000 | 0.003 | | 0.007 | -0.003 | -0.001 | -0.001 | | -0.002 | 0.002 | -0.001 |
| | LFA (x1000) | -0.002 | | -0.019 | 0.012 | -0.003 | -0.054 | | -0.054 | -0.008 | -0.005 | -0.004 | | -0.006 | -0.001 | -0.008 |
| | RDP Other (x1000) | -0.052 | | 0.008 | -0.001 | -0.043 | -0.015 | | 0.047 | -0.005 | 0.000 | -0.002 | | 0.004 | 0.005 | -0.003 |
| | RDP inv (x1000) | -0.000 | | 0.001 | -0.002 | -0.000 | -0.012 | | 0.058 | 0.001 | -0.001 | -0.001 | | 0.001 | 0.000 | 0.001 |
| | Economic Size (x1000) | -0.000 | | 0.001 | -0.000 | -0.000 | 0.000 | | 0.004 | 0.000 | -0.000 | 0.000 | | 0.000 | 0.000 | 0.000 |
| Control variables | Debt on asset | 0.072 | | 0.098 | 0.053 | -0.058 | -0.466 | | -0.138 | -0.091 | 0.040 | 0.005 | | 0.007 | -0.004 | -0.036 |
| | UAA Rented | 0.000 | | 0.000 | 0.001 | 0.000 | 0.001 | | -0.000 | -0.000 | -0.000 | 0.000 | | 0.000 | -0.000 | -0.000 |
| | H Index | 0.086 | | -0.048 | 0.026 | 0.182 | 1.485 | | -0.138 | 0.285 | 0.207 | 0.140 | | 0.283 | -0.008 | 0.069 |
| | Insurance | 0.000 | | 0.000 | -0.000 | 0.000 | -0.000 | | -0.000 | -0.000 | -0.000 | -0.000 | | -0.000 | -0.000 | -0.000 |
| | Selection Bias | Inverse Mills Ratio | | | -0.009 | 0.128 | 0.021 | | | -0.031 | -0.052 | -0.062 | | | 0.001 | 0.047 |

| | | Italy (IT) | | | | | Poland (PL) | | | | | United Kingdom (UK) | | | | |
|-------------------|-----------------------|---------------|-----------|---------------|---------------|---------------|---------------|-----------|---------------|---------------|---------------|---------------------|-----------|---------------|--------------|---------------|
| | | Overall | Sparkline | Low | Medium | High | Overall | Sparkline | Low | Medium | High | Overall | Sparkline | Low | Medium | High |
| | | Sample | L M H | TFP | TFP | TFP | Sample | L M H | TFP | TFP | TFP | Sample | L M H | TFP | TFP | TFP |
| Rho | $T F P_{t-1}$ | 0.331 | | 0.331 | 0.420 | 0.359 | 0.251 | | 0.319 | 0.328 | 0.725 | 0.184 | | 0.397 | 0.711 | -0.218 |
| Regressors | CDP (x1000) | -0.000 | | -0.002 | -0.001 | -0.000 | -0.001 | | -0.001 | 0.000 | -0.001 | -0.005 | | -0.050 | -0.004 | -0.012 |
| | DDP (x1000) | -0.000 | | -0.002 | -0.005 | -0.001 | 0.000 | | -0.014 | -0.002 | 0.000 | 0.000 | | -0.002 | -0.001 | 0.000 |
| | AES (x1000) | -0.000 | | 0.004 | 0.003 | -0.000 | -0.001 | | 0.013 | 0.007 | 0.001 | 0.001 | | -0.000 | 0.002 | -0.000 |
| | LFA (x1000) | -0.003 | | 0.003 | -0.009 | -0.003 | -0.009 | | -0.023 | -0.001 | -0.005 | NA | | NA | NA | NA |
| | RDP Other (x1000) | -0.001 | | -0.002 | -0.001 | 0.000 | -0.002 | | 0.001 | -0.000 | -0.005 | -0.002 | | -0.006 | -0.001 | -0.003 |
| | RDP inv (x1000) | 0.001 | | 0.000 | 0.001 | -0.003 | 0.000 | | 0.000 | -0.005 | 0.001 | -0.001 | | 0.000 | 0.001 | -0.001 |
| Control variables | Economic Size (x1000) | 0.000 | | -0.001 | 0.000 | 0.000 | 0.000 | | 0.002 | -0.000 | -0.000 | -0.000 | | 0.000 | -0.000 | -0.000 |
| | Debt on asset | 0.588 | | 1.279 | 0.021 | 0.287 | -0.207 | | -0.231 | -0.005 | -0.124 | -0.016 | | -0.003 | 0.189 | -0.453 |
| | UAA Rented | 0.001 | | 0.000 | 0.001 | 0.000 | 0.000 | | 0.000 | -0.001 | 0.000 | 0.000 | | 0.001 | 0.000 | 0.000 |
| | H Index | 0.136 | | 0.050 | 0.166 | 0.243 | 0.499 | | -0.021 | -0.003 | -0.427 | -0.723 | | 0.243 | 0.121 | 0.921 |
| | Insurance | -0.000 | | -0.000 | -0.000 | -0.000 | -0.000 | | 0.000 | 0.000 | 0.000 | 0.000 | | -0.000 | -0.000 | -0.000 |
| Selection Bias | Inverse Mills Ratio | | | 0.027 | 0.118 | -0.006 | | | 0.029 | 0.018 | 0.003 | | | 0.001 | 0.022 | -0.025 |

Table 10

Graphical summary of the impacts of CAP subsidies and control variables on TFP (Step 3). Overall samples (upper row of each variable slot) and by sub-groups of farms' productivity level (low, medium, and high levels; the lower row of each variable slot) in each country.

| | | Germany (DE) | | | Spain (ES) | | | France (FR) | | | Italy (IT) | | | Poland (PL) | | | United Kingdom (UK) | | | |
|-------------------|---------------------|----------------|---|---|----------------|---|---|----------------|---|---|----------------|---|---|----------------|---|---|---------------------|---|---|---|
| | | Overall sample | | | Overall sample | | | Overall sample | | | Overall sample | | | Overall sample | | | Overall sample | | | |
| | | L | M | H | L | M | H | L | M | H | L | M | H | L | M | H | L | M | H | |
| Rho | TFP _{t-1} | | ↑ | | | ↑ | | | ↔ | | | ↑ | | | ↑ | | | | ↑ | |
| Regressors | CDP | ↑ | ↔ | ↑ | ↓ | ↓ | ↑ | ↔ | ↑ | ↑ | ↑ | ↑ | ↑ | ↑ | ↑ | ↑ | ↑ | ↑ | ↓ | |
| | DDP | ↔ | ↓ | ↔ | ↓ | ↔ | ↔ | ↔ | ↓ | ↓ | ↔ | ↔ | ↓ | ↔ | ↔ | ↓ | ↓ | ↔ | ↔ | |
| | AES | ↔ | ↓ | ↔ | ↔ | ↓ | ↓ | ↔ | ↑ | ↔ | ↔ | ↑ | ↔ | ↑ | ↑ | ↔ | ↔ | ↔ | ↑ | |
| | LFA | ↔ | ↔ | ↔ | ↔ | ↓ | ↓ | ↔ | ↑ | ↔ | ↔ | ↑ | ↔ | ↑ | ↑ | ↔ | ↔ | ↔ | ↔ | |
| | RDP Other | ↓ | ↑ | ↔ | ↓ | ↓ | ↔ | ↔ | ↔ | ↓ | ↔ | ↓ | ↔ | ↓ | ↔ | ↔ | ↔ | ↔ | ↔ | |
| | RDP inv | ↔ | ↔ | ↓ | ↔ | ↓ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↓ |
| | Economic Size | ↔ | ↔ | ↔ | ↑ | ↑ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↓ | ↑ | ↔ | ↔ | ↔ |
| | Debt on asset | ↑ | ↔ | ↔ | ↔ | ↔ | ↓ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↑ | ↔ | ↔ | ↔ | ↔ | ↔ | ↓ |
| Control variables | UAA Rented | ↑ | ↑ | ↓ | ↔ | ↔ | ↔ | ↔ | ↔ | ↓ | ↑ | ↔ | ↔ | ↓ | ↔ | ↔ | ↔ | ↔ | ↔ | |
| | H Index | ↔ | ↑ | ↔ | ↔ | ↑ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↑ | ↔ | ↑ | ↔ | ↔ | |
| | Insurance | ↔ | ↑ | ↑ | ↓ | ↔ | ↑ | ↔ | ↔ | ↑ | ↔ | ↑ | ↑ | ↔ | ↔ | ↓ | ↑ | ↔ | ↑ | |
| | Inverse Mills Ratio | ↔ | ↔ | ↔ | ↔ | ↓ | ↓ | ↔ | ↓ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↑ | ↔ | ↔ | ↔ | |
| | Selection Bias | ↔ | ↑ | ↔ | ↔ | ↔ | ↓ | ↔ | ↔ | ↔ | ↔ | ↑ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | ↔ | |

Note: ↑Positive; ↔Non-significant; ↓Negative; L = Low productivity level; M = Medium productivity level; H = High productivity level. Detailed results are provided in the Appendix (Significativity p.value < 0.10).

impact of subsidies on productivity, agreeing on the ability of subsidies to buffer negative income situations while (negatively) shaping farmers' willingness to improve their productivity.

On the aggregated samples, DDP do not entail a significant influence on TFP. However, when productivity groups are analyzed, results point to a rather negative role in at least one group for all countries but France and the United Kingdom. Interestingly, the TFP of all productivity groups in Italy is negatively affected by DDP, as is also the case of medium-productive farms in Germany and the least-productive ones in Spain and Poland. Since decoupled payments are not linked to any production quantity, they may weaken farmers' willingness to invest and hence improve productivity, even being detrimental for the TFP itself. Notably, their productivity-depressing role on least-productive farms may push these farmers out of the sector, as other scholars already conclude (Chau & Gorter, 2005; Kazukauskas et al., 2013).

Regarding Pillar 2 payments, the situation mirrors that of Pillar 1, reflecting CAP's negative role on farms' productivity.

On the aggregated sample, AES bear a non-significant effect for all but Germany (negative) and, surprisingly, a positive effect in the UK. Nevertheless, when productivity levels are investigated, medium-productive farms in Germany and medium- and highly-productive ones in Spain are negatively affected (as suggested by Mennig & Sauer, (2020), AES may reduce farm's flexibility for further development). However, it is important to underline that medium-productive farms in France, Italy, and Poland are positively influenced, together with the least-productive group in Poland. The obtained positive effects could be linked to the objective of AES payments, that is, counterbalancing negative income trade-off when complying with more sustainable production techniques (Dudu & Kristkova, 2017; Latruffe & Desjeux, 2016; Mennig & Sauer, 2020; Pufahl & Weiss, 2009). However, the heterogeneity of results may be due to the heterogeneity encountered among countries in terms of the amount of resources devoted to each group of RDP measures and how these are designed.

Similarly, LFA is intended as an additional support for farms in disadvantaged areas, which often starts from lower productivity performances than their counterparts (Vigani & Dwyer, 2020) as per the lack of services and natural constraints. All countries and productivity groups but medium-productive farms in Germany feature either a negative or non-significant effect of LFA on TFP¹⁹. Non-significant effects hint that LFA payments may prevent productivity losses; on the other hand, adverse effects may suggest that such financial support is insufficient to contain the negative trend in productivity. Moreover, farms already operating at economic losses may lack the willingness to engage in productivity-enhancing activities. Our results are in line with those of Khafagy & Vigani (2022a) and Mary (2013) but opposite to those in Dudu & Kristkova (2017) and Garrone et al. (2019a), showing, once again, the controversial results the literature offers.

Regarding Pillar 2 support for investments, whole-sample estimates point to a detrimental effect on TFP for Spain, France, and the UK; when accounting for different productivity levels, Spain shows a generally positive influence for low- and medium-productivity farms; France and UK turn non-significant, while Poland shows negative and positive effects for medium- and highly-productive farms, respectively. The misalignment between the provision of such lump sum and the realization of the investment may explain the negative effect, with the farm experiencing a significant change in the production system as per the initial stage of the new investment. Besides, such subsidies may be designed for investments to comply with regulations regarding safety work conditions and environmental and/or animal welfare, which do not intend to increase productivity (Kirchweger & Kantelhardt, 2015). On the other hand, positive results could be related to how the support is granted, that is, 'in advance' of the investment or when the investment is

¹⁹ The UK was excluded from the analysis as the number of observations with non-zero LFA payments was not sufficient for the model to be estimated.

already in place. Nevertheless, such mixed results are in line with the literature; Dudu & Kristkova (2017), Khafagy & Vigani (2022a), and Nilsson (2017) conclude on the positive role of investment subsidies on productivity, while Mary (2013) finds negative influence, and Latruffe et al., (2008) and Latruffe & Desjeux, (2016) non-significant impact.

Finally, “other” Pillar 2 subsidies do not provide a significant result. This seems due to two main reasons: first, the fact that this category often refers to a very negligible amount of resources (Fig. 3); second is, the mixed nature of this variable. These reasons may prevent any meaningful interpretation of the results. Nevertheless, we account for such payments to consider the remaining part of Pillar 2 subsidies in the model, avoiding these feeding the omitted variable bias.

Regarding the effect of further control variables, economic size (the standard output in thousands of euros) shows a positive influence on the TFP of least-productive farms in Germany and Poland, while negative for highly-productive farms in the UK and Spain as in Aragón et al., (2022a, 2022b) and Barrett et al. (2010). Probably, highly-productive farms cannot improve their productivity more and struggle to allocate resources efficiently. France and Italy show positive relationships when the aggregated sample is analyzed, while no significant effects when exploring different TFP categories.

Ratio debts on the total assets generate controversial results when considering the overall sample. Indeed, increasing the ratio seems positive for the TFP of German farms while harmful for Spanish and Polish farmers. Nevertheless, when different TFP levels are analyzed, farms with low productivity benefit from increasing debt over assets; on the contrary, increasing the ratio negatively affects the TFP of highly-productive farms. Such results find an interesting explanation in the work of Khafagy & Vigani (2022b), where the authors conclude on the inverted U-shaped relationship between external finance and productivity.

The effect of the rented land ratio is generally positive, particularly for the overall sample for all countries but Italy and the UK; the positive effect persists even when subsamples of productivity categories are analyzed, except for medium-productive farms in Poland. Such results are not surprising: when land is more costly – the rent they have to pay – farmers put more effort into increasing productivity. Moreover, when land is rented, part of CAP subsidies may be leaked into the land value (Baldoni & Ciaian, 2021), reinforcing the idea that the lesser the CAP received, the higher the likelihood of a productivity increase.

The diversification Herfindahl – Hirschman Index that accounts for production complexity shows a neutral-to-positive impact on TFP. Nevertheless, the effect becomes controversial when looking into subsamples: positively correlated to TFP for highly-productive farms in all countries but Poland, and for medium-productive units in Italy and low-productive in the UK. Nevertheless, the result is in line with the recent literature (Ayouba et al., 2017; Bakucs et al., 2010). Finally, concerning the effect of insurance on TFP, results are mixed as in the literature. On the one hand, scholars found positive relationships since insurance can incentivize investments reducing the risk-aversion (Quiroga et al., 2017; Sabasi et al., 2021; Zhu & Lansink, 2010). On the other hand, Bousse-mart et al. (2019) and Zhu et al. (2012) assert that the effect of insurance is discouraging investments, hence entailing a negative impact on productivity. Nevertheless, our results may indicate a more consistent negative effect on TFP.

IMR signals that selection bias is significant in only three cases out of 18. This indicates that even when self-selection is at work, the bias effect on the SYS-GMM estimator is very marginal, as already demonstrated by other scholars and support the idea that the Blundell Bond estimator is robust to selection as shown in the literature (Al-Sadoon et al., 2019; Arellano et al., 1999; Asmare et al., 2019, 2022; Hayakawa, 2007).

5. Discussion and policy implications

Despite the generous literature studying the relationship between productivity and policy subsidies, most of its empirical applications do not account for the (significant) autoregressive trait of productivity, hence assuming of a static relationship. Such a “persistence” (Hirsch & Gschwandtner, 2013; Hirsch & Hartmann, 2014) explains how the present TFP value is correlated with its own past levels. Therefore, we add to previous analysis accounting for the autoregressive feature of TFP, and comparing different EU countries and policy measures, differentiating between groups of farms with diverse intrinsic productivity levels. In our analysis, the autoregressive coefficient in 22 out of 24 examples is significant and has a value between 0.10 and 0.75.

When looking at the overall impact of the diverse CAP measures on farms’ productivity per country, results are partially in line with those of previous analyses. As suggested by Garrone et al. (2019a), CDP potentially disrupts the efficient allocation of inputs and outputs. On the other hand, DDP, providing additional revenues, should enhance farms’ capital and access to credit, boosting productivity (Kazukauskas et al., 2014). Nevertheless, their tight link with land may convey their benefits to landowners instead of farmers via their capitalization into land rents (O’Neill & Hanrahan, 2016; Varacca et al., 2021). Indeed, the results of our analysis suggest that DDP, when significant, negatively affects productivity for all the considered countries. This is particularly true for Italy as a whole and for the least-productive farms in Spain and Poland.

The same negligible-to-negative effect on productivity applies to LFA, RDP investment, and RDP other. While, theoretically, subsidies on investments should boost productivity, our results are consistent with the most recent literature (Lakner, 2009; Latruffe et al., 2016; Nilsson, 2017). Such subsidies may push farmers to (over) invest in less productive activities, leaving aside the more productive ones (Khafagy & Vigani, 2022a).

AES payments show controversial results: farms receiving such subsidies are linked to environmentally-friendly activities, hence not necessarily the most productive methods (Vigani et al., 2015). Indeed, AES are designed to provide financial support to farmers choosing to reduce negative externalities and provide public goods (e.g., landscape, biodiversity, resources’ quality), and this could reduce the productivity of these farms when compared with their conventional counterparts (Mennig & Sauer, 2020). Nevertheless, results show that AES also enhances productivity for some specific farms: sometimes, this entails reducing the production costs linked to specific factors – e.g. energy, work, chemicals, among others – and/or increasing output value (Mennig & Sauer, 2020; Pufahl & Weiss, 2009). Dudu & Kristkova (2017) also conclude on the positive effect of AES on productivity, explaining how such measures reduce land use but not intermediate inputs. Finally, LFA subsidies are paid to farms already in disadvantaged areas with more difficult access to essential services and resources, intended to avoid their exit from the sector instead of boosting their productivity (Vigani & Dwyer, 2020). All in all, RDP payments are of voluntary nature, related to very specific investment projects, paving the way for distortive and subsidy-seeking farm practices (Khafagy & Vigani, 2022a).

To summarize, results unveil that the extent to which policy instruments shape farms’ productivity, besides other factors, is significant and generally negative. Albeit different policy instruments serve different objectives than boosting productivity, their side effects on the latter should be considered for a more comprehensive trade-off assessment between objectives and priorities of the CAP. For instance, DDP are shown to decrease TFP, particularly for least- and medium-productivity farms, somewhat facilitating their exit from the sector (Andrews & Cingano, 2014; Restuccia & Rogerson, 2013; Schiantarelli, 2008).

Kornai (1986) already advised on the distortive role of subsidies, and how they may lead to inefficient resource allocation as additional costs are not borne by the farm itself but by the public. Moreover, because subsidies may maintain inefficient farms in the sector, capital is shifted towards these less competitive agricultural units merely on a political basis, lowering the productivity of the whole system (Khafagy & Vigani, 2022a).

One of the main contributions of the research is the analysis of different farms' productivity levels. Results feed the idea that tailoring the CAP according to some specific farms' characteristics may achieve higher efficiency levels. The second relevant result is that the TFP is a highly persistent variable that is only partially affected by CAP measures, at least in the considered farm type and countries.

In light of the recent debate on how to boost the productivity of grain farms, results suggest that, especially in the short-term, any of the investigated subsidies seem adequate. Interestingly, increasing the budget devoted to AES to improve the environmental sustainability of agriculture may not have significant negative consequences on farm productivity, on the opposite, TFP may even increase. Note that DDP can depress TFP in less productive farms, increasing the risk of putting them out of the market. Indeed, the take-home message seems that the market itself, via price signals, may encourage farms to boost productivity to inflate their profits; indeed, policy interventions may eventually weaken grains' productivity.

6. Conclusions

Relying on the comprehensive but controversial literature on the relationship between CAP and productivity, we used micro-level data for modelling the total factor productivity of field crop farms for six major European producers. A three-step procedure has been used to assess the link between CAP subsidies and total factor productivity for field crop farms in six different European countries for the 2008 – 2018 period. A Cobb-Douglas production function was estimated considering the CAP's land, capital, labour, materials, and subsidies as production factors. This allowed obtaining TFP through the Solow residual and evaluating the relationship between TFP and CAP measures through the SYS-GMM approach.

We contribute to the existing literature by providing a multi-country analysis of field crop farms and investigating the dynamic behaviour of TFP. To our knowledge, this is the first study that accounts explicitly for the autoregressive feature of productivity and suggests that this aspect deserves attention in future research. From a policy point of view, this indicates that policymakers should be aware of this when designing productivity-specific policy measures: such stickiness may significantly affect the impact of CAP measures on farm productivity.

As stated by Khafagy & Vigani (2022a, 2022b) in their EU-wide analysis of CAP and productivity, subsidies differ in nature, having specific aims and hence diverse impacts on TFP and farms' behaviour. Therefore, studying a homogeneous type of farm may ensure higher precision in estimating the relationship between productivity and CAP subsidies.

Results raise warnings about considering farms as an aggregated and undifferentiated population, potentially leading to biased results. For instance, the productivity-detrimental effect of decoupled payments seems more substantial for least-productivity farms; thus, it seems advisable to move towards a CAP tailored to specific characteristics of the farms and the agriculture in which they operate. In line with Khafagy & Vigani (2022b), a 'one-size fits all' CAP is far from being efficient and fair, and frequent measurements of subsidies' effectiveness are needed. Nevertheless, designing tailored subsidies is not an easy task besides

going beyond the scope of the study. Indeed, results hint that different intrinsic productivity levels could be a starting point, although we left further research to define which variables and criteria could be further used.

On the policy side, the analysis warns policymakers of overinflating coupled payments to grain farms to boost productivity; all Pillar 1 payments entail a non-significant-to-negative effect on TFP. The market itself, through price increases, may be sufficient to push farmers to seek more productive production strategies to inflate profits. On the other hand, and within a long-term vision, agro-environmental schemes may enhance productivity, even if we cannot discern windfall effects; all in all, the strong EU policy effort to foster the application of eco-friendly practices (e.g., organic farming as per the Farm to Fork strategy) may not hamper the agricultural production because of the positive effect on productivity.

Finally, the current analysis is not exempt of limitations. Firstly, the results presented here may not be applicable to understand the current (and future) relationship between the CAP subsidies and farms' productivity. The recent CAP Reform allows each MS to tailor how subsidies are applied and distributed within their national boundaries, hence needing a brand new analysis to unveil how this new approach influences the relationship between the farm productivity and CAP subsidies. Moreover, the countries analyzed differ in their farms' economic, structural, and environmental conditions and how the CAP is implemented. Which elements and how explain the differences encountered among countries is left to further research. On the methodological side, different production functions and estimators may be applied. Using a CD production function, however reasonably argued and defended in the dedicated section, is subjected to criticism, as there is yet no consensus on which functional production form is the best, and, more pragmatically, with which econometric tool one should estimate production functions. Indeed, it is not trivial to evaluate complex production functions via SYS-GMM, preventing researchers from applying a very efficient and bias-reducing estimator and casting doubts on whether the trade-off between less robust and efficient estimates and more relaxed production functions is positive.

CRedit authorship contribution statement

L. Biagini: Conceptualization, Formal analysis, Investigation, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **F. Antonioli:** Conceptualization, Investigation, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing. **S. Severini:** Conceptualization, Investigation, Supervision, Validation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

A.1. Definition of the variables

Variables are defined according to appendix 1 on (Rizov et al., 2013). In particular, following the codes adopted by FADN (FADN, 2014).

- *outputvalue*(*Y*) is defined as the real value of total annual output (SE131)
- *K* is capital is defined as the Total fixed assets (SE441) minus agricultural land value (in EU FADN dataset is ALNDAGR_CV_X). Land value is defined according to the procedure of (Rizov et al., 2013) to include rental land. First, we determine the rental value of land, then, we evaluate the rate of return of land and finally, we discount the rental payments using the estimated rate of return as a discount rate.
 - o The farm own Utilized Agricultural Area (UAA) is calculated

$$TotalUAA(SE025) - RentedUAA(SE030)$$

- o Value of fixed assets (SE441) per UAA hold is defined as
- o $Fix_K_UAA_hold = \text{value of fixed assets} / UAA \text{ hold}$
- o Rent per rented UAA is:

$$Rent_{UAA} = \frac{Rentpaid_{SE375}}{Rented} U.A.A.(SE030)$$

- o Rate of Return of Rent at farm level (*RoRR*) is:

$$RoRR - Farmlevel = \frac{Rent_{UAA}}{Fix_{K_{UAA}hold}}$$

The Rate of Return of Rent for NUTS2 for FADN type of farming 1 is obtained by using the median of *RoRR - Farm level*. Regional aggregation is performed through the use of the median rather than the estimated value per single farm. This is necessary to avoid inconsistencies or individual values that are too high or too low due to specific characteristics that cannot be repeated in other farms (for example, cases of land speculation): *RoRR - Aggregated*. Finally, we use *RoRR - Aggregated* to discount the total rental payments (SE375), which gives us the capital value of land.

- *L* Land value is given by the sum of the capital value of the land and agricultural land value (in FADN dataset is ALNDAGR_CV_X)
- *N* t is total full-time equivalent labour input (SE011) measured in hours worked annually
- *M* is materials measured variable costs consisting of total annual specific costs (SE281) plus total annual farming overheads (SE336). SE281 represents current costs specific to production conversly SE 336 includes costs related to fixed capital (machinery and building costs).
- For CAP measures, we consider:
 - o $CDP = CoupledDirectPayments = Totalsubsidiesoncrops(SE610) + Totalsubsidiesonlivestock(SE615)$
 - o $DDP = DirectDecoupledPayments(SE630)$
 - o $RDPa = Rural\ Development\ Payments\ excluding\ investment$
 - o $RDPa = Totalsupportforruraldevelopment(SE624) - RuralDevelopmentSubsidiesoninvestments(SE406)$
 - o $AES = RuralDevelopmentPaymentsforAgri - EnvironmentalSchemes(SE621)$
 - o $LFA = RuralDevelopmentPaymentsforLessFavourableAreas(SE622)$
 - o $RDPOther = OtherAnnualRuralDevelopmentPayments = RuralDevelopmentPaymentsexcludinginvestment, AESandLFA$
 - o $= RDPa - AES - LFA$
 - o $RDP\ Inv = RuralDevelopmentSubsidiesoninvestments = (SE406)$
- *Economicssize* is the Total economic size in EUR (SIZEUR)
- *Debt on asset* is $\frac{TotalLiabilities}{TotalAssets}$ where $TotalLiabilities = TotalAssets(SE436) - NetWorth(SE501)$;
- *UAA Rented*: Rented U.A.A. (SE030)
- *HIndex* represents measure of diversification using Herfindahl– Hirschman Index (Herfindahl, 1950; Hirschman, 1969) calculated using the value of output for Cereals (SE140), Protein crops (SE145), Energy crops (SE146), Potatoes (SE150), Sugar beet (SE155), Oil-seed crops (SE160), Industrial crops (SE165), Vegetables & flowers (SE170), Fruit trees and berries grown in the open (including tropical fruit), excluding citrus fruit orchards and grapes (SE175), Citrus fruit (SE180), Wine and grapes (SE185), Olives & olive oil (SE190), Forage crops (roots and brassicas, other fodder plants, temporary grass, meadows and permanent pastures, rough grazing, fallows and set-aside land) SE195, Cows' milk & milk products (SE216), Beef and veal (SE220), Pigmear (SE225), Sheep and goats (SE230), Poultrymeat (SE235), Eggs (SE240), Ewes' and goats' milk (SE245), Other livestock & products (SE251), and Other output (SE256);
- *Insurance* are payments for insurance premiums (IOTHINS_AGR_V)

Finally, in order to reduce the possible distortions of prices in the economic value of inputs and outputs, we use different sources of price indexes specified in the following table, which allow us to have a proxy of the quantities of inputs and output where the variables are expressed in currency values (De Loecker, 2011; Rizov et al., 2013; Zhu & Lansink, 2010).

A.2. Minimum distance estimators

The reduced form of production function is the following:

$$y_{i,t} = \rho y_{i,t-1} + \beta_k k_{i,t} - \rho \beta_k k_{i,t-1} + \beta_n n_{i,t} - \rho \beta_n n_{i,t-1} + \beta_l l_{i,t} - \rho \beta_l l_{i,t-1} + \beta_m m_{i,t} - \rho \beta_m m_{i,t-1} + \beta_g g_{i,t} - \rho \beta_g g_{i,t-1} + (1 - \rho)\eta_i + (\omega_{i,t} - \rho \omega_{i,t-1}) + (\varepsilon_{i,t} - \rho \varepsilon_{i,t-1}) \tag{13}$$

To avoid excessive recourse to notations, without loss in clarity, we include the production factors in a generic factor x and the term $(1 - \rho)\eta_i + (\omega_{i,t} - \rho \omega_{i,t-1}) + (\varepsilon_{i,t} - \rho \varepsilon_{i,t-1}) = \nu_{i,t}$

$$y_{i,t} = \rho y_{i,t-1} + \beta_x x_{i,t} - \rho \beta_x x_{i,t-1} + \nu_{i,t} \tag{14}$$

Or, using a notation suitable in SYS-GMM:

$$y_{i,t} = \pi_1 y_{i,t-1} + \pi_2 x_{i,t} + \pi_3 x_{i,t-1} + \nu_{i,t} \tag{15}$$

Consequently, the coefficients found should satisfy the mapping $\pi_1 = \rho, \pi_2 = \beta_x, \pi_3 = \rho \beta_x$

Given consistent estimates of the unrestricted coefficients in (9) the common factor restriction can be imposed using a minimum distance estimator following (Blundell et al., 1996; Chamberlain, 1982).

Letting $\pi = (\pi_1, \pi_2, \pi_3)$ and $\Theta = (\beta, \rho)'$, the restriction is $\pi(\Theta) = (\beta, -\beta\rho, \rho)'$

The restricted parameter estimates Θ are chosen to minimise the quadratic distance:

$$\min [g(\hat{\pi}) - g(\pi(\Theta))] \hat{\Omega}^{-1} [g(\hat{\pi}) - g(\pi(\Theta))] \tag{16}$$

Where $\hat{\Omega} = (\partial g(\hat{\pi}) / \partial \pi') \widehat{\text{var}}(\hat{\pi}) (\partial g(\hat{\pi}) / \partial \pi)'$ and $g(\pi) = (\pi_2, -\pi_3 / \pi_1, \pi_1)'$ is chosen to make $g(\pi(\Theta)) = (\beta, \beta, \rho)'$ linear in β and ρ

A.3. Inverse Mills Ratio estimation

In order to obtain the Inverse Mills Ratio (IMR), we have followed the latent variable approach (Arellano et al., 1999; Semykina & Wooldridge, 2013; Wooldridge, 1995) using Inverse Mills Ratio (IMR) (Heckman, 1979). Since we may also have dynamics in the selection over the period examined, an autoregressive model with individual effects is estimated with observation-specific IMR to account for the fact that the same farm may fall into different categories of productivity within the period.

IMR is calculated considering all the variables explaining the belonging to each one of the three subsets, including at least one additional time-varying variable explaining the fact of belonging to that specific productivity-category (i.e., correlated to the latent variable) but not correlated to the dependent output variable (Semykina & Wooldridge, 2013). For selecting at least one additional time-varying variable remain explaining the belonging to the specific productivity-category but that does not correlate to the output TFP variable, we adopted a Double LASSO approach as in (Belloni et al., 2012; Windmeijer et al., 2018). Considering that we have three subsets, the procedure is repeated for each TFP category along the following four phases: (1) estimation of a probit regression with dichotomic dependent variable (1 if the observation belongs to the selected productivity tertile; 0 otherwise) - therefore, three IMRs are estimated for each observation, one for each tertile. 120 variables were used in this step, retrieved form the FADN dataset (see Table A.11). In this stage the adaptative-LASSO procedure is applied, allowing for a robust regressors selectivity (Windmeijer et al., 2018; Zou, 2006). First, a Ridge regression is estimated and the (inverse) coefficients of each regressor are used as weights in the subsequent LASSO estimation. This procedure allows retrieving unbiased estimates, that is, reducing the likelihood of weakly-correlated regressors; (2) in this second step, as in the first one, we follow the adaptative-LASSO method but changing the dependent variable: TFP derived from the Blundell-Bond estimator is used, hence a continuous and assumed normally-distributed variable. This to select those variables that significantly explain the farm-specific TFP level. 3) in the third and final phase, IMR to correct for selection-bias in equation (12) are retrieved. Specifically, those variables that significantly explain the belonging to the specific productivity-category (significant regressors from phase 1) but that do not correlate to the TFP (non-significant in phase 2), together with the variables included in equation (11) - CDP, DDP, AES, LFA, RDP_Other, RDP_inv, Economic_Size, Debts-on-asset, UAA_Rented, H_Index, Insurance) - are used as regressors in a Probit selection model for each productivity-category (dichotomic dependent variable is then 1 when the observation belongs to the productivity tertile and 0 otherwise). IMR are calculated as $(\varphi(\gamma))/(1-\Phi(\gamma))$ where γ is the threshold parameter estimated from the probit model as explained above, $\varphi(\cdot)$ is the standard normal probability density function, and $\Phi(\cdot)$ is the standard normal cumulative distribution function.

A.4. Other Tables

Table A1

Source of price indexes used for the estimation.

| Variable | Price index | Source | Description |
|---------------|------------------------------------|----------|---|
| Total Output | Cereal Price Index base 100 = 2015 | Eurostat | Price indices of agricultural products, output - rebased to 2015 = 100 |
| Capital | GDP Deflator Index base 100 = 2015 | FRED | Gross domestic product (implicit price deflator) |
| Land | GDP Deflator Index base 100 = 2015 | FRED | Gross domestic product (implicit price deflator) |
| Labour | Not deflated | | |
| Material | Input Price Index base 100 = 2015 | Eurostat | Price indices of the means of agricultural production, input- rebased to 2015 = 100 |
| CDP | HICP - base 100 = 2015 | Eurostat | HICP - annual data - rebased to 2015 = 100 |
| DDP | HICP - base 100 = 2015 | Eurostat | HICP - annual data - rebased to 2015 = 100 |
| AES | HICP - base 100 = 2015 | Eurostat | HICP - annual data - rebased to 2015 = 100 |
| LFA | HICP - base 100 = 2015 | Eurostat | HICP - annual data - rebased to 2015 = 100 |
| RDP Other | HICP - base 100 = 2015 | Eurostat | HICP - annual data - rebased to 2015 = 100 |
| RDP inv | HICP - base 100 = 2015 | Eurostat | HICP - annual data - rebased to 2015 = 100 |
| Economic Size | HICP - base 100 = 2015 | Eurostat | HICP - annual data - rebased to 2015 = 100 |
| Debt on asset | GDP Deflator Index base 100 = 2015 | FRED | Gross domestic product (implicit price deflator) |
| UAA Rented | Not deflated | | |
| H Index | Not deflated | | |
| Insurance | Input Price Index base 100 = 2015 | Eurostat | Price indices of the means of agricultural production, input- rebased to 2015 = 100 |

Table A2
Variations of TFP in the samples of the six countries.

| Year | Germany (DE) | | | | Spain (ES) | | | | France (FR) | | | |
|------|--------------|--------|--------|------------|------------|--------|--------|------------|-------------|--------|--------|------------|
| | Mean | Delta | % | Cumulated* | Mean | Delta | % | Cumulated* | Mean | Delta | % | Cumulated* |
| 2008 | 1.091 | | | 1.000 | 1.007 | | | 1.000 | 1.172 | | | 1.000 |
| 2009 | 1.118 | 0.027 | 2.47% | 1.025 | 1.002 | -0.005 | -0.50% | 0.995 | 1.188 | 0.016 | 1.37% | 1.014 |
| 2010 | 1.106 | -0.012 | -1.07% | 0.989 | 1.01 | 0.008 | 0.80% | 1.008 | 1.19 | 0.002 | 0.17% | 1.002 |
| 2011 | 1.088 | -0.018 | -1.63% | 0.984 | 1.005 | -0.005 | -0.50% | 0.995 | 1.171 | -0.019 | -1.60% | 0.984 |
| 2012 | 1.092 | 0.004 | 0.37% | 1.004 | 0.988 | -0.017 | -1.69% | 0.983 | 1.17 | -0.001 | -0.09% | 0.999 |
| 2013 | 1.097 | 0.005 | 0.46% | 1.005 | 1.004 | 0.016 | 1.62% | 1.016 | 1.163 | -0.007 | -0.60% | 0.994 |
| 2014 | 1.112 | 0.015 | 1.37% | 1.014 | 1.023 | 0.019 | 1.89% | 1.019 | 1.17 | 0.007 | 0.60% | 1.006 |
| 2015 | 1.109 | -0.003 | -0.27% | 0.997 | 1.032 | 0.009 | 0.88% | 1.009 | 1.18 | 0.01 | 0.85% | 1.009 |
| 2016 | 1.116 | 0.007 | 0.63% | 1.006 | 1.051 | 0.019 | 1.84% | 1.018 | 1.174 | -0.006 | -0.51% | 0.995 |
| 2017 | 1.112 | -0.004 | -0.36% | 0.996 | 1.037 | -0.014 | -1.33% | 0.987 | 1.186 | 0.012 | 1.02% | 1.010 |
| 2018 | 1.097 | -0.015 | -1.35% | 0.987 | 1.048 | 0.011 | 1.06% | 1.011 | 1.179 | -0.007 | -0.59% | 0.994 |

| Year | Italy (IT) | | | | Poland (PL) | | | | United Kingdom (UK) | | | |
|------|------------|--------|--------|------------|-------------|--------|--------|------------|---------------------|--------|--------|------------|
| | Mean | Delta | % | Cumulated* | Mean | Delta | % | Cumulated* | Mean | Delta | % | Cumulated* |
| 2008 | 1.072 | | | 1.000 | 0.931 | | | 1.000 | 1.298 | | | 1.000 |
| 2009 | 1.104 | 0.032 | 2.99% | 1.030 | 0.919 | -0.012 | -1.29% | 0.987 | 1.314 | 0.016 | 1.23% | 1.012 |
| 2010 | 1.105 | 0.001 | 0.09% | 1.001 | 0.923 | 0.004 | 0.44% | 1.004 | 1.329 | 0.015 | 1.14% | 1.011 |
| 2011 | 1.077 | -0.028 | -2.53% | 0.975 | 0.898 | -0.025 | -2.71% | 0.973 | 1.299 | -0.03 | -2.26% | 0.977 |
| 2012 | 1.082 | 0.005 | 0.46% | 1.005 | 0.901 | 0.003 | 0.33% | 1.003 | 1.302 | 0.003 | 0.23% | 1.002 |
| 2013 | 1.083 | 0.001 | 0.09% | 1.001 | 0.898 | -0.003 | -0.33% | 0.997 | 1.284 | -0.018 | -1.38% | 0.986 |
| 2014 | 1.093 | 0.010 | 0.92% | 1.009 | 0.960 | 0.062 | 6.90% | 1.069 | 1.296 | 0.012 | 0.93% | 1.009 |
| 2015 | 1.099 | 0.006 | 0.55% | 1.005 | 0.959 | -0.001 | -0.10% | 0.999 | 1.312 | 0.016 | 1.23% | 1.012 |
| 2016 | 1.110 | 0.011 | 1.00% | 1.010 | 0.958 | -0.001 | -0.10% | 0.999 | 1.304 | -0.008 | -0.61% | 0.994 |
| 2017 | 1.112 | 0.002 | 0.18% | 1.002 | 0.957 | -0.001 | -0.10% | 0.999 | 1.286 | -0.018 | -1.38% | 0.986 |
| 2018 | 1.111 | -0.001 | -0.09% | 0.999 | 0.949 | -0.008 | -0.84% | 0.992 | 1.285 | -0.001 | -0.08% | 0.999 |

*(2008 = 1.000)

Table A3
TFP estimates using [Akerberg, Caves, and Frazer \(2015\)](#) Approach – ACF- (TFP_{ACF}) - (Step 2b).

| Year | Germany(DE) | | Spain (ES) | | France (FR) | | Italy (IT) | | Poland (PL) | | United Kingdom (UK) | |
|------|-------------|---------|------------|---------|-------------|---------|------------|---------|-------------|---------|---------------------|---------|
| | Mean | St.d. | Mean | St.d. | Mean | St.d. | Mean | St.d. | Mean | St.d. | Mean | St.d. |
| 2008 | 9.681 | (0.887) | 7.919 | (0.790) | 4.867 | (0.469) | 6.847 | (1.004) | 3.060 | (0.695) | 11.551 | (0.854) |
| 2009 | 9.932 | (0.894) | 7.840 | (0.782) | 5.093 | (0.479) | 7.125 | (1.006) | 3.041 | (0.741) | 11.701 | (0.895) |
| 2010 | 9.812 | (0.882) | 7.949 | (0.749) | 5.088 | (0.465) | 7.120 | (0.984) | 3.129 | (0.715) | 11.842 | (0.865) |
| 2011 | 9.544 | (0.865) | 7.874 | (0.703) | 4.895 | (0.469) | 6.880 | (0.967) | 2.821 | (0.698) | 11.504 | (0.861) |
| 2012 | 9.635 | (0.895) | 7.827 | (0.767) | 4.905 | (0.525) | 6.963 | (0.967) | 2.859 | (0.758) | 11.598 | (0.868) |
| 2013 | 9.672 | (0.950) | 8.024 | (0.710) | 4.835 | (0.526) | 6.934 | (0.983) | 2.830 | (0.735) | 11.447 | (0.874) |
| 2014 | 9.777 | (0.934) | 8.000 | (0.747) | 4.977 | (0.498) | 7.067 | (1.045) | 3.005 | (0.689) | 11.809 | (0.828) |
| 2015 | 9.734 | (0.916) | 8.090 | (0.720) | 5.087 | (0.477) | 7.187 | (0.965) | 2.988 | (0.682) | 11.989 | (0.854) |
| 2016 | 9.788 | (0.908) | 8.327 | (0.753) | 5.046 | (0.490) | 7.297 | (0.979) | 2.922 | (0.690) | 11.925 | (0.892) |
| 2017 | 9.736 | (0.888) | 8.224 | (0.792) | 5.152 | (0.482) | 7.308 | (0.974) | 2.932 | (0.671) | 11.795 | (0.861) |
| 2018 | 9.531 | (0.914) | 8.323 | (0.733) | 5.087 | (0.522) | 7.290 | (1.000) | 2.827 | (0.720) | 11.820 | (0.865) |

Table A4
Impacts of CAP subsidies on overall TFP (Step 3).

| Tipology | Name | Germany (DE) | | | Spain (ES) | | | France (FR) | | | Italy (IT) | | | Poland (PL) | | | United Kingdom (UK) | | |
|-------------------|------------------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|---------------------------|----------------|----------------|---------------------------|---------------------|----------------|----------------|
| | | Value | St.d | p. value | Value | St.d | p. value | Value | St.d | p. value |
| Rho | T F Pt – 1 | 0.4323 | (0.057) | < 0.001 | 0.1969 | (0.089) | 0.0260 | 0.1725 | (0.134) | 0.2000 | 0.3312 | (0.064) | < 0.001 | 0.2506 | (0.090) | 0.0050 | 0.1838 | (0.078) | 0.0190 |
| Regressor | CDP (x1000) | -0.0018 | (0.001) | 0.1240 | -0.0005 | (0.000) | 0.0640 | -0.0003 | (0.001) | 0.6010 | -0.0002 | (0.000) | 0.1430 | -0.0006 | (0.000) | 0.0090 | -0.0048 | (0.004) | 0.1800 |
| | DDP (x1000) | -0.0001 | (0.000) | 0.4810 | 0.0000 | (0.000) | 0.9320 | -0.0002 | (0.000) | 0.5070 | -0.0004 | (0.000) | 0.0150 | 0.0003 | (0.000) | 0.2080 | 0.0001 | (0.000) | 0.6830 |
| | AES (x1000) | -0.0008 | (0.000) | 0.0440 | 0.0034 | (0.002) | 0.1290 | -0.0007 | (0.001) | 0.3630 | -0.0001 | (0.001) | 0.9190 | -0.0007 | (0.001) | 0.4130 | 0.0007 | (0.000) | 0.0200 |
| | LFA (x1000) | -0.0016 | (0.002) | 0.3920 | -0.0539 | (0.009) | < 0.001 | -0.0041 | (0.002) | 0.0070 | -0.0034 | (0.003) | 0.3170 | -0.0086 | (0.003) | 0.0040 | Not Available | | |
| | RDP Other (x1000) | -0.0518 | (0.022) | 0.0190 | -0.0151 | (0.016) | 0.3320 | -0.0022 | (0.001) | 0.0330 | -0.0007 | (0.001) | 0.6320 | -0.0023 | (0.004) | 0.5590 | -0.0020 | (0.002) | 0.2660 |
| | RDP inv (x1000) | 0.0000 | (0.000) | 0.9040 | -0.0116 | (0.004) | 0.0090 | -0.0008 | (0.000) | 0.0520 | 0.0011 | (0.002) | 0.5920 | 0.0004 | (0.001) | 0.6160 | -0.0009 | (0.001) | 0.0850 |
| | Economic Size (x1000) | 0.0000 | (0.000) | 0.1130 | 0.0001 | (0.000) | 0.3940 | 0.0001 | (0.000) | 0.0100 | 0.0001 | (0.000) | 0.0100 | 0.0000 | (0.000) | 0.6620 | -0.0001 | (0.000) | 0.0530 |
| | Debt on asset | 0.0715 | (0.032) | 0.0270 | -0.4659 | (0.223) | 0.0370 | 0.0050 | (0.044) | 0.9090 | 0.5881 | (0.401) | 0.1420 | -0.2069 | (0.072) | 0.0040 | -0.0158 | (0.029) | 0.5870 |
| Control variables | UAA Rented | 0.0001 | (0.000) | 0.0240 | 0.0010 | (0.000) | < 0.001 | 0.0002 | (0.000) | 0.0180 | 0.0010 | (0.000) | < 0.001 | 0.0004 | (0.000) | < 0.001 | 0.0000 | (0.000) | 0.9760 |
| | H Index | 0.0863 | (0.026) | < 0.001 | 1.4848 | (0.266) | < 0.001 | 0.1400 | (0.171) | 0.4140 | 0.1358 | (0.124) | 0.2740 | 0.4986 | (0.234) | 0.0330 | -0.7227 | (0.470) | 0.1240 |
| | Insurance | 0.0000 | (0.000) | 0.0190 | 0.0000 | (0.000) | < 0.001 | 0.0000 | (0.000) | 0.5480 | 0.0000 | (0.000) | 0.0170 | 0.0000 | (0.000) | 0.0030 | 0.0000 | (0.000) | 0.7970 |
| Test | Sargan test (p. value) | 0.169 | | | 0.713 | | | 0.152 | | | 0.817 | | | 0.092 | | | 0.587 | | |
| | m1 (p. value) | 0.000 | | | 0.000 | | | 0.015 | | | 0.000 | | | 0.000 | | | 0.052 | | |
| | m2 (p. value) | 0.247 | | | 0.078 | | | 0.313 | | | 0.122 | | | 0.100 | | | 0.220 | | |
| | Wald coeff. (p. value) | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | | 0.006 | | |
| | Wald time (p.value) | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | |
| Observations | 22,175 | | | 21,107 | | | 19,307 | | | 31,786 | | | 31,712 | | | 5269 | | | |
| Instruments | TFP | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₁ | to | t ₃ | t ₂ | to | t ₅ | t ₂ | to | t ₃ | t ₁ | | |
| | CDP (x1000) | | t ₂ | | t ₁ | to | t ₃ | | t ₂ | | t ₁ | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | |
| | DDP (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₅ | t ₂ | to | t ₉ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| AES (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₅ | t ₂ | to | t ₉ | t ₂ | to | t ₃ | t ₁ | to | t ₃ | |

(continued on next page)

Table A4 (continued)

| Tipology | Name | Germany (DE) | | | Spain (ES) | | | France (FR) | | | Italy (IT) | | | Poland (PL) | | | United Kingdom (UK) | | |
|----------|-----------------------|---------------------------|------|-----------------|---------------------------|------|-----------------|---------------------------|------|------------------|---------------------------|------|-----------------|---------------------------|------|------------------|---------------------------|------|-----------------|
| | | Value | St.d | p. value | Value | St.d | p. value | Value | St.d | p. value | Value | St.d | p. value | Value | St.d | p. value | Value | St.d | p. value |
| | LFA (x1000) | t ₋₂ | to | t ₋₃ | t ₋₂ | to | t ₋₃ | t ₋₂ | to | t ₋₅ | t ₋₂ | to | t ₋₉ | t ₋₂ | to | t ₋₃ | Not Available | | |
| | RDP Other (x1000) | t ₋₂ | to | t ₋₃ | t ₋₂ | to | t ₋₃ | t ₋₂ | to | t ₋₅ | t ₋₂ | to | t ₋₉ | t ₋₂ | to | t ₋₃ | t ₋₁ | to | t ₋₃ |
| | RDP inv (x1000) | t ₋₂ | to | t ₋₃ | t ₋₂ | to | t ₋₃ | t ₋₂ | to | t ₋₅ | t ₋₂ | to | t ₋₉ | t ₋₂ | to | t ₋₃ | t ₋₁ | to | t ₋₃ |
| | Economic Size (x1000) | t ₋₂ | to | t ₋₃ | t ₋₃ | to | t ₋₇ | t ₋₂ | to | t ₋₃ | t ₋₂ | to | t ₋₉ | t ₋₁ | to | t ₋₉₉ | t ₋₂ | to | t ₋₅ |
| | Debt on asset | t ₋₂ | to | t ₋₃ | t ₋₃ | to | t ₋₇ | t ₋₃ | to | t ₋₇ | t ₋₂ | to | t ₋₉ | t ₋₁ | to | t ₋₉₉ | t ₋₂ | | |
| | UAA Rented | Assumed Stricly exogenous | | | t ₋₃ | to | t ₋₇ | Assumed Stricly exogenous | | | t ₋₁ | to | t ₋₂ | t ₋₁ | to | t ₋₉₉ | t ₋₂ | | |
| | H Index | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | t ₋₂ | | |
| | Insurance | t ₋₂ | to | t ₋₃ | t ₋₃ | to | t ₋₇ | t ₋₁ | to | t ₋₉₉ | t ₋₂ | to | t ₋₉ | t ₋₁ | to | t ₋₉₉ | Assumed Stricly exogenous | | |

The GMM instrument list contains lagged regressors of at least 1 and with a maximum equal to all available periods. CDP, UAA Rented, H Index and Insurance are assumed strictly exogenous

Estimate of impact of CAP subsidies in farms with Low, Medium and High absolute levels of productivity (TFP_{ACF}) by countries

Table A5

Impacts of farm subsidies on TFP on Germany (DE): for Low, Medium and High absolute levels of productivity.

| | Name | Low TFP | | | Medium TFP | | | High TFP | | |
|----------------|-----------------------|----------------------------|---------|-----------------|----------------------------|---------|----------------|----------------------------|---------|----------------|
| | | Value | St.d | p.value | Value | St.d | p.value | Value | St.d | p.value |
| Rho | T F Pt – 1 | 0.1533 | (0.050) | 0.0020 | 0.3769 | (0.065) | < 0.001 | 0.4399 | (0.105) | < 0.001 |
| Regressor | CDP (x1000) | -0.0059 | (0.004) | 0.1770 | -0.0014 | (0.001) | 0.0700 | -0.0018 | (0.001) | 0.1490 |
| | DDP (x1000) | -0.0015 | (0.001) | 0.2930 | -0.0030 | (0.001) | < 0.001 | -0.0001 | (0.000) | 0.7120 |
| | AES (x1000) | 0.0016 | (0.001) | 0.2260 | -0.0030 | (0.001) | 0.0020 | 0.0003 | (0.000) | 0.3240 |
| | LFA (x1000) | -0.0186 | (0.007) | 0.0130 | 0.0125 | (0.005) | 0.0170 | -0.0025 | (0.002) | 0.1010 |
| | RDP Other (x1000) | 0.0084 | (0.030) | 0.7770 | -0.0015 | (0.010) | 0.8820 | -0.0434 | (0.018) | 0.0140 |
| | RDP inv (x1000) | 0.0013 | (0.004) | 0.7450 | -0.0024 | (0.003) | 0.4850 | -0.0001 | (0.000) | 0.5880 |
| | Economic Size (x1000) | 0.0008 | (0.000) | 0.0160 | 0.0000 | (0.000) | 0.9700 | 0.0000 | (0.000) | 0.0670 |
| | Debt on asset | 0.0976 | (0.020) | < 0.001 | 0.0534 | (0.015) | < 0.001 | -0.0581 | (0.033) | 0.0770 |
| | UAA Rented | 0.0001 | (0.000) | 0.7600 | 0.0006 | (0.000) | < 0.001 | 0.0001 | (0.000) | 0.3240 |
| | H Index | -0.0476 | (0.062) | 0.4400 | 0.0263 | (0.035) | 0.4470 | 0.1816 | (0.033) | < 0.001 |
| Selection Bias | Insurance | 0.0000 | (0.000) | 0.3930 | 0.0000 | (0.000) | 0.4760 | 0.0000 | (0.000) | 0.5850 |
| | Inverse Mills Ratio | -0.0092 | (0.015) | 0.5260 | 0.1284 | (0.028) | < 0.001 | 0.0207 | (0.022) | 0.3430 |
| Test | Sargan test (p.value) | | 0.292 | | | 0.727 | | | 0.760 | |
| | m1 (p.value) | | 0.000 | | | 0.000 | | | 0.000 | |
| | m2 (p.value) | | 0.108 | | | 0.888 | | | 0.642 | |
| | Wald coeff. (p.value) | | 0.015 | | | 0.000 | | | 0.000 | |
| | Wald time (p.value) | | 0.000 | | | 0.000 | | | 0.000 | |
| Observations | | | 7392 | | | 7391 | | | 7392 | |
| Instruments | TFP | t ₋₁ | to | t ₉₉ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | CDP (x1000) | Assumed Strictly exogenous | | | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | DDP (x1000) | t ₋₁ | to | t ₉₉ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | AES (x1000) | t ₋₁ | to | t ₉₉ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | LFA (x1000) | t ₋₁ | to | t ₉₉ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | RDP Other (x1000) | t ₋₁ | to | t ₉₉ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | RDP inv (x1000) | t ₋₁ | to | t ₉₉ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | Economic Size (x1000) | t ₋₁ | to | t ₉₉ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | Debt on asset | t ₋₁ | to | t ₉₉ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | UAA Rented | Assumed Strictly exogenous | | | Assumed Strictly exogenous | | | Assumed Strictly exogenous | | |
| | H Index | Assumed Strictly exogenous | | | Assumed Strictly exogenous | | | Assumed Strictly exogenous | | |
| | Insurance | t | | | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | Inverse Mills Ratio | t ₋₁ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |

The GMM instrument list contains lagged regressors of at least 1 and with a maximum equal to all available periods. CDP, UAA Rented and H Index are assumed strictly exogenous

Table A6

Impacts of farm subsidies on TFP on Spain (ES) for Low, Medium and High absolute levels of productivity.

| | Name | Low TFP | | | Medium TFP | | | High TFP | | |
|----------------|-----------------------|----------------------------|---------|----------------|----------------------------|---------|-----------------|----------------------------|---------|----------------|
| | | Value | St.d | p.value | Value | St.d | p.value | Value | St.d | p.value |
| Rho | T F Pt – 1 | -0.0970 | (0.047) | 0.0390 | 0.3950 | (0.097) | < 0.001 | 0.2794 | (0.058) | < 0.001 |
| Regressor | CDP (x1000) | -0.0021 | (0.001) | 0.0260 | -0.0007 | (0.001) | 0.2170 | -0.0001 | (0.000) | 0.2880 |
| | DDP (x1000) | -0.0032 | (0.002) | 0.0350 | -0.0001 | (0.000) | 0.7670 | -0.0002 | (0.000) | 0.2320 |
| | AES (x1000) | 0.0074 | (0.009) | 0.4350 | -0.0025 | (0.001) | < 0.001 | -0.0013 | (0.001) | 0.0220 |
| | LFA (x1000) | -0.0536 | (0.020) | 0.0070 | -0.0076 | (0.004) | 0.0610 | -0.0054 | (0.004) | 0.1560 |
| | RDP Other (x1000) | 0.0469 | (0.241) | 0.8460 | -0.0049 | (0.002) | 0.0040 | 0.0003 | (0.001) | 0.8080 |
| | RDP inv (x1000) | 0.0579 | (0.031) | 0.0620 | 0.0015 | (0.000) | 0.0020 | -0.0007 | (0.000) | 0.1050 |
| | Economic Size (x1000) | 0.0036 | (0.003) | 0.2450 | 0.0001 | (0.000) | 0.3980 | -0.0002 | (0.000) | 0.0240 |
| | Debt on asset | -0.1375 | (0.558) | 0.8050 | -0.0907 | (0.100) | 0.3640 | 0.0400 | (0.037) | 0.2820 |
| | UAA Rented | -0.0004 | (0.001) | 0.6020 | 0.0000 | (0.000) | 0.8230 | -0.0001 | (0.000) | 0.3400 |
| | H Index | -0.1384 | (0.077) | 0.0710 | 0.2849 | (0.184) | 0.1220 | 0.2065 | (0.042) | < 0.001 |
| Selection Bias | Insurance | 0.0000 | (0.000) | < 0.001 | 0.0000 | (0.000) | < 0.001 | 0.0000 | (0.000) | 0.0270 |
| | Inverse Mills Ratio | -0.0305 | (0.087) | 0.7260 | -0.0519 | (0.035) | 0.1410 | -0.0615 | (0.027) | 0.0210 |
| Test | Sargan test (p.value) | | 0.880 | | | 0.131 | | | 0.140 | |
| | m1 (p.value) | | 0.000 | | | 0.000 | | | 0.000 | |
| | m2 (p.value) | | 0.337 | | | 0.172 | | | 0.141 | |
| | Wald coeff. (p.value) | | 0.000 | | | 0.000 | | | 0.000 | |
| | Wald time (p.value) | | 0.000 | | | 0.000 | | | 0.000 | |
| Observations | | | 7036 | | | 7035 | | | 7036 | |
| Instruments | TFP | t ₋₁ | to | t ₃ | t ₋₁ | to | t ₅ | t ₂ | to | t ₅ |
| | CDP (x1000) | Assumed Strictly exogenous | | | Assumed Strictly exogenous | | | Assumed Strictly exogenous | | |
| | DDP (x1000) | t ₂ | to | t ₃ | t ₋₁ | to | t ₅ | t ₁ | to | t ₅ |
| | AES (x1000) | t ₂ | to | t ₃ | t ₋₁ | to | t ₅ | t ₁ | to | t ₅ |
| | LFA (x1000) | t ₂ | to | t ₃ | t ₋₁ | to | t ₅ | t ₁ | to | t ₂ |
| | RDP Other (x1000) | t ₂ | to | t ₃ | t ₋₁ | to | t ₅ | t ₁ | to | t ₅ |
| | RDP inv (x1000) | t ₂ | to | t ₅ | t ₋₁ | to | t ₉₉ | t ₁ | to | t ₅ |
| | Economic Size (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₅ | t ₂ | to | t ₃ |

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Table A6 (continued)

| Name | Low TFP | | | Medium TFP | | | High TFP | | |
|---------------------|---------------------------|------|----------------|---------------------------|------|----------------|---------------------------|------|----------------|
| | Value | St.d | p.value | Value | St.d | p.value | Value | St.d | p.value |
| Debt on asset | t ₂ | to | t ₃ | t ₂ | to | t ₅ | t ₂ | to | t ₃ |
| UAA Rented | t ₂ | to | t ₃ | t ₂ | to | t ₅ | t ₂ | to | t ₃ |
| H Index | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | |
| Insurance | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | |
| Inverse Mills Ratio | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |

The GMM instrument list contains lagged regressors of at least 1 and with a maximum equal to all available periods. CDP, H Index and insurance are assumed strictly exogenous

Table A7

Impacts of farm subsidies on TFP on France (FR) for Low, Medium and High absolute levels of productivity.

| Name | Low TFP | | | Medium TFP | | | High TFP | | | |
|-------------------|-----------------------|---------------------------|---------|----------------|---------------------------|---------|----------------|---------------------------|---------|----------------|
| | Value | St.d | p.value | Value | St.d | p.value | Value | St.d | p.value | |
| Rho | T F Pt – 1 | 0.1608 | (0.134) | 0.2320 | 0.0863 | (0.049) | 0.0760 | 0.1855 | (0.036) | < 0.001 |
| Regressor | CDP (x1000) | -0.0010 | (0.001) | 0.0810 | -0.0018 | (0.000) | < 0.001 | -0.0006 | (0.000) | 0.0010 |
| | DDP (x1000) | -0.0007 | (0.001) | 0.3270 | -0.0007 | (0.001) | 0.2400 | -0.0005 | (0.000) | 0.2500 |
| | AES (x1000) | -0.0021 | (0.002) | 0.2600 | 0.0017 | (0.001) | 0.0130 | -0.0009 | (0.001) | 0.3240 |
| | LFA (x1000) | -0.0056 | (0.003) | 0.0760 | -0.0005 | (0.002) | 0.7800 | -0.0076 | (0.002) | < 0.001 |
| Control variables | RDP Other (x1000) | 0.0042 | (0.002) | 0.0870 | 0.0048 | (0.003) | 0.1290 | -0.0027 | (0.001) | 0.0300 |
| | RDP inv (x1000) | 0.0006 | (0.002) | 0.7210 | 0.0004 | (0.001) | 0.7060 | 0.0012 | (0.001) | 0.0420 |
| | Economic Size (x1000) | 0.0000 | (0.000) | 0.9570 | 0.0002 | (0.000) | 0.2230 | 0.0000 | (0.000) | 0.3480 |
| | Debt on asset | 0.0070 | (0.044) | 0.8730 | -0.0045 | (0.017) | 0.7950 | -0.0356 | (0.017) | 0.0360 |
| | UAA Rented | 0.0003 | (0.000) | 0.0580 | -0.0002 | (0.000) | 0.1040 | -0.0001 | (0.000) | 0.1090 |
| | H Index | 0.2835 | (0.159) | 0.0750 | -0.0081 | (0.025) | 0.7480 | 0.0687 | (0.030) | 0.0220 |
| | Insurance | 0.0000 | (0.000) | 0.4060 | 0.0000 | (0.000) | 0.0060 | 0.0000 | (0.000) | 0.2400 |
| Selection Bias | Inverse Mills Ratio | 0.0008 | (0.025) | 0.9740 | 0.0468 | (0.038) | 0.2140 | -0.0289 | (0.024) | 0.2330 |
| Test | Sargan test (p.value) | 0.983 | | 0.488 | | 0.113 | | 0.113 | | |
| | m1 (p.value) | 0.004 | | 0.000 | | 0.000 | | 0.000 | | |
| | m2 (p.value) | 0.172 | | 0.295 | | 0.639 | | 0.639 | | |
| | Wald coeff. (p.value) | 0.008 | | 0.000 | | 0.000 | | 0.000 | | |
| | Wald time (p.value) | 0.000 | | 0.000 | | 0.000 | | 0.000 | | |
| Observations | 6436 | | 6435 | | 6436 | | 6436 | | | |
| Instruments | TFP | t ₁ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | CDP (x1000) | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | |
| | DDP (x1000) | t ₂ | to | t ₅ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | AES (x1000) | t ₂ | to | t ₅ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | LFA (x1000) | t ₂ | to | t ₅ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | RDP Other (x1000) | t ₂ | to | t ₅ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | RDP inv (x1000) | t ₂ | to | t ₅ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | Economic Size (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | Debt on asset | t ₁ | to | t ₅ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | UAA Rented | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | |
| | H Index | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | |
| | Insurance | t ₁ | to | t ₇ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | Inverse Mills Ratio | t ₁ | to | t ₅ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |

The GMM instrument list contains lagged regressors of at least 1 and with a maximum equal to 7. CDP, UAA Rented and H Index are assumed strictly exogenous

Table A8

Impacts of farm subsidies on TFP on Italy (IT) for Low, Medium and High absolute levels of productivity.

| Name | Low TFP | | | Medium TFP | | | High TFP | | | |
|-------------------|-----------------------|---------|---------|------------|---------|---------|----------|---------|---------|---------|
| | Value | St.d | p.value | Value | St.d | p.value | Value | St.d | p.value | |
| Rho | T F Pt – 1 | 0.3305 | (0.041) | < 0.001 | Tab. A. | (0.049) | < 0.001 | 0.3591 | (0.040) | < 0.001 |
| Regressor | CDP (x1000) | -0.0017 | (0.002) | 0.3870 | -0.0006 | (0.001) | 0.4000 | -0.0003 | (0.000) | 0.0160 |
| | DDP (x1000) | -0.0019 | (0.001) | 0.0680 | -0.0047 | (0.001) | < 0.001 | -0.0005 | (0.000) | < 0.001 |
| | AES (x1000) | 0.0039 | (0.005) | 0.4330 | 0.0031 | (0.002) | 0.0960 | -0.0001 | (0.001) | 0.9130 |
| | LFA (x1000) | 0.0029 | (0.006) | 0.6430 | -0.0091 | (0.004) | 0.0270 | -0.0034 | (0.005) | 0.4830 |
| Control variables | RDP Other (x1000) | -0.0024 | (0.008) | 0.7520 | -0.0010 | (0.005) | 0.8300 | 0.0001 | (0.002) | 0.9650 |
| | RDP inv (x1000) | 0.0002 | (0.004) | 0.9610 | 0.0009 | (0.002) | 0.6100 | -0.0026 | (0.003) | 0.4060 |
| | Economic Size (x1000) | -0.0005 | (0.001) | 0.6840 | 0.0002 | (0.000) | 0.5420 | 0.0000 | (0.000) | 0.4210 |
| | Debt on asset | 1.2792 | (0.572) | 0.0250 | 0.0207 | (0.177) | 0.9070 | 0.2865 | (0.206) | 0.1640 |
| | UAA Rented | 0.0002 | (0.000) | 0.5850 | 0.0006 | (0.000) | 0.0030 | 0.0001 | (0.000) | 0.2630 |
| | H Index | 0.0505 | (0.056) | 0.3650 | 0.1662 | (0.032) | < 0.001 | 0.2429 | (0.040) | < 0.001 |
| | Insurance | -0.0001 | (0.000) | 0.3180 | 0.0000 | (0.000) | 0.9270 | 0.0000 | (0.000) | 0.1290 |
| Selection Bias | Inverse Mills Ratio | 0.0268 | (0.033) | 0.4220 | 0.1178 | (0.035) | < 0.001 | -0.0064 | (0.036) | 0.8600 |
| Test | Sargan test (p.value) | 0.705 | | 0.339 | | 0.714 | | 0.714 | | |
| | m1 (p.value) | 0.000 | | 0.000 | | 0.000 | | 0.000 | | |

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Table A8 (continued)

| | Name | Low TFP | | | Medium TFP | | | High TFP | | |
|--------------|-----------------------|---------------------------|--------|----------------|---------------------------|--------|----------------|---------------------------|--------|----------------|
| | | Value | St.d | p.value | Value | St.d | p.value | Value | St.d | p.value |
| | m2 (p.value) | | 0.373 | | | 0.179 | | | 0.114 | |
| | Wald coeff. (p.value) | | 0.000 | | | 0.000 | | | 0.000 | |
| | Wald time (p.value) | | 0.000 | | | 0.000 | | | 0.000 | |
| Observations | | | 10,596 | | | 10,595 | | | 10,595 | |
| Instruments | TFP | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | CDP (x1000) | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | |
| | DDP (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | AES (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | LFA (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | RDP Other (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | RDP inv (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | Economic Size (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | Debt on asset | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | UAA Rented | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | |
| | H Index | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | |
| | Insurance | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |
| | Inverse Mills Ratio | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₃ |

The GMM instrument list contains lagged regressors of at least 2 and with a maximum equal to 3. CDP, UAA Rented and H Index are assumed strictly exogenous

Table A9

Impacts of farm subsidies on TFP on Poland (PL) for Low, Medium and High absolute levels of productivity.

| | Name | Low TFP | | | Medium TFP | | | High TFP | | |
|-------------------|-----------------------|---------------------------|---------|-----------------|---------------------------|---------|-----------------|---------------------------|---------|----------------|
| | | Value | St.d | p.value | Value | St.d | p.value | Value | St.d | p.value |
| Rho | T F Pt – 1 | 0.3193 | (0.043) | < 0.001 | 0.3278 | (0.142) | 0.0210 | 0.7253 | (0.176) | < 0.001 |
| Regressor | CDP (x1000) | -0.0006 | (0.002) | 0.6820 | 0.0001 | (0.001) | 0.8370 | -0.0006 | (0.000) | 0.0330 |
| | DDP (x1000) | -0.0142 | (0.005) | 0.0030 | -0.0019 | (0.003) | 0.5090 | 0.0001 | (0.000) | 0.7920 |
| | AES (x1000) | 0.0128 | (0.004) | 0.0020 | 0.0066 | (0.003) | 0.0390 | 0.0005 | (0.001) | 0.4290 |
| | LFA (x1000) | -0.0232 | (0.012) | 0.0450 | -0.0012 | (0.009) | 0.8930 | -0.0053 | (0.004) | 0.1500 |
| | RDP Other (x1000) | 0.0007 | (0.017) | 0.9670 | -0.0002 | (0.001) | 0.8860 | -0.0052 | (0.007) | 0.4670 |
| | RDP inv (x1000) | 0.0002 | (0.002) | 0.9380 | -0.0053 | (0.002) | 0.0100 | 0.0008 | (0.000) | 0.0730 |
| Control variables | Economic Size (x1000) | 0.0023 | (0.001) | 0.0970 | -0.0005 | (0.000) | 0.2370 | -0.0001 | (0.000) | 0.1670 |
| | Debt on asset | -0.2308 | (0.117) | 0.0490 | -0.0047 | (0.158) | 0.9760 | -0.1238 | (0.090) | 0.1690 |
| | UAA Rented | 0.0001 | (0.000) | 0.7810 | -0.0008 | (0.000) | 0.0140 | 0.0001 | (0.000) | < 0.001 |
| | H Index | -0.0208 | (0.035) | 0.5540 | -0.0026 | (0.034) | 0.9390 | -0.4271 | (0.246) | 0.0820 |
| | Insurance | 0.0000 | (0.000) | 0.1590 | 0.0000 | (0.000) | 0.5020 | 0.0000 | (0.000) | 0.0120 |
| Selection Bias | Inverse Mills Ratio | 0.0289 | (0.027) | 0.2900 | 0.0175 | (0.034) | 0.6050 | 0.0031 | (0.038) | 0.9340 |
| Test | Sargan test (p.value) | | 0.213 | | | 0.996 | | | 0.917 | |
| | m1 (p.value) | | 0.000 | | | 0.000 | | | 0.000 | |
| | m2 (p.value) | | 0.159 | | | 0.138 | | | 0.231 | |
| | Wald coeff. (p.value) | | 0.000 | | | 0.000 | | | 0.000 | |
| | Wald time (p.value) | | 0.000 | | | 0.000 | | | 0.000 | |
| Observations | | | 10,571 | | | 10,570 | | | 10,571 | |
| Instruments | TFP | t ₂ | to | t ₃ | t ₁ | to | t ₃ | t ₂ | to | t ₅ |
| | CDP (x1000) | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | |
| | DDP (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₅ |
| | AES (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₅ |
| | LFA (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₅ |
| | RDP Other (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₅ |
| | RDP inv (x1000) | t ₂ | to | t ₃ | t ₂ | to | t ₃ | t ₂ | to | t ₅ |
| | Economic Size (x1000) | t ₂ | to | t ₉₉ | t ₂ | to | t ₉₉ | t ₂ | to | t ₅ |
| | Debt on asset | t ₂ | to | t ₉₉ | t ₂ | to | t ₉₉ | t ₂ | to | t ₅ |
| | UAA Rented | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | |
| | H Index | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | |
| | Insurance | t ₂ | to | t ₉₉ | t ₂ | to | t ₉₉ | t ₂ | to | t ₅ |
| | Inverse Mills Ratio | t ₂ | to | t ₉₉ | t ₂ | to | t ₉₉ | t ₂ | to | t ₅ |

The GMM instrument list contains lagged regressors of at least 2 and with a maximum equal to all available periods. CDP, UAA Rented and H Index are assumed strictly exogenous

Table A10

Impacts of farm subsidies on TFP on the United Kingdom (UK) for Low, Medium and High absolute levels of productivity.¹

| | Name | Low TFP | | | Medium TFP | | | High TFP | | |
|-----------|-------------|---------|---------|---------|------------|---------|---------|----------|---------|---------|
| | | Value | St.d | p.value | Value | St.d | p.value | Value | St.d | p.value |
| Rho | T F Pt – 1 | 0.3969 | (0.054) | < 0.001 | 0.7115 | (0.106) | < 0.001 | -0.2183 | (0.011) | < 0.001 |
| Regressor | CDP (x1000) | -0.0496 | (0.023) | 0.0310 | -0.0044 | (0.005) | 0.4080 | -0.0120 | (0.003) | < 0.001 |
| | DDP (x1000) | -0.0021 | (0.002) | 0.3920 | -0.0008 | (0.001) | 0.4920 | 0.0002 | (0.000) | 0.4180 |

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Table A10 (continued)

| Name | Low TFP | | | Medium TFP | | | High TFP | | | |
|-----------------------|---------------------------|---------|-----------------|---------------------------|---------|-----------------|---------------------------|---------|-----------------|---------|
| | Value | St.d | p.value | Value | St.d | p.value | Value | St.d | p.value | |
| AES (x1000) | -0.0003 | (0.002) | 0.8880 | 0.0019 | (0.001) | 0.1680 | -0.0002 | (0.000) | | 0.2180 |
| LFA (x1000) | | NA | | | NA | | | | NA | |
| RDP Other (x1000) | -0.0056 | (0.005) | 0.3020 | -0.0007 | (0.009) | 0.9410 | -0.0027 | (0.001) | | 0.0390 |
| RDP inv (x1000) | 0.0002 | (0.001) | 0.9030 | 0.0005 | (0.001) | 0.6540 | -0.0005 | (0.000) | | 0.1570 |
| Economic Size (x1000) | 0.0004 | (0.000) | 0.4420 | -0.0004 | (0.000) | 0.1070 | -0.0001 | (0.000) | | 0.0790 |
| Debt on asset | -0.0028 | (0.006) | 0.6270 | 0.1894 | (0.130) | 0.1460 | -0.4527 | (0.128) | | < 0.001 |
| UAA Rented | 0.0008 | (0.000) | 0.0240 | 0.0001 | (0.000) | 0.5390 | 0.0001 | (0.000) | | 0.2950 |
| H Index | 0.2431 | (0.077) | 0.0020 | 0.1209 | (0.129) | 0.3470 | 0.9211 | (0.174) | | < 0.001 |
| Insurance | 0.0000 | (0.000) | 0.5420 | 0.0000 | (0.000) | 0.7300 | 0.0000 | (0.000) | | < 0.001 |
| Inverse Mills Ratio | 0.0014 | (0.032) | 0.9670 | 0.0219 | (0.044) | 0.6210 | -0.0253 | (0.028) | | 0.3730 |
| Sargan test (p.value) | | 0.918 | | | 0.334 | | | | 0.917 | |
| m1 (p.value) | | 0.034 | | | 0.023 | | | | 0.000 | |
| m2 (p.value) | | 0.126 | | | 0.406 | | | | 0.231 | |
| Wald coeff. (p.value) | | 0.000 | | | 0.000 | | | | 0.000 | |
| Wald time (p.value) | | 0.000 | | | 0.000 | | | | 0.000 | |
| Observations | | 1756 | | | 1756 | | | | 10,571 | |
| TFP | t ₋₁ | to | t ₋₃ | t ₋₂ | to | t ₋₃ | t ₋₁ | to | t ₋₅ | |
| CDP (x1000) | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | |
| DDP (x1000) | t ₋₁ | to | t ₋₅ | t ₋₂ | to | t ₋₃ | t ₋₁ | to | t ₋₅ | |
| AES (x1000) | t ₋₁ | to | t ₋₅ | t ₋₂ | to | t ₋₃ | t ₋₁ | to | t ₋₅ | |
| LFA (x1000) | Not Available | | | Not Available | | | Not Available | | | |
| RDP Other (x1000) | t ₋₁ | to | t ₋₅ | t ₋₂ | to | t ₋₃ | t ₋₁ | to | t ₋₉ | |
| RDP inv (x1000) | t ₋₁ | to | t ₋₅ | t ₋₂ | to | t ₋₃ | t ₋₁ | to | t ₋₂ | |
| Economic Size (x1000) | t ₋₁ | to | t ₋₅ | t ₋₂ | to | t ₋₃ | t ₋₁ | to | t ₋₉ | |
| Debt on asset | t ₋₁ | to | t ₋₅ | t ₋₂ | to | t ₋₃ | t ₋₂ | to | t ₋₉ | |
| UAA Rented | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | t ₋₁ | to | t ₋₅ | |
| H Index | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | Assumed Stricly exogenous | | | |
| Insurance | t ₋₁ | to | t ₋₂ | t ₋₂ | to | t ₋₃ | Assumed Stricly exogenous | | | |
| Inverse Mills Ratio | t ₋₁ | to | t ₋₅ | t ₋₂ | to | t ₋₃ | t ₋₁ | to | t ₋₃ | |

The GMM instrument list contains lagged regressors of at least 1 and with a maximum equal to 5 periods. CDP, UAA Rented, H Index and Insurance are assumed strictly exogenous

Standard errors are indicated between the brackets in italics, Source: our elaboration on FADN data.

¹In the United Kingdom, the farmers that participate in the LFA scheme in the sample are very low. This does not allow System- GMM estimator to reach solutions.

Table A11

Variables used in Double LASSO procedure for IMR estimation.

| Variables used in Double LASSO procedure for IMR estimation | | | |
|---|---|--------------------------------|---|
| Agricultural fallows/UAA | Feed for grazing livestock home-grown | Oil-seed crops | Specific livestock costs/Livestock unit |
| Agricultural insurance Value | Feed for pigs&poultry home-grown | Olive | Stock Agricultural Products |
| Area out of production | Feed for pigs-poultry | Olive groves/UAA | Stocking density |
| Average farm capital | Fertiliser-Quantity of K2O in mineral fertilisers used | Orchards/UAA | Sugar beet |
| Balance of interest paid and received | Fertiliser-Quantity of N in mineral fertilisers used | Other cattle | Taxes |
| Balance subsidies taxes on investments | Fertiliser-Quantity of P2O5 in mineral fertilisers used | Other Circulating Capital | Total Assets |
| Beef Veal | Fertilisers | Other crop output | Total assets opening valuation |
| Breeding livestock | FNI | Other crop specific costs | Total crops output |
| Buffalo dairy cows | FNVA | Other Direct Inputs | Total crops output/ha |
| Buildings | Forage Crops | Other field crops/UAA | Total current assets |
| Cattle dairy cows | Forage crops/UAA | Other Livestock Products | Total external factors |
| Cereals Value | Forestry specific costs | Other livestock specific costs | Total farming overheads |
| Cereals/UAA | Fruit trees | Other Output | Total fixed assets |
| Change in net worth | Gross Farm Income | Other permanent crops/UAA | Total Inputs |
| Citrus fruit | H Index | Paid Labour (Hours) | Total interm Costs |
| Contract Work | Ha SE136 | Payments to dairy outgoers | Total Liabilities |
| Cows milk products | Industrial crops | Permanent crops/UAA | Total livestock output/Livestock unit |
| Crop protection | Interest | Pigmeat | Total Output |
| Crops Tot Out | Inventories | Pigs | Total output/Total input |
| Dairy cows | Labour (Hours) | Potatoes | Total specific Costs |
| Debt asset ratio | Land permanent crops quotas | Poultry | UAA |
| Depreciation | Livestock | Poultrymeat | UAA rented |
| Eggs | Livestock Tot Out | Protein crops | VAT balance excluding on investments |
| Energy | Long-medium-term Loans | RDP inv | VAT on investments |
| Energy crops Output | Machinery | Rent | Vegetables flowers/UAA |
| Energy crops/UAA | Machinery Building Costs | Seeds and plants | Vegetables-flowers |
| Ewes goats-milk | Milk yield | Seeds and plants home-grown | Vineyards/UAA |
| Family Labour (Hours) | Milk yield buffalo dairy cows | Set aside/UAA | Wages |
| Farm use Value Products Produced | Milk yield cattle dairy cows | Sheep Goats | Wine grapes |
| Farmhouse Consumption | Net worth | Short-term Loans | Woodland/UAA |
| Feed for grazing livestock | Non-breeding Livestock | Specific crop costs/ha | Yield of wheat |

Table A12
 Estimation of production function using translog with Bludell-Bond Estimator.

| | Germany (DE) | | | Spain (ES) | | | France (FR) | | | Italy (IT) | | | Poland (PL) | | | United Kingdom (UK) | | |
|------------------------|--------------|----------|----------|------------|---------|----------|-------------|----------|----------|------------|---------|----------|-------------|----------|----------|---------------------|---------|----------|
| | Value | St.d | p. value | Value | St.d | p. value | Value | St.d | p. value | Value | St.d | p. value | Value | St.d | p. value | Value | St.d | p. value |
| $y_{(t-1)}$ | -0.232 | (0.099) | 0.019 | -0.127 | (0.084) | 0.133 | -0.458 | (0.106) | < | -0.229 | (0.071) | 0.001 | -0.289 | (0.100) | 0.004 | -0.308 | (0.127) | 0.015 |
| $k_{(t)}$ | 6.161 | (4.287) | 0.151 | -1.525 | (8.546) | 0.858 | 7.506 | (5.804) | 0.196 | 5.707 | (3.497) | 0.103 | 28.660 | (9.896) | 0.004 | -5.030 | (4.205) | 0.232 |
| $k_{(t-1)}$ | -1.719 | (3.330) | 0.606 | 5.147 | (5.554) | 0.354 | -7.524 | (4.424) | 0.089 | -7.571 | (2.901) | 0.009 | -27.998 | (9.344) | 0.003 | 5.389 | (4.842) | 0.266 |
| $l_{(t)}$ | 4.233 | (2.074) | 0.041 | 1.390 | (3.660) | 0.704 | 10.837 | (5.193) | 0.037 | 1.698 | (1.416) | 0.230 | 12.686 | (2.980) | < | -2.564 | (2.465) | 0.298 |
| $l_{(t-1)}$ | -1.728 | (1.718) | 0.314 | -3.538 | (2.770) | 0.201 | -8.174 | (4.140) | 0.048 | -2.264 | (1.282) | 0.077 | -13.288 | (2.761) | < | 3.783 | (2.623) | 0.149 |
| $n_{(t)}$ | -26.319 | (10.890) | 0.016 | -12.776 | (8.089) | 0.114 | -37.913 | (23.028) | 0.100 | 7.999 | (7.727) | 0.301 | 24.435 | (16.556) | 0.140 | 6.458 | (7.959) | 0.417 |
| $n_{(t-1)}$ | 10.772 | (10.823) | 0.320 | -10.753 | (6.127) | 0.079 | 25.918 | (16.828) | 0.124 | -5.940 | (4.152) | 0.153 | -38.419 | (16.813) | 0.022 | 0.832 | (6.987) | 0.905 |
| $m_{(t)}$ | -6.926 | (8.122) | 0.394 | 0.175 | (7.454) | 0.981 | 7.771 | (12.579) | 0.537 | 14.453 | (5.858) | 0.014 | 31.519 | (10.513) | 0.003 | 12.942 | (7.742) | 0.095 |
| $m_{(t-1)}$ | 6.488 | (7.915) | 0.412 | -4.822 | (6.853) | 0.482 | -0.191 | (9.275) | 0.984 | -6.577 | (3.382) | 0.052 | -23.165 | (8.133) | 0.004 | -2.142 | (7.296) | 0.769 |
| $k_{(t)}^2$ | 0.063 | (0.086) | 0.464 | 0.881 | (0.245) | < | -0.003 | (0.104) | 0.974 | 0.070 | (0.111) | 0.526 | 0.349 | (0.198) | 0.078 | 0.115 | (0.098) | 0.241 |
| $k_{(t-1)}^2$ | 0.024 | (0.074) | 0.745 | -0.592 | (0.180) | 0.001 | 0.047 | (0.110) | 0.667 | 0.241 | (0.131) | 0.065 | -0.150 | (0.242) | 0.536 | 0.072 | (0.086) | 0.404 |
| $l_{(t)}^2$ | 0.035 | (0.115) | 0.763 | 0.275 | (0.115) | 0.017 | 0.060 | (0.112) | 0.594 | -0.079 | (0.077) | 0.302 | 0.443 | (0.122) | < | 0.198 | (0.094) | 0.036 |
| $l_{(t-1)}^2$ | -0.064 | (0.113) | 0.573 | -0.130 | (0.109) | 0.235 | -0.110 | (0.113) | 0.332 | 0.112 | (0.074) | 0.129 | -0.300 | (0.112) | 0.007 | -0.199 | (0.102) | 0.050 |
| $n_{(t)}^2$ | 0.273 | (0.796) | 0.732 | 1.783 | (0.627) | 0.004 | 4.820 | (1.258) | < | 1.160 | (0.587) | 0.048 | 0.858 | (1.179) | 0.467 | -0.103 | (0.183) | 0.575 |
| $n_{(t-1)}^2$ | -0.009 | (0.985) | 0.993 | 1.030 | (0.570) | 0.071 | -3.183 | (1.091) | 0.004 | 0.096 | (0.426) | 0.822 | 0.853 | (1.066) | 0.424 | 0.400 | (0.253) | 0.113 |
| $m_{(t)}^2$ | -0.341 | (0.741) | 0.646 | 1.670 | (0.364) | < | 0.222 | (0.698) | 0.751 | 1.586 | (0.307) | < | 1.206 | (0.452) | 0.008 | -0.163 | (0.375) | 0.664 |
| $m_{(t-1)}^2$ | -0.013 | (0.766) | 0.986 | 0.128 | (0.470) | 0.785 | -0.483 | (0.528) | 0.360 | -0.244 | (0.222) | 0.272 | -0.581 | (0.581) | 0.318 | -0.202 | (0.436) | 0.643 |
| $(k \times l)_{(t)}$ | -0.094 | (0.058) | 0.108 | 0.103 | (0.134) | 0.444 | -0.207 | (0.117) | 0.077 | 0.125 | (0.063) | 0.048 | -0.581 | (0.168) | < | 0.286 | (0.119) | 0.016 |
| $(k \times l)_{(t-1)}$ | 0.038 | (0.055) | 0.498 | 0.283 | (0.111) | 0.011 | 0.214 | (0.092) | 0.020 | -0.094 | (0.059) | 0.111 | 0.625 | (0.175) | < | -0.207 | (0.104) | 0.048 |
| $(k \times n)_{(t)}$ | -0.455 | (0.677) | 0.502 | 0.104 | (0.410) | 0.800 | -1.174 | (0.885) | 0.185 | 0.733 | (0.413) | 0.076 | -0.539 | (1.324) | 0.684 | 0.044 | (0.402) | 0.912 |
| $(k \times n)_{(t-1)}$ | 0.074 | (0.428) | 0.863 | -0.132 | (0.152) | 0.385 | 0.666 | (0.634) | 0.293 | -0.171 | (0.209) | 0.412 | 0.587 | (0.833) | 0.481 | -0.725 | (0.469) | 0.123 |
| $(k \times m)_{(t)}$ | -0.222 | (0.457) | 0.627 | -1.608 | (0.417) | < | 0.320 | (0.523) | 0.541 | -1.416 | (0.327) | < | -2.271 | (0.625) | < | -0.016 | (0.306) | 0.959 |
| $(k \times m)_{(t-1)}$ | 0.017 | (0.322) | 0.957 | 0.380 | (0.312) | 0.224 | -0.063 | (0.338) | 0.851 | 0.460 | (0.184) | 0.012 | 1.705 | (0.656) | 0.009 | 0.007 | (0.266) | 0.980 |
| $(l \times n)_{(t)}$ | -0.179 | (0.207) | 0.387 | 0.025 | (0.196) | 0.898 | -0.523 | (0.484) | 0.280 | 0.127 | (0.117) | 0.279 | -0.451 | (0.311) | 0.147 | -0.064 | (0.172) | 0.709 |
| $(l \times n)_{(t-1)}$ | 0.059 | (0.135) | 0.662 | 0.112 | (0.085) | 0.190 | 0.313 | (0.363) | 0.389 | -0.007 | (0.055) | 0.905 | 0.485 | (0.200) | 0.015 | -0.140 | (0.151) | 0.355 |
| $(l \times m)_{(t)}$ | -0.164 | (0.271) | 0.545 | -0.643 | (0.154) | < | -0.464 | (0.413) | 0.262 | -0.273 | (0.110) | 0.013 | -0.811 | (0.234) | < | -0.376 | (0.175) | 0.032 |
| $(l \times m)_{(t-1)}$ | 0.176 | (0.213) | 0.409 | 0.103 | (0.080) | 0.197 | 0.455 | (0.264) | 0.085 | 0.148 | (0.076) | 0.053 | 0.581 | (0.232) | 0.012 | 0.351 | (0.132) | 0.008 |

(continued on next page)

Table A12 (continued)

| | Germany (DE) | | | Spain (ES) | | | France (FR) | | | Italy (IT) | | | Poland (PL) | | | United Kingdom (UK) | | |
|------------------------|----------------|----------------|----------|----------------|----------------|----------|----------------|----------------|----------|----------------|----------------|----------|----------------|----------------|----------|---------------------|----------------|----------|
| | Value | St.d | p. value | Value | St.d | p. value |
| $(n \times m)_{(t)}$ | 2.434 | (1.381) | 0.078 | -1.454 | (0.747) | 0.052 | -1.584 | (1.129) | 0.161 | -3.443 | (0.615) | < 0.001 | -2.585 | (1.047) | 0.014 | -0.397 | (0.477) | 0.406 |
| $(n \times m)_{(t-1)}$ | -0.997 | (1.382) | 0.471 | -0.400 | (0.414) | 0.333 | 1.117 | (1.022) | 0.275 | 0.639 | (0.309) | 0.039 | 1.144 | (1.010) | 0.257 | 0.349 | (0.421) | 0.407 |
| T | | 11 | | | 11 | | | 11 | | | 11 | | | 11 | | | 11 | |
| Num. obs. | | 22,399 | | | 21,151 | | | 19,347 | | | 32,107 | | | 31,776 | | | 5282 | |
| Sargan test (p. value) | | 0.087 | | | 0.209 | | | 0.072 | | | 0.241 | | | 0.806 | | | 0.999 | |
| m1 (p.value) | | 0.041 | | | 0.092 | | | 0.012 | | | 0.000 | | | 0.000 | | | 0.002 | |
| m2 (p.value) | | 0.784 | | | 0.1435 | | | 0.254 | | | 0.318 | | | 0.630 | | | 0.776 | |
| Wald coeff. (p.value) | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | |
| Wald time (p.value) | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | |
| R ² | | 0.427 | | | 0.184 | | | 0.139 | | | 0.343 | | | 0.364 | | | 0.372 | |
| Instruments | $y_{(t-1)}$ | t ₁ | to | t ₅ | t ₁ | to |
| | k | t ₂ | to | t ₅ | t ₂ | to |
| | l | t ₂ | to | t ₅ | t ₂ | to |
| | n | t ₂ | to | t ₅ | t ₂ | to |
| | m | t ₂ | to | t ₅ | t ₂ | to |
| | k ² | t ₂ | to | t ₅ | t ₂ | to |
| | l ² | t ₂ | to | t ₅ | t ₂ | to |
| | n ² | t ₂ | to | t ₅ | t ₂ | to |
| | m ² | t ₂ | to | t ₅ | t ₂ | to |
| | k × l | t ₁ | to | t ₂ | t ₁ | to | t ₂ | t ₁ | to | t ₂ | t ₁ | to | t ₅ | t ₁ | to | t ₃ | t ₁ | to |
| | k × n | t ₁ | to | t ₂ | t ₁ | to | t ₂ | t ₁ | to | t ₂ | t ₁ | to | t ₅ | t ₁ | to | t ₃ | t ₁ | to |
| | k × m | t ₁ | to | t ₂ | t ₁ | to | t ₂ | t ₁ | to | t ₂ | t ₁ | to | t ₅ | t ₁ | to | t ₃ | t ₁ | to |
| | l × n | t ₁ | to | t ₂ | t ₁ | to | t ₂ | t ₁ | to | t ₂ | t ₁ | to | t ₅ | t ₁ | to | t ₃ | t ₁ | to |
| | l × m | t ₁ | to | t ₂ | t ₁ | to | t ₂ | t ₁ | to | t ₂ | t ₁ | to | t ₅ | t ₁ | to | t ₃ | t ₁ | to |
| | n × m | t ₁ | to | t ₂ | t ₁ | to | t ₂ | t ₁ | to | t ₂ | t ₁ | to | t ₅ | t ₁ | to | t ₃ | t ₁ | to |

The list of the GMM instruments contains all the regressors lagged at least 1 and maximum 5 periods.

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