Does agriculture matter to rural economies? Evidence from agricultural multipliers in the EU*

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Abstract

Does agriculture benefit rural economies? In this paper, I show the surprisingly limited economic contribution of agriculture across EU regions, including rural regions. Even in remote rural regions, the direct economic contribution of agriculture is smaller than that of the service sector, as measured by the Gross Value Added and employment. Yet, agriculture could still matter if it has large positive multiplier effects on local economies. To investigate this indirect channel, I estimate agricultural multipliers for employment and for income in EU regions using shift-share instruments. For employment, estimates show little effect of agriculture on other sectors. For income, rather than a positive effect, I find that agriculture may crowd out manufacturing activity. This negative effect is robust to different income indicators and alternative compositions of the shift-share instrument. These findings suggest that attempts to stimulate rural economies in the EU by supporting agriculture may be misguided.

Key words: agricultural multipliers, agriculture, rural economy, regional economy, local multipliers
JEL codes: Q10, Q18, R11, R12, R15, J43

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1 Introduction

In the public imagination, rural regions are farming regions and vice versa. This assumption is also embedded in European policy. For example, one of the stated aims of the EU Common Agricultural Policy (CAP) is to achieve "balanced territorial development", usually interpreted as inclusive growth, by reducing the income gap between the agriculture and other sectors and by supporting economic development in rural areas. The second pillar of the CAP, responsible for 23% of budget in 2021, is nominally dedicated to rural development (Nègre, 2022). At the same time, the actual policy measures overwhelmingly target agriculture. This is true for the first pillar of the CAP (77% of the total budget), which consists of farm income support. But it is also true for the second pillar, which contains only a few "non-agricultural" measures aimed at development in rural regions (e.g. village renewal, see the EU regulation No 808/2014). The EU does not rely exclusively on agricultural policy to achieve rural development: in addition to the CAP (39% of the EU budget in the 2014-20 period), another important lever is the Cohesion Policy (34%) (European Union, 2013). Nevertheless, the rhetorical blending of "rural development" and "agriculture" in the CAP is striking. Taken at face value, European policy thus seems to assume that stimulating the agricultural sector is effective in strengthening rural economies.

It is surprising, then, that the contribution of agriculture to rural economies has received so little scrutiny. The relationship between agriculture and rural economies in high-income countries is not quite so simple. Research by OECD (2020) highlights that the direct contribution of agriculture to rural regions is not as large as many would expect; in fact, across OECD countries, even remote regions tend to have a level of service sector employment similar to that found in metropolitan regions. Likewise, agriculture accounted for only 6% of employment in rural economies in the United States in 2010 (Irwin *et al.*, 2010). Yet, these low direct contributions could still mask a significant indirect role of agriculture: as a sector exporting tradable goods, incomes generated through agriculture and spent in local economies could in theory support activities in local non-tradable sectors, either to support agricultural activities (e.g. services of veterinarians or agronomists) or through consumption expenditures of those active in agriculture (e.g. local restaurants or hairdressers). In contrast with a large literature on such "agricultural multipliers" in low-income countries, there is surprisingly little empirical evidence for high-income countries, and more specifically the EU. The lack of evidence is particularly surprising given the large policy support provided to agriculture in many high-income countries.

In this paper, I investigate the direct and indirect economic contribution of agriculture to EU regions. I analyse the direct economic contribution through descriptive analyses using the recent year data of Gross Value Added (GVA) and employment. I do not find a large direct contribution of agriculture in rural economies: Even in remote rural regions, agriculture contributes 7% to the total GVA and 14% to the total employment. Conversely, I also find that rural regions are not as important to overall agricultural activity as often thought: Non-rural regions account for more than half of the agricultural GVA and agricultural employment of the EU. In order to capture the indirect contribution, I estimate agricultural multipliers on employment and income through econometric analyses. I use detailed employment and income data by the type of farming for each region to capture how a region responds to the EU-wide employment and income shifts, which are then used as a shift-share instrument variable (SSIV). This way, I attempt to isolate the unobserved time-varying local economic conditions in the multiplier estimation. The analyses are based on the balanced panel data of 130 regions in the EU for the periods of 2008-2012 and 2012-2017. Regarding indirect effects, the estimates of agricultural employment multipliers show no significant effects in other sectors, except a positive effect on food and beverage manufacturing. But the positive employment multiplier is rather larger in urban regions, than in rural regions. I find negative agricultural income multipliers in the manufacturing sector, which could be driven by input competition. The negative effects remain robust when I use different income indicators and alternative compositions of the SSIV.

To the best of my knowledge, this is the first paper to estimate the direct and indirect economic contribution of agriculture to rural economies in the EU. While some papers have studied the effects of agricultural subsidies, this paper looks at the overall effects of agricultural activity. My findings thus complement the earlier studies and at the same time provide a benchmark for comparison. Moreover, this is the first paper to use shift-share instrument approach to estimate agricultural multipliers. While this approach has been commonly used to estimate multipliers of manufacturing activity (e.g. Moretti, 2010), it has not previously been used to estimate effects of agriculture. Instead, estimates of agricultural multipliers in the United States have either used soil quality as an instrument (Weber *et al.*, 2015) or exploited a historical episode as an exogenous shock (Hornbeck and Keskin, 2015). I also apply recent methodological advances of Goldsmith-Pinkham *et al.* (2020) in examining the identifying variation of the SSIV to explore any potential endogeneity concerns.

My findings show that there is no obvious link between agriculture and rural economic outcomes: not only is the direct economic contribution of agriculture in rural regions limited, but there is no evidence of large positive multipliers on other sectors. A clear policy implication is that policies targeting the agricultural sector may not be the most effective way of supporting rural economies.

The remainder of this paper is organized as follows. In Section 2, I present the direct economic contribution of agriculture. In Section 3, I provide a conceptual framework explaining potential channels of agricultural multipliers together with a literature review. In Section 4, I explain the empirical framework used to study the research questions, followed by data descriptions in Section 5. In Section 6, I analyse empirical results. I discuss the results and conclude in Section 7.

2 The direct economic contribution of agriculture in EU regions

A straightforward way to show agriculture's contribution to regional economies is to investigate agriculture's share of employment and GVA in EU regions, especially rural regions. Economic data for EU regions is available from Eurostat and the ARDECO dataset (discussed in more detail in Section 5). Comparing between rural and non-rural regions requires a classification of EU regions according to whether or not they are rural. For the analysis here, I use the EU urban-rural typology developed by DG REGIO (Dijkstra and Poelman, 2008). This typology has several advantages. First, it is based on a harmonized methodology and was explicitly designed to analyze EU regions. Second, the typology is sophisticated as it takes into account population density and the presence of main cities, as well as remoteness.

The resulting typology classifies each NUTS3 region of the EU into five categories (predominantly urban; intermediate and close to a city; intermediate and remote; rural and close to a city; and rural and remote).[1] The regions are first classified into three regional categories (urban, intermediate, and rural regions) based on the population density and the presence of main cities.[2] For example, urban regions have a high population density and large urban centers. Intermediate and rural regions are then further divided into "close to a city" vs. "remote". A region is considered "close to a city" if more than half of its residents can drive to the center of a city of at least 50,000 inhabitants within 45 minutes; otherwise it is categorized as "remote" (Dijkstra and Poelman, 2008). Instead of using a simpler classification with three categories as urban, intermediate, and rural, I use the most detailed regional clas-

[1]NUTS stands for nomenclature of territorial units for statistics. The unit is for collecting statistical data and is thus different from the administrative unit.

[2]NUTS3 regions are classified into *rural* if the share of population living in "rural areas" is higher than 50%; *intermediate* if it is between 20% and 50%; and *urban* if it is below 20%. "Rural areas" are all areas outside "urban clusters". "Urban clusters" are defined at a more granular level than NUTS3 regions: they are clusters of contiguous grid cells of 1 km^2 with a density of at least 300 inhabitants per km^2 and a minimum population of 5,000. In a second step this initial classification is adjusted based on the size of the urban centers: a rural region with an urban center of more than 200,000 inhabitants making up at least 25% of the regional population is reclassified as intermediate; while a intermediate region with an urban center of more than 500,000 inhabitants making up at least 25% of the regional population is reclassified predominantly urban.

sification as the structure of economic activity can differ substantially depending on access to cities. The geographical distribution of the regional classifications in the EU-28 is mapped in Figure 1.

Table 1 summarizes the data. Of the 1348 NUTS3 regions in the EU-28, 363 are urban, 500 are intermediate and close to a city, 55 are intermediate and remote, and 272 are rural and close to a city, 158 are rural and remote. Together, rural regions (both close to a city and remote) thus constitute 32% of all regions.[3]

Panel A of Table 1 shows the relative importance of agriculture to regional economies.[4] In the EU regions, agriculture on average contributes 3.0% to total GVA and 6.1% to total employment. In rural remote regions, agriculture accounts for 6.7% of total GVA and 13.7% of total employment, which is twice as high as the EU-wide figure. Among the five categories of regions, the relative contribution of agriculture is indeed highest for remote rural regions; this is particularly the case for regions in Eastern European countries (e.g. Poland, Romania, and Bulgaria), Greece, and Spain (Figure 2). But even here, agriculture is not the main sector. In no region was agriculture the largest sector in terms of GVA. In terms of employment, agriculture is the largest sector in only 11 NUTS3 regions (0.8% of all regions); all of these are located in Bulgaria and Romania, and all are either rural and close to a city, or rural and remote. Yet, the share of agricultural employment in those regions is on average less than 50%. In general, the dominant sector in rural regions is the service sector (orange colour in varying gradients in Figure 3).[5]

As additional context, Panel B of Table 1 shows the importance of the different regions for agriculture in the EU. Rural regions (both close to a city and remote) account for 34% of agricultural GVA in the EU. It is urban regions and intermediate regions close to a city that make up more than half (62%) of the share in the EU.[6] Similarly, for agricultural employment, almost half (49%) of the EU's agricultural employment occurs in the two regions.

The data in Panel B also provide an indication about the productivity of the agricultural sector in different regions. In the two non-rural regions (urban and intermediate close to

[3]The low share of "Intermediate - remote regions" may be explained by its definition. These are the regions with a moderate level of population density but with limited access to a city center. There will not be many regions in the category of "Intermediate - remote regions" if we assume that people like to live in regions with a good connection to city centers.

[4]Agriculture is defined according to the Nomenclature statistique des activités économiques dans la Communauté européenne (NACE) classification. NACE is the "statistical classification of economic activities in the European Community" (Eurostat, 2008, p.5). Agriculture only includes the primary production without any kinds of service activities related to agriculture.

[5]I here define the service sector as sectors F, G-J, K-N, and O-U in the NACE classification.

[6]There are a few highly productive regions in urban regions and intermediate regions close to a city. Among the 14 regions whose agricultural GVA is over 1 billion euro in 2018, 12 are urban or intermediate and close to a city (e.g. Valencia, Córdoba, Sevilla, Murcia, Gironde, Delft en Westland, etc.). Daniel (2003) similarly documented the agglomeration of agricultural activities in urban regions in the EU.

city), the share of agricultural GVA is greater than the share of agricultural employment. This indicates that the agricultural labor productivity is above average. Moreover, their share of agricultural GVA is greater than their share of agricultural area, which also suggests that their land productivity is higher. Agriculture thus seems to be more productive outside of rural areas. While the main focus of this paper is on the direct and indirect contribution of agriculture in EU regions, the findings about the important role of urban regions and intermediate regions close to a city in EU agriculture provide important context. Agricultural policy instruments are typically not differentiated by region; within the same country, the parameters of agricultural policy are generally the same regardless of whether the activity takes place in urban, intermediate, or rural regions. Attempts to use agricultural policy to stimulate rural regions might then end up mainly favoring producers in urban regions or intermediate regions close to a city, rather than the intended beneficiaries.

3 Conceptual framework

As the data in the previous section shows, agriculture has only a small direct role even in remote rural regions. However, there could still be an important indirect role of agriculture through positive multiplier effects on other sectors. In this section, I explain potential channels through which agriculture can have such indirect effects, and discuss existing estimates of these agricultural multipliers.

3.1 Potential channels of agricultural multipliers

There are several potential channels through which agriculture could indirectly affect other sectors of the economy.

First, agriculture needs non-tradable inputs in the production process such as veterinarians or trade intermediaries of agricultural inputs (Nolte and Ostermeier, 2017). Thus, when there is a positive demand or productivity shock for agriculture, these non-tradable sectors supplying agriculture will also increase their economic activity. The emphasis here is on non-tradable sectors: other inputs such as fertilizers or fuel are in principle traded globally, so that a positive shock to agriculture in one region would not be expected to result in a local multiplier for these industries.

Second, in addition to backward linkages with non-tradable sectors, agriculture may also have some forward linkages, e.g. with nearby processing industries. In some cases, agricultural output can be shipped over long distances, so that processing does not need to happen in the same region (apart from some minimal processing for transport). But in other cases, processing may take place closer to the farm. This might be the case for perishable and bulky products (e.g. dairy) or for products with a geographical indication, where production is required to take place in the same region. A positive productivity shock to agriculture could then lead to greater processing activity.[7]

A third channel occurs when agriculture competes with other sectors for the same inputs. In contrast with the previous two channels, in this case an economic expansion in agriculture can have negative local multipliers on other sectors. For example, greater labor demand in agriculture might raise wage costs for other businesses, leading them to reduce their activity. The effect will be stronger for inputs with a fairly inelastic supply (e.g. land) and weaker for inputs with a fairly elastic supply (e.g. capital goods). The negative effect is likely to be more pronounced for sectors that are heavily dependent on inputs with inelastic supply which are also used in agriculture. The negative effect will also be stronger for tradable sectors: while local non-tradable firms may be able to raise their prices in response to higher costs, firms in tradable sectors are less likely to have this option and may over time relocate production to regions with lower costs instead.

A fourth potential channel is that incomes from agriculture (including both labor income and profits) may be spent on local non-tradable services such as restaurants. While the previous channels concern the production side, multipliers can therefore also occur through the consumption side. A positive demand or productivity shock in agriculture could lead to higher incomes in the sector, which may in turn increase demand for local non-tradable services.

The net multiplier effect of agriculture is therefore an empirical question, and depends on the balance between these positive and negative effects. The effects may also differ depending on whether we look at income or employment multipliers, depending on how easy it is to substitute labor in the production function. However, it is clear that negative effects from an expansion of agriculture would be more likely to occur in other tradable sectors. Higher demand from the agricultural sector might drive up input prices, but as output prices for tradable sectors are largely determined in international markets there would be limited scope for compensating higher costs through output price increases. Moreover, even if the tradable sectors provide inputs into agricultural production, the expansion of agriculture in one region would not necessarily benefit suppliers in that region, given the international nature of the market. By contrast, it would seem less likely for negative multipliers to be found in non-tradable sectors. First, if an expansion of agriculture pushes up costs in non-tradable sectors, part of the cost increase may be passed on to consumers. Second, an increase in income in

[7]For both the backward linkage with non-tradables and the forward linkage with nearby processing, greater agricultural activity might also create agglomeration effects, e.g. through knowledge or skill spillovers (Hornbeck and Keskin, 2015).

agriculture may translate into greater demand for local non-tradables.

3.2 Agricultural multipliers in the literature

This question has been studied extensively in the context of economic development, both in historical perspectives (Olmstead and Rhode, 2008) and in present-day developing countries, where many studies find large agricultural multipliers (e.g. Dorosh and Thurlow, 2013; Gollin *et al.*, 2021).

In high-income countries, the question of multipliers has mostly been discussed for the manufacturing sector (e.g. Moretti, 2010; Moretti and Thulin, 2013; Van Dijk, 2018; van Dijk, 2017; Osman and Kemeny, 2021). A common finding in this literature is that jobs in tradable sectors create jobs in non-tradable sectors, with estimates ranging 0.17~1.6 in the US and 0.5~2.1 in European countries (Osman and Kemeny, 2021). On the other tradable sectors, the job multipliers are much smaller than those on non-tradable sectors (0.26 vs. 1.59 in Moretti (2010); 0.33 vs. 0.48 in Moretti and Thulin (2013)) but the standard errors of the estimates are often large.

Only a few studies have looked at agricultural multipliers in high-income countries, and these studies find limited or no effect.[8] Weber *et al.* (2015) present evidence that the increase in crop revenue in the US heartland raises mostly the income of the farm sector, not that of the non-farm sector. One additional dollar in crop revenue increases total personal income by 64 cents, with farm income accounting for 40 cents and nonfarm income for the rest. A back of the envelope calculation gives us a nonfarm to farm income multiplier of 0.6 ($= 0.24/0.4$). The same rough calculation implies a nonfarm to farm employment multiplier of 1 ($= 1.44/1.39$). but their employment estimates are often insignificant. He (2020) shows that in the US a 1% change in agricultural export raises farm employment by 0.433% but it does not have any significant effects on nonfarm employment (-0.018%). Back of the envelope estimate for a nonfarm to farm employment is -0.04 ($= -0.018/0.433$). Hornbeck (2012) and Hornbeck and Keskin (2015) find that the historical events in the US (the American Dust Bowl and the access to the Ogallala aquifer) that affected agricultural productivity had almost no impact on the non-agricultural sectors.

Few studies have estimated agricultural multipliers for European countries, and none have done so for the EU as a whole. Loizou *et al.* (2019) estimate input-output multipliers of the Greek region of Eastern Macedonia and Thrace. They do not find a large contribution of

[8]Several studies estimate agricultural multipliers with a focus on some aspects of agriculture. Heringa *et al.* (2013) focus on multi-functional agriculture in the Netherlands, Brown *et al.* (2014) on community-focused agriculture, and Sneeringer and Hertz (2013) on large-scale hog production. Their results show these aspects of agriculture are not the main drivers for local economic growth. Similarly, no evidence is found in Kilkenny and Partridge (2009) for the role of export sectors (including agriculture) on rural growth.

agriculture to the regional economy: 1% demand change in agriculture leads to the changes in the total demand only by 0.026%. My paper thus contributes to the small body of literature by estimating agricultural multipliers across the EU.

In the EU context, rather than estimating agricultural multipliers, more attention has been devoted to understanding the potential effects of subsidies both in terms of employment effects and in terms of regional growth.[9] The literature on the effects of CAP subsidies is related to, but distinct from, my research question. To understand the connections between the topics, it is instructive to draw a simple causal diagram.

$$\begin{tikzcd} CAP \arrow[r, "(1)"] \arrow[rr, bend right, "(3)"'] & Agricultural\,activity \arrow[r, "(2)"] & Regional\,economy \end{tikzcd}$$

The CAP can directly affect agricultural activity (1), which might in turn affect the broader regional economy (2). Alternatively, the CAP might also directly affect the regional economy (3). My research question here is essentially to identify (2), the effect of agriculture on the regional economy. A large literature has studied the effects of the CAP on the farm sector (i.e. (1)), see e.g. Schuh *et al.* (2016) for a review. Another literature studies the effects of the CAP on the broader regional economy. In some cases, these studies are essentially a "reduced form" estimate of the combined effect of (1) and (2), see e.g. Blomquist and Nordin (2017); Rizov *et al.* (2018); Michalek *et al.* (2020); Esposti (2007); in other cases, they study the direct effect (3), see e.g. Mattas *et al.* (2011); Daniel and Kilkenny (2009); in yet other cases, the distinction is unclear and the estimates are a combination of the two channels, see e.g. Gohin and Latruffe (2006).

The relevance of these different channels becomes clear when we consider the different instruments of the CAP. Simplifying, some CAP instruments such as coupled subsidies directly affect agricultural activity (1); any impact on the broader regional economy would then have to come through agricultural multipliers (2). The same goes for import tariffs and other trade restrictions which provide protection to the agricultural sector. While much of the attention is focused on the budgetary support provided by CAP, estimates by OECD (2021) show that 18% of total support to the agricultural sector in the EU comes from such market price support in 2018-2020. Over time, EU agricultural policy has moved away from coupled forms of support towards more decoupled payments. In theory, these payments

[9]For Canada, Bollman and Ferguson (2019) investigate the local non-agricultural effects of the 1995 abolition of grain export subsidy for railway shipments which had resulted in the increase of freight rates. They find that one additional dollar increase in freight rates led to 0.9% point decrease in the number of farms, and 1.3% point decrease in the non-agricultural employment. This gives us a back of the envelope estimate of multiplier of 1.4.

should be less distortive, i.e. they are expected to have a smaller impact on agricultural activity (1). But by providing income to farmers, they could still exert a positive effect on the regional economy (2), or even via (3) when the income are spent on non-agricultural activities. As noted earlier, the CAP also contains a second pillar nominally dedicated to rural development. This includes a wide range of programs (e.g. support to food processing, village renewal) for which it is more likely that they have a direct effect on regional economies (3) rather than an effect on agricultural activity (1).

There is a large volume of literature studying the effects of CAP on the creation of local jobs. Most of them find that agricultural subsidies contribute to job creation outside the agricultural sector. Some studies specifically focus on the job-creating effects of CAP on processing industries. Michalek *et al.* (2020) show that the second pillar payment can create maximum 3768 additional food processing firms in Poland. Gohin and Latruffe (2006) theoretically show that decoupling CAP subsidy would reduce a modest number of jobs (3000 workers at most) in food processing industries in the old member states.

Others take the effect of CAP to a broader perspective. Rizov *et al.* (2018) address the effect of CAP on employment in small and medium-sized enterprises (SMEs), beyond the agri-food sector and rural regions. They find that a 1% increase in CAP payments will increase total employment by 0.014%, which is equivalent to 220,000 additional jobs of the SMEs in the UK. Blomquist and Nordin (2017) find a large job creation effect of decoupling subsidy in Sweden: a 1% increase of of decoupling subsidy creates private jobs outside the agricultural sector by 0.024%. It implies that the CAP reform of introducing decoupling subsidy created private jobs at a cost of about $26,000 per job. They also explain the mechanism of this effect; it is through the increased farm income as a result of CAP that creates the private jobs, not through the CAP affecting land price or farm employment. Mattas *et al.* (2011) find that the second pillar payment in period 2007-2013 contributes 5% to the total employment in Eastern Macedonia and Thrace.

When it comes to the effect of CAP on regional growth, existing studies show mixed results. Only a few studies look at the effects of CAP on regional growth. Daniel and Kilkenny (2009) theoretically show that decoupled first pillar subsidy raises the welfare of regions. Esposti (2007) empirically shows no significantly positive effects of coupled CAP subsidies on regional growth. A report of Dumangane *et al.* (2021) concludes that CAP has a positive effect in rural economy but their definitions of rural regions include the indicators related to agriculture.

The findings on the effects of CAP in the literature can be related to the analyses of this paper even though agricultural subsidies are simply not the same as agricultural activities. For example, coupled subsidies or trade tariffs will have changed agricultural activities; CAP subsidies for supporting the development of rural areas (e.g. village renewal or support for public infrastructure in the second pillar of CAP) will have eased the access to inputs or output markets for the agricultural sector. It will be hard to strictly separate the effects of subsidies from my focus on agricultural activity, but I try to capture any interfering subsidy effects by controlling for CAP subsidies (discussed more in Section 4.4).

In this section, we have explored the various channels through which agriculture could have indirect economic effects. Production (i.e. backward and forward linkages of the agricultural sector and potential productivity spillovers) and consumption (i.e. agricultural income spent on local non-tradable services) related to agriculture can both induce positive multiplier effects, but competition for inputs can also have negative effects on other sectors. Now the net multiplier effect of agriculture comes down to an empirical question. Given the potential channels, we expect positive agricultural multipliers for the service sector, while negative effects are likely to occur for the manufacturing sector. There is not much research on agricultural multipliers in high-income countries but existing studies show that agriculture has little or no effect on regional economies.

4 Empirical framework

4.1 Estimating equation

I am interested in estimating the causal effect of an increase in agricultural activity on other nonagricultural activity (i.e. multipliers) in a region. As measures of activity, I analyse both employment and income. I run regressions separately for employment and income (X = employment, income). Multipliers are estimated using the following equation:

$$\triangle X_{i,t+s}^{other} = \alpha + \beta \triangle X_{i,t+s}^{ag} + \gamma C_{i,t} + \varepsilon_{i,t},$$

where β represents the multiplier expressing how a change in activity in the agricultural sector affects the change in activity in either manufacturing or services. $\triangle X_{i,t+s}$ is defined as the change over time ($=X_{i,t+s} - X_{i,t}$) divided by initial total employment for employment regressions and by total income for income regressions. Therefore, $\triangle X_{i,t+s}^{ag}$ represents the contribution of agricultural employment to total employment growth for region i during the period between time t and $t+s$. The dependent and independent variables are in first-difference to eliminate the effect of time-invariant unobserved heterogeneity at the region level. As with the usual within- or first-difference transformation for panel estimation, the coefficient beta can be interpreted as the change in the dependent variable caused by a one-unit increase in the independent variable. In other words, β_{emp} are generated in other sectors by a unit change in agricultural employment; β_{income} is generated in other sectors by a unit change in agricultural income. The other sectors considered as dependent variables are the manufacturing and service sectors; thus I will have estimates of β^{mfg}_{emp}, $\beta^{service}_{emp}$, β^{mfg}_{income} and $\beta^{service}_{income}$. Standard errors are clustered at the country level at which the data are collected in the EU (Abadie *et al.*, 2017).

Note that this way it is assumed that agricultural employment and income have multiplier effects within a region, not in the neighboring regions. The estimation thus has a limitation in taking into account the spatial correlations in the multiplier estimation although, as I will argue below, the bias is likely to be small.

4.2 Identification strategy

One challenge to estimate the equation is that unobserved local economic conditions could create endogeneity problems. For example, an improvement in local infrastructure or changes in local taxes could simultaneously benefit agriculture and other sectors, giving a false positive multiplier. To address the potential endogeneity associated with the local characteristics, I use a shift-share instrument variable (SSIV), also known as a Bartik instrument (Bartik, 1991). The application of the SSIV method to estimate multipliers is based on Moretti (2010), who studied local multipliers of manufacturing; to my knowledge, I am the first to apply this method to agricultural multipliers.[10]

My main SSIV is constructed as the sum of the EU-wide growth of each subsector of agriculture (the "shift") weighted by the regional "share" of each subsector. The SSIV thus reflects the expected response of a region i towards the EU-wide shifts in the subsectors of agriculture. For example, if there is strong EU-wide growth in economic activity in the dairy sector, we would expect a region where dairy accounts for a large share of agricultural activity to exhibit strong growth in its agricultural sector. I create a SSIV for both of my economic activity indicators: thus, I have a separate SSIV for employment (based on EU-wide trends in employment at the level of agricultural subsectors) and for income (based on EU-wide trends in income for agricultural subsectors).

I use 14 agricultural subsectors (e.g. 'specialist cereals, oilseeds and protein crops', 'specialist other fieldcrops', 'specialist horticulture'; 'specialist wine', etc.) in line with the available definitions and data from FADN, which will be discussed in more detail in Section 5. More formally, the SSIV is constructed by multiplying the EU-wide shifts of each subsector j in agriculture (i.e. shift: $\sum_i \frac{\Delta X^j_{i',t+s}}{X^j_{i',t}}$) with the share of the subsector j agricultural

[10] Biophysical factors such as climate-induced variation (Fiszbein, 2022) or land quality (Weber *et al.*, 2015) are often used as instruments for agricultural production. But those instruments can fit crop production only, not the entire agricultural activities.

employment and income (i.e. share: $\frac{X^j_{i,t}}{X^{ag}_{i,t}+X^{other}_{i,t}}$) in the region i at the initial time point in the analyses: $\Delta Z^{ag}_{i,t+s} = \sum_{j=1}^{14} \left\{ \frac{X^j_{i,t}}{X^{ag}_{i,t}+X^{other}_{i,t}} \sum_i \frac{\Delta X^j_{i',\ t+s}}{X^j_{i',t}} \right\}$. To strengthen the validity of the instrument, I do not include the value of own region i when calculating the EU-wide shift term, marked with i'. I use the SSIV in a two-stage least square (2SLS) estimation. I add the squared term of the SSIVs in the first stage regressions to improve the statistical relevance of the instrument.[11] Furthermore, given the recent discussions on SSIVs in Goldsmith-Pinkham *et al.* (2020) and Borusyak *et al.* (2022), I will assess the identifying variation of my SSIV.

As robustness checks, I explore some alternative approaches as well. One approach is to make use of firm-level data for the manufacturing and service sectors, besides using the regional datasets. This is useful because I can disaggregate the sectors into more detail. First, I can estimate agricultural multipliers on the manufacturing sector (section C of the NACE) more precisely. My regional dataset (discussed in more detail in Section 5) defines the manufacturing sector broadly as "industry" including mining, electricity and water supply, etc.[12] Second, I can explore the specific potential channels of agricultural multipliers that I discussed in Section 3.1. Instead of the manufacturing sector as a whole, agricultural multipliers can be estimated for the food processing sector. For local non-tradables, I choose "Wholesale and retail trade; repair of motor vehicles and motorcycles" (NACE G) and "Accommodation and food service activities" (NACE I) because they are typical non-tradable sectors where income can be spent as indicated by the low Gini coefficient in Appendix B. In addition, as they are also closely related to the agricultural production, positive multipliers are likely to occur, if any.

Another approach is to create an alternative SSIV for agricultural income by using EU-wide price shifts of each agricultural product. For example, when the price of cereal increases across the EU, we can expect that farm income of cereals producers will also increase in the same period. This approach is less ideal than income shifts, however, as input costs are not considered. Nevertheless, using the price shifts as an alternative shift-term in the SSIV can be useful to assess the robustness of the income multiplier estimates.

[11]See Appendix A.

[12]In the main analyses, I consider agriculture and the broadly defined manufacturing (B-E, including mining and quarrying, manufacturing, electricity, gas, steam and air conditioning supply, water supply; sewerage, waste management and remediation activities) as the tradable sectors, and the rest as the non-tradable service sectors, following Moretti and Thulin (2013). Appendix B confirms the the tradability of the manufacturing sector in my data.

4.3 Heterogeneous effects

As a next step, I analyse heterogeneous effects of agricultural multipliers, along several dimensions. First, I compare the different periods, to allow the multipliers to vary in each period. Second, I compare the old member states (OMS) and the new member states (NMS). Third, I analyse the heterogeneity of agricultural multipliers between urban and rural regions.

Unfortunately, the detailed EU urban-rural classification used in Section 2 cannot be used here, as the data for building the SSIV are not available at the same level of geographical detail. Instead, I rely on the share of households living in urban areas to construct a dummy variable for urban regions. If a region has this share below the 25th percentile of the EU regions, that region is considered rural; the rest is considered urban.[13] I also use the share as a continuous variable to capture the degree of urbanisation in addition to the dummy variable.

Dummy variables for the period, the OMS and the urban region are used to interact with agricultural employment and agricultural income, respectively. For the urban vs. rural heterogeneity, I also interact the share of households living urban areas with agricultural employment and agricultural income. Furthermore, I interact the OMS and urban dummy to see if the agricultural multipliers are different across the two dimensions simultaneously.

4.4 Control variables

All regressions include an extensive set of control variables ($C_{i,t}$). Control variables include regional and period fixed effects, a start-of-period share of employment and income in the manufacturing or service sectors respectively, GDP per capita, unemployment rate, the share of women in employment, the share of population with tertiary education, the farm average machinery and equipment costs, the average farm size, and the average CAP payments.

- The period fixed effect will capture the time-specific shocks. Regional fixed effects are also included. As noted above, my estimating equation is in first-differences, which already removes potential bias from unobserved time-invariant heterogeneity. For this reason, some authors do not include regional fixed effects. Several other papers do include regional fixed effects in a first-difference model, as I do here; this would control for region-specific factors affecting the growth rates (rather than levels) of my variables of interest.[14]

[13]For more explanation on how I categorize the regions into rural and urban, please see Appendix C.

[14]Some papers do not include regional fixed effects (e.g. Autor *et al.*, 2013; Bartik and Sotherland, 2019; Moretti, 2010; Tsvetkova and Partridge, 2016; Leduc and Wilson, 2017) but many other papers do even in first-differences (e.g. Van Dijk, 2018; Moretti and Thulin, 2013; Partridge *et al.*, 2017; Cerqua and Pellegrini, 2020; Weber *et al.*, 2015; Kilkenny and Partridge, 2009; He, 2020; Hornbeck and Keskin, 2015). Those not

- To control for long-run trends in the manufacturing and service sectors (e.g. related to structural transformation), I control for the initial share of employment and income of the manufacturing and service sector at the beginning of each time period. It will also address the concern that the agricultural employment and income variables may pick up the overall trend of structural transformation as economies grow.[15] GDP per capita is also added to capture any remaining effects related to this.

- Unemployment rate, the share of population that received tertiary education, and the share of women in employment are included as controls as they are correlated with the stock of workers that would be willing to respond to any changes in other sector demand. For example, lower stock of workers will produce smaller multiplier effects especially for the non-tradable sectors.

- Machinery and equipment cost (i.e. major farming equipment such as tractors, motor cultivators, lorries, etc.) is added to control for the degree of mechanization in the agricultural sector which affects the level of agricultural employment and income. This control will separate the effect of changes in agricultural employment from the effects of the better mechanization in agricultural production. If the labor-saving technologies are introduced in agricultural production, the labor demand would decline but channels through which the positive multipliers occur remain intact.

- The average farm size is included to eliminate potential threats to my SSIV. Each type of farming has its typical farm size (e.g. a large farm size required for fieldcrop productions). At the same time, farm size can be correlated with the labor or income of other sectors. For example, smaller farms are more likely to expand into off-farm (i.e. other sector) economic activities than larger farms (Augère-Granier, 2016). This implies that a region dominant with a certain type of farming, through its typical farm

including the regional fixed effects commonly explain that the time-variant regional fixed effect is already taken into account and removed in the first-differenced equation. However, it could be argued that regional characteristics might affect the growth rate (rather than the level) of income and employment variables. Including regional fixed effects takes care of this concern.

[15] This paper is related to the literature on the process of structural transformation, typically described as decreasing labor share in agriculture, a hump-shape trend in manufacturing, and increasing labor share in service sector (Alvarez-Cuadrado and Poschke, 2011). The phenomenon of structural transformation is mainly about long-term changes (for example, the growing importance of services), while my focus is on interaction effects between sectors (for example, the impact of agricultural growth on local non-tradables). The two issues are not completely distinct, however. For example, one interaction between sectors is competition for scarce inputs (labor, land, capital). Some theories of structural transformation (e.g. the Lewis (1954) model) posit that resources are under-utiilzed in agriculture, so that growth in manufacturing is not hampered by competition for scarce inputs, up to a point. Still, my focus is on interaction effects themselves, rather than broad processes of structural transformation.

size, could be correlated with the labor supply in the the manufacturing or service sectors.

- The decoupled and the second pillar CAP payments are included as controls. Decoupled payment are correlated with farming activities but its effect as income support does not always go through farming itself. Thus, it is necessary to isolate the effect of decoupled payment from agricultural activities. The second pillar payment also needs to be controlled as it can be correlated both to farming activities and to other sector activities (e.g. support to food processing). It is hard to separate the effect of coupled subsidies from that of farming activities; including coupled subsidies may be over-controlling (e.g. GVA contains coupled subsidy). Thus, I do not control for coupled subsidies. Given the substantial decline in coupled payment since 1992, my estimate however will not capture much of its effect.

5 Data

5.1 Data sources

I compile regional datasets from the Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy (ARDECO), Eurostat, and the Farm Accountancy Data Network (FADN).[16] Agricultural data are retrieved from FADN, other sector data from ARDECO, and control variables both from FADN and Eurostat. I use FADN for agricultural data, instead of ARDECO or Eurostat, to benefit from its greater level of detail needed to construct the SSIV; as I show later, the detailed FADN data is consistent with the less granular data in ARDECO.

The three datasets used in this paper are all publicly available and maintained by EU institutions, thus harmonized at the EU level. ARDECO is a novel regional database made available online since December 2019 and maintained by the European Commission's Joint Research Centre. ARDECO provides NUTS3 or NUTS2 level data related to labour markets, economic indicators, and demographics.

FADN is a sample survey based on agricultural holdings included in the Farm Structure Survey (FSS). FSS is an EU-wide survey managed by Eurostat and conducted by member states every three to four years, and it includes even very small agricultural holdings;[17]

[16] For the FADN database see: https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html; for ARDECO see : https://ec.europa.eu/knowledge4policy/territorial/ardeco-database_en.

[17] FSS itself is already a survey carried out by the EU countries and managed by Eurostat. FSS includes all agricultural holdings in the EU of at least one hectare. Agricultural holdings with less than one hectare

FADN, by contrast, is an annual survey which focuses on larger - commercially oriented - farms by only including farms whose economic size exceeds a minimum threshold.[18] Given the potential channels of indirect effects, market-oriented farms would have greater multipliers than the entire population, which includes farms producing for self-consumption. As a result, I would estimate the agricultural multipliers at their largest.

As the data provided by FADN are the average values of farms in each region, I multiply by the number of farms represented in a given region to arrive at an overall estimate for the region. I verify the data constructed from FADN by comparing it with each corresponding variable in ARDECO (Figure 4).[19]

The definition of regions in FADN differs from that in ARDECO and Eurostat; FADN regions are similar to the NUTS2 level, but are often bigger than that.[20] Several countries (AT, CY, CZ, DK, EE, IE, LT, LU, LV, MT, SI, SK, NL) are considered a single region in FADN; while for Germany and Belgium the NUTS1 level is used. Regions in a few countries (UK, PT, SE, HU, PL) are grouped differently from the NUTS2 regions. FADN is designed so that its farm samples are representative of the farm population at the level of FADN regions. For this reason, I use FADN regions as my units of observation.[21] I therefore compile regional data from ARDECO and Eurostat to match these FADN regions.

In addition to these three datasets, I additionally exploit the firm-level data of Bureau van Dijk (BvD) to investigate agricultural multipliers on more granular subsectors. The BvD database collects financial statements of firms from national business registers.[22] I aggregate

are included in the survey when they sell certain proportion of their output to the market or produce more than a specified amount of output (FADN, 2020). Each member state carries out the survey every three or four years, and census once in ten years.

[18]The minimum threshold differs by member state, reflecting the different farm structure of each country.

[19]When comparing GVA in agriculture from ARDECO with my FADN, the FADN estimate is in line with the ARDECO values, although the ARDECO values are often somewhat larger than the FADN values. This is to be expected, as national accounts also capture firms for whom agriculture is not their primary activity (and which are therefore not included in FADN).

[20]See Appendix D for the map of FADN regions.

[21]Farm-level micro data of FADN including the information on location are accessible upon request at the European Commission. Even though I can extract NUTS information this way, I use the public database of FADN provided at the level of FADN regions for representativeness of regional data. FADN data guarantee the representativeness of farm samples only at the "FADN regions", not at the "NUTS regions". FADN samples farms by using three criteria (FADN region, economic size, farm types) to be able to represent the variety of farm populations; therefore NUTS information of the farm-level data does not fully represent the farm population of the NUTS regions.

[22]In most European countries, it is mandatory for firms to report to the national business registers (Kalemli-Ozcan *et al.*, 2019). Furthermore, Kalemli-Ozcan *et al.* (2019) show that the firm size for the manufacturing sector from the BvD database is representative when compared to the firm-size distribution from the official Eurostat data. Eurostat's Structural Business Statistics (SBS) provides similar information at the detailed subsectors for each NUTS2 region of the EU. SBS includes all active enterprises at least a part of the reference period (see EU regulation no. 250/2009). But a large number of missing values does not make it ideal to rely on SBS.

the firm-level data to the regional level by using the NUTS information of each firm. This information indicates the location of the firm's official address, which does not necessarily correspond to the region where production takes place. However, the territorial units used in the analyses are relatively large, which should mitigate potential measurement error. As noted above, for several EU countries the FADN region corresponds to the entire country. For other countries, some measurement error might exist, although it still seems likely that a firm based in e.g. Bavaria will have much of its activity in the region as well. Still, because of possible measurement error, the findings are best seen as suggestive only. Appendix E describes how I clean the BvD firm-level data.

5.2 Employment

My preferred measure of employment is the number of hours worked. An alternative would be to use the number of employed persons, which is also available. However, this measure does not differentiate between part-time and full-time workers, creating measurement error.

ARDECO has data on hours worked for manufacturing and services. Measuring employment in agriculture needs some attention, because farm work is often carried out by unpaid labor of family members and this is often not included in standard employment data.[23] By contrast, FADN does collect information on family and part-time labors (European Commission, 2013). As explained in more detail below, data at the subsector of the agricultural sector is necessary to construct the SSIV; FADN has disaggregated employment data by the type of farming which can be used for this purpose.

As noted earlier, for some analyses I additionally rely on firm-level data to better understand impacts across different manufacturing or services sub-sectors. The firm-level dataset does not have the employment data as a number of hours worked, but as the "total number of employees". While not ideal, I therefore use the total number of employees of manufacturing and service sector firms for these additional analyses, and adjust the interpretation of employment multipliers accordingly.

5.3 Income

As a measure of income for different sectors and regions, I use Gross Value Added (GVA), which is defined as the value of output minus the value of intermediate inputs used. GVA indicates the net contribution of each sector to the total economy, and is closely related to Gross Domestic Product (GDP). The only difference is the price used to measure GVA

[23]FADN data indicates that the average share of family labor (i.e. unpaid labor) of a farm in the EU was 72% in 2019.

and GDP. GVA is expressed with basic prices and GDP with market price. GVA ultimately equals to GDP when adding product taxes and deducting product subsidies. GDP is typically not available at regional or sectoral level, making GVA the best alternative. One possible concern to use GVA as a measure of income is that GVA is calculated based on the place of work, which may differ from the place of residence. This matters for estimating income multipliers, as income is likely to be spent mainly in the worker's place of residence. However, this is probably not a major concern in my dataset. The FADN regions that I use as unit of observation are similar to or larger than NUTS2 regions, which means that for the vast majority of workers, the place of work will coincide with the place of residence. To take French regions as an example, people working in Brittany are less likely to live and spend money in Normandy unless they live near the border; thus I expect the differences between the place of work and the place of residence to be marginal.

GVA in agriculture is not directly available at FADN. In order to use the equivalent income measure across the sectors, I construct an equivalent indicator of GVA in agriculture from FADN (see Appendix F). One complication here is that FADN data also includes the income earned from "other gainful activities" (OGA) directly related to the farm holding apart from farming itself. These include e.g. tourism, handicraft, processing of farm products, etc. By contrast, the statistical unit in national accounts is the local kind-of-activity unit (KAU), not the institutional unit (e.g. firms) (Eurostat, 2013). Strictly speaking, these other gainful activities should be removed from my agricultural GVA variable. But while FADN distinguishes between market income from farming and OGA on the revenue side, it does not separate input indicators. For this reason, an exact separation is not possible. However, as a robustness check, I also create a "market income" variant of agricultural GVA, which deducts OGA revenues.

As an additional robustness check, I also use a readily available farm income indicator at FADN. Gross Farm Income (GFI) is similar to how I construct the GVA in agriculture; but GFI includes the decoupled subsidy and deducts the farm taxes (recall that GVA is measured at prices as received by producers, including coupled subsidies). Compared to the GFI, the GVA in agriculture that I create is more compatible to how the GVA is calculated in the national accounts; but given the importance of decoupled subsidies, the GFI could conceivably be a better variable to capture the effect of higher agricultural incomes on other sectors.

I compare the two additional variables of GVA in agriculture with the value of ARDECO in Appendix G. Income variables are all adjusted for inflation by the sectoral GVA deflators available at AMECO (annual macro-economic database of the European Commission's Directorate General for Economic and Financial Affairs).

Using the firm-level accounting data can also complement the different statistical units of the FADN and national accounts (ARDECO). Similar to FADN, BvD collects data at the firm-level (cfr. the KAU in national accounts) and one NACE code is allocated to each firm by its primary economic activity. For the additional analyses using firm-level data, I similarly need to construct a GVA equivalent. I use the "Added Value" of the firm's income statement aggregated at the regional level. Added Value is defined by BvD as "Profit for period (=net income) + Depreciation + Taxation + Interests paid + Cost of employees", which corresponds to the GVA concept.

5.4 Construction of the shift-share instrument

I use agricultural employment and income data by the 14 agricultural subsectors available in FADN (See Appendix H). The subsectors indicate the types of farming, and FADN allocates an agricultural holding to one of the 14 types based on the relative economic importance of different activities on the farm. For example, if the monetary value of agricultural output from producing milk exceeds more than two-thirds of the total monetary output of a farm, the farm is classified as "specialist milk".

In addition, I also construct an alternative shift-share instrument using price shifts. For this, I use the producer prices index (PPI) of agricultural products, as an alternative shift-term to be used in the estimation of income multipliers. The EU-wide PPIs are available at Eurostat for several categories of agricultural products.[24] The categories of agricultural products of the PPIs are different from the 14 types of farming in FADN. See Appendix H for how I match the PPI's agricultural products to the 14 types of farming. In constructing a shift-share instrument with these new "shift" variables, I use two different specifications for the "shares". A first one is simply using the income share as in my main SSIV. A second approach is using revenue shares instead.

5.5 Data summary

The resulting dataset covers the year 2008, 2012, and 2017 and includes all FADN regions except Croatia (which only joined the EU in 2013) and French overseas departments.[25] The

[24] I use the EU27 (excluding Croatia) values of "apri_pi05_outa" for the year of 2008 and 2012. Due to data availability, I rely on "apri_pi10_outa" for the 2017 data although the EU27 in this dataset excludes Estonia.

[25] Among the 136 FADN reigons in the data for year 2017, five regions (two in Croatia and three in France) are dropped. FADN divides Croatia into two regions; and has only three overseas departments (Guadeloupe, Martinique, and La Réunion). Two FADN regions (680 and 700) in Finland are merged into one region to match with the Eurostat NUTS region (FI1D). As a results, I have 130 regions in my dataset.

period of the analyses is chosen to keep as many as the same regions over time.[26] As a result, I have a balanced panel dataset of 130 regions at each time point. Even though it is not a large number of observations, the data cover almost all regions in the EU.

Table 2 shows the summary statistics of the variables used in the analyses. In the EU regions, agricultural employment on average contribute to the total employment growth by -0.7%. The decline is larger in the NMS and rural regions, as compared to OMS and urban regions (Table 3). Agricultural income contributes to the regional income growth by 0.2%. Their growth is larger in NMS and rural regions.

Manufacturing employment declined by -1.1%, more than agricultural employment. The decrease in manufacturing employment in the EU shows little difference between OMS vs. NMS and rural vs. urban regions. Service employment was essentially flat, although growth was positive in in NMS and urban regions. Manufacturing income grew by 0.6%, but was almost flat in the OMS and increased by 2.8% in the NMS. Service sector income grew by 2.5%, with stronger growth in the NMS (6.2%).

6 Results

6.1 Main results

Table 4 shows the agricultural employment and income multipliers on the manufacturing and service sectors. Agriculture does not seem to have any employment effects on either sector; while it has negative effects on manufacturing income. Its effect on service sector income is insignificant. The estimated β^{mfg}_{income} indicates that 1 million euros of additional agricultural income will reduce manufacturing income by 1.1 million euros in a given region of the EU. The results are robust to different control variables (see Appendix I). First-stage F statistics are around 10, satisfying the rule of thumb. Figure 5 shows the coefficients of the main variables with confidence levels.

To address possible concerns around the correct measurement of agricultural income, I show robust results using other agricultural income indicators in Table 5. The agricultural income multipliers are still negative. When other outputs are excluded from agricultural income, the estimate becomes slightly larger than the main result (-0.888 vs. -1.132). When using GFI as an alternative measure of farm income, the income multipliers become even more negative than the main estimate (-1.378 vs. -1.132). GFI includes the decoupled subsidy and deducts farm taxes, as compared to the main agricultural income indicator. The stronger

[26] For example, ARDECO provides the data on polish regions only from 2008; FADN data for Bulgaria and Romania are only available from 2007, thus I would lose 12 observations if I include years before 2008.

negative effects may imply that the decoupled subsidy has negative effects on manufacturing income.

To show the robustness of the income multiplier estimates, I alternatively use EU-wide price shifts for each agricultural product in the composition of the SSIV instead of the EU-wide income shifts. It is another potential shock that would affect the farm income. Table 6 shows that the results of agricultural income multipliers are robust when using this alternative construction of the SSIV.

Table 7 shows the estimation results using the alternative firm-level data from BvD. The estimates are all insignificant, but income multipliers on the manufacturing sector are still negative.

Even though not every estimate is significant, it is useful to compare it with the multiplier estimates of other studies. Most of the other empirical works has a focus on manufacturing job multipliers on the service sector. As noted earlier, Osman and Kemeny (2021) summarize a range of the multipliers from 0.5 to 2.1 for the case of European countries. My employment multiplier for the service sector is 0.859, which falls within the range. Moretti (2010) and Moretti and Thulin (2013) find the multipliers on the other manufacturing sector in the range of 0.26~0.33. My employment multiplier on the manufacturing sector is smaller (0.179) than the range but is consistent with the overall prediction. It is smaller than my service sector estimate (0.859) as expected in the conceptual framework in Section 3.1. The smaller magnitude of the service sector estimate also coincides with the findings of Moretti (2010) and Moretti and Thulin (2013). From the agriculture-specific literature, back of the envelope calculations give a range of nonfarm to farm employment multipliers of -0.4~1.4 (Weber *et al.*, 2015; He, 2020; Bollman and Ferguson, 2019). It is unfortunately not possible in this case to separate the multipliers on manufacturing and service. But my employment multipliers on both manufacturing and service are within this range as well. When it comes to income multipliers, there are not so many benchmarks to compare my estimates. One comparison could be made with the nonfarm to farm income multiplier of 0.6, roughly calculated from Weber *et al.* (2015). My main income estimates (-1.132 for manufacturing and -0.565 for service) are different from it. Yet, the smaller negative effect on service than on manufacturing is consistent with the predictions of the conceptual framework as well as Moretti (2010) and Moretti and Thulin (2013).

6.2 Heterogeneous effects

Table 8 reports the heterogeneous effects of agricultural employment multipliers across the different time periods, the OMS vs. NMS and urban vs. rural regions.

For manufacturing employment, I do not find any significant heterogeneous effects except the differences between urban vs. rural regions when the share of households living in urban areas is used as a degree of urbanisation. Column (4) in Panel A indicates that the effect of agricultural employment on manufacturing employment is significantly different by the degree of urbanisation. But one should be careful to interpret the estimate given the low F statistics. For service employment, agricultural employment has significantly higher multiplier effects in the OMS than in the NMS (Column (2) in Panel B).

Although none of the interactions in Column (5) are significant, for completeness I calculate the marginal effects by the two dimensions of OMS vs. NMS and urban vs. rural regions. Table 9 shows that in urban regions of the NMS, agricultural employment crowds out manufacturing employment. In rural regions of the OMS, agricultural employment leads to more service sector employment.

Table 10 shows the heterogeneous effects of agricultural income multipliers. The estimates are less reliable than agricultural employment multipliers because of the low F statistics. If I take the estimates of F statistics over five as reliable, agriculture appears to have a higher income multiplier on the service sector in more urbanised regions (Column (4) in Panel B). Given the very small values of F statistics in Column (5) for the case of income regressions, I do not calculate the marginal effects by the two dimensions of OMS vs. NMS and urban vs. rural regions.

6.3 Identifying variation of the shift-share instruments

Because SSIVs consist of two separate elements (the "shift" and the "share"), it is difficult to see what is creating the identifying variation. Ideally, both the shift and the share would be exogenous, but this will not always be the case, and better understanding the source of variation in the instrument is then important to evaluate its exogeneity. Recent contributions by Goldsmith-Pinkham *et al.* (2020) and Borusyak *et al.* (2022) greatly improve our insight into the identifying variation of SSIVs. They look at the main identifying variation of SSIVs differently: Goldsmith-Pinkham *et al.* (2020) focus on the share term using the shift as weight, while Borusyak *et al.* (2022) focus on the shift term using the share as weight. The former proves that SSIV results are numerically the same as results from using each subsector share as an instrument and the shift just gives weights in the generalized method of moments estimation. The latter shows that when shares cannot be considered exogenous, one can derive identifying variation from shifts if many independent exogenous shocks (i.e. shifts) are present.

The approach of Goldsmith-Pinkham *et al.* (2020) is the relevant one in my case.[27] The

[27]I have only 14 types of farming and it is relatively a small number of subsectors compared to other studies (e.g. 397 industries in Autor *et al.*, 2013) and it is not a large number to satisfy asymptotic properties

identifying variation in my SSIV comes from the mixture of agricultural subsector shares. The key assumption for exogeneity is then that the agricultural subsector shares are exogenous to the *change* in employment or incomes of non-agricultural sectors. Note that this still allows for the agricultural subsector shares to be correlated with the *level* of employment and income of other sectors; this would not threaten the exogeneity of the SSIV (Goldsmith-Pinkham *et al.*, 2020).

To examine the identifying variation of the SSIV, I follow the steps suggested in Goldsmith-Pinkham *et al.* (2020). They decompose SSIVs into a weighted ($\hat{\alpha_j}$) sum of just-identified instrumental variable estimators ($\hat{\beta}_j$) that use each subsector share as a separate instrument:

$$\hat{\beta}_{ssiv} = \sum_j \hat{\alpha}_j \hat{\beta}_j,$$

where $\hat{\beta}_j = (Z_j'X)^{-1}Z_j'Y$, $\hat{\alpha}_j = \frac{g_j Z_j' X}{\sum_j g_j Z_j' X}$, $\sum_j \hat{\alpha}_j = 1$, and g_j indicates the shift of the subsector j over time. In other words, SSIV estimate can be derived by estimating the equation using each subsector share as an instrument ($\hat{\beta}_j$) and then creating a weighted sum of these estimates. The weight ($\hat{\alpha}_j$) tells us which subsets of instruments, that is which subsectors, are driving the SSIV estimate. This allows us to take a closer look at the most influential instruments to evaluate whether there are any endogeneity concerns specific to that instrument (i.e. that subsector).

The top three weights of agriculture subsectors are reported in Table 11. For employment, the top three subsectors account for almost 70% of the variation; for income over 90%. Having a few subsectors with high weights is not problematic itself. Rather, identifying these subsectors helps probing the channels that may cause potential endogeneity bias. To this end, Goldsmith-Pinkham *et al.* (2020) suggest exploring the relationship between the share of the subsectors and regional characteristics that are correlated to supply shifts. I regress the share of each subsector value on the regional characteristics. Table 12 and Table 13 present the regression coefficients.

When we focus on the results for manufacturing income, particularly for the subsector with the highest weight (Column (1) in Table 13), the share of cereals, oilseeds, and protein crops (COP) income in a given region is positively correlated with the share of manufacturing income and negatively correlated with the share of women in employment. Again, the level

to use shifts as the main identifying variation. Furthermore, there is little endogeneity concern that affects employment and income of other sectors through the same mixture of agricultural subsector shares. By contrast, it is difficult to argue the exogeneity of the share term for the case of Autor *et al.* (2013). Their SSIV combines the changes in Chinese import competition (i.e. shifts) with the mixture of manufacturing subsector shares of US regions, and unobserved shocks (e.g. automation or innovation trend) can affect other sectors through the same mixture of the manufacturing shares.

of the correlates can be correlated with the level of the outcome, but it is only problematic if the levels of the correlates are causally connected to the *changes* in the outcome. There is no obvious mechanism through which the share of women in employment and the share of initial manufacturing income could affect the changes in the manufacturing income.

Furthermore, the values of R-squared are high, particularly for the income regressions. For example, 33% of the variation in the share of the COP income can be explained by the covariates. A high value of R-squared suggests that the control variables (i.e. regional characteristics) can explain a significant portion of the variation in the subsector shares. It is not surprising to see the high share of identifying variation explained by the COP because all EU member states produce cereals (Kelly, 2019). This is in line with the findings of the canonical example in Goldsmith-Pinkham *et al.* (2020) that the high-weighted industries tend to be tradables as they vary across locations. Therefore, I conclude that there is little endogeneity concern in the estimation results.

6.4 Mechanisms

To see if positive effects are present for the specific manufacturers that are closely related to agriculture, I estimate the agricultural multipliers for the two subsectors "Manufacture of food products and beverages" (NACE 10, 11) by using the firm-level data (Table 14). I find a positive employment multiplier on the manufacturing of food products and beverages, which indicates that 1000 additional hours of agricultural work will lead to 0.09 additional employees. If we roughly calculate the total number of hours worked per year for one employed person as 2028 hours (= $39\, hours * 52\, weeks$), this means that 1000 additional hours of agricultural work leads to 189 hours of additional work in manufacturing food products and beverages.[28] It is interesting to note that the magnitude of estimate is close to the magnitude of my main estimate (0.179 in Table 4). This implies that if there is any positive employment multiplier, it would be on the manufacturing sector of food and beverage. The income multiplier is insignificantly negative but it is smaller than the main income estimate (-0.146 vs -1.132).

If the manufacturing sector of food and beverage is the main industry in rural regions, the positive employment multiplier may indicate a sizable contribution of agriculture to rural economies. To see if the agricultural multipliers on manufacturing food and beverage are different by the degree of urbanisation, I run the same heterogeneous analyses as before. For employment, I find that the multipliers are significantly different with the varying degree of urbanisation: the more a region is urbanised, the larger the employment multipliers (Table

[28] $189\, hours = 0.093\, persons * 39\, hours * 52\, weeks$. EU-28 average number of actual weekly hours of work in manufacturing for the year 2008, 2012, and 2017 is 39 hours (see Eurostat data "lfsa_ewhan2").

15).[29] Agriculture creates jobs in manufacturing of food and beverage more substantially in urban regions, than in rural regions. By contrast, I do not find any heterogeneous effects of income multipliers by the degree of urbanisation.

To find if there are consumption effects from agriculture on the demand for local non-tradables, I estimate the agricultural multipliers for "Wholesale and retail trade; repair of motor vehicles and motorcycles" (NACE G) and "Accommodation and food service activities" (NACE I), respectively. I chose these specific non-tradable sectors as they are linked to both the production and consumption channels of the agricultural multipliers. Agriculture thus would have a high chance of showing positive multipliers on the two sectors. But none of the estimates are significant. Although insignificant, the employment multiplier on wholesale and retail trade appears to be larger than employment multipliers on other sectors; 1000 additional hours of agricultural work leads to 604 hours of additional work in wholesale and retail trade.[30] The income multipliers on these service sectors are not significant either. Yet, the magnitude of negative effect is smaller (-0.044 for wholesale and retail trade) than the other income estimates, or it becomes even positive (0.019 for accommodation and food service activities).

Given the potential channels explored in Section 3.1, it is possible to have positive employment multipliers and negative income multipliers at the same time. This may indicate that the manufacture food and beverage is a labor-intensive industry; and agriculture and other manufacturing sectors are competing for the same inelastic inputs. As I find the positive employment multipliers, the negative income multipliers may be mainly driven by the increased land price. The high share of identifying variation of COP (as well as the two other subsectors) supports the potential mechanism of the negative multipliers because the production of these types of farming often requires a large scale of land, putting pressure on land competition.

In this section, I have estimated multipliers on specific sectors to explore channels through which agriculture could have positive effects. The consumption channel of agricultural multipliers does not seem evident. For the production channel of forward linkages on manufacturing of food and beverage, agriculture does have a positive employment multiplier. But agriculture does not specifically benefit rural economies; rather the positive effects are larger in urbanised regions.

[29] I do not present the heterogeneous analyses with "urban dummy" because of the low F statistics.

[30] $604\,hours = 0.314\,persons * 37\,hours * 52\,weeks$. EU-28 average number of actual weekly hours of work in wholesale and retail trade for the year 2008, 2012, and 2017 is 37 hours (see Eurostat data "lfsa_ewhan2").

7 Discussion and conclusion

Policymakers often target agriculture as a way to boost rural economies. I challenge this approach by providing empirical evidence on the direct and indirect economic contributions of agriculture to rural economies in the EU. The direct contribution of agriculture to rural economies is limited, as indicated by the low share of GVA and employment in agriculture. Even in remote rural regions where we often think agriculture to be the dominant industry, agriculture turns out to be not as important as the service sector. The indirect contribution of agriculture is likewise insignificant or even negative. I capture the indirect contribution by estimating agricultural multipliers on employment and income using a shift-share instrument. For employment, agriculture does not appear to create jobs in other sectors. If there is to be any positive effect, it would be on manufacturing of food and beverage. However, the positive effects benefit urbanised regions more than rural regions. For income, I find the negative income multipliers on the manufacturing sector which could arise from input competitions. The negative income multiplier is robust when I use different income indicators and alternative compositions of the SSIV.

These findings show that there is no obvious link between agriculture and rural economic outcomes: not only is the direct economic contribution of agriculture in rural regions limited, but there is no evidence of large positive multipliers on other sectors. The evidence from this study suggests that policies targeting the agricultural sector may not be the most effective way of supporting rural economies. It is therefore misleading to use a geographically-blind agricultural policy to achieve spatial goals.

A limitation of this study in the multiplier estimation is that it does not take into account any indirect effects occurring in other neighboring regions. However, as the territorial unit used in the estimation is large, I believe that those effects are negligible. At the same time, the large territorial units may be an issue for discussing local multipliers. While this paper is the first to provide benchmarks for agricultural multipliers of the EU regions, a future study focusing on a single country using a smaller territorial unit could be a useful way of assessing agricultural multipliers further.

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Tables

Table 1: The direct economic contribution of agriculture and distribution of agriculture by the urban-rural classification of the EU-28

		Urban	Intermediate close to city	Intermediate remote	Rural close to city	Rural remote	All regions
Number of regions	number	363	500	55	272	158	1348
	EU share	27%	37%	4%	20%	12%	100%
Panel A. Relative importance of agriculture in regional economy							
Ag GVA (%, 2018)	mean	0.7	2.6	4.5	4.1	6.7	3.0
	25 percentile	0.1	0.8	1.7	1.5	3.3	0.6
	median	0.3	1.6	3.5	3.1	5.4	1.7
	75 percentile	0.9	3.2	6.7	5.4	8.6	4.1
Ag employment (%, 2017)	mean	1.4	5.0	7.8	9.5	13.7	6.1
	25 percentile	0.1	1.6	3.3	3.1	6.4	1.1
	median	0.6	3.0	4.9	5.3	10.3	3.2
	75 percentile	1.7	5.3	11.7	11.4	17.7	7.1
Panel B. Distribution of agricultural activities of the EU-28 by the regional classification							
Ag GVA (billion €, 2018)	total	44	90	10	48	25	216
	EU share	20%	42%	4%	22%	12%	100%
Ag employment (million persons, 2017)	total	1.3	4.0	0.4	3.5	1.5	10.5
	EU share	12%	37%	4%	33%	14%	100%
Ag area (million km^2, 2016)	total	0.2	0.7	0.1	0.4	0.3	1.7
	EU share	12%	42%	5%	26%	15%	100%

Notes: Data are based on the NUTS3 regions. For agricultural Gross Value Added (Ag GVA), the data for 3 urban regions (Malta, Gozo and Comino, and Brent) are missing, resulting in the total number of observations of 1345. For agricultural land area (Ag area), the data for 15 regions are missing: 4 urban (Gran Canaria, Tenerife, La Réunion, Madeira), 4 intermediate and close to a city (Melilla, Lanzarote, Martinique, Açores), 5 intermediate and remote (Fuerteventura, La Palma, Guadeloupe, Guyane, Mayotte) and 2 rural and remote (El Hierro, La Gomera) regions. Note that most of missing values are those of urban regions and intermediate regions. Ag GVA and Ag employment are retrieved from ARDECO and Ag area from Eurostat. Ag employment refers to number of persons employed. EU-28 are AT, BE, BG, CY, CZ, DE, DK, EE, EL, ES, FU, FR, HR, HU, IE, IT, LT, LU, LV, MT, NL, PL, PT, RO, SE, SI, SK, and UK.

Table 2: Summary statistics of variables

		mean	s.d.	min	max	observation
independent variables	Δag employment	-0.007	0.023	-0.165	0.063	260
	Δag income	0.002	0.010	-0.022	0.080	260
dependent variables	Δmanufacturing employment	-0.011	0.019	-0.079	0.058	260
	Δservice employment	0.00009	0.057	-0.162	0.207	260
	Δmanufacturing income	0.006	0.039	-0.072	0.273	260
	Δservice income	0.025	0.066	-0.182	0.449	260
control variables	GDP per capita (million euros)	0.022	0.011	0.002	0.069	260
	unemployment rate	0.097	0.055	0.024	0.344	260
	share of women in employment	0.570	0.092	0.273	0.724	260
	share of tertiary educated population	0.240	0.083	0.086	0.460	260
	farm average machinery and equipment costs (million euros)	0.062	0.074	0.002	0.558	260
	average farm size (1000 ha)	0.072	0.097	0.003	0.585	260
	farm average CAP decoupled payment (million euros)	0.016	0.025	0	0.168	260
	farm average CAP pillar 2 payment (million euros)	0.004	0.007	0	0.054	260

Notes: Summary statistics are pooled over two periods.

Table 3: Summary statistics of variables for OMS vs. NMS and rural vs. urban regions

		OMS mean(sd)	NMS mean(sd)	Rural mean(sd)	Urban mean(sd)
independent variables	Δag employment	-0.004	-0.016	-0.016	-0.004
		(0.014)	(0.039)	(0.040)	(0.010)
	Δag income	-0.0003	0.008	0.006	-0.00004
		(0.005)	(0.017)	(0.016)	(0.005)
dependent variables	Δmanufacturing employment	-0.011	-0.013	-0.013	-0.011
		(0.016)	(0.028)	(0.025)	(0.017)
	Δservice employment	-0.003	0.010	-0.002	0.001
		(0.054)	(0.065)	(0.063)	(0.055)
	Δmanufacturing income	-0.0002	0.028	0.015	0.003
		(0.031)	(0.054)	(0.060)	(0.028)
	Δservice income	0.014	0.062	0.024	0.025
		(0.055)	(0.084)	(0.077)	(0.062)
control variables	GDP per capita (million euros)	0.026	0.007	0.016	0.024
		(0.009)	(0.005)	(0.011)	(0.010)
	unemployment rate	0.100	0.086	0.100	0.095
		(0.059)	(0.035)	(0.055)	(0.055)
	share of women in employment	0.577	0.543	0.538	0.580
		(0.098)	(0.063)	(0.090)	(0.090)
	share of tertiary educated population	0.252	0.200	0.196	0.256
		(0.082)	(0.076)	(0.080)	(0.079)
	farm average machinery and equipment costs (million euros)	0.071	0.030	0.042	0.069
		(0.079)	(0.042)	(0.063)	(0.076)
	average farm size (1000 ha)	0.077	0.054	0.057	0.076
		(0.096)	(0.101)	(0.084)	(0.101)
	farm average CAP decoupled payment (million euros)	0.018	0.006	0.010	0.017
		(0.027)	(0.012)	(0.022)	(0.026)
	farm average CAP pillar 2 payment (million euros)	0.005	0.003	0.004	0.005
		(0.007)	(0.009)	(0.006)	(0.008)
	Observations	202	58	66	194

Table 4: Agricultural employment and income multipliers

VARIABLES	(1) $\Delta mfg\, employment$	(2) $\Delta service\, employment$	(3) $\Delta mfg\, income$	(4) $\Delta service\, income$
$\Delta ag\, employment$	0.179	0.859		
	(0.290)	(0.777)		
$\Delta ag\, income$			-1.132**	-0.565
			(0.552)	(0.752)
Number of id	130	130	129	129
Observations	260	260	258	258
F stats	19.520	24.094	44.011	36.605

Notes: The control variables in each IV regression are regional and period fixed effects, a start-of-period share of employment and income in the manufacturing or service sectors respectively, GDP per capita, unemployment rate, the share of women in employment, the share of population with tertiary education, the farm average machinery and equipment costs, the average farm size, and the average CAP payments. Each shift-share instrument is used for agricultural employment and agricultural income. Robust standard errors clustered by country are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 5: Agricultural income multipliers using different farm income indicators

VARIABLES	(1) $\Delta mfg\, income$	(2) $\Delta service\, income$	(3) $\Delta mfg\, income$	(4) $\Delta service\, income$
$\Delta market\, income$	-0.888**	-0.320		
	(0.386)	(0.560)		
$\Delta grossfarmincome$			-1.378**	-1.055
			(0.700)	(0.923)
Number of id	130	130	130	130
Observations	260	260	260	260
F stats	69.769	69.769	10.010	10.010

Notes: The control variables in each IV regression are regional and period fixed effects, a start-of-period share of income in the manufacturing or service sectors respectively, GDP per capita, unemployment rate, the share of women in employment, the share of population with tertiary education, the farm average machinery and equipment costs, the average farm size, and the average CAP payments. Each agricultural income indicator is instrumented with its shift-share instrument. Robust standard errors clustered by country are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 6: Agricultural income multipliers using price shifts in the shift-share instrument

Panel A: Manufacturing

VARIABLES	(1) $\Delta mfg\,income$	(2) $\Delta mfg\,income$	(3) $\Delta mfg\,income$	(4) $\Delta mfg\,income$
$\Delta ag\,income$	-1.102*			-1.420*
	(0.564)			(0.778)
$\Delta market\,income$		-1.149**		
		(0.571)		
$\Delta gross\,farm\,income$			-2.324*	
			(1.352)	
Number of id	130	130	130	130
Observations	260	260	260	260
F stats	116.495	217.963	26.830	183.967

Panel B: Service

VARIABLES	(1) $\Delta service\,income$	(2) $\Delta service\,income$	(3) $\Delta service\,income$	(4) $\Delta service\,income$
$\Delta ag\,income$	-0.213			-0.268
	(0.694)			(0.731)
$\Delta market\,income$		-0.286		
		(0.733)		
$\Delta gross\,farm\,income$			-0.559	
			(1.170)	
Number of id	130	130	130	130
Observations	260	260	260	260
F stats	166.135	128.334	38.094	348.783

Notes: The control variables in each IV regression are regional and period fixed effects, a start-of-period share of income in the manufacturing or service sectors respectively, GDP per capita, unemployment rate, the share of women in employment, the share of population with tertiary education, the farm average machinery and equipment costs, the average farm size, and the average CAP payments. Each agricultural income indicator is instrumented with its shift-share instrument using the EU-wide price shifts for each agricultural product. Robust standard errors clustered by country are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 7: Agricultural multipliers on the manufacturing sector using firm-level data

VARIABLES	(1) $\Delta Jobs$	(2) $\Delta Added\, value$
$\Delta ag\, employment$	0.310	
	(0.234)	
$\Delta ag\, income$		-0.105
		(0.740)
Number of id	130	130
Observations	260	260
F stats	22.085	57.007

Notes: The control variables in each IV regression are regional and period fixed effects, a start-of-period share of jobs or added value in the manufacturing sector respectively, GDP per capita, unemployment rate, the share of women in employment, the share of population with tertiary education, the farm average machinery and equipment costs, the average farm size, and the average CAP payments. Each agricultural employment and income indicator is instrumented with its shift-share instrument. Robust standard errors clustered by country are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 8: Heterogeneous effects of agricultural employment multipliers

Panel A: Agricultural employment multipliers on the manufacturing sector

VARIABLES	(1) $\Delta mfg\,employment$	(2) $\Delta mfg\,employment$	(3) $\Delta mfg\,employment$	(4) $\Delta mfg\,employment$	(5) $\Delta mfg\,employment$
$\Delta ag\,employment$	0.210	-0.208	0.186	0.103	-0.022
	(0.170)	(0.215)	(0.243)	(0.182)	(0.388)
$\Delta ag\,emp * 12-17$	-0.216				
	(0.161)				
$\Delta ag\,emp * oms$		0.213			0.275
		(0.237)			(0.297)
$\Delta ag\,emp * urb\,dummy$			-0.196		-0.597
			(0.570)		(0.609)
$\Delta ag\,emp * urban\,share$				-0.479**	
				(0.221)	
$\Delta ag\,emp * oms * urb\,dummy$					-0.035
					(1.053)
$\Delta ag\,emp + interaction$	-0.006	0.005	-0.011	-0.207	
	(0.284)	(0.249)	(0.468)	(0.221)	
Number of id	130	130	130	130	130
Observations	260	260	260	260	260
F stats	21.640	14.517	4.677	7.737	20.390

Panel B: Agricultural employment multipliers on the service sector

VARIABLES	(1) $\Delta service\,employment$	(2) $\Delta service\,employment$	(3) $\Delta service\,employment$	(4) $\Delta service\,employment$	(5) $\Delta service\,employment$
$\Delta ag\,employment$	0.884**	-0.444	0.735	0.592	0.055
	(0.386)	(0.334)	(0.693)	(0.387)	(0.695)
$\Delta ag\,emp * 12-17$	0.180				
	(0.736)				
$\Delta ag\,emp * oms$		1.185*			1.151*
		(0.707)			(0.690)
$\Delta ag\,emp * urb\,dummy$			1.112		-0.837
			(2.927)		(1.180)
$\Delta ag\,emp * urban\,share$				-0.707	
				(0.899)	
$\Delta ag\,emp * oms * urb\,dummy$					-2.889
					(2.702)
$\Delta ag\,emp + interaction$	1.063	0.740	1.847	0.134	
	(0.690)	(0.566)	(2.932)	(0.854)	
Number of id	130	130	130	130	130
Observations	260	260	260	260	260
F stats	13.101	19.387	1.499	20.911	12.375

Notes: The control variables in each IV regression are regional and period fixed effects, a start-of-period share of employment in the manufacturing or service sectors respectively, GDP per capita, unemployment rate, the share of women in employment, the share of population with tertiary education, the farm average machinery and equipment costs, the average farm size, and the average CAP payments. Dummy is set to one for the period 2012-2017, old member states (OMS), and urban regions (”urb dummy”). ”urban share” is a continous variable of the share of households living in urban areas. Thus, the marginal effect of ag employment is evaluated at the mean value of the ”urban share”. ”Δag emp + interaction” indicates the summation of the coefficient of ”Δag employment” and the interaction of each regression to calculate the marginal effects. Agricultural employment is instrumented with its shift-share instrument. When the period dummy variable is interacted with agricultural employment, the interactions of period dummy with the share of start-of-period manufacturing and service employment are also included such that the effects of these controls could vary over the period, as the agricultural employment. Robust standard errors clustered by country are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 9: The marginal effects of agriculture employment by the OMS vs. NMS and urban vs.rural

	Manufacturing			Service	
	OMS	NMS		OMS	NMS
Urban	-0.379 (0.562)	-0.619** (0.254)	Urban	-2.519 (2.146)	-0.781 (0.807)
Rural	0.253 (0.160)	-0.022 (0.388)	Rural	1.206***(0.457)	0.055 (0.695)

Notes: These are the marginal effects of agricultural employeemnt in Column (5) of Table 8. The marginal effect for the OMS and Urban is summation of coeffcients of Δag emp + Δag emp*oms + Δag emp*urb dummy + Δ ag emp*oms*urb dummy. For the NMS and Urban, it is Δag emp + Δag emp*urb dummy. For the OMS and Rural, it is Δag emp + Δag emp*oms. For the NMS and Rural, it is the coefficient of Δag emp. Robust standard errors clustered by country are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 10: Heterogeneous effects of agricultural income multipliers

Panel A: Agricultural income multipliers on the manufacturing sector

VARIABLES	(1) $\Delta mfg\, income$	(2) $\Delta mfg\, income$	(3) $\Delta mfg\, income$	(4) $\Delta mfg\, income$	(5) $\Delta mfg\, income$
$\Delta ag\, income$	-2.240	-2.839	0.014	0.527	-3.186
	(5.130)	(2.418)	(0.951)	(1.996)	(3.788)
$\Delta ag\, income * 12-17$	-10.261				
	(27.102)				
$\Delta ag\, income * oms$		11.105			22.832
		(13.351)			(38.041)
$\Delta ag\, income * urb\, dummy$			-0.457		1.626
			(0.892)		(2.614)
$\Delta ag\, income * urban\, share$				-1.839	
				(4.577)	
$\Delta ag\, income * oms * urb\, dummy$					-14.074
					(33.479)
$\Delta ag\, income + interaction$	-7.004	4.447	-0.192	-0.332	
	(15.59)	(5.751)	(0.450)	(0.893)	
Number of id	130	130	130	130	130
Observations	260	260	260	260	260
F stats	0.074	0.560	4.472	4.986	1.755

Panel B: Agricultural income multipliers on the service sector

VARIABLES	(1) $\Delta service\, income$	(2) $\Delta service\, income$	(3) $\Delta service\, income$	(4) $\Delta service\, income$	(5) $\Delta service\, income$
$\Delta ag\, income$	0.149	-1.493	-0.565	-1.356	-2.610
	(0.572)	(1.970)	(0.840)	(1.048)	(2.381)
$\Delta ag\, income * 12-17$	3.953				
	(3.798)				
$\Delta ag\, income * oms$		5.423			12.158
		(8.570)			(15.379)
$\Delta ag\, income * urb\, dummy$			1.940		2.491
			(1.316)		(1.613)
$\Delta ag\, income * urban\, share$				3.920*	
				(2.251)	
$\Delta ag\, income * oms * urb\, dummy$					-1.919
					(13.110)
$\Delta ag\, income + interaction$	0.920	3.239	1.176**	1.074	
	(2.825)	(4.073)	(0.584)	(0.696)	
Number of id	130	130	130	130	130
Observations	260	260	260	260	260
F stats	0.498	0.459	4.261	7.443	1.926

Notes: The control variables in each IV regression are regional and period fixed effects, a start-of-period share of income in the manufacturing or service sectors respectively, GDP per capita, unemployment rate, the share of women in employment, the share of population with tertiary education, the farm average machinery and equipment costs, the average farm size, and the average CAP payments. Dummy is set to one for the period 2012-2017, old member states (OMS), and urban regions ("urb dummy"). "urbans hare" is a continous variable of the share of households living in urban areas. Thus, the marginal effect of ag employment is evaluated at the mean value of the "urban share". "Δag income + interaction" indicates the summation of the coefficient of "Δag income" and the interaction of each regression to calculate the marginal effects. Agricultural income is instrumented with its shift-share instrument. When the period dummy variable is interacted with agricultural income, the interactions of period dummy with the share of start-of-period manufacturing and service income are also included such that the effects of these controls could vary over the period, as the agricultural income. Robust standard errors clustered by country are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 11: Top three agricultural subsectors used in the shift-share instrument

Panel A: Employment

Manufacturing				**Service**			
Negative and positive weights							
	Sum	Mean	Share		Sum	Mean	Share
Negative	-0.431	-0.108	0.231	Negative	-0.352	-0.176	0.207
Positive	1.431	0.143	0.769	Positive	1.352	0.113	0.793
Top 3 agricultural subsectors							
	$\hat{\alpha}_j$	g_j	$\hat{\beta}_j$		$\hat{\alpha}_j$	g_j	$\hat{\beta}_j$
Mixed livestock	0.661	-0.442	-0.108	Mixed livestock	0.629	-0.442	0.010
Permanent crops combined	0.199	-0.391	-0.189	Permanent crops combined	0.189	-0.391	-0.817
Milk	0.136	-0.227	0.763	Other fieldcrops	0.111	0.038	1.994

Panel B: Income

Manufacturing				**Service**			
Negative and positive weights							
	Sum	Mean	Share		Sum	Mean	Share
Negative	-0.019	-0.004	0.018	Negative	-0.020	-0.007	0.019
Positive	1.019	0.113	0.982	Positive	1.020	0.093	0.981
Top 3 agricultural subsectors							
	$\hat{\alpha}_j$	g_j	$\hat{\beta}_j$		$\hat{\alpha}_j$	g_j	$\hat{\beta}_j$
COP	0.908	0.639	-2.030	COP	0.897	0.609	0.136
Other fieldcrops	0.045	-0.071	-0.509	Other fieldcrops	0.048	-0.087	-2.305
Olives	0.022	-0.354	0.398	Olives	0.022	-0.380	23.567

Notes: COP stands for cereals, oilseeds and protein crops. The control variables are regional and period fixed effects, a start-of-period share of employment and income in the manufacturing or service sectors respectively, GDP per capita, unemployment rate, the share of women in employment, the share of population with tertiary education, the farm average machinery and equipment costs, the average farm size, and the average CAP payments. Robust standard errors are clustered on country.

Table 12: Relationship between the top three subsector shares and regional characteristics: Employment

	Manufacturing			Service		
	(1)	(2)	(3)	(1)	(2)	(3)
VARIABLES	Mixed livestock	Permanent crops	Milk	Mixed livestock	Permanent crops	Other fieldcrops
share of mfg employment	-0.172	-0.018	0.229			
	(0.187)	(0.040)	(0.179)			
share of service employment				-0.136*	0.014	-0.018
				(0.071)	(0.018)	(0.033)
GDP per capita	-0.128	0.468	0.154	-0.198	0.455	0.533
	(0.774)	(0.308)	(0.839)	(0.679)	(0.279)	(0.359)
unemployment rate	-0.040	0.008	0.015	-0.078	0.010	0.008
	(0.032)	(0.012)	(0.020)	(0.059)	(0.012)	(0.025)
share of women in employment	-0.099	0.003	-0.047	-0.123	0.004	0.007
	(0.088)	(0.013)	(0.067)	(0.110)	(0.014)	(0.025)
share of tertiary educated population	-0.007	0.025	0.075	-0.023	0.024	-0.003
	(0.033)	(0.017)	(0.075)	(0.026)	(0.015)	(0.021)
machinery and equipment costs	0.051	-0.002	0.026	0.013	-0.003	-0.025
	(0.047)	(0.010)	(0.036)	(0.025)	(0.012)	(0.021)
average farm size	-0.069	0.004	-0.055	-0.073	0.008	-0.028
	(0.065)	(0.012)	(0.089)	(0.067)	(0.017)	(0.027)
decoupled	-0.013	-0.026	-0.071	0.068	-0.025	-0.028
	(0.075)	(0.026)	(0.061)	(0.054)	(0.023)	(0.053)
CAP pillar2	0.336	0.013	-0.032	0.468	-0.009	0.108
	(0.273)	(0.042)	(0.365)	(0.354)	(0.058)	(0.140)
Period fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of id	130	130	130	130	130	130
Observations	260	260	260	260	260	260
R-squared	0.070	0.081	0.138	0.081	0.082	0.061

Notes: Robust standard errors clustered by country are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 13: Relationship between the top three subsector shares and regional characteristics: Income

	Manufacturing			Service		
	(1)	(2)	(3)	(1)	(2)	(3)
VARIABLES	COP	Other fieldcrops	Olives	COP	Other fieldcrops	Olives
share of mfg income	0.026**	0.015*	0.006			
	(0.012)	(0.008)	(0.004)			
share of service income				0.036	-0.009	-0.009
				(0.022)	(0.009)	(0.010)
GDP per capita	1.759	-0.153	-0.147	2.127*	-0.141	-0.183
	(1.044)	(0.101)	(0.186)	(1.153)	(0.157)	(0.226)
unemployment rate	-0.029	0.006	-0.002	-0.024	0.007	-0.002
	(0.031)	(0.007)	(0.007)	(0.034)	(0.006)	(0.006)
share of women in employment	-0.091**	-0.003	-0.015*	-0.097***	0.000	-0.012
	(0.035)	(0.009)	(0.009)	(0.032)	(0.007)	(0.007)
share of tertiary educated population	-0.068	-0.010	0.003	-0.058	-0.013	0.000
	(0.062)	(0.011)	(0.011)	(0.057)	(0.013)	(0.013)
machinery and equipment costs	-0.044	0.007	0.009	-0.036	0.005	0.007
	(0.040)	(0.014)	(0.010)	(0.039)	(0.012)	(0.008)
average farm size	0.299	-0.024*	-0.008	0.294	-0.021*	-0.006
	(0.243)	(0.012)	(0.010)	(0.236)	(0.011)	(0.008)
decoupled	0.186	0.002	-0.003	0.183	0.003	-0.002
	(0.215)	(0.023)	(0.012)	(0.214)	(0.024)	(0.012)
CAP pillar2	-0.692	0.046	-0.008	-0.741	0.032	-0.010
	(0.833)	(0.049)	(0.024)	(0.825)	(0.043)	(0.024)
Period fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of id	130	130	130	130	130	130
Observations	260	260	260	260	260	260
R-squared	0.329	0.166	0.096	0.336	0.156	0.118

Notes: COP stands for cereals, oilseeds and protein crops. Robust standard errors clustered by country are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 14: Agricultural multipliers on specific sectors by using firm-level data

	F&B mfg		Wholesale&retail		Accom&food	
	(1)	(2)	(1)	(2)	(1)	(2)
VARIABLES	$\Delta Jobs$	$\Delta Added\,value$	$\Delta Jobs$	$\Delta Added\,value$	$\Delta Jobs$	$\Delta Added\,value$
$\Delta ag\,employment$	0.093**		0.314		0.074	
	(0.045)		(0.199)		(0.049)	
$\Delta ag\,income$		-0.146		-0.044		0.019
		(0.092)		(0.257)		(0.048)
Number of id	129	129	260	260	252	252
Observations	258	258	130	130	126	126
F stats	22.476	39.601	21.298	56.235	21.302	43.367

Notes: The control variables in each IV regression are regional and period fixed effects, a start-of-period share of jobs or added value in the manufacturing or service sectors respectively, GDP per capita, unemployment rate, the share of women in employment, the share of population with tertiary education, the farm average machinery and equipment costs, the average farm size, and the average CAP payments. Each agricultural employment and income indicator is instrumented with its shift-share instrument. For food and beverage manufacturing (F&B mfg), one observation (Sachsen) is missing; for accommodation and food service activities (Accom&food), four observations (Rheinland-pfalz, Saarland, Sachsen-anhalt, Slovakia) are missing because no firms are found in the regions for the year 2017 after cleaning the data. Robust standard errors clustered by country are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1

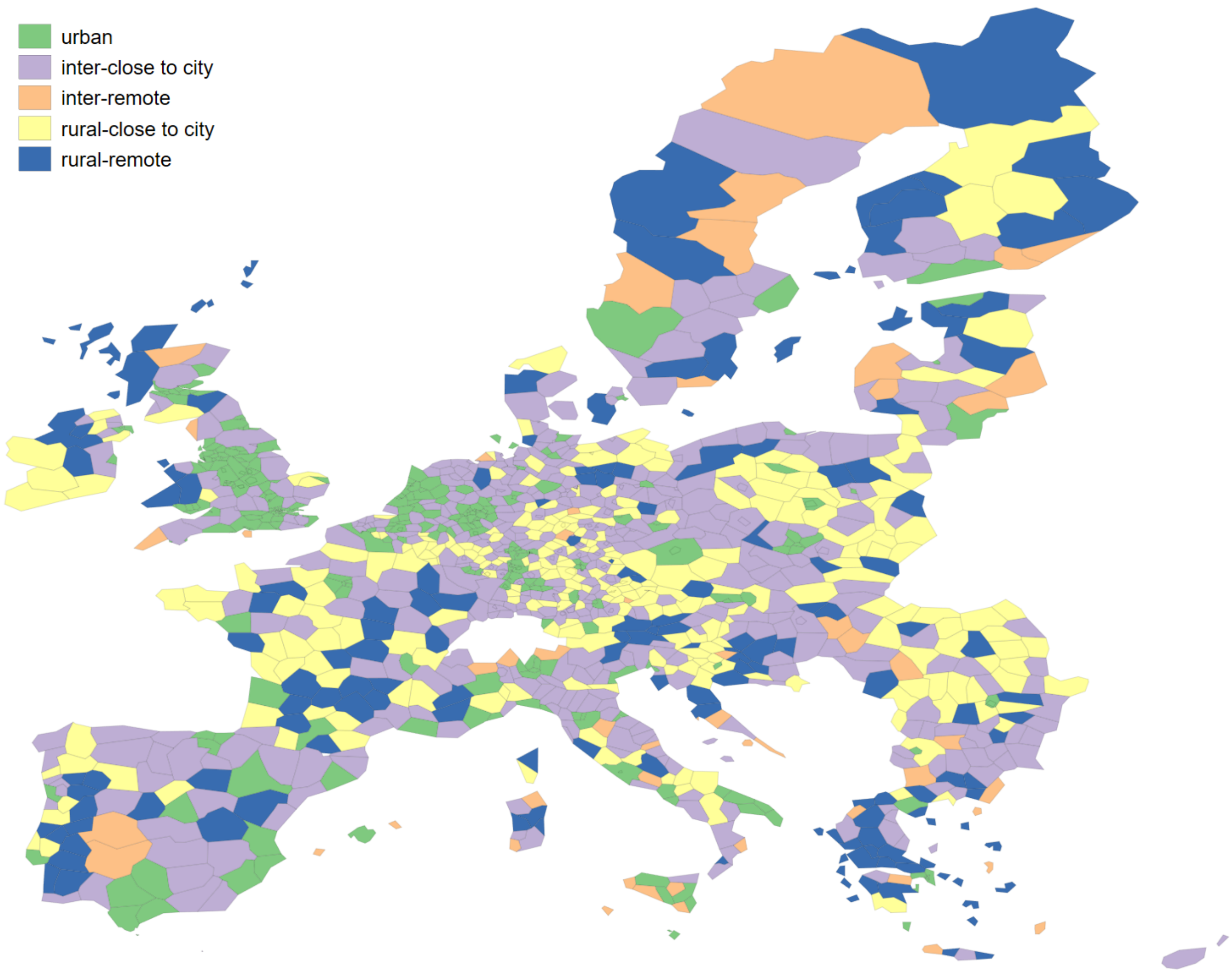
Table 15: Heterogeneous effects of agricultural multipliers on food and beverage manufacturing

	(1) $\Delta Jobs$	(2) $\Delta Added\,value$
$\Delta ag\,employment$	0.075**	
	(0.030)	
$\Delta ag\,employment * urban\,share$	0.141***	
	(0.040)	
$\Delta ag\,income$		-0.064
		(0.313)
$\Delta ag\,income * urban\,share$		-0.287
		(0.727)
$\Delta ag\ + interaction$	0.166***	-0.249
	(0.048)	(0.177)
Number of id	129	129
Observations	258	258
F stat	11.424	6.858

Notes: The control variables in each IV regression are regional and period fixed effects, a start-of-period share of jobs or added value in food and beverage manufacturing respectively, GDP per capita, unemployment rate, the share of women in employment, the share of population with tertiary education, the farm average machinery and equipment costs, the average farm size, and the average CAP payments. "urban share" is a continous variable of the share of households living in urban areas. Thus, the marginal effect of ag employment is evaluated at the mean value of the "urban share". "Δag + interaction" indicates the summation of the coefficient of "Δag employment" or "Δag income" and the interaction of each regression to calculate the marginal effects. Each agricultural employment and income indicator is instrumented with its shift-share instrument. One observation (Sachsen) is missing because no firms are found in the regions for the year 2017 after cleaning the data. Robust standard errors clustered by country are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Figures

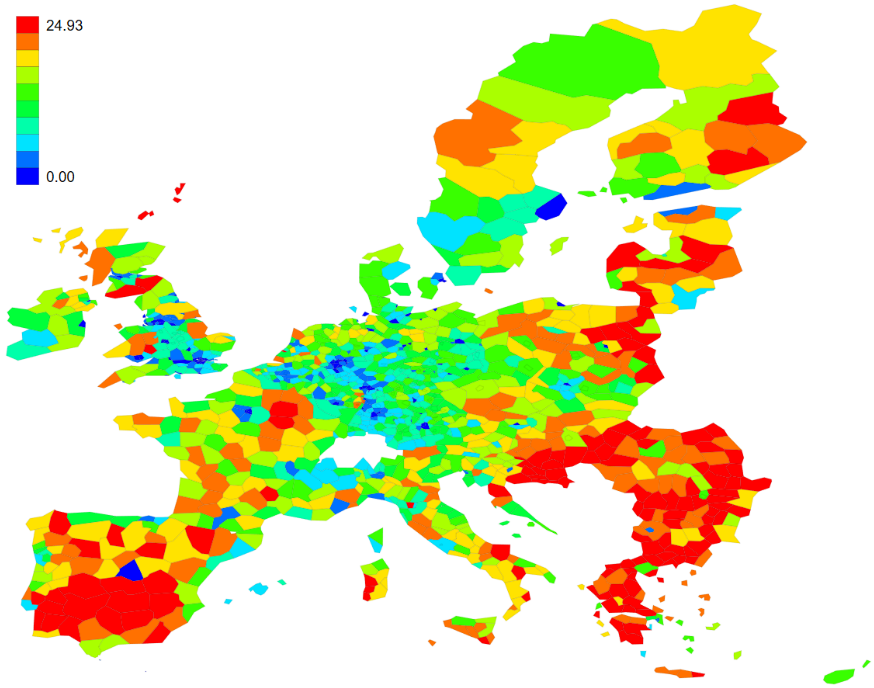
Figure 1: NUTS3 regional classifications including remoteness



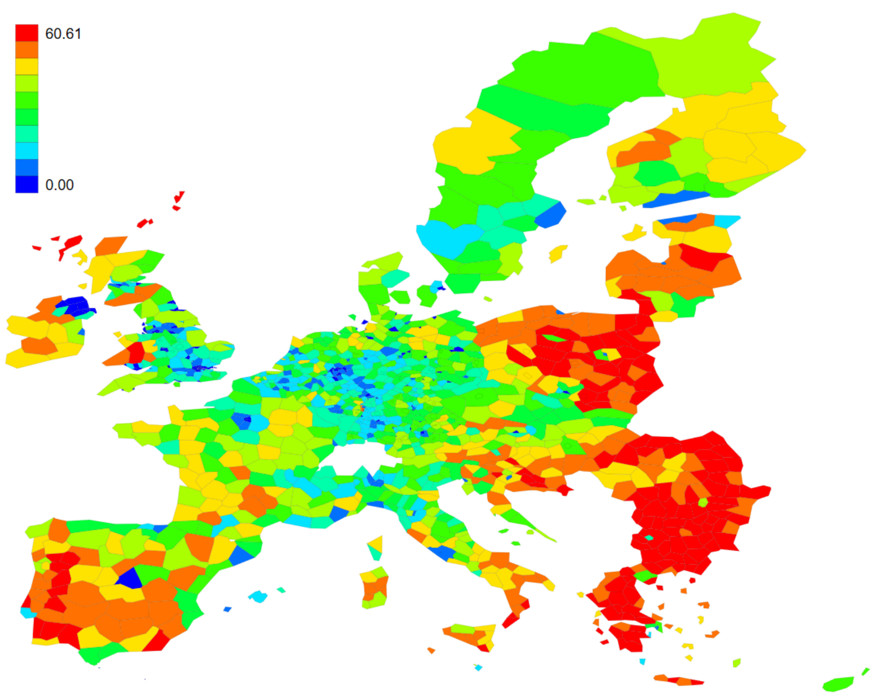
Notes: Departements d'Outre Mer in France, Canary islands in Spain, two autonomous regions in Portugal are not included in the map.

Figure 2: Share of GVA and employment in agriculture of the EU regions

(a) Share of agricultural GVA (%, 2018)



(b) Share of agricultural employment (%, 2017)



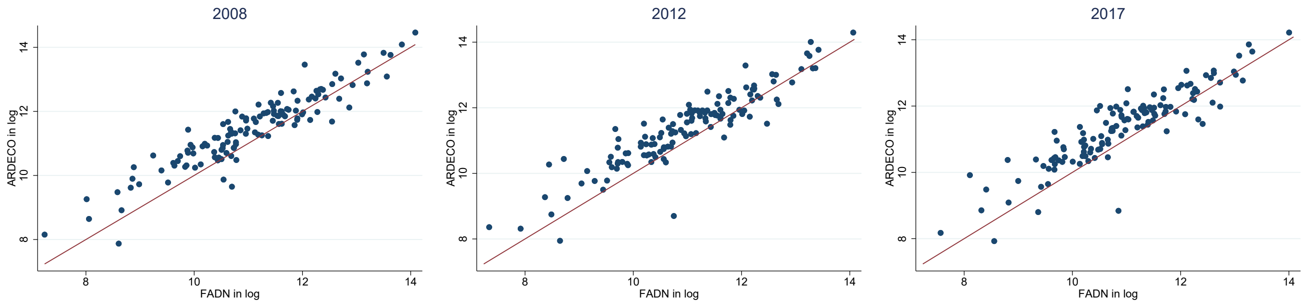
Notes: Departements d'Outre Mer in France, Canary islands in Spain, two autonomous regions in Portugal are not included in the map. For agricultural GVA, Malta and a region (Brent) in the UK are also dropped.

Figure 3: Sectoral contribution to GVA and employment, by regional classification

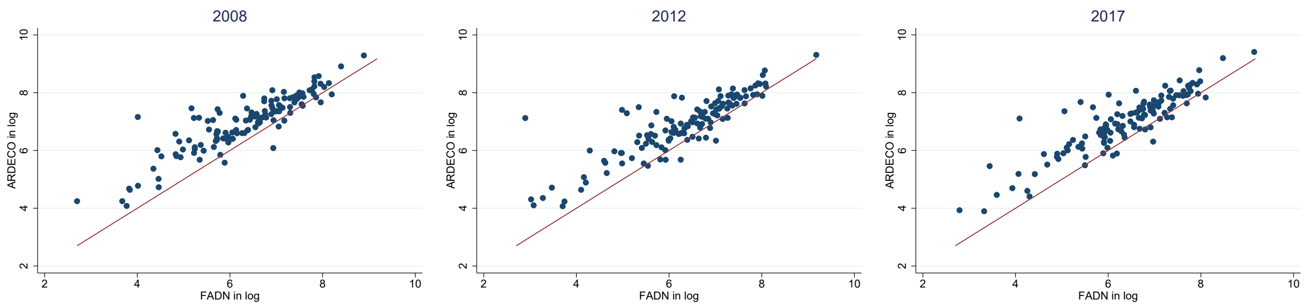
Notes: The sectoral classification is based on ARDECO data. **A**: Agriculture, forestry and fishing, **B-E**: Mining and quarrying, Manufacturing, Electricity, gas, steam and air conditioning supply, Water supply; sewerage, waste management and remediation activities, **F** Construction, **G-J**: Wholesale and retail trade; repair of motor vehicles and motorcycles, Transportation and storage, Accommodation and food service activities, Information and communication, **K-N**: Financial and insurance activities, Real estate activities, Professional, scientific and technical activities, Administrative and support service activities, **O-U**: Public administration and defence; compulsory social security, Education, Human health and social work activities, Arts, entertainment and recreation. Other service activities, Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use, Activities of extraterritorial organisations and bodies.

Figure 4: Comparing the FADN's agricultural employment and income data with ARDECO data

(a) Number of hours worked

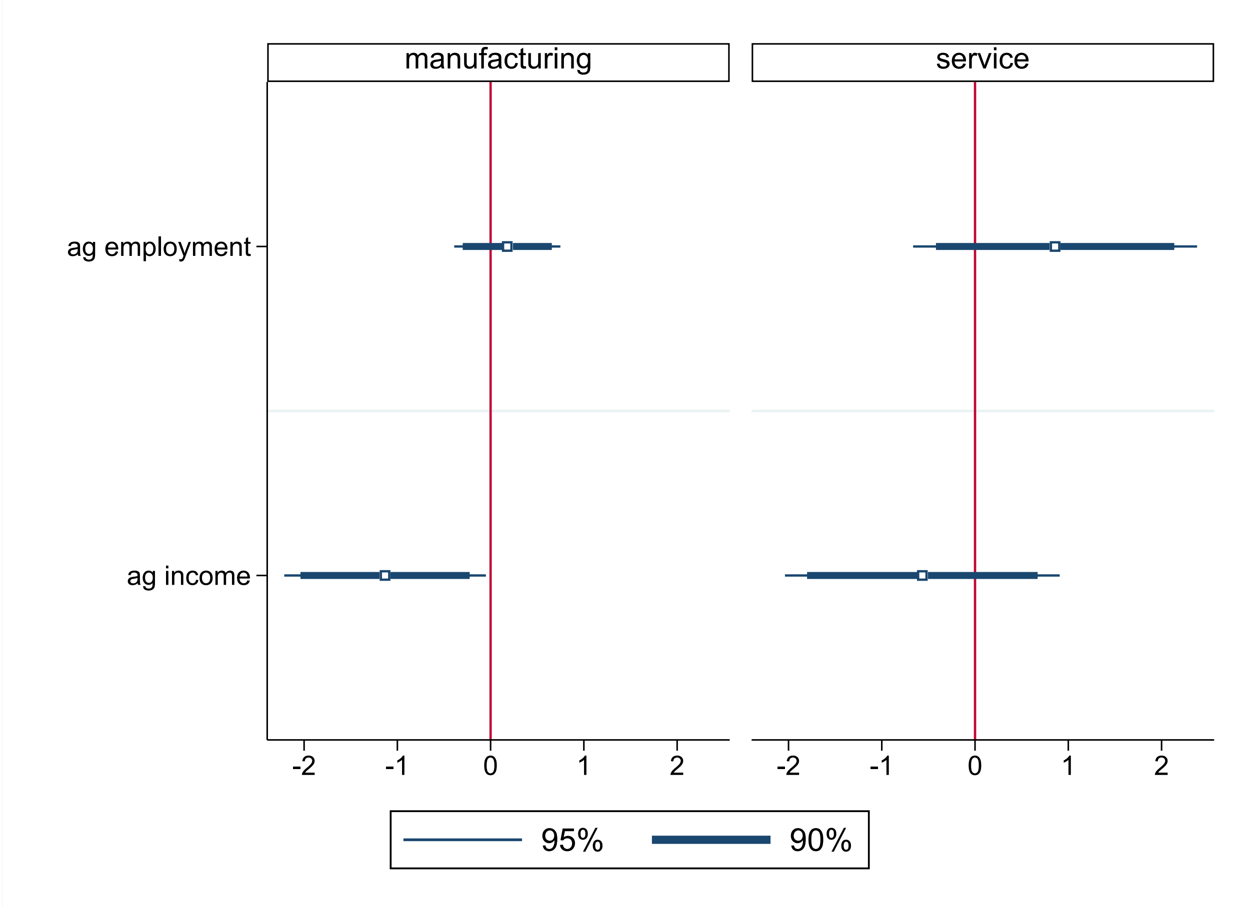


(b) Gross Value Added



Notes: The data of each region in two different datasets are plotted together with a 45 degree line. I use log transformations to better compare the values. Agricultural employment and income of the two regions (Hamburg, Bucuresti-Ilfov) are zeros in the FADN, thus could not be plotted in the graphs.

Figure 5: The estimates of agricultural employment and income multipliers with confidence levels

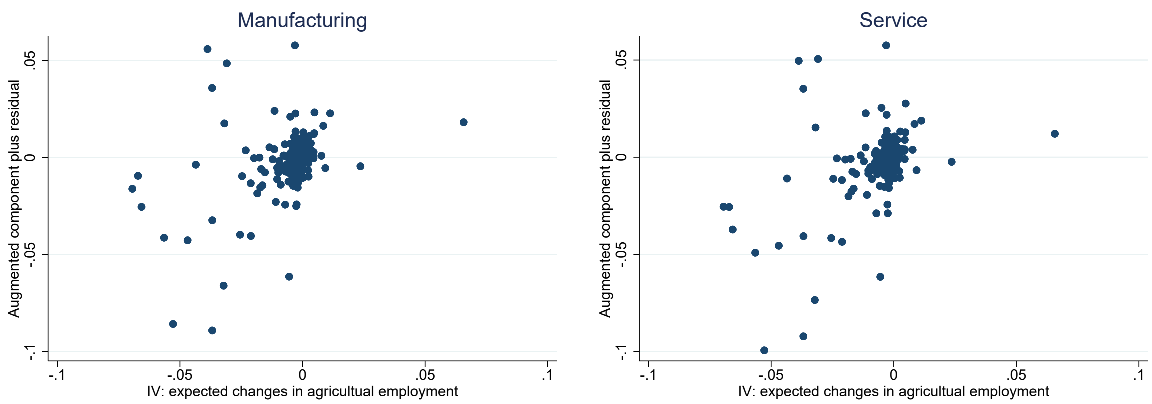


Appendix

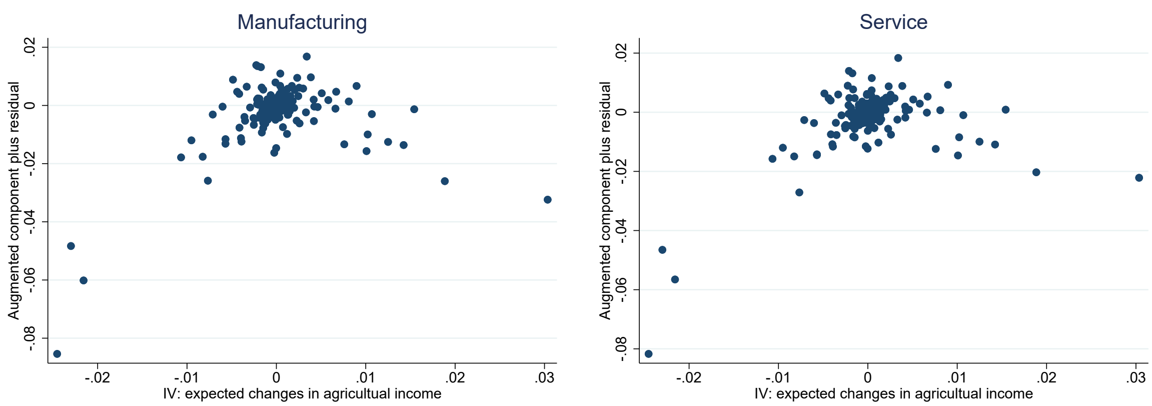
A Partial residual plots

Partial residual plots as a regression diagnostic help examine the nonlinearities in the model. They show the relationship between the covariate of interest and the dependent variable, conditional on other controls in the regression (Mallows, 1986). The figures below show the partial residual plots of the first-stage regressions of the 2SLS. My instruments (expected changes in agricultural employment, expected changes in agricultural income) have nonlinear relationships with the endogenous variables (changes in agricultural employment, changes in agricultural income). Therefore I add the squared term of each instrument in the first-stage regression, which substantially increases the F-statistics.

(a) Employment



(b) Income



Notes: The partial residual plots control for the regional and period fixed effects, a start-of-period share of employment and income in the manufacturing or service sectors respectively, GDP per capita, unemployment rate, the share of women in employment, the share of population with tertiary education, the farm average machinery and equipment costs, the average farm size, and the average CAP payments. Robust standard errors are clustered by country.

B Tradability of sectors

To classify sectors into tradable and non-tradable, some papers use a locational Gini coefficient indicating the geographical concentration of each sector (e.g. Jensen and Kletzer, 2005; Kazekami, 2017; Kemeny and Osman, 2018; Van Dijk, 2018). Following Jensen and Kletzer (2005), I calculate a Gini index as follows: $G_k = \sum_i (s_{ik} - x_i)^2$. It compares the region i's sector k employment as a share of the EU's employment of the sector k (s_{ik}), with the region i's total employment as a share of the EU's total employment (x_i) over years of 2008, 2012, and 2017. Table B1 shows the Gini coeffients of each sector in my main data (i.e. ARDECO).

The intuition behind this measure is that a non-tradable sector (e.g. hairdressing) will be spread over the EU, more or less proportionally with where people live. As a result, one region's share of total EU activity in a non-tradable sector will be more or less identical to that region's share in total EU employment. In this case, the Gini coefficient is close to zero. By contrast, a tradable sector does not need to be located close to its final consumer, and is likely to be geographically concentrated, whether due to agglomeration effects, natural resource availability, low production costs, or other factors. For such sectors, some regions will have a share of EU activity much higher than the region's share in total EU employment would suggest, while for other regions this share will be much lower (or even zero). In this case, the Gini coefficient is greater than zero. For a hypothetical industry entirely located in a single EU region, the Gini would be equal to one.

Table B1: The Gini coefficients of each sector

	A	B-E	F	G-J	K-N	O-U
Gini coefficient	0.0052	0.0011	0.0002	0.0001	0.0011	0.0001

Notes: The sectoral classification is based on ARDECO data. **A**: Agriculture, forestry and fishing, **B-E**: Mining and quarrying, Manufacturing, Electricity, gas, steam and air conditioning supply, Water supply; sewerage, waste management and remediation activities, **F** Construction, **G-J**: Wholesale and retail trade; repair of motor vehicles and motorcycles, Transportation and storage, Accommodation and food service activities, Information and communication, **K-N**: Financial and insurance activities, Real estate activities, Professional, scientific and technical activities, Administrative and support service activities, **O-U**: Public administration and defence; compulsory social security, Education, Human health and social work activities, Arts, entertainment and recreation. Other service activities, Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use, Activities of extraterritorial organisations and bodies.

This shows that agriculture and the broadly defined manufacturing are indeed highly concentrated in certain locations of the EU. Interestingly, the Gini coefficient suggests that service sectors K-N (Financial and insurance activities, Real estate activities, Professional, scientific and technical activities, Administrative and support service activities) have a similar degree of geographical concentration as manufacturing. The estimates of the agricultural employment and income multipliers for the service sector remain robust when K-N is excluded from the service sector (results available upon request).

C Rural-urban typology for multiplier analysis

As the observation unit of our multiplier analyses is FADN regions, it is not possible to use the EU urban-rural typology defined at NUTS3. I instead classify each region into rural or urban by using the Eurostat data of "Number of households by degree of urbanisation and NUTS2 regions" (lfst_r_lfsd2hh). I consider "Cities" and "Towns and suburbs" as urban areas and calculate the share of households living in urban area at the NUTS2 level.

Regions are categorized into four classifications by the quartile of the share of households living in urban areas for year 2008, 2012, and 2017. The first quartile of the urban share is 54.0%, and the second quartile (i.e. median) is 65.2%, and the third quartile is 78.4%. I define the regions in the first quartile as rural and the others as urban to construct a dummy variable. This means that a region is considered urban or rural across the year 2008, 2012, and 2017.

To use the share of households living in urban areas as a continuous variable varying over the three years, I replace four missing values of the year 2008 with the available value of the closest year: Slättbyggdslän, Skogs-och mellanbygdslän and Län i norra Sverige with their 2009 values, and for Denmark with the 2010 value.

Table C1: Category of FADN regions by urban shares

Category	Rural	Urban		
Urban share	share $\leq$54.0%	54.0% <share $\leq$ 65.2%	65.2% < share $\leq$ 78.4%	share >78.4%
Regions	Alentejo e Algarve	Alföld	Abruzzo	Baden-Württemberg
	Anatoliki-Makedonia-Thraki	Aquitaine	Alsace	Campania
	Basilicata	Austria	Andalucía	Canarias (ES)
	Bourgogne	Auvergne	Aragón	Cataluña
	Castilla-la Mancha	Açores e Madeira	Bayern	Comunidad Valenciana
	Centru	Basse-Normandie	Calabria	Comunidad de Madrid
	Corse	Brandenburg	Cantabria	England - East Region
	Dunántúl	Bretagne	Cyprus	England - North Region
	Extremadura	Bucuresti - Ilfov	Emilia-Romagna	England - West Region
	Ipiros-Peloponissos-Nissi Ioniou	Castilla y León	Etelä-Suomi	Hamburg
	Ireland	Centre - Val de Loire	Friuli-Venezia Giulia	Hessen
	Limousin	Champagne-Ardenne	Galicia	Lazio
	Lithuania	Comunidad Foral de Navarra	Haute-Normandie	Liguria
	Länsi-Suomi	Czechia	Illes Balears	Lombardia
	Mecklenburg-Vorpomm	Denmark	La Rioja	Län i norra Sverige

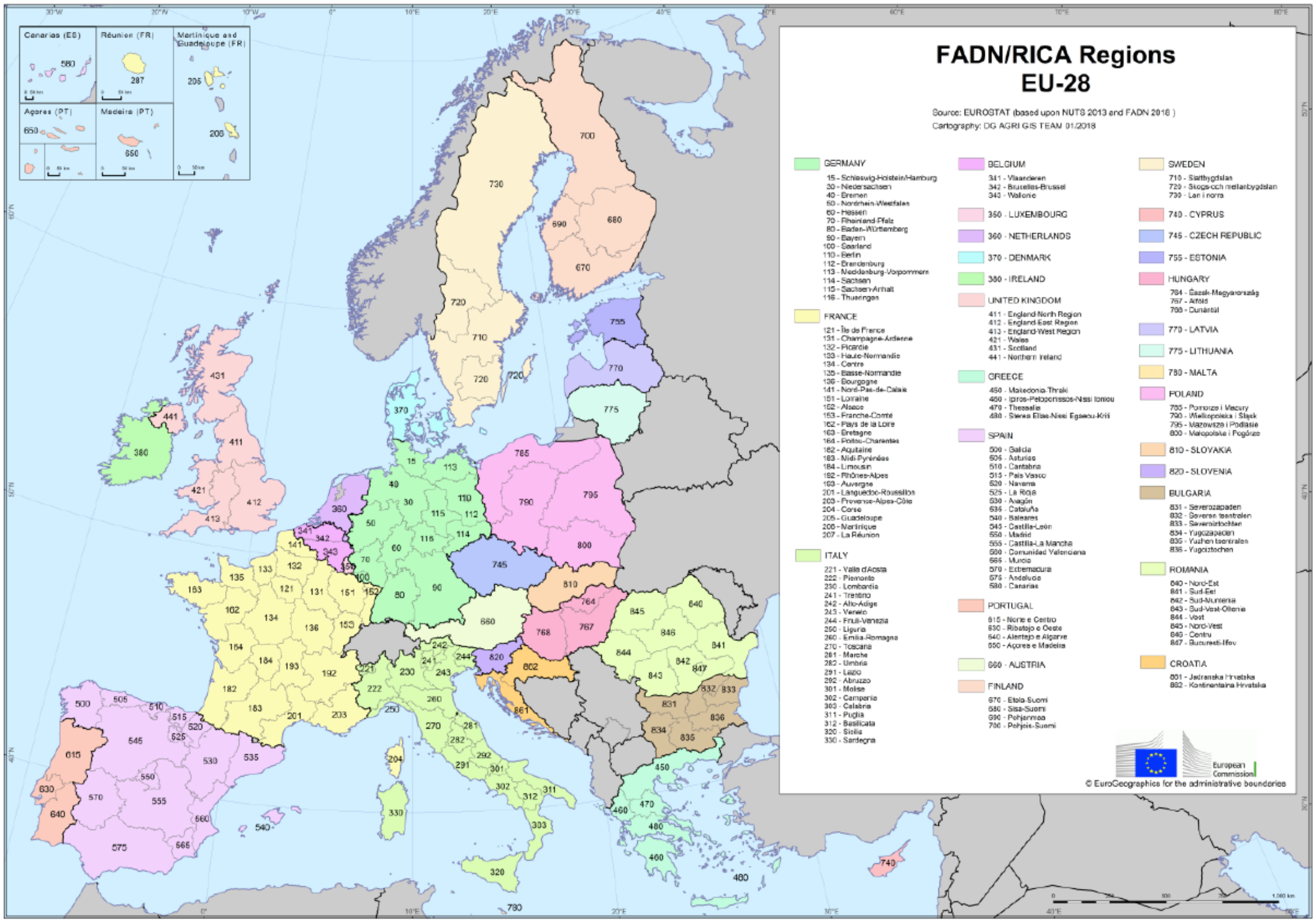
Molise	Estonia	Languedoc-Roussillon	Malta
Nord-Est	Etelä-Suomi	Lorraine	Marche
Nord-Vest	Franche-Comté	Luxembourg	Netherlands
Pohjois- ja Itä-Suomi	Latvia	Malopolska i Pogórze	Nord-Pas-de-Calais
Poitou-Charentes	Mazowsze i Podlasie	Niedersachsen	Nordrhein-Westfalen
Pomorze i Mazury	Midi-Pyrénées	Norte e Centro	País Vasco
Bolzano	Northern Ireland (UK)	Picardie	Principado de Asturias
Sardegna	Pays-de-la-Loire	Piemonte	Provence-Alpes-Côte d'Azur
Severen tsentralen	Trento	Puglia	Región de Murcia
Severozapaden	Sachsen-Anhalt	Rheinland-Pfalz	Saarland
Slättbyggdslän	Slovakia	Rhône-Alpes	Sachsen
Sud - Muntenia	Slovenia	Région wallonne	Scotland
Sud-Est	Severoiztochen	Schleswig-Holstein	Skogs-och mellanbygdslan
Sud-Vest Oltenia	Sterea Ellas-Nissi -Egaeou -Kriti	Sicilia	Veneto
Valle d'Aosta.	Thüringen	Thessalia	Vlaams Gewest
Vest	Umbria	Toscana	Área Metropolitana de Lisboa
Wielkopolska and Slask	Yugoiztochen	Wales	Île de France
Észak-Magyarország	Yuzhen tsentralen	Yugozapaden	

Table C2 compares rural and urban FADN regions defined above with the NUTS3 regional classifications by the EU urban-rural typology. Although the definitions used in each classification are different, relatively large shares of NUTS3 rural regions (both close to a city and remote) are classified as rural FADN regions.

Table C2: Compare rural and urban FADN regions to NUTS3 regions by the EU urban-rural typology

	Urban	Intermediate close to city	Intermediate remote	Rural close to city	Rural remote
Total number of NUTS3 regions	363	500	55	272	158
Number of rural FADN regions	8	70	12	62	45
Number of urban FADN regions	355	430	43	210	113
Rural share	2%	14%	22%	23%	28%
Urban share	98%	86%	78%	77%	72%

D A map of FADN regions



Source: FADN (2020)

E Cleaning procedure of the firm-level data

I download the BvD firm-level data of the EU-28 countries by each section of NACE for the years 2008, 2009, 2012, 2013, 2017, and 2018. In the BvD dataset, these years refer to the closing date of the accounting year, which may differ from the calendar year. The "closing date" and the "number of accounting months" are used to determine the calendar year. The key principle to deciding a calendar year is to cover a large share of accounting period.

- For those with 12 months of accounting period and the closing date before July (until 30 June), I decide the calendar year as the previous year of the closing date. For those of closing date after that, the calendar year is the same as the accounting year. For the case of manufacturing, more than 99% of the firms in the downloaded data (out of 4,403,758 firms) have 12 months of accounting period.

- For those with less than 12 months of accounting period, I allocate the calendar year as the previous accounting year if less than half of the accounting months falls into the accounting year. For example, when the accounting period is six months with the closing date before April (until 31 March), the calendar year is the previous year of the closing date. Only 0.52% of the manufacturing firms in my data has less than 12 months of accounting period. I drop observations indicating zero month for accounting period.

- For those with more than 12 months of accounting period, the same principle applies. Only 0.41% of the manufacturing firms in my data has more than 12 months of accounting period. There are nine firms whose accounting period is more than 24 months. I decide their calendar year to the closest year from the closing date.

Once the year of the financial data is allocated, I correct reporting mistakes by following the common practice explained in Kalemli-Ozcan *et al.* (2019).

- First I drop observations when the first 2-digits from the identification number ("BvD ID number") do not match with the country code ("ISO code"). The IDs are uniquely assigned to each firm starting with the country code. The subsidiaries and headquarters are separately registered as a unique ID.

- Next, I drop the duplicates of the ID-year based on a flow variable of "net income". As the duplicates could arise from the presence of both quarterly and annual reports, I remove financials of the ID-year duplicates whose “net income” values are lower.

- Third, the observations with negative values of "cost of employees" are dropped.

- Fourth, I drop the observations whose "number of employees" is missing.
- Last, the firms with missing values of "net income" and "added value" are dropped.

To aggregate the observations from the firm-level to the regional-level, I use the NUTS information of each firm, provided by the BvD dataset. This refers to the location of the official seat of the company. When the NUTS information is missing, I use the name of the “Region” to allocate each observation’s NUTS region. When both items are missing, the observations are inevitably not included. However, the numbers are very small. Among 4791 firms of the manufacturing sector (NACE section C) in the EU-28, only 200 firms (i.e. 4%) are excluded for not having any information on regions. Among 8396 firms of the wholesale and retail trade including repair of motor vehicles and motorcycles (NACE section G), 341 firms (i.e. 4%) are excluded for the same reason. Among 2232 firms of the accommodation and food service activities (NACE section I), 72 firms (i.e. 3%) are excluded likewise.

F Constructing agricultural GVA from FADN data

In order to use an equivalent income measure across sectors, I therefore construct agricultural GVA estimates based on FADN data. In the following, I first describe how GVA is constructed, and how FADN data is structured. I then discuss how I constructed a GVA-equivalent based on FADN data.

GVA can be defined as output value at basic prices less intermediate consumption valued at purchasers prices (Eurostat, 2013). The basic price is the amount receivable by the producer from the purchaser for a unit of a good or service produced as output, minus any tax payable and plus any subsidy receivable, by the producer as a consequence of its production or sale. The purchaser price is the amount paid by the purchaser, excluding any VAT or similar tax deductible by the purchaser, in order to take delivery of a unit of a good or service at the time and place required by the purchaser.

FADN measures the output value at farm gate price, which does not include VAT, taxes and subsidies (European Commission, 2020). Farm taxes and other dues are not included in the total input costs; instead, those are registered in another item under "subsidies and taxes".

First, "subsidies on products" (i.e. coupled subsidies) should be included in my GVA measure, but I should not add "subsidies on production" (i.e. decoupled subsidies) because I am constructing the GVA from the production side.

Second, the item "farm taxes" in FADN refers to taxes charged on buildings and lands. As these taxes are not linked to the volume of production, they should not be deducted.

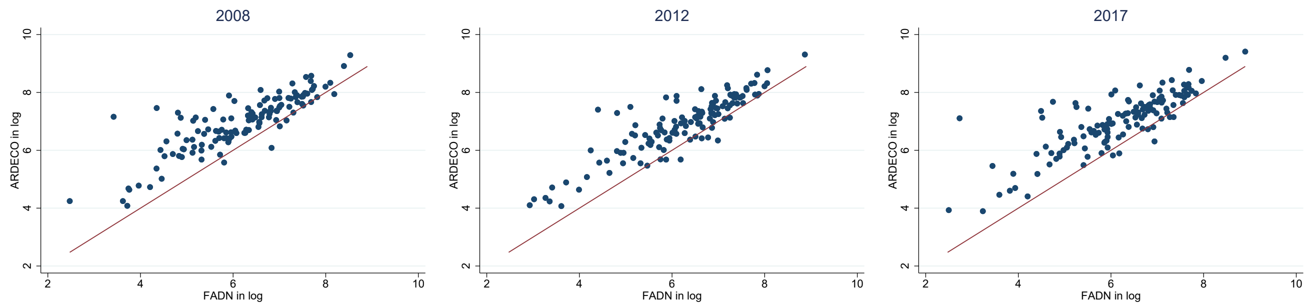
Third, I do not add or deduct FADN items of "VAT on purchase" and "VAT on sales". This depends on the different measures of price used to calculate the output and the intermediate consumption in GVA. The basic price excludes the VAT on sales and purchaser price includes the VAT on purchase, implying that GVA does not include the values of VAT.

As a result, I construct the GVA in agriculture by using FADN items as follows: Total output - Total intermediate consumption + Coupled subsidies (Total subsidies on crops, Total subsidies on livestock)

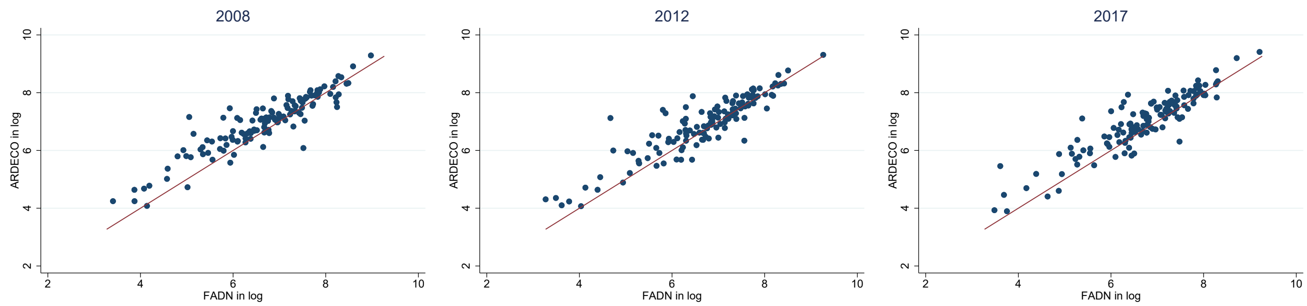
G Comparing the additional values of GVA in agriculture with ARDECO

I use two additional values of agricultural GVA as robustness checks. I create a "market income" variant of agricultural GVA which deducts OGA revenues, and use "gross farm income" readily available in FADN data. The figures below compare the two additional GVA values of FADN and the value of ARDECO.

(a) Market farm income



(b) Gross farm income



Notes: The data of each region in two different datasets are plotted together with a 45 degree line. I use log transformations to better compare the values. Four regions could not be included in the market farm income graph because of negative (Slovakia for 2012 and Län i norra Sverige for 2012) or zero values (Bucuresti - Ilfov for 2008 and Hamburg in 2017). Two regions could not be included in the gross farm income graph because of zero values (Bucuresti - Ilfov for 2008 and Hamburg for 2017). The furthest point from the 45 degree line is the region "Län i norra Sverige" (FADN code 730) in Sweden. This is because "Län i norra Sverige" is larger than the two NUTS regions (SE32+SE33) I match with the region. The regional divisions of Sweden in NUTS and FADN are very different.

H Matching the type of farming in FADN and agricultural products in Eurostat

The table below shows how I match the categories of agricultural products in producer prices index (PPI) to the 14 types of farming.

Type of farming in FADN	Agricultural products in Eurostat
(15) Specialist COP	Cereals, Oil seeds and oleaginous fruits, Protein crops, Fodder maize
(16) Specialist other fieldcrops	Raw tobacco, Sugar beet, Other industrial crops, Fodder root crops, Other forage plants, Potatoes, Other crop products
(20) Specialist horticulture	Vegetables and horticultural products
(35) Specialist wine	Wine
(36) Specialist orchards - fruits	Fresh fruit, Citrus fruit, Tropical fruit, Grapes
(37) Specialist olives	Olives
(38) Permanent crops combined	Average of 35, 36, 37
(45) Specialist milk	Milk
(48) Specialist sheep and goats	Equines, Sheep and goats
(49) Specialist cattle	Cattle
(50) Specialist granivores	Pigs, Poultry, Eggs
(60) Mixed crops	Average of 15, 16, 20, 35
(70) Mixed livestock	Average of 45, 48, 49, 50
(80) Mixed crops and livestock	Average of 15, 16, 20, 35, 36, 37, 45, 48, 49, 50

Notes: Price data of agricultural products in Eurostat is "apri_pi10_outa". Equines are classified into the "(48) Specialist sheep and goats", because FADN's "Specialist sheep and goats" includes other grazing livestocks.

I Full regression results of the agricultural multipliers

Table I1: Agricultural employment multipliers on the manufacturing sector employment

VARIABLES	(1) $\Delta mfg\,emp$	(2) $\Delta mfg\,emp$	(3) $\Delta mfg\,emp$	(4) $\Delta mfg\,emp$	(5) $\Delta mfg\,emp$	(6) $\Delta mfg\,emp$	(7) $\Delta mfg\,emp$	(8) $\Delta mfg\,emp$	(9) $\Delta mfg\,emp$	(10) $\Delta mfg\,emp$
$\Delta ag\,emp$	-0.505**	-0.238	-0.178	0.181	0.203	0.189	0.174	0.182	0.184	0.179
	(0.243)	(0.230)	(0.220)	(0.330)	(0.307)	(0.277)	(0.288)	(0.312)	(0.288)	(0.290)
share of mfg employment		-1.127***	-1.140***	-1.307***	-1.286***	-1.285***	-1.257***	-1.265***	-1.329***	-1.321***
		(0.205)	(0.204)	(0.256)	(0.292)	(0.289)	(0.319)	(0.349)	(0.361)	(0.360)
GDP per capita			-0.769	4.009*	4.434**	4.419**	4.401**	4.420**	4.725***	4.538***
			(1.995)	(2.113)	(1.876)	(1.819)	(1.791)	(1.811)	(1.684)	(1.689)
unemployment rate				0.202***	0.138	0.134	0.127	0.129	0.141	0.144
				(0.051)	(0.154)	(0.149)	(0.159)	(0.166)	(0.162)	(0.163)
share of women in employment					-0.141	-0.150	-0.152	-0.152	-0.165	-0.152
					(0.248)	(0.240)	(0.240)	(0.239)	(0.228)	(0.231)
share of tertiary educated population						0.032	0.028	0.028	0.105	0.107
						(0.086)	(0.088)	(0.087)	(0.097)	(0.099)
machinery and equipment costs							-0.025	-0.012	-0.186	-0.222*
							(0.088)	(0.135)	(0.126)	(0.123)
average farm size								-0.032	0.046	0.147
								(0.153)	(0.134)	(0.148)
decoupled									-0.668	-0.719*
									(0.418)	(0.419)
CAP pillar2										-0.840
										(0.638)
Observations	260	260	260	260	260	260	260	260	260	260
Number of id	130	130	130	130	130	130	130	130	130	130
Period fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F stats	8.370	6.614	10.804	13.883	12.883	14.175	11.875	17.171	17.101	19.520

Notes: Robust standard errors clustered by country are reported in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table I2: Agricultural employment multipliers on the service sector employment

VARIABLES	(1) $\Delta service\, emp$	(2) $\Delta service\, emp$	(3) $\Delta service\, emp$	(4) $\Delta service\, emp$	(5) $\Delta service\, emp$	(6) $\Delta service\, emp$	(7) $\Delta service\, emp$	(8) $\Delta service\, emp$	(9) $\Delta service\, emp$	(10) $\Delta service\, emp$
$\Delta ag\, emp$	-2.330**	-1.516**	-0.191	1.095	0.955	0.881	0.881	0.949	0.879	0.859
	(0.981)	(0.687)	(0.666)	(0.908)	(0.829)	(0.798)	(0.797)	(0.832)	(0.775)	(0.777)
share of service employment		-1.482*	-1.474**	-1.105***	-1.004**	-1.011***	-1.011***	-1.003***	-0.939***	-0.905***
		(0.888)	(0.653)	(0.368)	(0.394)	(0.387)	(0.372)	(0.361)	(0.337)	(0.325)
GDP per capita			-18.109**	1.773	-0.033	-0.116	-0.116	0.004	0.657	0.148
			(7.538)	(6.938)	(5.858)	(5.501)	(5.510)	(5.571)	(5.360)	(5.560)
unemployment rate				0.893***	1.137***	1.112***	1.112***	1.132***	1.153***	1.168***
				(0.145)	(0.291)	(0.289)	(0.286)	(0.296)	(0.273)	(0.273)
share of women in employment					0.538	0.491	0.491	0.478	0.426	0.463
					(0.495)	(0.488)	(0.489)	(0.494)	(0.453)	(0.452)
share of tertiary educated population						0.171	0.171	0.157	0.386	0.394
						(0.366)	(0.368)	(0.367)	(0.365)	(0.359)
machinery and equipment costs							-0.001	0.133	-0.441	-0.528
							(0.151)	(0.206)	(0.277)	(0.347)
average farm size								-0.353	-0.072	0.198
								(0.445)	(0.372)	(0.593)
decoupled									-2.089***	-2.238***
									(0.760)	(0.811)
CAP pillar2										-2.250
										(2.985)
Observations	260	260	260	260	260	260	260	260	260	260
Number of id	130	130	130	130	130	130	130	130	130	130
Period fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F stats	8.370	9.178	14.106	21.587	19.589	20.621	19.175	25.026	22.750	24.094

Notes: Robust standard errors clustered by country are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table I3: Agricultural income multipliers on the manufacturing sector income

VARIABLES	(1) $\Delta mfg\, income$	(2) $\Delta mfg\, income$	(3) $\Delta mfg\, income$	(4) $\Delta mfg\, income$	(5) $\Delta mfg\, income$	(6) $\Delta mfg\, income$	(7) $\Delta mfg\, income$	(8) $\Delta mfg\, income$	(9) $\Delta mfg\, income$	(10) $\Delta mfg\, income$
$\Delta ag\, income$	-0.817*	-0.997*	-1.124**	-1.209**	-1.121**	-1.057**	-1.103**	-1.117**	-1.211**	-1.132**
	(0.490)	(0.522)	(0.517)	(0.508)	(0.542)	(0.517)	(0.517)	(0.565)	(0.544)	(0.552)
share of mfg income		-0.477*	-0.359	-0.331	-0.321	-0.318	-0.305	-0.306	-0.296	-0.322
		(0.279)	(0.271)	(0.270)	(0.287)	(0.281)	(0.275)	(0.277)	(0.279)	(0.277)
GDP per capita			-7.088	-9.269*	-8.754*	-8.798*	-8.509*	-8.535*	-8.405*	-8.724*
			(4.506)	(5.061)	(4.648)	(4.612)	(4.845)	(4.840)	(4.731)	(4.693)
unemployment rate				-0.099	-0.178	-0.172	-0.203	-0.202	-0.188	-0.175
				(0.083)	(0.191)	(0.195)	(0.197)	(0.202)	(0.193)	(0.196)
share of women in employment					-0.174	-0.152	-0.116	-0.116	-0.121	-0.084
					(0.317)	(0.336)	(0.338)	(0.337)	(0.329)	(0.326)
share of tertiary educated population						-0.186	-0.209	-0.210	-0.121	-0.111
						(0.205)	(0.217)	(0.216)	(0.233)	(0.235)
machinery and equipment costs							-0.242	-0.230	-0.456	-0.570*
							(0.233)	(0.230)	(0.312)	(0.310)
average farm size								-0.033	0.055	0.404
								(0.185)	(0.242)	(0.283)
decoupled									-0.811	-0.984
									(0.612)	(0.627)
CAP pillar2										-2.874
										(1.899)
Observations	260	260	260	260	260	260	260	260	260	260
Number of id	129	130	130	130	130	130	130	130	130	130
130										
Period fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F stats	84.301	63.106	70.375	61.165	71.049	64.820	54.872	44.385	42.481	44.011

Notes: Robust standard errors clustered by country are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table I4: Agricultural income multipliers on the service sector income

VARIABLES	(1) $\Delta service\,income$	(2) $\Delta service\,income$	(3) $\Delta service\,income$	(4) $\Delta service\,income$	(5) $\Delta service\,income$	(6) $\Delta service\,income$	(7) $\Delta service\,income$	(8) $\Delta service\,income$	(9) $\Delta service\,income$	(10) $\Delta service\,income$
$\Delta ag\,income$	-0.030	-0.076	-0.546	-0.228	-0.435	-0.488	-0.486	-0.598	-0.674	-0.565
	(0.777)	(0.770)	(0.764)	(0.783)	(0.781)	(0.785)	(0.791)	(0.796)	(0.770)	(0.752)
share of service income		-0.143	-0.237	-0.157	-0.169	-0.138	-0.137	-0.117	-0.110	-0.110
		(0.295)	(0.311)	(0.291)	(0.287)	(0.267)	(0.241)	(0.226)	(0.228)	(0.227)
gdp per capita			-16.069**	-8.677	-9.913	-9.632	-9.637	-9.742	-9.543	-9.951
			(7.488)	(7.132)	(6.678)	(6.645)	(6.645)	(6.567)	(6.541)	(6.526)
unemployment rate				0.336***	0.489**	0.483**	0.484**	0.496**	0.508**	0.518**
				(0.113)	(0.242)	(0.240)	(0.242)	(0.242)	(0.239)	(0.243)
share of women in employment					0.341	0.309	0.307	0.299	0.293	0.325
					(0.461)	(0.460)	(0.481)	(0.486)	(0.481)	(0.490)
share of tertiary educated population						0.203	0.204	0.198	0.274	0.284
						(0.385)	(0.398)	(0.391)	(0.375)	(0.369)
machinery and equipment costs							0.009	0.105	-0.081	-0.197
							(0.279)	(0.364)	(0.466)	(0.518)
average farm size								-0.265	-0.193	0.165
								(0.443)	(0.453)	(0.621)
decoupled									-0.674	-0.847
									(0.713)	(0.822)
CAP pillar2										-2.891
										(3.661)
Observations	260	260	260	260	260	260	260	260	260	260
Number of id	130	130	130	130	130	130	130	130	130	130
Period fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F stats	84.301	55.813	56.697	53.151	50.638	51.452	45.912	35.852	35.333	36.605

Notes: Robust standard errors clustered by country are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1