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**Subsidies and Agricultural Productivity:
CAP payments and labour productivity (convergence) in EU agriculture***

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Abstract

This paper investigates the relationship between EU agricultural subsidies and agricultural labour productivity by estimating a conditional growth equation. 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, CAP subsidies increase agricultural labour productivity, and the effect is almost entirely due to decoupled Pillar I payments. Coupled Pillar I payments have no impact. The impact of Pillar II is mixed.

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1. Introduction

Traditional economic theory and policy analysis posit that agricultural subsidies distort incentives and reduce productivity (e.g. Johnson, 1973; OECD, 2008). Subsidies may reduce agricultural productivity by causing allocative and technical efficiency losses: (i) farmer investment decisions may be distorted towards relatively less productive activities that are supported by subsidies (Alston and James, 2002); (ii) farmers may over-invest in subsidised inputs (Rizov et al., 2013); (iii) subsidies may reduce a farmer's incentive to adopt cost-optimising strategies (Leibenstein, 1966; Minviel and Latruffe, 2017); or (iv) subsidies may lead to soft budget constraints, causing inefficient use of resources (Kornai, 1986).

However, some studies have challenged that these arguments always hold. 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 et al., 2006; Ciaian and 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 and 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 New Member States joined the EU in the mid-2000s, as credit constraints were very important for farms in those regions in that period (Ciaian and Swinnen, 2009).

Another potential explanation for heterogeneous effects is the nature of the subsidies. Within the EU's *Common Agricultural Policy* (CAP) (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 inefficiency 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 et al., 2001; Guyomard et al., 2004; Rizov et al., 2013). Empirical studies indeed find (a) negative correlations between coupled subsidies and various measures of productivity (Latruffe et al., 2009; Zhu and Oude Lansink, 2010; Zhu et al., 2012; Mary, 2013) and (b) that agricultural productivity in the EU increased with the shift from "coupled" to "decoupled" subsidies (Mary, 2013; Rizov et al., 2013; Kazukauskas et al., 2014).

Other studies have also argued that there may be heterogeneous effects for different types of rural development subsidies (so-called Pillar II payments in the CAP). For example, *less favoured areas* (LFA) payments, granted to farms solely on the basis of their unfavourable geographic location, may keep inefficient farms going, thereby reducing efficiency, but may also help maintain agricultural land in good condition in these areas, thereby enhancing efficiency (Latruffe and Desjeux, 2016). Investments in human and physical capital may be productivity enhancing and cost-reducing, as improved knowledge of efficient farming practices can lead to better use of technology and land (Boulanger and Philippidis, 2015; Dudu and Kristkova, 2017). Agro-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 agro-environmental payments is mixed. Some find a negative effect on productivity (Lakner, 2009), while others find no or a positive effect (Mary, 2003; Dudu and Kristkova, 2017). Finally, more general rural development payments are 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 location and the type of subsidy. The expected net impact is likely to depend on the relative size of the different sub-effects.

Our paper contributes to this literature by using (a) more accurate subsidy data, (b) a wider coverage of countries and (c) a longer time period than has been done before. More specifically, our analysis uses data for the 213 regions from the EU-27 (compared to EU-15 in previous studies).¹ This allows to disentangle the effect for sub-groups of countries and in particular whether there are differences between *old member states* (OMS) and *new member states* (NMS). Our analysis uses ten years of annual data starting from the year when the NMS acceded to the EU (2004-2014).

Our analysis is one of the first to use the *Clearance Audit Trail System* (CATS) dataset from the European Commission as indicators of subsidies to assess the link between agricultural subsidies and productivity growth in the EU.² The CATS data include details on all payments made to all recipient farmers for each individual budget component of the CAP funds. This CATS dataset reduces the sample selection bias which was inherent in previous EU agricultural productivity studies which typically used *Farm Accountancy Data Network* (FADN) data to

¹ There are not sufficient data to include Croatia, the 28th and most recent EU member country.

² The only other studies using CATS that we are aware of are Boulanger and Philippidis, (2015), examining the potential trade and welfare implications of CAP budgetary reform, Dudu and Kristkova (2017), analysing the impact of Pillar II support on agricultural productivity, and Garrone et al (2018), studying the impact of the CAP on agricultural employment.

construct agricultural subsidy indicators.³ The CATS data also 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 in five classes of payments (for which we follow the categorization of Boulanger and Philippidis (2015)). This allows to test whether these various types of payments have different effects on agricultural productivity growth.

Our analysis uses a regional conditional convergence model to estimate the impact of CAP on agricultural labour productivity growth in the EU. Past studies have generally used other econometric models (e.g. Kazukauskas et al. (2014) and Rizov et al. (2013)). The convergence model has the advantage that it has a stronger 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.⁴

Only a few studies have used the convergence growth model to study the impact of the CAP on agricultural productivity in the EU. However these studies (Sassi, 2010; Montresor et al., 2011; Cuerva, 2012) only used data from two time periods (and thus use cross-sectional estimations), for a restricted number of EU countries (EU-15), and cannot capture the effect of the shift from coupled to decoupled 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

³ As is well known, FADN data cover only agricultural holdings whose size exceeds a minimum threshold.

⁴ Several applications of the convergence growth model study convergence in European agricultural productivity and its determinants without measuring the impact of subsidies (e.g. Esposti, 2010; Gutierrez, 2000; Schimmelpfennig and Thirtle, 1999). Paci (1997) finds no evidence of absolute convergence in labour productivity in a sample of 109 European agricultural regions during the 1980s. Convergence is only found within groups of similar types of farming and it has taken place quicker in Northern Europe. Sondermann (2014) finds evidence for labour productivity convergence in agriculture for 12 EU countries between 1970 and 1998, but none between 1999 and 2007. Baráth and Fertő (2016) do find convergence in agricultural productivity among OMS and NMS for the period 2004-2013. Alexiadis (2010) testing regional convergence in agricultural productivity in the 258 EU regions over the period 1995–2004 finds little evidence of absolute convergence, but suggests a pattern of club convergence. Cechura et al. (2016) use regional data on the EU dairy sector in 2004–2011 and find no evidence of convergence. Some studies focus on regional convergence of a specific EU country (e.g. Esposti (2010) in Italy) or make extra-EU comparisons (Gutierrez, 2000; Ball et al., 2001; and Rezitis 2010 with the US). Rizov (2005) finds that the shift to individual farming has positively contributed to productivity growth in agriculture during the 1990s for 15 European transition countries. Other studies measuring agricultural productivity differences across Europe include Matthews (2014) on differences between OMS and NMS; Wang et al. (2012) focusing on Western Europe; Swinnen and Vranken (2010) on agricultural productivity in Central and Eastern Europe.

panel model by means of an appropriate generalized method of moments (GMM) estimator (Caselli et al. 1996; Bond et al. 2001).

The rest of this paper is structured as follows. In the next section, we discuss our empirical approach. In Section 3, we describe our dataset and empirical estimation strategy. Results are presented in Section 4, and results of robustness checks follow in Section 5. We quantify the economic size of effects of CAP subsidies and decoupling in Section 6. Section 7 concludes.

2. Empirical Approach

To analyse 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)⁵ 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 and Sala-i-Martin, 1995).⁶ A frequently used method to test convergence is Barro and Sala-i-Martin's (1991) β -convergence,⁷ which implies a negative relationship between the growth rate of productivity and the initial level of productivity.⁸

⁵ 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.

⁶ For a review of the convergence literature see Snowdon and Vane (2005) and Islam (2003).

⁷ Barro and Sala-i-Martin's (1991) also introduced the notion of σ -convergence, which refers to decreasing cross-country dispersion in productivity, i.e. that differences in productivity levels become smaller over time. Another approach is the *time series approach*, which is mostly based on stochastic approaches like cointegration (Gáspár, 2012).

⁸ Either cross-sectional and panel data models can be used to test β -convergence hypothesis (see Caselli et al. 1996, for a discussion). In the case of a dynamic panel framework, the negative relationship to test is between actual growth in productivity, over a one or five years period, and initial productivity level, lagged one or five years, respectively.

There are two types of convergence (Barro and Sala-i-Martin, 1995): *absolute* convergence and *conditional* convergence. The *absolute* convergence hypothesis assumes that the productivity of *all* economies (countries/regions) converge to the same steady-state⁹ in the long term, regardless of the initial condition. *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.^{10,11}

For our study, which analyses the role of CAP payments on productivity, it is appropriate to conduct a conditional β -convergence analysis¹² using the following reduced form dynamic panel model:

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

where $\Delta y_{it} \equiv \ln Y_{it} - \ln Y_{it-1}$, denotes region i 's agricultural labour productivity growth between t and $t-1$; y_{it-1} is the lagged (log) agricultural VA per worker, i.e. 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 labour productivity, such as the logarithm of the labour force growth (LF), the logarithm of the population density (PD) and additional regional expenditures of the EU Structural and Investment Funds ($ESIF$)¹³. The subsidy variables as well as the other covariates

⁹ The idea of an economy reaching steady state is central to neoclassical growth model. Sala-i-Martin (2004) defines a *steady state* "as a situation in which the various quantities grow at constant (perhaps zero) rates" (p.34).

¹⁰ Neoclassical growth models with convergence have been challenged by endogenous growth theory which argues that there is no steady state (Romer, 1986, 1990; Lucas, 1988).

¹¹ Depending on whether absolute or conditional hypothesis is tested, there are two different types of β -convergence. If the β -convergence model is regressed on the lagged values 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, to identify 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).

¹² One critique on β -convergence is that it ignores distribution dynamics (Quah 1996).

¹³ Most EU funding is delivered through the five European structural and investment funds (ESIF): European regional development fund (ERDF), Cohesion Fund (CF), European agricultural fund for rural development

enter the equation lagged by 1 year. This reflects the assumption that farmers need time to adjust to a new situation, e.g. 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) models will generate biased estimates in the regression coefficients, because lagged dependent value is correlated with the model's error term ε_{it} (see Nickell (1981)).¹⁴ The most widely used approach of accounting for unobserved for individual country (region) effects and dealing with this type of endogeneity of the regressors applies estimation techniques based on *generalized methods of moments* (GMM) (Arellano and Bond, 1991; Blundell and Bond, 1998). We use the *two-step system GMM* (SYS-GMM) estimator proposed by Blundell and Bond (1998)¹⁵ with Windmeijer's correction method for the variance-covariance matrix.¹⁶

3. Data and Econometric Model

Our dataset covers 27 EU member states¹⁷ and 213 regions over the period 2004-2014. The choice of the period of analysis (2004-2014) is due to data availability. The subsidy (CATS)

AFRD/old 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 not available.

¹⁴ In AR(1) panel model OLS estimator is found to be biased upwards, while the fixed effect estimator is found to be biased downwards (see Bond et al., 2001).

¹⁵ The first generation of *GMM-models using transformations in first differences* (DIFF-GMM) has been proven to perform poorly in small T and large N panels (see Bond et al., 2001). Since our dataset includes almost 2000 observations (i.e. large N) over a 10-year period (i.e. small T), we chose not to use it.

¹⁶ Monte Carlo studies (e.g. Blundell and 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.

¹⁷ The 15 “old” member states (OMS, also often referred to as “EU-15”) joined the EU before 2004; the 13 “new” member states (NMS) joined since 2004. Croatia, which joined the EU most recently, is not included as CATS data are not available for the period covered in our analysis.

data were available only from 2004; and the agricultural productivity data coming from the *Cambridge Econometrics Regional Database (CERD)* was available only until 2014.

The data were aggregated based on the *Nomenclature of Territorial Units for Statistics (NUTS)*¹⁸ at NUTS 2 level with the exception of Denmark, Germany, Slovenia and the United Kingdom, for which NUTS 1 level of aggregation was applied.¹⁹ We had to drop some regional observations due to the lack of data for some variables employed in our econometric analysis, and a few outliers.²⁰ This resulted in a final sample consisting of 1,980 observations and 213 regions.

3.1 *Dependent variable*

We measure productivity growth in agriculture as annual growth in gross agricultural value added (VA-Agr.) per worker in real terms, using CERD data.²¹ Table 1 shows that the average rate of agricultural labour productivity growth is around 1.2 % in the EU as a whole. It also shows that the growth rate is heterogeneous between the OMS and NMS: the growth rate in NMS (3.0%) is more than four times higher than is the OMS (0.7%).

¹⁸ The *Nomenclature of Territorial Units for Statistics (NUTS)* is a geographical nomenclature subdividing the economic territory of EU into regions at three different levels: NUTS 1, 2 and 3 respectively, moving from larger to smaller territorial units (Eurostat, 2013).

¹⁹ The choice of employing NUTS 1 level data for Germany and the UK is because these countries adopted a regional approach to the implementation of both CAP and *Structural Fund (SF)* policies at NUTS 1 level. As for Denmark and Slovenia, the choice of employing NUTS 1 level is due to the fact that agricultural subsidy data are not available at NUTS 2 level for the entire period of analysis.

²⁰ We dropped a few observations based on a number of diagnostic tests to detect potential outliers. Partial-regression plots and the DFBETA test in STATA clearly identifies the values of CAP subsidies for Wales in 2006, Border, Midland and Western in 2012 and Bucharest region in 2010/11 as outliers. Our main results remain robust to the inclusion of these outliers.

²¹ Although labour 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).

3.2 Agricultural subsidy rate (independent variable)

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 value added at regional level.²²

What is different in our study is that we calculate the regional CAP payments with data from the CATS database²³ aggregated at NUTS 2 regional level. The CATS database includes information on payments of each individual budget component of the CAP funds to all farms that receive payments. As shown in Garrone et al. (2018), this represents a major improvement compared to most previous studies on agricultural productivity and subsidies, as they construct EU agricultural subsidy indicators using FADN data, which biases the sample towards larger farms.²⁴ To the best of our knowledge, only Dudu and Kristakova (2017) use CATS data in their analysis. They only focus on the impact of CAP Pillar II payments on agricultural productivity and for a short period of analysis.

3.3 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 decoupled and coupled payments. Coupled payments are those linked to the production of a specific crop or animal commodities. Over the last decade, the CAP has been a general move away from coupled and most of the Pillar I

²² Other studies relating agricultural productivity (efficiency) to this subsidy rate are for example Fogarasi and Latruffe (2009) and Bakucs et al. (2010). See Minvel and Latruffe (2017) for an overview.

²³ 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.

²⁴ In their work on off-farm migration and CAP subsidies, Garrone et al. (2018) compare the CATS subsidy rates and the FADN subsidy rates. The average ratio of CAP payments per value added is 57% higher with FADN data than with CATS data (53% in OMS and 69% in NMS), which confirms that FADN-based subsidy indicators are higher compared to those constructed from the CATS data because of the bias towards larger farms.

payments are now decoupled from production. A residual component of coupled subsidies, linked to production, still 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 human capital (HK); (b) investment in physical capital (PK); (c) agri-environmental payments (ENV); (d) less favoured areas (LFA); and (e) wider rural development (RD) instruments.²⁵

3.4 Control variables

To control for other types of (non-agricultural) EU support to the region, we include a variable covering the *EU regional structural and investment funds* (ESIF). We use annual EU expenditures of the *European Regional Development Fund* (ERDF), the *Cohesion Fund* (CF), and the *European Social Fund* (ESF)²⁶ at the NUTS 2 level of regional aggregation per unit of regional GDP.²⁷ Descriptive statistics in Table 1 indicates that ESIF, on average, accounts for a larger share of regional GDP in NMS than in 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). According to Esposti (2007) these expenditures can be considered as mostly consisting of investment. However, *a priori* it is difficult to say something about the direction of this variable on agricultural productivity, because these policies do not target the agricultural sector directly.

²⁵ The wider rural development measures include diversification into non-agricultural activities; encouragement of rural tourism; village renewal and development, etc.

²⁶ As explained before, our ESIF variable does not include EAFRD (i.e. Pillar II support), which is treated separately because it is one of our policy variables of interest. Together with the EAFRD, these funds account for almost 95% of total EU funds remitted. EMFF data are not available in this dataset.

²⁷ 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 CERD.

Other control variables include labour force, growth and population density. Data for these variables are also from CERD. As is common in the growth literature, the growth of labour force is calculated as the logarithm of the lagged labour growth rate adjusted by common exogenous rate of technical change and common depreciation rate, the sum of which is assumed to be 0.05 (see Mankiw et al. (1992)). Population density, calculated as the total population over regional area in km², is an indicator accounts for several market conditions, such as product and land markets.

4. Results

Tables 2 to 4 report the estimates of conditional convergence using equation 1 for the EU-27, OMS and NMS, respectively. In each table, results are presented in sequence of different estimation techniques and specifications. The SYS-GMM (Column 1) point estimates of the lagged dependent variable (i.e. the one year lagged agricultural VA per worker) fall within the range of the OLS (Columns 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 presence of a negative first-order autocorrelation, while it cannot reject the null hypothesis that there is no second order autocorrelation, indicating 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, but we can reject it at the 10% level. However, because Hansen's test has very little power in presence of many instruments, and given the validity of the AR(1) and AR(2) tests, we can conclude that the model is well specified.

Column 1 presents SYS-GMM regression results when the total CAP subsidy rate is included. Columns 2 to 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” and the five components of Pillar II (Columns 3 and 4). Key results are the following.

The total CAP subsidy rate (Column 1 of Tables 2-4) 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.

Pillar I subsidies have a significant positive effect on agricultural labour productivity growth in the EU-27 and the OMS, but not in the NMS. This effect is entirely due to decoupled Pillar I subsidies. The estimated effect is significant and positive for the EU-27 and OMS, but not in the NMS while coupled Pillar I subsidies have no significant effect for the EU-27 as a whole, or the OMS and NMS separately. For the EU-27 and OMS the estimated coefficient of decoupled payments is higher than for total Pillar I payments with coupled payments having a negative (but insignificant) estimated coefficient.

The finding that decoupled Pillar I subsidies have a positive effect on agricultural labour productivity growth in the EU-27 and OMS is consistent with findings of Rizov et al. (2013) and Kazukauskas et al. (2014). These authors conclude that this is caused by increased specialization in more efficient farming activities. As argued before, a possible explanation is that decoupled payments, rather than coupled payments, may help reduce credit constraints and risk aversion of farmers, allowing them to make more productive investment decisions. However, the lack of a significant effect of any form of Pillar I spending in NMS is inconsistent with the argument that market imperfections and credit-enhancing effects of subsidies are more prevalent in the NMS (Ciaian and Swinnen, 2009).

The estimated coefficients of total Pillar II payments are always positive but only significant for EU-27 and for OMS in one specification (Column 3). The estimate effects of the different components of Pillar II payments show some different effects for OMS and NMS.

Only for Pillar II spending on physical capital (PK) is the effect positive and significant in both OMS and NMS (and EU-27 as a whole), suggesting that these payments lead to investment-induced productivity gains. The coefficients of investments in human capital (HK) are also positive for all regions, but the effect is only significant for the EU-27 as a whole.

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 negative in the OMS, a result that is in line with earlier empirical findings documenting higher efficiency losses associated with these types of payments (Lakner, 2009; Mary, 2013). In contrast, we find that LFA payments have a positive and significant coefficients in the NMS. We also find a positive effect of agri-environmental payments (ENV) in the NMS and no significant impact in the OMS. Wider Pillar II rural development (RD) payments have no effect in the EU-27 and OMS, but they have a negative and significant effect in the NMS.

The results show evidence of convergence of productivity among regions.²⁸ The convergence effect is captured by the estimated coefficient of the (lagged) agricultural VA per worker. The coefficient is negative and significant in all three regional specifications (EU-27, OMS and NMS). Convergence differs across these regions. The implied rate of estimated convergence is quite high. It is around 5% for the EU-27 and between 6% and 12% within the OMS and NMS (Columns 1-4 of Tables 2-4).

Finally, with regard to the control variables, labour force growth and population density are not significant in the EU-27.²⁹ There is a negative and significant coefficient for ESIF spending in most regression specifications. If ESIF support has spill-over effects on the

²⁸ For comparison and completeness, we also estimated “absolute” convergence following Solow’s (1956) growth framework. The results are in Table A.1 in Appendix A. Both pooled OLS and SYS-GMM estimates show the presence of *absolute* convergence for all three regional specifications (EU-27, OMS and NMS).

²⁹ The effect of labour force growth is positive and significant in two specifications in NMS (Columns 2 and 3 of Table 4). This result might capture the competition effect between agricultural and non-agricultural sectors induced by regional employment growth (with general economic growth) which may cause an outflow of labour from agriculture. Replacement of workers with capital inputs may lead to a higher agricultural labour productivity.

agricultural sector, for example through technology transfer and better infrastructure, this could stimulate agricultural labour productivity growth. If, on the other hand, ESIF expenditures are negatively associated with agricultural labour productivity due to a competition effect with EU agricultural subsidies (as ESIF expenditures are typically for non-agricultural sectors), a higher ESIF support may lead to a higher growth of these sectors leading to competition for resources with the agricultural sector. The negative effect suggests that the “competition effect” is stronger than the “spill-over effect”.³⁰

5. Robustness checks

5.1 Endogeneity

With time and regional fixed effects included our baseline results discussed so far should be quite immune from endogeneity bias due to selection and omitted variables bias. However, the estimated relationship between agricultural productivity growth and CAP payments may still be affected by simultaneity bias, as CAP payments are not assigned randomly to farmers (or regions). This additional endogeneity issue is, in principle, particularly relevant for Pillar I payments, both coupled and decoupled. Past productivity of farms and regions affected the allocation of coupled Pillar I payments. The relationship between productivity and decoupled payments may also be subject to endogeneity. While decoupled Pillar I payments are not linked to current regional production activities, the allocation of these payments among MS was agreed to be based on the average coupled payments received in the reference period (2000-2002), before decoupling was introduced with the 2003 CAP reforms.³¹ This implies that regions that

³⁰ Additional regression specification where the ESIF variable is excluded as robustness check show that the effect of agricultural subsidies is robust to this change in specification (see Appendix B for these results.)

³¹ This aspect is particularly relevant for the OMS, which already received CAP support before the 2003 reforms. However, similar holds for the decoupled support system for NMS, i.e. the *Single Area Payment Scheme* (SAPS). The SAPS was not based on farm productivities directly, yet it was linked to the pre-accession average country/regional productivities of the NMS (Ciaian et al. 2015).

were more productive and/or produced more subsidized output in the past receive higher decoupled payments today (and in the period of our analysis).

While this (potential) 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 labour productivity in a recent period (2004-2014) and not productivity levels, it is not obvious that the relationship between this growth variable and the change in the allocation of current coupled/decoupled payments could be affected by a potential endogeneity coming from yield levels of more than ten years earlier. In other words, this endogeneity bias seems a more serious issue when it is related to productivity levels rather than changes (as in our analysis). Second, our convergence model specification already controls for these differences in past productivities, as the high CAP recipients are expected to be at a different point on the convergence curve, i.e. we should expect that they will have less potential to grow.

Third, as discussed in Garrone et al. (2018) and Olper et al. (2014), 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 MS) are decided by EU authorities rather than by regional authorities (Pillar I) or through negotiations between EU and national authorities (Pillar II).³² To further control for this, all the CAP variables are lagged by 1 year, which would reduce a potential bias caused by a spurious correlation due to shocks simultaneously affecting CAP payments and agricultural output.

Despite these arguments, which suggest that this endogeneity bias is limited in our econometric analysis, we still perform a robustness check to test potential endogeneity of these variables. We use the SYS-GMM estimator but now the coupled and decoupled Pillar I

³² More specifically, the CAP is financed by two funds: the *European Agricultural Guarantee Fund* (EAGF) and *European Agricultural Fund for Rural Development* (EAFRD), and up until financial year 2006 the *European Agricultural Guarantee and Guidance Fund* (EAGGF).

payment variables are also treated as endogenous, using the t-2, t-3 and longer lag levels (and differences) as instruments. This strategy should shed further light on the robustness of our findings to this bias or other forms of endogeneity.

The results of the three regional specifications are presented in Table 5. Statistics of consistency tests of the SYS-GMM estimators are reported at the bottom of the table. The Arellano-Bond tests AR(1) and AR(2) indicate that the dynamic model is correctly specified. The p-value of the Hansen's test statistic is higher than the p-values reported in the previous tables, where the policy variables are treated as exogenous (Tables 2-4), and confirms the joint validity of our instruments.

The results show that the estimation of the Pillar I effects are robust to this alternative specification and if anything reinforce our key findings. The estimated coefficients on the coupled Pillar I payments are negative in all specifications (as before) but for one of the OMS specifications the effect is now significantly negative (Column 4 of Table 5). The effect is not significant in all other specifications -- as in our main models. Decoupled Pillar I payments have a significant positive effect in the EU-27 and OMS, as before, and the magnitude of the estimated coefficient is close to that in the model where coupled and decoupled Pillar I payments are treated as exogenous. The only significant difference is that in one specification of the NMS decoupled Pillar I payments is now also positive and significant (Column 5 in Table 5).³³

³³ The Pillar II payment coefficients are consistent in terms of sign, significance and magnitude as in the previous estimations in all three regional specifications. The picture of the effects on agricultural productivity growth changes when we split the effect of Pillar II payments in its different components. The coefficients of investments in physical capital are insignificant in EU-27 and NMS, but it is still significant and positive in OMS, as expected. The coefficients of investment in human capital are now positive and is significant for all three regional specifications. In the OMS, both agro-environmental measures and LFA payments are significant and negative (Column 4 of Table 5), confirming productivity loss associated to these type of support for this regional specification. In the NMS, LFA payments are positive but no longer significant (Column 6 of Table 5). For the convergence variable, the estimated coefficient is negative and significant in most specifications, except for one specification in OMS and NMS (Columns 3 and 6 of Table 5).

5.2 *Additional controls*

As a further robustness check, we add additional covariates to control for regional economic conditions, farm structures and production structure. Specifically, we include GDP growth rate, share of large farms in total land and share of grassland in total land as additional control variables in our regression specifications. All of these variables might affect agricultural labour productivity because they might, among others, imply different labour intensity in production or differences in agricultural productivities.³⁴

Table 6 summarizes key regression results for the EU-27, OMS and NMS (with more results in Appendix C). The results of these alternative specifications show that the key results are largely robust to these changes. The estimated effects of the coupled Pillar I payments and decoupled Pillar I payments are also robust to these variations in the regression specification. Coupled Pillar I payments are found to have no impact on agricultural labour productivity growth, while decoupled payments are consistently found to have a positive and significant impact on agricultural labour productivity growth in the EU-27 and OMS (Columns 1-4 of table 6). With inclusion of these additional controls, the impact of decoupled payments is now also significant (positive) in NMS in one specification (Column 5 of Table 6).

The estimated effects of all Pillar II components are very similar for the EU-27. For OMS, the coefficients on human capital (HK) investments and agri-environmental (ENV) measures are slightly higher and therefore significant (Column 4).

Overall, our robustness tests show that the estimated effects of the subsidy variables on agricultural productivity are robust. If anything, they reinforce the estimated effects.

³⁴ We did not include more controls because their inclusion makes our dynamic panel specification not correctly specified, as AR (2) test systematically rejects the null hypothesis and standard Hansen test of over-identifying restrictions systematically suggests that the model is not well specified.

6. Economic Size of the Effects of CAP Subsidies and Decoupling

We can now use our regression results to estimate the magnitude of the policy coefficients. The estimated coefficients represent marginal effects. According to the estimated coefficient in Column 1 of Table 2, a marginal increase of 1 percentage point in the “total CAP subsidy rate” variable leads to an increase of the dependent variable of 0.062 percentage point. At the average level of the CAP subsidy rate (34.20%, see Table 1) and agricultural labour productivity growth rate (1.20%) in the EU-27, a 1% increase in the subsidy rate in the EU as a whole would lead to an increase in productivity growth by 1.77%,³⁵ meaning that the EU annual agricultural productivity growth rate would increase from 1.20% to 1.22%.

We can also use our estimates to quantify the effect of decoupling in terms of annual gain in agricultural labour productivity. According to the regression coefficients reported in Column 3 of Table 2, a 1 percentage point shift of CAP subsidies from Pillar I coupled subsidies to Pillar I decoupled subsidies, would result in a net marginal increase of 0.109 (=0.089+0.020) percentage point in labour agricultural growth rate. At the average level of the Pillar I decoupled subsidy rate (16.40%, see Table 1) and the agricultural labour productivity growth rate in our sample, a 1% increase in the Pillar I decoupled subsidy rate would increase the average agricultural labour productivity growth rate by 1.49%, meaning that agricultural labour productivity growth rate would increase to from 1.20 % to 1.22%.

³⁵ These calculation is done by computing the elasticities at the sample mean using the following formula:

$$\varepsilon_{y/s} = \frac{dy/y}{ds/s} = \frac{d \ln(y)}{d \ln(s)} = \beta \frac{\bar{s}}{\bar{y}}$$

where \bar{s} refers to the estimated sample mean of the total CAP payment rate; \bar{y} refers to the estimated sample mean of our dependent variables (i.e. agricultural labor productivity growth) (see Table 1); β is the estimated marginal effect of the total CAP payment rate on our dependent variables (see Table 2).

7. Conclusions

This paper estimates the impact of CAP subsidies on EU agricultural labour productivity within a conditional growth convergence framework. We estimate a dynamic model using the SYS-GMM estimator. We use an EU-wide panel dataset covering 213 regions and the 2004–2014 period, and CATS data with detailed information on CAP payments to farms.

We find that CAP subsidies, as a whole, have a positive impact on labour productivity in EU-27 agriculture, but this positive effect is entirely due to decoupled subsidies. If anything, coupled subsidies have the opposite effect, but this is mostly not significant.

In the OMS, the positive effect from subsidies on labour productivity is only due to non-distortionary payments, i.e. Pillar I decoupled payments and Pillar II components related to human and physical capital investments.

In the NMS, the overall CAP effect is positive but we find no significant effect when separating coupled and decoupled Pillar I payments in the regressions. In NMS Pillar II spending on physical capital investments, agri-environmental measures and LFA payments is significantly positively correlated with agricultural labour productivity growth.

A series of robustness tests include a SYS-GMM specification where coupled and decoupled payments are treated as endogenous variables to address the issue of potential endogeneity bias related to agricultural subsidies. We also include a number of additional controls, which may also affect agricultural labour productivity.

These robustness tests show that alternative specifications yield results which are consistent with our key findings. In some alternative specifications the estimated negative effects of coupled Pillar I payments are significant in OMS (reinforcing the general conclusions) and the estimated effects of decoupled Pillar I payments are significant in NMS (also reinforcing the general conclusions).

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 good for agricultural labour productivity. While coupled Pillar I payments have a negative effect (which is significant in some regressions and not in others), decoupled payments are generally associated with increases in agricultural labour productivity growth. This is consistent with earlier findings and arguments that by breaking the link between support and production, agricultural subsidies can allow farmers to shift farming activities (e.g. to production with higher value added), so are less likely to cause inefficiency (Dewbre et al., 2001; Guyomard et al., 2004; Rizov et al., 2013). This is also in line with previous research documenting increased agricultural productivity in the EU with the shift from “coupled” to “decoupled” subsidies (Rizov et al., 2013; Mary, 2013; Kazukauskas et al., 2014).

A final caveat is that our results do not necessarily imply that even the decoupled payments are an efficient policy instrument to stimulate productivity growth in EU agriculture. Our analysis only analyses 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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Table 1: Descriptive Statistics

Variables	Description	EU-27		OMS		NMS	
		Obs.	Mean	Obs.	Mean	Obs.	Mean
Total CAP payments/VA	Subsidy rate	1,980	0.342	1,530	0.337	450	0.362
Pillar I payments/VA		1,980	0.259	1,530	0.274	450	0.211
Pillar II payments/VA		1,980	0.089	1,530	0.063	450	0.151
Pillar I coupled payments/VA		1,980	0.095	1,530	0.117	450	0.020
Pillar I decoupled payments/VA		1,980	0.164	1,530	0.156	450	0.192
Pillar II HK/VA		1,980	0.009	1,530	0.006	450	0.019
Pillar II PK/VA		1,980	0.014	1,530	0.010	450	0.030
Pillar II ENV/VA		1,980	0.025	1,530	0.023	450	0.032
Pillar II LFA/VA		1,980	0.015	1,530	0.012	450	0.024
Pillar II RD/VA		1,980	0.015	1,530	0.010	450	0.031
Agricultural productivity growth		Growth rate of VA-Agr. per worker	1,980	0.012	1,530	0.007	450
Employment growth	Growth rate of employment	1,980	0.003	1,530	0.003	450	0.002
Population density	1,000 person/km ²	1,980	0.287	1,530	0.314	450	0.195
European Structural and Investment Funds	ESIF payments/regional GDP	1,980	0.010	1,530	0.005	450	0.026
GDP growth	Annual growth rate of regional GDP	1,971	0.008	1,521	0.005	450	0.019
Large farm	Share of large farms in total land and	1,971	0.722	1,521	0.743	450	0.650
Share of grass land	Share of grassland in total land	1,971	0.343	1,521	0.373	450	0.250

Note: *European Structural and Investment Funds* (ESIF) include: *European Regional Development Fund* (ERDF), *Cohesion Fund* (CF) and *European Social Fund* (ESF). Source: CATS database provided by the European Commission, CERD, DG REGIO.

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

Dependent Variable: Δ VA-Agr. per worker	(1) SYS-GMM Exogenous	(2) SYS-GMM Exogenous	(3) SYS-GMM Exogenous	(4) SYS-GMM Exogenous	(5) OLS	(6) FE
Total CAP subsidy rate (t-1)	0.062*** (3.85)				0.016 (0.83)	-0.010 (0.41)
Pillar I total (t-1)		0.063*** (2.80)				
Pillar I coupled (t-1)			-0.020 (0.88)	-0.025 (0.99)		
Pillar I decoupled (t-1)			0.089*** (13.31)	0.110*** (6.49)		
Pillar II total (t-1)		0.051 (1.32)	0.085** (2.27)			
Pillar II HK (t-1)				0.492*** (2.70)		
Pillar II PK (t-1)				0.196** (2.58)		
Pillar II ENV (t-1)				-0.243 (0.79)		
Pillar II LFA (t-1)				-0.088 (0.29)		
Pillar II RD (t-1)				0.045 (0.20)		
VA-Agr. per worker (t-1)	-0.047*** (6.81)	-0.060*** (3.60)	-0.044*** (3.31)	-0.043*** (3.31)	-0.022*** (4.24)	-0.447*** (12.36)
Labour force growth (t-1)	0.006 (0.74)	0.006 (0.74)	0.007 (0.79)	0.009 (1.09)	-0.002 (0.29)	-0.002 (0.23)
Population density (t-1)	-0.001 (0.34)	-0.001 (0.20)	0.002 (0.39)	-0.002 (0.59)	0.001 (0.21)	0.187 (0.68)
ESIF payments (t-1)	-1.815*** (3.96)	-2.265*** (3.01)	-1.688*** (2.61)	-1.695*** (2.69)	-0.717** (2.22)	0.651 (1.14)
Speed of convergence	0.048	0.062	0.045	0.044	0.022	0.592
R ² (within)					0.057	0.263
No. of Observations	1980	1980	1980	1980	1980	1980
No. of Instruments	211	210	211	212		
AR (1) p-value	0.000	0.000	0.000	0.000		
AR (2) p-value	0.861	0.881	0.343	0.352		
Hansen J-Stat. p-value	0.072	0.071	0.066	0.063		

Notes: OLS regression includes time fixed effects; LSDV regression includes region and time fixed effects; SYS-GMM regressions include time fixed effect and Pillar I payments are treated as exogenous. AR (n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; Hansen is the over-identification test for the instruments in the first difference equation. Absolute t statistics based on clustered standard error by region in parentheses. * p<0.10, ** p<0.05, *** p<0.01

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

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
Δ VA-Agr. per worker	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM	OLS	FE
	Exogenous	Exogenous	Exogenous	Exogenous		
Total CAP subsidy rate (t-1)	0.053*** (3.61)				0.013 (0.69)	-0.008 (0.34)
Pillar I total (t-1)		0.051** (2.46)				
Pillar I coupled (t-1)			-0.022 (0.93)	-0.027 (1.10)		
Pillar I decoupled (t-1)			0.079*** (10.13)	0.121*** (7.81)		
Pillar II total (t-1)		0.039 (1.00)	0.085** (2.32)			
Pillar II HK (t-1)				0.346 (1.59)		
Pillar II PK (t-1)				0.334*** (3.30)		
Pillar II ENV (t-1)				-0.440 (1.65)		
Pillar II LFA (t-1)				-0.962*** (3.16)		
Pillar II RD (t-1)				0.246 (0.84)		
VA-Agr. per worker (t-1)	-0.071*** (3.92)	-0.096*** (3.16)	-0.056* (1.93)	-0.102*** (3.43)	-0.022** (2.10)	-0.397*** (10.33)
Labour force growth (t-1)	-0.012 (1.23)	-0.012 (1.28)	-0.011 (1.25)	-0.009 (0.97)	-0.019** (2.34)	-0.012* (1.67)
Population density (t-1)	0.002 (0.41)	0.002 (0.45)	0.005 (1.16)	-0.009* (1.71)	0.004 (0.81)	0.193 (0.66)
ESIF payments (t-1)	-2.326** (2.45)	-2.977** (2.36)	-1.736 (1.59)	-3.273** (2.48)	-1.165** (2.43)	-0.829 (0.83)
Speed of convergence	0.074	0.101	0.058	0.108	0.022	0.506
R ² (within)					0.039	0.214
No. of Observations	1530	1530	1530	1530	1530	1530
No. of Instruments	157	155	157	158		
AR (1) p-value	0.000	0.000	0.000	0.000		
AR (2) p-value	0.894	0.867	0.601	0.674		
Hansen J-Stat. p-value	0.067	0.063	0.067	0.098		

Notes: OLS regression includes time fixed effects; LSDV regression includes region and time fixed effects; SYS-GMM regressions include time fixed effect and Pillar I payments are treated as exogenous. AR (n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; Hansen is the over-identification test for the instruments in the first difference equation. Absolute t statistics based on clustered standard error by region in parentheses. * p<0.10, ** p<0.05, *** p<0.01

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

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
Δ VA-Agr per worker	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM	OLS	FE
	Exogenous	Exogenous	Exogenous	Exogenous		
Total CAP subsidy rate (t-1)	0.191*** (3.07)				0.057 (1.09)	-0.075 (0.72)
Pillar I total (t-1)		0.175 (1.29)				
Pillar I coupled (t-1)			-0.409 (0.96)	-0.189 (0.49)		
Pillar I decoupled (t-1)			0.268 (1.56)	0.216 (1.23)		
Pillar II total (t-1)		0.183 (1.67)	0.175 (1.52)			
Pillar II HK (t-1)				0.433 (0.61)		
Pillar II PK (t-1)				0.192* (1.85)		
Pillar II ENV (t-1)				1.364*** (2.72)		
Pillar II LFA (t-1)				1.509*** (2.68)		
Pillar II RD (t-1)				-0.780*** (3.56)		
VA-Agr. per worker (t-1)	-0.049*** (3.33)	-0.108*** (3.15)	-0.118*** (3.36)	-0.081** (2.55)	-0.020** (2.28)	-0.655*** (12.43)
Labour force growth (t-1)	0.035 (1.38)	0.038** (2.03)	0.035* (1.88)	0.028 (1.39)	0.025* (1.95)	0.002 (0.13)
Population density (t-1)	-0.019 (0.97)	0.004 (0.14)	0.009 (0.30)	-0.010 (0.36)	-0.021 (1.41)	-0.653 (1.55)
ESIF payments (t-1)	-1.266 (1.12)	-1.240 (0.94)	-1.349 (0.97)	-2.533* (1.99)	-0.537 (0.73)	-1.025 (0.79)
Speed of convergence	0.050	0.114	0.126	0.084	0.020	1.064
R ² (within)					0.182	0.477
No. of Observations	450	450	450	450	450	450
No. of Instruments	53	55	55	54		
AR (1) p-value	0.000	0.000	0.000	0.000		
AR (2) p-value	0.217	0.263	0.383	0.341		
Hansen J-Stat. p-value	0.090	0.064	0.062	0.082		

Notes: OLS regression includes time fixed effects; LSDV regression includes region and time fixed effects; SYS-GMM regressions include time fixed effect and Pillar I payments are treated as exogenous. AR (n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; Hansen is the over-identification test for the instruments in the first difference equation. Absolute t statistics based on clustered standard error by region in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 5: Convergence regressions for agricultural productivity – Pillar I endogenous

Dependent Variable: Δ VA-Agr per worker	EU-27 (213 regions)		OMS (158 regions)		NMS (55 regions)	
	(1)	(2)	(3)	(4)	(5)	(6)
	SYS-GMM Endogenous	SYS-GMM Endogenous	SYS-GMM Endogenous	SYS-GMM Endogenous	SYS-GMM Endogenous	SYS-GMM Endogenous
Pillar I coupled (t-1)	-0.026 (1.08)	-0.021 (0.87)	-0.020 (1.37)	-0.027* (1.81)	-0.243 (0.69)	-1.549 (1.27)
Pillar I decoupled (t-1)	0.089*** (11.46)	0.105*** (7.18)	0.082*** (5.51)	0.123*** (7.84)	0.339** (2.45)	0.447 (1.55)
Pillar II total (t-1)	0.092*** (2.69)		0.097*** (2.80)		0.004 (0.07)	
Pillar II HK (t-1)		0.529*** (3.08)		0.366* (1.67)		1.420** (2.41)
Pillar II PK (t-1)		0.097 (1.38)		0.288** (2.50)		0.072 (0.79)
Pillar II ENV (t-1))		-0.271 (0.92)		-0.495* (1.95)		0.296 (0.40)
Pillar II LFA (t-1)		0.023 (0.07)		-0.610* (1.91)		0.884 (1.27)
Pillar II RD (t-1)		0.077 (0.44)		0.292 (1.04)		-0.099 (0.32)
VA-Agr. per worker (t-1)	-0.033*** (3.47)	-0.032*** (3.37)	-0.029 (0.89)	-0.073* (1.88)	-0.056* (1.82)	0.042 (1.27)
Labour force growth (t-1)	0.008 (0.90)	0.011 (1.35)	-0.013 (1.47)	-0.009 (1.03)	0.031** (2.23)	0.038** (2.03)
Population density (t-1)	0.001 (0.31)	-0.002 (0.61)	0.005 (1.24)	-0.007 (1.50)	-0.009 (0.46)	-0.045** (2.64)
ESIF payments (t-1)	-1.236*** (2.60)	-1.192*** (2.63)	-0.978 (1.01)	-2.340* (1.73)	-1.624** (2.12)	-2.470* (1.68)
No. of Observations	1980	1980	1530	1530	450	450
No. of Instruments	211	212	158	158	53	53
AR (1) p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR (2) p-value	0.309	0.388	0.574	0.645	0.191	0.418
Hansen J-Stat. p-value	0.102	0.160	0.129	0.129	0.193	0.114

Notes: SYS-GMM regressions include time fixed effect and coupled Pillar I payments and decoupled Pillar I payments are treated as endogenous. AR (n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; Hansen is the over-identification test for the instruments in the first difference equation. Absolute t statistics based on clustered standard error by region in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 6: Convergence regressions for agricultural productivity - additional controls

Dependent Variable: Δ VA-Agr. per worker	EU-27 (213 regions)		OMS (158 regions)		NMS (55 regions)	
	(1)	(2)	(3)	(4)	(5)	(6)
	SYS-GMM Exogenous	SYS-GMM Exogenous	SYS-GMM Exogenous	SYS-GMM Exogenous	SYS-GMM Exogenous	SYS-GMM Exogenous
Pillar I coupled (t-1)	-0.029 (1.34)	-0.023 (1.06)	-0.039 (1.22)	-0.029 (1.13)	-0.736 (1.51)	-0.208 (0.40)
Pillar I decoupled (t-1)	0.092*** (11.20)	0.109*** (6.88)	0.104*** (8.18)	0.122*** (7.52)	0.380* (2.00)	-0.127 (0.47)
Pillar II total (t-1)	0.129*** (2.73)		0.179** (2.00)		0.194** (2.29)	
Pillar II HK (t-1)		0.571*** (4.15)		0.405** (1.99)		1.027* (1.86)
Pillar II PK (t-1)		0.202*** (2.82)		0.343*** (4.36)		0.293** (2.42)
Pillar II ENV (t-1)		-0.323 (1.08)		-0.478* (1.71)		1.140* (1.74)
Pillar II LFA (t-1)		0.164 (0.57)		-0.498* (1.73)		2.574*** (4.59)
Pillar II RD (t-1)		0.028 (0.13)		0.209 (0.69)		-0.548* (1.88)
VA-Agr. per worker (t-1)	-0.013 (0.59)	-0.034* (1.72)	0.057 (0.66)	-0.067** (2.22)	0.003 (0.10)	-0.079 (1.66)
Labour force growth (t-1)	0.018* (1.94)	0.021** (2.35)	-0.004 (0.42)	-0.008 (0.78)	0.027 (1.54)	0.027 (1.34)
Population density (t-1)	0.001 (0.22)	-0.003 (0.74)	0.007 (1.61)	-0.007 (1.62)	-0.031 (1.67)	-0.005 (0.15)
ESIF payments (t-1)	-0.806 (1.19)	-1.318* (1.82)	0.587 (0.33)	-2.070* (1.76)	-1.810* (1.80)	-1.205 (0.91)
GDP growth (t-1)	-0.432** (2.30)	-0.476*** (2.60)	-0.232 (0.88)	-0.083 (0.36)	-1.032*** (3.02)	-0.935** (2.53)
Share of large farms (t-1)	-0.021 (0.41)	0.029 (0.86)	-0.091 (1.15)	0.031 (0.81)	-0.067 (1.03)	0.147 (1.34)
Grass land ratio	-0.042* (1.81)	-0.030 (1.31)	-0.022 (1.12)	-0.028 (0.94)	-0.032 (0.49)	-0.209** (2.26)
No. of Observations	1971	1971	1521	1521	450	450
No. of Instruments	208	212	154	158	53	52
AR (1) p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR (2) p-value	0.190	0.246	0.386	0.567	0.208	0.267
Hansen J-Stat. p-value	0.052	0.059	0.096	0.083	0.166	0.094

Notes: OLS regression includes time fixed effects; LSDV regression includes region and time fixed effects; SYS-GMM regressions include time fixed effect and Pillar I payments are treated as exogenous. AR (n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; Hansen is the over-identification test for the instruments in the first difference equation. Absolute t statistics based on clustered standard error by region in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Appendix A: Absolute Convergence

Table A.1: Absolute convergence in agricultural value added per worker across EU regions

Dependent Variable:	OLS		
Δ VA-Agr. per worker	EU-27	OMS	NMS
	(1)	(2)	(3)
VA-Agr. per worker (t-1)	-0.019*** (6.00)	-0.016** (2.42)	-0.032*** (3.51)
R ²	0.011	0.003	0.022
No. of Observations	1,980	1,530	450

Notes: the absolute convergence is estimated by regressing the level of agricultural value added per worker of the previous year on the current year's growth rate of the agricultural value added over: $\Delta y_{it} = \alpha + \beta \ln Y_{it-1} + \varepsilon_{it}$, where $\Delta y_{it} = \ln Y_{it} - \ln Y_{it-1}$, denotes region i 's agricultural labour productivity growth between t and $t-1$; Y_{it-1} is the lagged agricultural VA per worker, i.e. the convergence variable. For the SYS-GMM, AR (n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; Hansen is the over-identification test for the instruments in the first difference equation. Absolute t statistics based on clustered standard error by region in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Appendix B: Robustness check with the exclusion of ESIF variable

Table B.1: Convergence regressions for agricultural productivity in EU-27 (213 regions)

Dependent Variable:	(1)	(2)	(3)	(4)
Δ VA-Agr. per worker	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM
Total CAP subsidy rate (t-1)	0.062*** (3.59)			
Pillar I total (t-1)		0.064*** (2.67)		
Pillar I coupled (t-1)			-0.022 (1.02)	-0.027 (1.11)
Pillar I decoupled (t-1)			0.092*** (13.17)	0.111*** (6.32)
Pillar II total (t-1)		0.039 (0.84)	0.074* (1.76)	
Pillar II HK (t-1)				0.478** (2.50)
Pillar II PK (t-1)				0.170** (2.05)
Pillar II ENV (t-1)				-0.228 (0.73)
Pillar II LFA (t-1)				-0.114 (0.35)
Pillar II RD (t-1)				0.029 (0.13)
VA-Agr. per worker (t-1)	-0.032*** (6.40)	-0.045*** (3.48)	-0.034*** (3.25)	-0.034*** (3.12)
Labour force growth (t-1)	0.009 (1.02)	0.009 (1.08)	0.009 (1.04)	0.012 (1.39)
Population density (t-1)	0.002 (0.61)	0.004 (0.92)	0.006 (1.25)	0.002 (0.47)
No. of Observations	1980	1980	1980	1980
No. of Instruments	210	210	211	209
AR (1) p-value	0.000	0.000	0.000	0.000
AR (2) p-value	0.871	0.915	0.360	0.366
Hansen J. -Stat p-value	0.077	0.081	0.076	0.064

Notes: OLS regression includes time fixed effects; LSDV regression includes region and time fixed effects; System GMM regressions include time fixed effect. AR (n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; Hansen is the over-identification test for the instruments in the first difference equation. Absolute statistics based on clustered standard error by region in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B.2: Convergence regressions for agricultural productivity in OMS (158 regions)

Dependent Variable:	(1)	(2)	(3)	(4)
Δ VA-Agr per worker	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM
Total CAP subsidy rate (t-1)	0.057*** (3.63)			
Pillar I total (t-1)		0.053** (2.37)		
Pillar I coupled (t-1)			-0.026 (1.13)	-0.034 (1.43)
Pillar I decoupled (t-1)			0.083*** (11.36)	0.121*** (7.48)
Pillar II total (t-1)		0.053* (1.67)	0.097*** (3.10)	
Pillar II HK (t-1)				0.271 (1.24)
Pillar II PK (t-1)				0.328*** (3.28)
Pillar II ENV (t-1)				-0.395 (1.29)
Pillar II LFA (t-1)				-0.708** (2.15)
Pillar II RD (t-1)				0.310 (1.04)
VA-Agr. per worker (t-1)	-0.051*** (3.51)	-0.067** (2.37)	-0.037 (1.46)	-0.069*** (2.68)
Labour force growth (t-1)	-0.005 (0.52)	-0.004 (0.43)	-0.007 (0.73)	0.001 (0.12)
Population density (t-1)	0.005 (1.22)	0.006 (1.34)	0.007* (1.75)	-0.002 (0.48)
No. of Observations	1530	1530	1530	1530
No. of Instruments	156	156	157	154
AR (1) p-value	0.000	0.000	0.000	0.000
AR (2) p-value	0.898	0.889	0.535	0.551
Hansen J. -Stat p-value	0.077	0.073	0.075	0.055

Notes: OLS regression includes time fixed effects; LSDV regression includes region and time fixed effects; System GMM regressions include time fixed effect. AR (n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; Hansen is the over-identification test for the instruments in the first difference equation. Absolute statistics based on clustered standard error by region in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B.3: Convergence regressions for agricultural productivity in NMS (55 regions)

Dependent Variable:	(1)	(2)	(3)	(4)
Δ VA-Agr per worker	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM
Total CAP subsidy rate (t-1)	0.179*** (3.00)			
Pillar I total (t-1)		0.127 (0.92)		
Pillar I coupled (t-1)			-0.408 (1.01)	-0.209 (0.59)
Pillar I decoupled (t-1)			0.217 (1.21)	0.143 (0.87)
Pillar II total (t-1)		0.181 (1.59)	0.168 (1.43)	
Pillar II HK (t-1)				0.323 (0.46)
Pillar II PK (t-1)				0.192* (1.83)
Pillar II ENV (t-1)				1.003** (2.22)
Pillar II LFA (t-1)				1.713*** (3.18)
Pillar II RD (t-1)				-0.700*** (3.03)
VA-Agr. per worker (t-1)	-0.049*** (3.22)	-0.113*** (3.09)	-0.121*** (3.13)	-0.073** (2.19)
Labour force growth (t-1)	0.033 (1.38)	0.037* (2.00)	0.036* (1.93)	0.030 (1.54)
Population density (t-1)	-0.011 (0.69)	0.013 (0.51)	0.018 (0.69)	0.004 (0.16)
No. of Observations	450	450	450	450
No. of Instruments	52	53	54	53
AR (1) p-value	0.000	0.000	0.000	0.000
AR (2) p-value	0.219	0.290	0.402	0.355
Hansen J-Stat. p-value	0.109	0.064	0.061	0.092

Notes: OLS regression includes time fixed effects; LSDV regression includes region and time fixed effects; System GMM regressions include time fixed effect. AR (n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; Hansen is the over-identification test for the instruments in the first difference equation. Absolute statistics based on clustered standard error by region in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Appendix C: Robustness check with additional controls

Table C.1: Convergence regressions for agricultural productivity in EU-27 (213 regions) - additional controls

Dependent Variable:	(1)	(42)	(3)	(4)
Δ VA-Agr per worker	SYS-GMM	SYS-GMM	OLS	FE
	Exogenous	Exogenous		
Total CAP subsidy rate (t-1)	0.060*** (4.87)		0.016 (0.78)	0.013 (0.69)
Pillar I total (t-1)		0.061*** (2.90)		
Pillar II total (t-1)		0.080 (1.63)		
VA-Agr. per worker (t-1)	-0.055*** (6.61)	-0.034 (1.50)	-0.026*** (4.03)	-0.447*** (12.97)
Labour force growth (t-1)	0.018** (2.12)	0.018** (2.00)	0.002 (0.25)	-0.002 (0.26)
Population density (t-1)	-0.002 (0.55)	-0.002 (0.52)	0.001 (0.14)	0.128 (0.48)
ESIF payments (t-1)	-1.915*** (3.69)	-1.317* (1.77)	-0.776** (2.41)	0.417 (0.75)
GDP growth (t-1)	-0.509*** (2.70)	-0.473** (2.57)	-0.223 (1.20)	-0.025 (0.17)
Share of large farms (t-1)	0.031 (0.74)	0.006 (0.12)	0.018 (0.74)	-0.122*** (4.84)
Grass land ratio	-0.038 (1.42)	-0.039 (1.65)	-0.034* (1.82)	0.093 (0.69)
R ² (within)			0.061	0.270
No. of Observations	1971	1971	1971	1971
No. of Instruments	207	207		
AR (1) p-value	0.000	0.000		
AR (2) p-value	0.726	0.737		
Hansen J-Stat. p-value	0.062	0.055		

Notes: OLS regression includes time fixed effects; LSDV regression includes region and time fixed effects; SYS-GMM regressions include time fixed effect and Pillar I payments are treated as exogenous. AR (n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; Hansen is the over-identification test for the instruments in the first difference equation. Absolute t statistics based on clustered standard error by region in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table C.2: Convergence regressions for agricultural productivity in OMS (158 regions) - additional controls

Dependent Variable: Δ VA-Agr per worker	(1) SYS-GMM Exogenous	(2) SYS-GMM Exogenous	(3) OLS	(4) FE
Total CAP subsidy rate (t-1)	0.053*** (4.02)		0.013 (0.60)	0.015 (0.76)
Pillar I total (t-1)		0.059*** (2.78)		
Pillar II total (t-1)		0.066 (1.18)		
VA-Agr. per worker (t-1)	-0.082*** (4.36)	-0.043 (1.65)	-0.029** (2.32)	-0.401*** (10.80)
Labour force growth (t-1)	-0.008 (0.79)	-0.008 (0.75)	-0.019** (2.06)	-0.016* (1.92)
Population density (t-1)	0.000 (0.05)	0.001 (0.26)	0.004 (0.75)	0.143 (0.49)
ESIF payments (t-1)	-2.437** (2.15)	-1.682* (1.66)	-1.207** (2.48)	-1.151 (1.10)
GDP growth (t-1)	-0.176 (0.78)	-0.193 (0.83)	0.004 (0.02)	0.170 (0.91)
Share of large farms (t-1)	0.028 (0.46)	0.001 (0.01)	0.010 (0.31)	-0.131*** (6.87)
Grass land ratio	-0.062** (1.98)	-0.046* (1.68)	-0.039** (2.08)	0.146 (1.24)
R ² (within)			0.043	0.226
No. of Observations	1521	1521	1521	1521
No. of Instruments	154	154		
AR (1) p-value	0.000	0.000		
AR (2) p-value	0.934	0.929		
Hansen J-Stat. p-value	0.060	0.057		

Notes: OLS regression includes time fixed effects; LSDV regression includes region and time fixed effects; SYS-GMM regressions include time fixed effect and Pillar I payments are treated as exogenous. AR (n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; Hansen is the over-identification test for the instruments in the first difference equation. Absolute t statistics based on clustered standard error by region in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

**Table C.3: Convergence regressions for agricultural productivity in NMS (55 regions)-
additional controls**

Dependent Variable: Δ VA-Agr per worker	(1) SYS-GMM Exogenous	(2) SYS-GMM Exogenous	(3) OLS	(4) FE
VA-Agr. per worker (t-1)	-0.054*** (3.11)	0.002 (0.08)	-0.026** (2.29)	-0.683*** (13.88)
Total CAP subsidy rate (t-1)	0.168*** (2.90)		0.055 (1.04)	-0.105 (1.12)
Pillar I total (t-1)		0.191 (1.45)		
Pillar II total (t-1)		0.205** (2.60)		
Labour force growth (t-1)	0.031* (1.86)	0.033* (1.79)	0.031** (2.47)	0.004 (0.29)
Population density (t-1)	-0.006 (0.28)	-0.033** (2.04)	-0.020 (1.20)	-0.480 (1.20)
ESIF payments (t-1)	-1.226 (1.43)	-1.187 (1.60)	-0.514 (0.70)	-0.797 (0.68)
GDP growth (t-1)	-0.872** (2.41)	-1.020*** (3.00)	-0.456 (1.19)	-0.237 (1.09)
Share of large farms (t-1)	0.048 (0.79)	-0.035 (0.66)	0.021 (0.51)	0.350* (1.68)
Grass land ratio	-0.017 (0.21)	-0.040 (0.76)	-0.043 (0.75)	-0.144 (0.25)
R ² (within)			0.189	0.489
No. of Observations	450	450	450	450
No. of Instruments	53	53		
AR (1) p-value	0.000	0.000		
AR (2) p-value	0.096	0.091		
Hansen J-Stat. p-value	0.124	0.139		

Notes: OLS regression includes time fixed effects; LSDV regression includes region and time fixed effects; SYS-GMM regressions include time fixed effect and CAP subsidies are treated as exogenous. AR (n) is the Arellano and Bond test for serial correlation of first (1) and second (2) order, respectively; Hansen is the over-identification test for the instruments in the first difference equation. Absolute t statistics based on clustered standard error by region in parentheses. * p<0.10, ** p<0.05, *** p<0.01.