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ORIGINAL ARTICLE

Subsidies and agricultural productivity in the EU

Maria Garrone[1] | **Dorien Emmers**[1] | **Hyejin Lee**[1] | **Alessandro Olper**[1,2] | **Johan Swinnen**[1,3,4]

[1]LICOS Centre for Institutions and Economic Performance & Department of Economics, KU Leuven, Leuven, Belgium

[2]Department of Environmental Science and Policy, University of Milan, Milan, Italy

[3]CEPS Centre for European Policy Studies, Brussels, Belgium

[4]Higher School of Economics, Moscow, Russia

Correspondence
Dorien Emmers, LICOS Centre for Institutions and Economic Performance & Department of Economics, KU Leuven, Leuven, Belgium.
Email: dorien.emmers@kuleuven.be

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Abstract

This paper investigates the relationship between EU agricultural subsidies and agricultural labor productivity growth by estimating a conditional convergence growth model. We use more representative subsidy indicators and a wider coverage (panel data from 213 EU regions over the period 2004–2014) than have been used before. We find that, on average, EU's Common Agricultural Policy (CAP) subsidies increase agricultural labor productivity growth, but this aggregate effect hides important heterogeneity of effects of different types of subsidies. The positive effect on productivity comes from decoupled subsidies, that is, Pillar I decoupled payments and some Pillar II payments. Coupled Pillar I subsidies have the opposite effect: they slow down productivity growth.

KEYWORDS
agricultural labor productivity, agricultural subsidies, conditional convergence growth model, panel data analysis

JEL CLASSIFICATIONS
J24, O13, Q10, Q18

1 | INTRODUCTION

Traditional economic theory and policy analysis posit that agricultural subsidies distort incentives and reduce productivity (Johnson, 1973; OECD, 2008). However, theoretical and empirical studies have shown that this is not always the case. Subsidies may enhance agricultural productivity in the presence of imperfections in credit or insurance markets (e.g., Ciaian & Swinnen, 2009; Hennessy, 1998; Roche & McQuinn, 2004). A recent review concludes that some studies find positive, other negative effects, and some find no effect of subsidies on agricultural productivity (Minviel & Latruffe, 2017). These different findings may be due to variations in rural market imperfections or to differences in the nature of the subsidies. Different types of agricultural subsidies cause different distortions and may thus have different productivity impacts (e.g., Latruffe et al., 2008; Rizov, Pokrivcak, & Ciaian, 2013). These differential effects are important to understand for policy makers when they consider reforms of agricultural policy to reduce market distortions or to make agricultural policies consistent with sustainability, resilience, and climate change objectives.

Our paper contributes to this literature by analyzing the impact of the more than 50 billion euros annual subsidies of the EU's Common Agricultural Policy (CAP) on agricultural productivity. In comparison with previous studies, we (a) use more accurate and complete CAP subsidy data, (b) disaggregate subsidy payments into payments of specific subsidy instruments, (c) have a wider coverage of EU regions, including the new member states (NMS), and (d) cover a longer and more recent time period than has been used before. Specifically, we use the *Clearance Audit Trail System* (CATS) data set which includes all farm subsidies and details on the types of payments for all subsidy categories. Our analysis uses a regional conditional convergence model and covers the 2004–2014 period and 213 regions of the EU-27 (compared to previous studies that covered the EU-15 only)[1] allowing to better test for regional heterogeneity effects for subgroups of countries and for different subsidy types.

Key results are that CAP subsidies, as a whole, have a positive impact on labor productivity in agriculture but that there are important differences in the impact of different types of subsidies. The positive effect comes from decoupled subsidies, that is, Pillar I decoupled payments and some Pillar II payments. Coupled Pillar I subsidies have the opposite effect: they slow down productivity growth.

The paper is structured as follows. In Section 2, we give an overview of the literature on subsidies and agricultural productivity. In Section 3, we discuss our empirical approach. In Section 4, we describe our data set and variable construction. Results are presented in Section 5. Section 6 concludes.

2 | SUBSIDIES AND AGRICULTURAL PRODUCTIVITY: RELATED LITERATURE

Improvements in agricultural labor productivity over time typically result from the movement of workers from farm to nonfarm occupations, a process driven by relatively higher wages and productivity in urban jobs, accommodated by adoption of labor-saving techniques of production by farmers. This process is supported by investments in agricultural research, development, and extension (see, e.g., Gardner, 2000, 2002). Agricultural subsidies may affect this process.

Agricultural subsidies can reduce agricultural productivity growth by causing allocative and technical efficiency losses: (a) farmer investment decisions may be distorted toward relatively less productive activities that are supported by subsidies (Alston & James, 2002); (b) farmers may overinvest in subsidized inputs (Rizov et al., 2013); (c) subsidies may reduce a farmer's incentive to adopt cost-optimizing strategies (Leibenstein, 1966; Minviel & Latruffe, 2017); or (d) subsidies may lead to soft budget constraints, causing inefficient use of resources (Kornai, 1986).

However, some studies have argued that subsidies may also stimulate productivity growth under specific conditions, and that the nature of the subsidies may play a role. Theoretical arguments that subsidies may enhance agricultural productivity are based on the impact of subsidies on farm constraints due to rural market imperfections. With (rural) capital market imperfections, subsidies may help overcome financial constraints of farmers (directly by boosting a farmer's financial resources and indirectly by improving access to credit), which may enhance farm productivity (Blancard, Boussemart, Briec, & Kerstens, 2006; Ciaian & Swinnen, 2009). With imperfect insurance markets, subsidies may mitigate risk and trigger investment in certain types of activity which the farmer may otherwise consider too risky (Hennessy, 1998; Roche & McQuinn, 2004). In both cases, productivity could increase with subsidies.

Empirical evidence is also mixed. Minviel and Latruffe (2017) review studies on the impact of subsidies on farms' technical efficiency and conclude that some studies find positive, other negative effects, and some find no effect of subsidies on agricultural productivity. This does not have to come as a surprise. Given that the theoretical arguments of the potential positive effect of subsidies are based on market imperfections, one would expect these potential positive effects to be stronger when these market imperfections are more important, and vice versa. Hence, one could imagine that the credit-enhancing effects of subsidies could be more important in cases such as when the NMS joined the EU in the mid-2000s, as credit constraints were very important for farms in those regions in that period (Ciaian & Swinnen, 2009).

Another potential explanation for heterogeneous effects is the nature of the subsidies. Within the EU's *Common Agricultural Policy* (and in agricultural subsidy discussions globally) a crucial differentiation is between "coupled" and "decoupled" subsidies. Coupled subsidies have traditionally been identified as the main source of distortion in agricultural markets due to efficiency losses. As they are tied to output, coupled support is likely to distort input and/or output allocation. The effect of decoupled subsidies may be different as they do not directly affect farmers' product choices, so are less likely to cause inefficiency (Dewbre, Antón, & Thompton, 2001; Guyomard, Le Mouël, & Gohin, 2004; Rizov et al., 2013). Empirical studies indeed find (a) negative correlations between coupled subsidies and various measures of productivity (Latruffe et al., 2008; Mary, 2013; Zhu & Oude Lansink, 2010; Zhu & Milán Demeter, 2012) and (b) that agricultural productivity in the EU increased with the shift from "coupled" to "decoupled" subsidies (Kazukauskas, Newman, & Sauer, 2014; Mary, 2013; Rizov et al., 2013). However, there are counterexamples. Indeed, Gardner (2005) working with a cross section of countries in the period 1980–2001, showed that the level of agricultural support measured by the producer support estimate (PSE), was positively correlated with agricultural productivity growth, in a sample of about 27 countries, mainly OECD countries.[2]

[1] Today there are 28 EU member states. The 15 "old" member states (OMS, also often referred to as "EU-15") joined the EU before 2004; the 13 "new" member states joined since 2004. More specifically, Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, and Slovenia joined in 2004, Bulgaria and Romania in 2007. Croatia, which joined the EU most recently in 2013, is not included as CATS data are not available for the period covered in our analysis.

[2] Note, Gardner (2005) used PSE data averaged over the 1985–1989 period in his growth regression, hence a mix of the commodity price support policy and coupled farm income subsidies were covered.

Other studies have also argued that there may be heterogeneous effects for different types of rural development (RD) subsidies (so-called Pillar II payments in the CAP). First, the impact of *less favored areas* (LFA) payments, granted to farms solely on the basis of their unfavorable geographic location, on agricultural productivity is ex ante not clear. On the one hand, LFA payments may keep inefficient farms going, thereby reducing efficiency (Latruffe & Desjeux, 2016). On the other hand, this type of payments may help maintain agricultural land in good condition by ensuring that agricultural land remains cultivated in areas with poor natural agricultural endowments, thereby enhancing efficiency (Knific & Bojnec, 2010; Latruffe & Desjeux, 2016). Moreover, Baráth, Fertő, and Bojnec (2018) found no significant difference in the technical efficiency between LFA and non-LFA farms in Slovenia, but they did find differences in the use of production-environment-specific technologies (e.g., adoption of less intensive technologies in areas with low soil fertility). This means that LFA payments may improve efficiency by allowing farmers to adopt technologies that offset negative impacts of LFA conditions on productivity.

Furthermore, Pillar II payments for investments in human capital (HK) and physical capital (PK) may be productivity-enhancing and cost-reducing, as improved knowledge of efficient farming practices can lead to better use of technology and land (Boulanger & Philippidis, 2015; Dudu & Kristkova, 2017). Agri-environmental measures are generally assumed to have a negative effect on productivity as they impose constraints on input use (such as fertilizers, pesticides, and land). However, empirical evidence on the productivity effect of agri-environmental payments is mixed. Some find a negative effect on productivity (Lakner, 2009), while others find no or a positive effect (Dudu & Kristkova, 2017; Mary, 2013). Finally, wider RD payments may have no effect on farming itself, but support other sectors such as rural infrastructure and tourism.

In summary, the impact of CAP payments on agricultural productivity is likely to differ by the geographic region and the type of subsidy considered. The expected net impact depends on the relative size of the different subeffects.

3 | EMPIRICAL APPROACH

3.1 | Theoretical model

To analyze the impact of CAP on regional productivity growth patterns, we use a conditional β-convergence equation in a dynamic panel data framework. This approach follows, for example, Rizov (2005)[3] and other empirical studies that rely on the neoclassical growth model (Solow, 1956) and implement growth regressions which allow to include a larger set of explanatory variables and test for convergence (Barro, 1991; Barro & Sala-i-Martin, 1995).[4] The method has been popularized by Barro, Sala-i-Martin, Blanchard, and Hall (1991) through the estimation of what they call β-convergence hypothesis,[5] namely, the idea of the Solow (1956) model according to which there exists a negative relationship between the growth rate of productivity and the initial level of productivity.

According to neoclassical growth theory, there are two types of convergence (Barro & Sala-i-Martin, 1995): *absolute* convergence and *conditional* convergence. The *absolute* convergence hypothesis assumes that, regardless of the initial conditions, in the long term the productivity growth in *all* economies (countries/regions) converges to the same steady state. The *conditional* convergence hypothesis contends that if economies have different structural characteristics and growth factors, then convergence is conditional on these parameters, giving rise to different steady states.[6]

The use of a conditional convergence model has a number of advantages. First, it has a strong theoretical base for productivity growth assessments, drawing on the seminal contributions of Solow (1956, 1957) and Swan (1956) and a variety of applications in growth models (see Barro et al., 1991). Second, studies have provided empirical evidence in support of agricultural productivity convergence in the EU.[7] However, only a few studies have used the convergence growth model to study the impact of the CAP on agricultural productivity in the EU. These studies (Cuerva, 2012; Montresor, Pecci, & Pontarollo, 2011; Sassi, 2010) used data for a restricted number of EU countries (EU-15) from at most two time periods (and thus used cross-sectional estimation methods) which did not cover the recent shift from coupled to decoupled

[3] Rizov (2005) uses an augmented neoclassical Solow growth model to analyse the impact of farm individualization in transition economies, so the variables of interest (and geographic focus) differ.

[4] For a review of the convergence literature, see Islam (2003) and Snowdon and Vane (2005).

[5] Barro et al. (1991) also introduced the notion of σ–convergence, which refers to decreasing cross-country dispersion in productivity, that is, differences in productivity levels becoming smaller over time.

[6] If the β-convergence model is regressed on the lagged value of the dependent variable alone, then it is an "absolute" β-convergence model. On the other hand, if the β-convergence model is regressed on other explanatory variables as well as the lagged value of the dependent variable, to identity factors which could foster productivity to converge, it is a "conditional" β-convergence model. An alternative type of conditional convergence is club-convergence, where convergence applies to only restricted groups of similar economies (Baumol, 1986; Galor, 1996).

[7] A number of studies provided evidence for convergence in agricultural productivity in EU regions. These studies include Paci (1997), Alexiadis (2012), Sondermann (2014), and Baráth and Fertő (2017). Other studies focused on regional convergence within specific EU countries (e.g., Esposti, 2011, for Italy) or made extra-EU comparisons (e.g., Ball, Bureau, Butault, & Nehring, 2001; Gutierrez, 2000; Rezitis, 2010; Schimmelpfennig & Thirtle, 1999; compared the EU with the United States).

subsidies. Since our analysis uses a wider set of countries (EU-27), better subsidy indicators, and 10 years of annual data, this allows to estimate a dynamic panel model by means of an appropriate *generalized method of moments* (GMM) estimator (Bond, Hoeffler, & Temple, 2001; Caselli, Esquivel, & Lefort, 1996) which is crucial to control for unobserved heterogeneity, dynamic issues, and reverse causation in our key policy variable of interest, that is, the CAP support rate.

Finally, though our conditional convergence equation has its logical derivation from the neoclassical growth model, both applications of neoclassical and endogenous growth models can be appropriate for explaining convergence and nonconvergence behavior. Throughout the convergence debate, the neoclassical and the endogenous growth models have evolved and the boundaries between the explanation for convergence and nonconvergence behavior in both theories have faded (Islam, 2003). The empirical evidence does not unanimously favor either of these growth theories (Esposti, 2007). Nevertheless, the geographical setting of this study in the EU, where a single market is pursued, fits well with the key assumption of the neoclassical model that is based on the idea that technological progress, being exogenously given, is the same for all regions.

3.2 | Estimation strategy

We estimate a conditional β-convergence analysis using the following reduced-form dynamic panel model:

$$\Delta y_{it} = \beta y_{it-1} + \xi CS_{it-1} + \delta' X_{it-1} + \gamma_t + \mu_i + \varepsilon_{it}, \qquad (1)$$

where $\Delta y_{it} \equiv \ln Y_{it} - \ln Y_{it-1}$ denotes region i's agricultural labor productivity growth between time t and $t-1$; y_{it-1} is the lagged log agricultural value added (VA) per worker, that is, the convergence term. Our variable of interest is the agricultural subsidy rate CS_{it-1}. X_{it-1} is a vector of control variables that may also affect labor productivity, such as the logarithm of the labor force growth, the logarithm of the population density and additional regional expenditures of the EU Structural and Investment Funds (ESIF).[8] The subsidy variables as well as the other covariates enter the equation lagged by 1 year. This reflects the assumption that farmers need time to adjust to a new situation, for example, a farmer's choice to leave at time t is affected by the level of CAP payments at time $t-1$.

To control for potential endogeneity bias due to omitted variables, we include regional and time fixed effects, μ_i and γ_t, respectively.

Using standard OLS or fixed effects (FE) estimators will generate biased estimates in the regression coefficients, because the lagged dependent value is correlated with the model's error term ε_{it} (Nickell, 1981). In AR(1) panel models, the OLS estimator is in general found to be biased upward, whereas the FE estimator is found to be biased downward (see Bond et al., 2001).

The most widely used approach to account for unobserved individual country (region) effects and to deal with endogeneity of some regressors is applying estimation techniques based on the *generalized method of moments* (Arellano & Bond, 1991; Blundell & Bond, 1998). Particularly, we rely on the *two-step system GMM* (SYS-GMM) estimator proposed by Blundell and Bond (1998) with Windmeijer's correction method for the variance–covariance matrix.[9] The SYM-GMM estimator is an extension of the first generation of GMM models using transformations in first differences (DIFF-GMM).[10]

The estimated relationship between agricultural productivity growth and CAP payments could, to a certain extent, be affected by simultaneity bias, as CAP payments are not assigned randomly to farmers (or regions). This issue is particularly relevant for coupled Pillar I payments. Past productivity of farms and regions directly affects the allocation of coupled Pillar I payments. The relationship between productivity and decoupled payments may also be subject to endogeneity. The allocation of decoupled Pillar I payments is not directly linked to current regional production activities, but the allocation of these payments among member states is based on the average amount of coupled payments received during the reference period (2000–2002) preceding the introduction of the 2003 CAP reforms.[11] This implies that regions that were more productive and/or produced more subsidized output in the past receive higher decoupled payments today (and in the period of our analysis).

[8] Most EU funding is delivered through the five ESIF: European Regional Development Fund (ERDF), Cohesion Fund (CF), European Agricultural Fund for Rural Development (EAFRD), the former European Agricultural Guarantee and Guidance Fund (EAGGF), European Social Fund (ESF), and European Maritime and Fisheries Fund (EMFF). They are jointly managed by the European Commission and the EU countries. They are designed to invest in job creation and growth. Our ESIF variable covers all funds, except for the EAFRD—to avoid double counting with our CAP payment data—and the EMFF—for which data are unavailable.

[9] Monte Carlo studies (e.g., Blundell & Bond, 1998) show that the two-step GMM estimator is asymptotically more efficient than the first step estimator but it may yield downward biased results in small samples. To deal with this potential bias, Windmeijer (2005) proposes a finite sample correction for the variance–covariance matrix in the two-step GMM estimator.

[10] DIFF-GMM has been proven to perform poorly in small T and large N panels (Bond, Hoeffler, & Temple, 2001). Since our data set includes almost 1,600 observations (i.e., large N) over a 10-year period (i.e., small T), we decided not to use this type of model.

[11] This aspect is particularly relevant for the OMS that already received CAP support before the 2003 reforms. However, a similar argument holds for the decoupled support system in the NMS, that is, the *Single Area Payment Scheme* (SAPS). The SAPS was not based on farm productivity directly, yet it was linked to the preaccession average country/regional productivity in the NMS (Ciaian & Kancs, 2012).

Although this (potential) source of endogeneity bias is certainly something to be concerned about, there are a number of reasons why such bias, if present, is likely to be (very) small in our empirical analysis. First, since our estimation model uses as a dependent variable a year to year change in agricultural labor productivity in a recent period (2004–2014) and not productivity levels, it is not obvious that the relationship between this growth variable and differences in the allocation of current coupled/decoupled payments could be affected by potential endogeneity coming from past yield levels (of more than 10 years earlier in the case of decoupled payments). In other words, this endogeneity bias would be a more serious issue if we would relate changes in the allocation of subsidy payments to productivity levels rather than to changes in productivity. Second, as discussed in Olper, Raimondi, Cavicchioli, and Vigani (2014) and Garrone, Emmers, Olper, and Swinnen (2019), the assumption of the exogeneity of our (lagged) CAP subsidy rate variable, CS_{it-1}, can be justified on the ground that CAP policy instruments (and their distribution among member states) are allocated by EU authorities rather than by regional authorities (Pillar I) or through negotiations between the EU and national authorities (Pillar II).[12] Third, all the CAP subsidy variables are lagged by 1 year, which reduces the potential bias caused by a spurious correlation due to shocks simultaneously affecting CAP payments and agricultural output.

Despite these arguments suggesting that the potential for endogeneity bias between agricultural labor productivity growth and the CAP subsidy rate is limited, we decided to apply a SYS-GMM model in order to rule out any residual component of endogeneity bias. CAP subsidy variables are treated as endogenous in this SYS-GMM model, using the $t-2$, $t-3$ and longer lag levels (and differences) as instruments. The SYS-GMM model used in our analysis has the advantage to better control for simultaneity bias (Ullah, Akhtar, & Zaefarian, 2018; Wintoki, Linck, & Netter, 2012) that might persist even after lagging explanatory variables (Bellemare, Masaki, & Pepinsky, 2017).

4 | DATA AND VARIABLES

Our data set covers 27 EU member states and 213 regions over the period 2004–2014. The choice of the period of analysis (2004–2014) is due to data availability. The (CATS) subsidy data were available only from 2004; and the agricultural productivity data coming from the *Cambridge Econometrics Regional Database* (CERD) were available only until 2014.

The data were aggregated based on the *Nomenclature of Territorial Units for Statistics* (NUTS)[13] at NUTS2 level with the exception of Denmark, Germany, Slovenia, and the United Kingdom, for which NUTS1 level of aggregation was applied.[14] We had to drop some regional observations due to the lack of data for some variables employed in our econometric analysis, and four strong outliers.[15] This resulted in a final sample consisting of 1,971 observations and 213 regions.

4.1 | Agricultural labor productivity growth (dependent variable)

We use CERD data to measure productivity growth in agriculture as annual growth in gross agricultural VA (VA-Agr.) per worker in real terms, where workers are defined as all persons engaged in some productive agricultural activity.[16] Gross agricultural VA embodies the productivity effect induced by (coupled) CAP payments.

The average rate of agricultural labor productivity growth is around 1.2% in the EU as a whole (see Table 1). The growth rate in the NMS (3.0%) is more than four times higher than in the OMS (0.7%). These growth differences are consistent with a process of convergence in productivity level between the NMS and OMS. Figure 1 illustrates that the growth in labor productivity between 2004 and 2014 was mostly due to a decline in labor use, which was larger than the decline in VA. In fact, VA declined by 0.4% annually on average over the 2004–2014 period, while agricultural employment declined by 1.7% annually (1.0% in OMS and 2.1% in the NMS).

In order to avoid endogeneity bias, we need a measure of the growth in agricultural VA per worker that is net of the effect of *coupled* CAP subsidy payments as this CAP subsidy component is included in the computation of agricultural VA (see European Commission, 2000). In principle, we can compute agricultural VA net of the effect of coupled payments by

[12] More specifically, the CAP is financed by two funds: the *European Agricultural Guarantee Fund* (EAGF) and the EAFRD, and up until financial year 2006 the EAGGF.

[13] The NUTS is a geographical nomenclature subdividing the economic territory of the EU into regions at three different levels: NUTS1, NUTS2, and NUTS3, respectively, moving from larger to smaller territorial units (Eurostat, 2013).

[14] The choice of employing NUTS1 level data for Germany and the United Kingdom is based on the fact that these countries adopted a regional approach to the implementation of both CAP and structural fund policies at NUTS1 level. As for Denmark and Slovenia, the choice of employing NUTS1 level is due to the fact that agricultural subsidy data are not available at NUTS2 level for the entire period of analysis.

[15] We dropped two observations based on a number of diagnostic tests. Partial-regression plots and the DFBETA test in STATA clearly identify the values of CAP subsidies for Wales in 2007, Border, Midland, and Western in 2013, and Bucharest region in 2010/2011 as outliers. Our main results remain robust to the inclusion of these outliers. See Table A.2 in the online appendix for result after inclusion of these outliers.

[16] Although labor productivity is a partial measure of productivity, this measure is still a main element of differences in the economic performance of regions and regional "competitiveness" (Martin, 2001).

TABLE 1 Descriptive statistics

Variables	Description	EU-27		OMS		NMS	
		Obs.	Mean	Obs.	Mean	Obs.	Mean
Total CAP payments/VA	Subsidy rate	1,971	0.343	1,521	0.338	450	0.362
Pillar I payments/VA	Subsidy rate	1,971	0.260	1,521	0.275	450	0.211
Pillar II payments/VA	Subsidy rate	1,971	0.083	1,521	0.063	450	0.151
Pillar I coupled payments/VA	Subsidy rate	1,971	0.095	1,521	0.118	450	0.020
Pillar I decoupled payments/VA	Subsidy rate	1,971	0.165	1,521	0.157	450	0.192
Pillar II HK/VA	Subsidy rate	1,971	0.009	1,521	0.006	450	0.019
Pillar II PK/VA	Subsidy rate	1,971	0.014	1,521	0.010	450	0.030
Pillar II ENV/VA	Subsidy rate	1,971	0.025	1,521	0.023	450	0.032
Pillar II LFA/VA	Subsidy rate	1,971	0.015	1,521	0.012	450	0.024
Pillar II RD/VA	Subsidy rate	1,971	0.015	1,521	0.010	450	0.031
Agricultural productivity growth	Growth rate of VA-Agr. per worker	1,971	0.012	1,521	0.007	450	0.030
Employment growth	Growth rate of employment	1,971	0.002	1,521	0.003	450	0.002
Population density	1,000 person/km^2	1,971	0.284	1,521	0.311	450	0.195
ESIF	ESIF payments/regional GDP	1,971	0.010	1,521	0.005	450	0.026
GDP growth	Annual growth rate of regional GDP	1,971	0.012	1,521	0.008	450	0.025
Share of large farms	Share of large farms (with a standard output of over 100,000 euros) in total number of farms	1,971	0.722	1,521	0.746	450	0.640
Grassland ratio	Share of grassland in total utilized agricultural area	1,971	0.341	1,521	0.372	450	0.239

Note: ESIF includes ERDF, CF, and ESF.
Sources: CATS database provided by the European Commission, CERD, DG REGIO, and Eurostat.

subtracting this CAP subsidy component from the agricultural VA. However, this approach implicitly assumes that the transfer efficiency of CAP payments is 100%, while studies have shown that the transfer efficiency is often lower, for example due to capitalization of CAP payments in land rents (Dewbre et al., 2001; Michalek, Ciaian, Kancs, & Gomez y Paloma, 2011). Thus, following Olper et al. (2014), we estimate agricultural labor productivity growth net of the effect of *coupled* CAP subsidies by first regressing agricultural productivity growth (the dependent variable) on the coupled CAP subsidy component, and then keeping the residuals from that regression. By using the residual as a dependent variable, we partial-out the effect of coupled subsidy to avoid endogeneity bias. Note that, in the observed period coupled CAP subsidy payments significantly decreased starting from 2005 onward. As an effect of the Fischler Reform, coupled CAP payments are largely substituted by decoupled CAP payments. As a result, this adjustment in the productivity growth rate is only relevant in the first 2 years of the period under analysis. Importantly, without this adjustment, all regression results of the paper are qualitatively and quantitatively similar.

4.2 | Agricultural subsidy rate

The key variable in the regression equation, CS_{it-1}, is the agricultural subsidy rate, which, as in previous analysis, is calculated as the ratio of agricultural subsidies over agricultural VA at regional level.[17] We compute the ratio between regional CAP payments and regional agricultural VA, because this ratio provides us with a consistent indicator of regional agricultural protection due to CAP policy measures.

What is different in our study is that we calculate the regional CAP payments with data from the CATS database[18] aggregated at NUTS2 regional level. The CATS database includes information on payments of each individual budget component of the CAP funds to all farms that receive payments. To the best of our knowledge, only Dudu and Kristakova (2017) use CATS data in their analysis of the impact of CAP payments on agricultural productivity. They only focus on the impact of CAP Pillar II payments over a short period of analysis.

By exploiting the unique data set, our analyses contribute to the literatures of the impact of CAP payments on agricultural productivity. First, the CATS data include details on all

[17] Other studies relating agricultural productivity (efficiency) to this subsidy rate are, for example, Fogarasi and Latruffe (2009) and Bakucs, Latruffe, Fertő, and Fogarasi (2010). See Minviel and Latruffe (2017) for an overview.

[18] The CATS was created to assist the European Commission in implementing audits on agricultural expenditures. It collects the digitalized files that each member state forwards to the European Commission concerning details of all individual payments (in euro) made to CAP recipients.

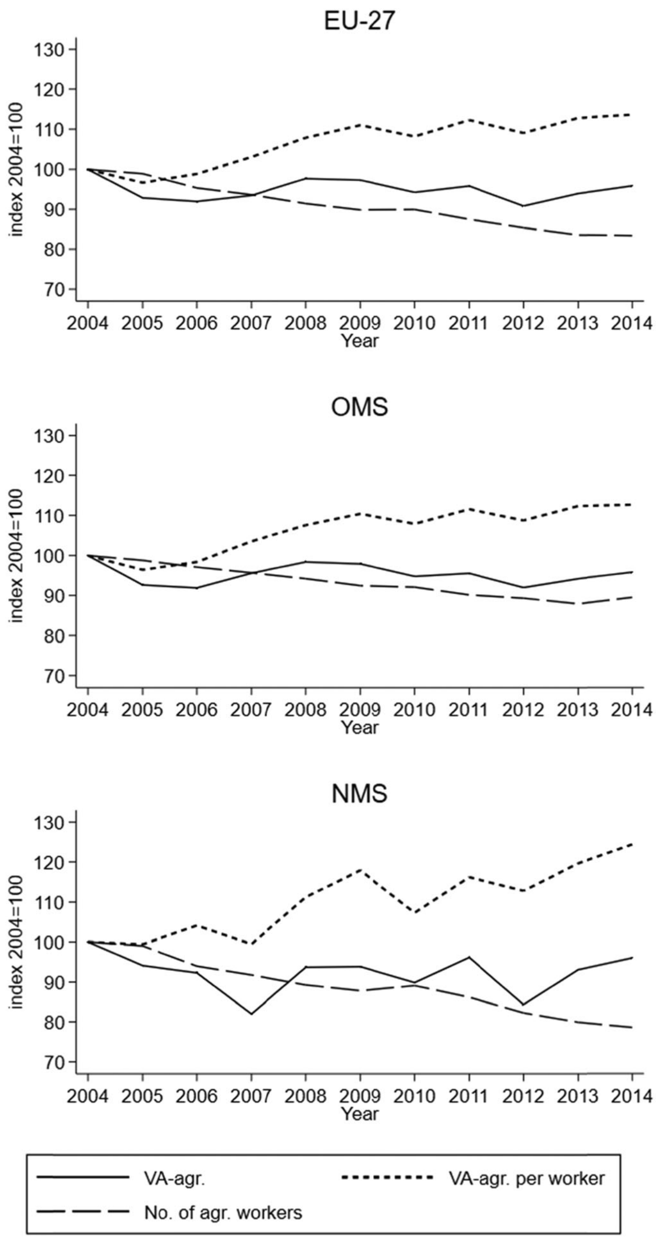

FIGURE 1 Trends in the agricultural value added (VA), the number of agricultural workers, and the agricultural labor productivity

payments made to all recipient farmers for each individual budget component of the CAP funds. Previous studies of EU agricultural productivity typically constructed subsidy indicators using the data set of the *Farm Accountancy Data Network* (FADN), which covers only agricultural holdings whose size exceeds a minimum threshold. Using CATS data reduces the sample selection bias inherent to studies based on FADN data. Second, the CATS data allow to distinguish (a) between Pillar I and Pillar II payments; (b) within Pillar I support between decoupled and coupled payments; and (c) within Pillar II payments between five classes of payments (for which we follow the categorization of Boulanger & Philippidis, 2015). This allows to test whether these various types of payments have different effects on agricultural productivity growth. Third, our analysis covers 213 regions of the EU-27 (as compared to previous studies that covered EU-15 regions). This allows to disentangle effects for subgroups of countries and, in particular, whether there are differences between the OMS and NMS. Fourth, we use 10 years of annual data starting from the year when the NMS acceded to the EU (2004–2014). The post-NMS accession period was not covered in previous studies.

Of course, concerning the use of CATS data, we should also mention that by including farm activities related to smaller farms may entail a number of drawbacks, at least to the extent that activities of "hobby" farmers with substandard efficiency levels are concerned. However, a critical point of our econometric exercise that differentiates our paper from analyses conducted at the farm level, is the possibility to generalize our results for the full population of farmers. This is an important point because agricultural subsidies have both direct and indirect effects. Indirect effects operate mainly through the adjustment of factor markets and output prices (see, e.g., Pufahl & Weiss, 2009). Thus by working at the aggregated (regional) level and considering the true amount of money related to the different policy measures targeted at each territorial unit, we are able to fully capture the indirect effects of agricultural policy in our analysis.[19]

To address potential endogeneity bias that might arise from having VA on both sides of our empirical model, we lag the subsidy variables by 1 year and instrument the CAP subsidy rate in the applied SYS-GMM model with its lagged values.

4.3 | Different types of agricultural subsidies

The CATS database allows to disaggregate total CAP payments into several components to test whether the impact on agricultural employment differs among types of agricultural subsidies. First, within Pillar I support we distinguish between coupled and decoupled payments. Coupled payments are those linked to the production of a specific crop or animal commodities. Over the last decade, reforms have generally moved the CAP away from coupled payments. Most of the Pillar I payments are now decoupled from production. The residual component of coupled subsidies, linked

[19] It is worth noting that by using CATS instead of FADN data to measure CAP subsidy rates, the differences in the level of support is substantial. For example, in Garrone, Emmers, Olper, and Swinnen (2018), considering the overall CAP payments (Pillar I and Pillar II), the average ratio of agricultural support over agricultural VA is equal to 32% using CATS data, a value that goes up to 51% when using FADN data. This is a considerable difference that cannot be attributed to the inclusion of "hobby" farmers. Importantly, the difference between the two types of subsidy indicators (CATS vs. FADN) is not only caused by the difference in levels of subsidy payments, but also by differences in the growth rate over time. This problem is particularly important for the NMS. This is at odds with an empirical framework that exploits within region variation in agricultural protection rates for identification.

to production, represents a small fraction of the overall support.

Second, within Pillar II payments we distinguish between five categories, following Boulanger and Philippidis (2015): (a) investment in HK; (b) investment in PK; (c) agri-environmental payments (ENV); (d) LFA payments; and (e) wider RD instruments.[20]

4.4 | Control variables

Control variables include changes in the labor force, population density, GDP growth, share of large farms, and share of grassland. Data for these variables are obtained from the CERD and Eurostat.[21] As is common in the growth literature, the growth of the labor force is calculated as the difference between the (log) labor force in year t minus the (log) labor force in year $t-1$, then adjusted by the common exogenous rate of technical change and the common depreciation rate, the sum of which is assumed to be 0.05 (Mankiw, Romer, & Weil, 1992).

The growth rate of regional GDP is an indicator of regional economic conditions and development. The regional share of large farms and the ratio of grassland over the total utilized agricultural area are both indicators of farm structure and production structure. In line with Glauben, Tietje, and Weiss (2006) we add population density, calculated as the total population over regional area in km^2, as control indicator for market conditions, such as the level of activity in product and factor markets. In areas with higher population density, the activities are expected to be more intense and market imperfections tend to be lower.

To control for other types of (nonagricultural) EU support to the region, we also include a variable covering ESIF spending. We use annual EU expenditures of the ERDF, the CF, and the ESF at the NUTS2 level of regional aggregation per unit of regional GDP.[22] According to Esposti (2007), these expenditures can be considered as mostly consisting of investment. Descriptive statistics in Table 1 indicate that ESIF, on average, accounts for a larger share of regional GDP in the NMS than in the OMS. Few previous studies have controlled for these payments, but these payments could influence the results if they are correlated with CAP subsidies (due to omitted variable bias). We later test the robustness of our results by running the models with and without this control variable.

5 | RESULTS

Tables 2–4 report the estimation results for the EU-27 (Table 2), OMS (Table 3), and NMS (Table 4). In each table, Column (1) presents SYS-GMM regression results with the total CAP subsidy rate as the main explanatory variable. Columns (2)—(4) present SYS-GMM regressions results with CAP expenditures disaggregated into Pillar I and Pillar II (Column 2); and further into "coupled Pillar I subsidies" and "decoupled Pillar I subsidies" (Column 3) and the five components of Pillar II (Column 4).

Column (5) presents results using OLS and Column (6) using FE with total CAP subsidies—to compare with the SYS-GMM estimates in Column (1). The SYS-GMM (Column 1) point estimates of the lagged dependent variable (i.e., the 1-year lagged agricultural VA per worker) fall within the range of the OLS (Column 5) and FE (Column 6) point estimates, suggesting that the SYS-GMM estimator yields consistent estimates (Bond et al., 2001).

Standard tests for consistency of the SYS-GMM estimators are reported at the bottom of Tables 2–4. The Arellano–Bond tests AR(1) and AR(2) indicate the absence of first-order autocorrelation, implying that the dynamic model is correctly specified. The p-value of Hansen's test suggests that we cannot reject the null hypothesis of the (joint) validity of our instruments at the 5% level of significance.[23,24]

Key results on the impact of CAP subsidies on productivity are the following. The total CAP subsidy rate (Column 1) has a positive and significant coefficient for all three regional specifications (EU-27, OMS, and NMS). Hence, on average, CAP subsidies have a positive impact on EU agricultural productivity growth. However, as the regressions in Columns (2)–(4) show, the different type of subsidies have very different effects.

[20] The wider rural development measures include payment for diversification into nonagricultural activities, encouragement of rural tourism, and village renewal and development.

[21] Data on labor force growth, population density, and regional GDP are obtained from CERD. Data on the share of large farms and the share of grassland are obtained from Eurostat.

[22] ESIF data come from the DG REGIO website https://cohesiondata.ec.europa.eu/EU-Level/Historic-EU-paymentsregionalised-and-modelled/tc55-7ysv. Regional GDP data come from the CERD.

[23] The SYS-GMM estimator requires relatively mild stationarity assumptions. To be specific, the assumption of mean stationarity is required to ensure the consistency of the SYS-GMM estimator under large N and fixed T asymptotics (Blundell & Bond, 1998). Overidentifying restriction tests, such as the Hansen's test (Bun & Sarafidis, 2015), can in principle be used to detect violations from mean stationarity. The literature suggests to combine such tests with difference overidentifying restrictions tests (Bun & Sarafidis, 2015). By computation of such differences between DIFF-GMM and SYS-GMM statistics, we detect no violations of the mean stationarity assumption.

[24] We did not test for panel cointegration across the main variables in our model because of two reasons. First, the assumptions underlying panel cointegration tests do not hold for studies with large N and small T (Breitung & Pesaran, 2008). Second, the Fisher test and the Im, Pesaran, and Shin test that are based on Augmented Dickey–Fuller tests show that the main variables are all stationary (p-value, .01).

TABLE 2 Convergence regressions for agricultural productivity in EU-27 (213 regions)

Dependent variable: Δlog VA-Agr. per worker	(1) SYS-GMM	(2) SYS-GMM	(3) SYS-GMM	(4) SYS-GMM	(5) OLS	(6) FE
Total CAP subsidy rate ($t-1$)	0.079***				0.016	0.013
	(5.57)				(0.78)	(0.69)
Pillar I total ($t-1$)		0.055**				
		(2.02)				
Pillar I coupled ($t-1$)			−0.027**	−0.013		
			(2.47)	(1.03)		
Pillar I decoupled ($t-1$)			0.080***	0.075***		
			(7.82)	(3.86)		
Pillar II total ($t-1$)		0.178***	0.207***			
		(4.31)	(5.09)			
Pillar II HK ($t-1$)				0.657**		
				(1.99)		
Pillar II PK ($t-1$)				0.040		
				(0.99)		
Pillar II ENV ($t-1$)				0.612		
				(1.55)		
Pillar II LFA ($t-1$)				−0.526		
				(1.05)		
Pillar II RD ($t-1$)				0.105		
				(0.37)		
VA-Agr. per worker ($t-1$)	−0.040***	−0.032**	−0.017	−0.026*	−0.026***	−0.447***
	(3.18)	(2.34)	(1.51)	(1.93)	(4.03)	(12.97)
Labor force growth ($t-1$)	−0.010	−0.008	−0.012	−0.015	0.002	−0.002
	(0.69)	(0.58)	(0.80)	(1.01)	(0.25)	(0.26)
Population density ($t-1$)	−0.002	−0.002	0.000	−0.002	0.001	0.128
	(0.43)	(0.68)	(0.10)	(0.38)	(0.14)	(0.48)
ESIF payments ($t-1$)	−1.937**	−1.880**	−1.323**	−1.877**	−0.777**	0.416
	(2.41)	(2.19)	(2.16)	(2.54)	(2.41)	(0.75)
GDP growth ($t-1$)	−0.368*	−0.415**	−0.343*	−0.275	−0.223	−0.025
	(1.77)	(2.02)	(1.66)	(1.29)	(1.19)	(0.17)
Share of large farms ($t-1$)	−0.006	−0.028	−0.042	−0.093	0.018	−0.122***
	(0.15)	(0.44)	(0.69)	(1.14)	(0.74)	(4.83)
Grassland ratio ($t-1$)	−0.046*	−0.053*	−0.052*	−0.045	−0.034*	0.093
	(1.65)	(1.93)	(1.91)	(1.64)	(1.81)	(0.69)
Speed of convergence	0.041	0.033	0.017	0.026		
R^2 (within)					0.061	0.270
No. of observations	1,971	1,971	1,971	1,971	1,971	1,971
No. of instruments	190	198	210	206		
AR(1) p-value	0.000	0.000	0.000	0.000		
AR(2) p-value	0.743	0.544	0.106	0.051		
Hansen J-Stat. p-value	0.115	0.137	0.140	0.120		
Diff-Hansen J-Stat. p-value	0.996	0.994	0.978	0.998		

Notes: OLS regression includes time fixed effects; LSDV regression includes region and time fixed effects; SYS-GMM regressions include time fixed effects, and CAP payments, labor force growth, and ESIF payments are treated as endogenous. AR(n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; the Hansen's test and Diff-Hansen's test are tests for the overidentification restrictions for the validity of instruments. Absolute t-statistics based on standard errors clustered by region are reported in parentheses. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

TABLE 3 Convergence regressions for agricultural productivity in OMS (158 regions)

Dependent variable: Δ log VA-Agr. per worker	(1) SYS-GMM	(2) SYS-GMM	(3) SYS-GMM	(4) SYS-GMM	(5) OLS	(6) FE
Total CAP subsidy rate ($t-1$)	0.068***				0.013	0.015
	(5.81)				(0.60)	(0.76)
Pillar I total ($t-1$)		0.052**				
		(2.20)				
Pillar I coupled ($t-1$)			−0.042***	−0.032**		
			(2.81)	(2.30)		
Pillar I decoupled ($t-1$)			0.067***	0.088***		
			(4.77)	(3.36)		
Pillar II total ($t-1$)		0.134***	0.205***			
		(3.43)	(9.20)			
Pillar II HK ($t-1$)				0.376		
				(1.00)		
Pillar II PK ($t-1$)				0.341***		
				(4.82)		
Pillar II ENV ($t-1$)				−0.132		
				(0.28)		
Pillar II LFA ($t-1$)				−0.298		
				(0.33)		
Pillar II RD ($t-1$)				0.274		
				(0.70)		
VA-Agr. per worker ($t-1$)	−0.090***	−0.073***	−0.053*	−0.092**	−0.029**	−0.401***
	(3.73)	(3.64)	(1.85)	(2.43)	(2.32)	(10.80)
Labor force growth ($t-1$)	−0.037*	−0.029	−0.035	−0.036	−0.019**	−0.016*
	(1.71)	(1.31)	(1.46)	(1.54)	(2.06)	(1.92)
Population density ($t-1$)	−0.002	−0.000	0.002	−0.005	0.004	0.143
	(0.55)	(0.08)	(0.51)	(0.80)	(0.75)	(0.49)
ESIF payments ($t-1$)	−5.310***	−3.655**	−3.767**	−4.164**	−1.208**	−1.152
	(3.07)	(2.51)	(2.43)	(2.54)	(2.48)	(1.10)
GDP growth ($t-1$)	−0.091	−0.194	−0.051	0.015	0.004	0.170
	(0.36)	(0.78)	(0.19)	(0.06)	(0.02)	(0.91)
Share of large farms ($t-1$)	−0.006	−0.018	−0.050	−0.013	0.010	−0.131***
	(0.11)	(0.23)	(0.71)	(0.25)	(0.31)	(6.87)
Grassland ratio ($t-1$)	−0.068*	−0.068*	−0.070**	−0.058	−0.038**	0.146
	(1.91)	(1.96)	(2.05)	(1.57)	(2.07)	(1.24)
Speed of convergence	0.094	0.076	0.054	0.097		
R^2 (within)					0.043	0.226
No. of observations	1,521	1,521	1,521	1,521	1,521	1,521
No. of instruments	147	156	155	157		
AR(1) p-value	0.000	0.000	0.000	0.000		
AR(2) p-value	0.945	0.936	0.272	0.350		
Hansen J-Stat. p-value	0.113	0.126	0.101	0.117		
Diff-Hansen J-Stat. p-value	0.933	0.803	0.986	0.832		

Notes: OLS regression includes time fixed effects; LSDV regression includes region and time fixed effects; SYS-GMM regressions include time fixed effects, and CAP payments, labor force growth, and ESIF payments are treated as endogenous. AR(n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; the Hansen's test and Diff-Hansen's test are tests for the overidentification restrictions for the validity of instruments. Absolute t-statistics based on standard errors clustered by region are reported in parentheses. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

TABLE 4 Convergence regressions for agricultural productivity in NMS (55 regions)

Dependent variable: Δ log VA-Agr. per worker	(1) SYS-GMM	(2) SYS-GMM	(3) SYS-GMM	(4) SYS-GMM	(5) OLS	(6) FE
Total CAP subsidy rate ($t-1$)	0.566***				0.055	−0.105
	(2.88)				(1.04)	(1.12)
Pillar I total ($t-1$)		0.017				
		(0.10)				
Pillar I coupled ($t-1$)			−2.510**	0.737		
			(2.10)	(0.79)		
Pillar I decoupled ($t-1$)			0.532***	0.060		
			(2.69)	(0.27)		
Pillar II total ($t-1$)		0.127*	0.026			
		(1.72)	(0.56)			
Pillar II HK ($t-1$)				0.236		
				(0.26)		
Pillar II PK ($t-1$)				0.057		
				(1.00)		
Pillar II ENV ($t-1$)				0.123		
				(0.15)		
Pillar II LFA ($t-1$)				2.474**		
				(2.56)		
Pillar II RD ($t-1$)				−0.622		
				(1.05)		
VA-Agr. per worker ($t-1$)	−0.183**	0.010	−0.036	−0.078	−0.026**	−0.683***
	(2.50)	(0.47)	(0.80)	(1.13)	(2.29)	(13.88)
Labor force growth ($t-1$)	0.053	−0.009	0.044	0.020	0.031**	0.004
	(1.33)	(0.32)	(1.30)	(0.81)	(2.47)	(0.29)
Population density ($t-1$)	0.036	−0.038**	−0.021	0.001	−0.020	−0.480
	(0.54)	(2.29)	(0.70)	(0.03)	(1.20)	(1.20)
ESIF payments ($t-1$)	−3.985*	−1.504	−2.716*	−1.004	−0.514	−0.797
	(1.83)	(1.57)	(1.71)	(0.59)	(0.70)	(0.68)
GDP growth ($t-1$)	−0.706	−0.557	−1.100**	−0.679	−0.456	−0.237
	(1.67)	(1.26)	(2.27)	(1.53)	(1.19)	(1.09)
Share of large farms ($t-1$)	0.285	−0.054	−0.013	0.128	0.021	0.350*
	(1.63)	(1.09)	(0.15)	(1.12)	(0.51)	(1.68)
Grassland ratio ($t-1$)	−0.002	−0.096	−0.016	−0.099	−0.043	−0.144
	(0.01)	(1.61)	(0.20)	(0.82)	(0.75)	(0.25)
Speed of convergence	0.202	−0.010	0.037	0.081		
R^2 (within)					0.189	0.488
No. of observations	450	450	450	450	450	450
No. of instruments	37	54	53	52		
AR(1) p-value	0.000	0.000	0.000	0.000		
AR(2) p-value	0.145	0.225	0.375	0.124		
Hansen J-Stat. p-value	0.104	0.144	0.110	0.101		
Diff-Hansen J-Stat. p-value	0.691	0.703	0.286	0.464		

Notes: OLS regression includes time fixed effects; LSDV regression includes region and time fixed effects; SYS-GMM regressions include time fixed effects, and CAP payments, labor force growth, and ESIF payments are treated as endogenous. AR(n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; the Hansen's test and Diff-Hansen's test are tests for the overidentification restrictions for the validity of instruments. Absolute t-statistics based on standard errors clustered by region are reported in parentheses. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

Total Pillar I subsidies have a significant positive effect on agricultural labor productivity growth in the EU-27 and the OMS, but not in the NMS. This aggregate result for Pillar I seems to be caused by the opposing effects of decoupled and coupled Pillar I subsidies. The estimated effect of decoupled Pillar I subsidies is positive and significant, whereas coupled Pillar I subsidies have the opposite effect: they are negatively correlated with productivity growth. The estimated coefficient of decoupled payments is higher than for total Pillar I payments with coupled payments having a negative (or insignificant) estimated coefficient.

The estimated coefficients of total Pillar II payments are always positive. If we analyze the different components of Pillar II payments (Column 4), we find that in all regions there is a positive effect of Pillar II spending on HK, but the effect is only significant for the EU-27 as a whole. The coefficients of investments in PK are also positive for all regions, but the effect is only significant in the OMS. These finding suggests that HK and PK payments may lead to investment-induced productivity gains as improved knowledge of efficient farming practices can lead to better use of technology and land (Boulanger & Philippidis, 2015; Dudu & Kristkova, 2017).

The coefficients of the other Pillar II components are opposite for the OMS and NMS and not significant for the EU-27. The coefficient for LFA payments is significant and positive in the NMS. This finding indicates that this type of payments helps maintain agricultural land in good condition and improve efficiency by allowing farmers to adopt technologies that offset negative impacts of LFA conditions in the NMS. RD payments and ENV payments have no significant effect.

Regarding the control variables, the coefficients of labor force growth, population density, and the share of large farms are insignificant in the EU-27. GDP growth, the grassland ratio, and ESIF spending are negatively correlated with agricultural labor productivity growth in the EU-27.

The results indicate conditional β-convergence of productivity among regions. The conditional β-convergence effect is captured by the estimated coefficient of the (lagged) agricultural VA per worker. The coefficient is always negative and significant in most specifications. The speed of convergence is higher for the NMS (3.7–20.2%) than for the OMS (5.4–9.7%). Within the EU-27, the speed of convergence is between 1.7% and 4.1% (Columns (1)–(4) of Tables 2–4).

A series of additional analyses and robustness tests are presented in the online appendix. In the additional analyses, we estimate absolute convergence (Table A.1), test for σ–convergence (Figure A.1), and test for the impact of excluded outliers (Table A.2) and of potentially endogenous control variables (ESIF Payments) (Table A.3). These additional analyses show absolute convergence (in EU-27, OMS, and NMS), no evidence of σ–convergence[25] and that the overall results do not change with outliers and specific control variables. In summary, the results reported above are robust to these modifications and supported by additional analyses.

6 | CONCLUSIONS

This paper estimates the impact of CAP subsidies on EU agricultural labor productivity within a conditional growth convergence framework. We estimate a dynamic model using the SYS-GMM estimator. We use an EU-wide panel data set covering 213 regions and the 2004–2014 period, and CATS data with detailed information on CAP payments to farms. We use a SYS-GMM specification where CAP payments are treated as endogenous variables to address issues of potential endogeneity bias related to agricultural subsidies.

We find that CAP subsidies, as a whole, have a positive impact on labor productivity in agriculture in the EU-27, OMS, and NMS. However, this aggregate positive effect hides important differences in the impact of different types of subsidies. The positive effect comes from decoupled subsidies, that is, Pillar I decoupled payments and Pillar II payments. Coupled Pillar I subsidies have the opposite effect: they slow down productivity growth.

These findings support the argument that the CAP reforms of the past decades which have caused a shift from coupled subsidies to decoupled payments in Pillar I and an increase in Pillar II payments have been positive for agricultural labor productivity growth. This is consistent with earlier findings that the shift from “coupled” to “decoupled” subsidies increased agricultural productivity in the EU (Kazukauskas et al., 2014; Mary, 2013; Rizov et al., 2013). With decoupling of support, farmers can shift to production activities with higher VA, and inefficiencies are likely to reduce (Dewbre et al., 2001; Guyomard et al., 2004).

While total Pillar II payments are positively correlated with productivity growth, this effect seems to be caused only by one component: Pillar II spending on HK. This is the only component for which there is a positive and significant effect on productivity for the EU-27. Most components have no effect. PK payments are positively correlated with productivity in the OMS and LFA payments positively correlated in the NMS.

[25] Figure A.1 shows the dispersion of agricultural productivity across the EU-27 during the period 2004–2014. Since there is no strong downward trend in this dispersion, we find no (strong) evidence of σ–convergence. This finding is in line with earlier studies showing that β-convergence is a necessary, but not a sufficient condition for σ-convergence (Young, Higgins, & Levy, 2008).

Our results also show conditional β-convergence of agricultural labor productivity among regions. The speed of convergence is higher for the NMS than for the OMS.

A final caveat is that our results do not necessarily imply that decoupled payments are an efficient policy instrument to stimulate productivity growth in EU agriculture. Our analysis only considers the "gross effect" of the policy and ignores the costs of the policy and can, therefore, not evaluate the cost–benefit ratio and the net effect of these policies.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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