Designing a Roadmap for Effective and Sustainable Strategies for Assessing and Addressing the Challenges of EU Agriculture to Navigate within a Safe and Just Operating Space

Ex-post impact of first- and second-pillar CAP payments on farm structural change

Working paper

AUTHORS	Laurent Piet (INRAE)
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ACRONYMS

Acronym	Meaning
AC	Agricultural census
AWU	Agricultural working unit
CAP	Common agricultural policy
CCMSA	Caisse centrale de la mutualité sociale agricole
EU	European Union
FADN	Farm accounting data network
FSS	Farm structure survey
JOS	Just operating space
MCM	Markov chain model
NUTS	Nomenclature of territorial units for statistics
SGM	Standard gross margin
SO	Standard output

1. EXECUTIVE SUMMARY

The number of farms and the labour force employed in agriculture has been steadily declining for several decades across the European union (EU). In addition, the farming population is ageing, with a shrinking share of younger farmers –below 40– and a growing share of older ones –above 55. Agricultural employment is therefore a key just operating space (JOS) outcome and has recently been reaffirmed as a cornerstone of the European vision for agriculture and food, and its associated strategy for generation renewal in agriculture.

To date, the academic literature on ex-post analysis of farm structural change has drawn on a variety of econometric and modelling frameworks; among these, the Markov chain modelling approach has often been favoured. This method assumes that the year-to-year movement of farms from one category (e.g., a size class or farm type) to another is a stochastic process which can be represented by transition probabilities.

The objective of this contribution was therefore to investigate the impact of Common agricultural policy (CAP) payments on farm structural change and agricultural labour levels using individual, farm-level microdata. Initially, the planned approach was to use the database of self-employed agricultural workers held by the Caisse Centrale de la Mutualité Sociale Agricole (CCMSA), the French authority responsible for farmers' healthcare and social security. However, this database proved not entirely suitable for the intended purpose, and an alternative method was developed to estimate Markov chain models (MCM) directly from individual Farm accounting data network (FADN) data.

The main challenge in using FADN data to estimate a MCM was to account for farm entries and exits, as these data do not readily allow such transitions to be measured directly: farms may enter or leave the sample simply because they begin or cease participating in the survey, rather than because they start or discontinue operations. The strategy adopted therefore consisted in making use of the year-specific weights attached to each farm of the FADN sample to infer entry and exit flows. Based on a set of assumptions, the FADN database was thus restructured to reflect weight variations, duplicating sample farms where necessary and adjusting their extrapolating factors accordingly.

The restructured FADN data were then used to estimate a multinomial logit non-stationary MCM in which transition probabilities are allowed to vary over time, incorporating the following farm-level explanatory variables: i) a dummy identifying farms with a company legal status; ii) total utilised agricultural area; iii) ratio of unpaid labour to total labour; iv) family farm income per unpaid labour unit; v) debt ratio, defined as total liabilities divided by total assets; vi) total first-pillar CAP payments per total labour unit; and vii) total second-pillar CAP payments per total labour unit. Long-run probability and structure elasticities were then derived from the estimated coefficients for the two key policy variables, namely the first- and second-pillar CAP payments. In particular, structure elasticities measure the relative impact of a 1% increase in a given variable on the number of AWU in each economic size class and in aggregate.

France was used as a case study, with FADN data covering the 2004-2021 period. Sample farms were categorised into five classes according to their economic size, measured in thousands of euros of standard output (k€ of SO): i) up to 50 k€ of SO; ii) from 50 to 100 k€ of SO; iii) from 100 to 250 k€ of SO; iv) from 250 to 500 k€ of SO; and v) 500 k€ of SO or more. Finally, the extrapolating factors were multiplied by the total number of agricultural working units (unpaid and paid AWU) to study employment trends.

Compared with much of the existing literature, the estimated entry and exit probabilities appear overestimated, while the probabilities of remaining in the same initial economic size class appear underestimated. This was not unexpected as, as noted above, the adopted method cannot fully disentangle genuine entries and exits from sample ins and outs. From a statistical point of view, however, accounting for the implicit entries and exits embedded in the variations in extrapolating factors for farms that remain in the sample from year to year makes it possible to accurately replicate the evolution of farm and AWU numbers by economic size classes and in aggregate. It is therefore believed that the resulting structure elasticities reliably capture the impact of the studied policy variables on these numbers. Moreover, a key advantage of the proposed method is that, unlike much of the previous literature on farm structural change using an MCM approach, it allows explanatory variables to be evaluated at the individual farm level rather than only at the aggregate (typically national, or at best local) level.

Results show that both payment types exert a positive and, in most cases, statistically significant long-run impact on farm and AWU numbers in smaller economic size classes (up to 250 k€ of SO), while their long-run impact is significantly negative in larger classes (250 k€ of SO or more). The overall long-run impact of both payment types, though modest, is positive and significant, amounting to 0.013 and 0.006, respectively, in terms of AWU. Finally, while the long-run relative impact of first-pillar payments is found to be in general significantly larger than that of second-pillar payments across all economic size classes and in aggregate, second-pillar payments appear more efficient in supporting employment on a per euro basis.

Globally, these findings are consistent with previous literature conclusions which were obtained using different approaches. However, as other studies suggest that this positive effect is context-dependent, the MCM approach developed here will be applied to the FADN data from other EU Member States to assess the robustness and consistency of the results obtained for France. Finally, acknowledging that the present work is mainly a “proof-of-concept” study, other avenues for future research are also discussed.

2. INTRODUCTION

The number of farms and the agricultural labour force have been steadily declining for several decades across the European union (EU). In addition, the farming population is ageing, with a shrinking share of younger farmers – below 40 – and a growing share of older ones – above 55 (Détang-Dessendre et al., 2022). Agricultural employment is therefore a key just operating space (JOS) outcome and has recently been reaffirmed as a cornerstone of the European vision for agriculture and food and its associated strategy for generation renewal in agriculture.

To date, the academic literature on ex-post analysis of farm structural change has drawn on a variety of econometric and modelling frameworks; among these, the Markov chain modelling approach has often been favoured (Zimmermann et al., 2009). This method assumes that the year-to-year movement of farms from one category (e.g., a size class or farm type) to another is a stochastic process that can be represented by transition probabilities. In most cases, however, individual farm transitions are not directly observed as only 'grouped' data – that is, the annual breakdown of farms by category – are available. Accurately estimating the underlying transitions and probabilities from such aggregate, macro data is a challenging task, since the associated mathematical problem is ill-posed in general; several techniques have been investigated to address this issue (Karantininis, 2002). More recently, researchers have proposed using the Farm accounting data network (FADN) database – or similar microdata sources – as providing prior information on individual farm transitions, thereby enabling better recovery of transition probabilities from macro data (Zimmermann and Heckelei, 2012; Storm et al., 2015). Saint-Cyr (2022) relied on individual data only but did not account for entries and exits, and therefore focused on the evolution of farm shares by economic size class rather than farm numbers.

The objective of this paper is therefore to investigate the impact of Common agricultural policy (CAP) payments on farm structural change and agricultural labour levels using individual, farm-level microdata. Initially, the planned approach was to use the database of self-employed agricultural workers held by the Caisse centrale de la mutualité sociale agricole (CCMSA), the French authority responsible for farmers' healthcare and social security. However, this database proved not entirely suitable for the intended purpose, and an alternative method was therefore developed to estimate Markov chain models (MCM) directly from individual FADN data.

The remainder of this paper is structured as follows. Section 2 introduces the data and method used, with particular focus on the preliminary treatment required to implement the non-stationary Markov chain modelling framework presented here. Section 3 reports the results, both in terms of transition probability matrix estimation and of the impact of first- and second-pillar CAP payments on the total number of full-time equivalent of agricultural labour units, as assessed through probability and structure elasticities. Section 4 concludes with a discussion of the results and identifies avenues for future research.

3. DATA AND METHOD

3.1. Data used

The proposed method was developed using farm-level data from the FADN, a survey established in 1965 in the EU and conducted annually by each Member State to collect harmonised bookkeeping information on the physical, structural, economic, and financial characteristics of a national sample of farms (European Commission, 2025).

In each country, the FADN sample is designed to be representative of the population of commercial farms, defined those as exceeding a minimum economic size measured in euros of total Standard output (SO).[1] Since farm structures vary across the EU, the corresponding SO threshold is country-specific. To ensure representativeness, the FADN sample is stratified along three dimensions: location at the NUTS2 regional level,[2] economic size and type of farming (in terms of main production). Each farm in the database is accordingly assigned a year- and stratum-specific weight reflecting its annual stratified sampling probability, which allows for extrapolation to the population level for each cross-section. In the FADN database, these weights – or extrapolating factors – are stored in the variable SYS02 "Farms represented" (European Commission, 2025).

To illustrate the method, we draw on the French component of the FADN, which covers approximately 7,000 to 7,500 commercial farms per year. Using data for the 2004-2021 period yields 132,972 observations corresponding to 19,349 unique farms. The breakdown by number of observed years, reported in panel a) of Table 1, shows that: 2,447 farms (13%) are observed only once; 1,187 farms (6%) are observed across all 18 years; and almost half of the farms (49%) are observed for six years or more.

However, owing to the FADN sampling strategy, farms may be observed on a non-consecutive basis. According to panel b) of Table 1: only 392 farms are observed discontinuously, meaning that 98% of the sample is observed continuously (i.e., each farm enters or leaves the sample only once); 28% of farms are observed for at least 10 consecutive years; and 36 farms observed 17 times (representing 10% of such farms) are in fact present throughout the entire period except for one year.

[1] The Standard Output of a farm is a measure of its potential gross production defined as the average monetary value of the agricultural output at farm-gate prices for each agricultural product (crop or livestock) in a given region (Eurostat, 2026a).

[2] The Nomenclature of Territorial Units for Statistics (NUTS) provides a standardised breakdown of territorial units for the production of regional statistics in the EU (Eurostat, 2026b).

Table 1 Breakdown of French FADN sample farms per number of observed years

Years observed	Farms	
	Number	cum. %
1	2,447	13%
2	2,201	24%
3	2,109	35%
4	1,683	44%
5	1,501	51%
6	1,157	57%
7	1,084	63%
8	951	68%
9	818	72%
10	748	76%
11	623	79%
12	558	82%
13	548	85%
14	539	88%
15	483	90%
16	355	92%
17	357	94%
18	1,187	100%
Total	**19,349**	

a) All farms

Consecutive years	Farms		
	Number	*share of all farms (%)*	cum. %
1	2,447	*100.0%*	13%
2	2,168	*98.5%*	24%
3	2,083	*98.8%*	35%
4	1,654	*98.3%*	44%
5	1,469	*97.9%*	52%
6	1,129	*97.6%*	58%
7	1,058	*97.6%*	63%
8	923	*97.1%*	68%
9	793	*96.9%*	72%
10	731	*97.7%*	76%
11	603	*96.8%*	79%
12	537	*96.2%*	82%
13	523	*95.4%*	85%
14	518	*96.1%*	88%
15	470	*97.3%*	90%
16	343	*96.6%*	92%
17	321	*89.9%*	94%
18	1,187	*100.0%*	100%
Total	**18,957**	***98.0%***	

b) Farms observed consecutively

Source: Own calculation based on FADN data; EU-FADN – European Commission

According to the FADN, the total (i.e., extrapolated) number of French commercial farms declined from 315,100 in 2004 to 268,300 in 2021 (Table 2), representing a decrease of 15% over the 18-year period, or an average annual rate of –0.9%. Since the focus of this study is agricultural employment, Table 2 also reports the evolution of the total labour force of French commercial farms expressed in full-time equivalents (or 'agricultural working units', AWU),[3] as well as its annual breakdown across the five economic size categories – measured in thousands of euros of standard output (k€ of SO) – considered throughout this paper: i) up to 50 k€ of SO; ii) from 50 to 100 k€ of SO; iii) from 100 to 250 k€ of SO; iv) from 250 to 500 k€ of SO; and v) 500 k€ of SO or more.[4] The corresponding breakdown in terms of farm numbers is reported in Table A1 in the Appendix.

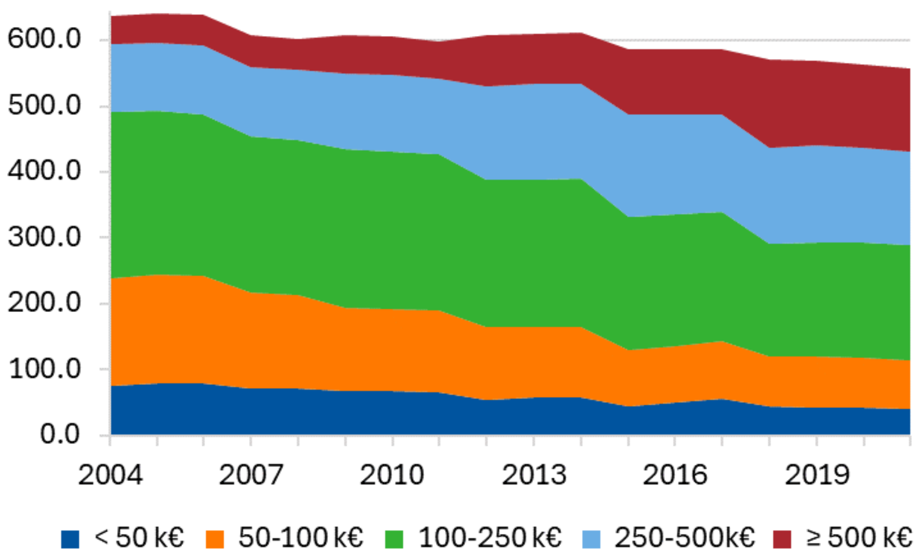
[3] In the FADN database, the total labour force is recorded in the standard result variable SE010 "Total labour input". The figures in Table 2 are obtained by multiplying the extrapolating factors (SYS02) by SE010 and summing across sample farms.

[4] In the FADN database, economic size is reported in the standard result variable SE005 "Economic size". The five size categories correspond to the following size classes: i) classes 1 to 6 for the up to 50 k€ of SO category; ii) class 7 for the 50–100 k€ of SO category; iii) class 8 for the 100–250 k€ of SO category; iv) class 9 for the 250–500 k€ of SO category; and v) classes 10 to 14 for the 500 k€ of SO or more category.

Table 2 Evolution of the total labour force by economic size (France)

Year	Labour force (1,000 AWU)						Farms (1,000)
	< 50 k€	50–100 k€	100–250 k€	250–500 k€	≥ 500 k€	Total	
2004	76.2	162.5	252.3	102.5	44.0	**637.5**	315.1
2005	79.7	163.8	250.3	102.4	45.0	**641.3**	318.2
2006	78.7	163.0	245.3	105.8	46.7	**639.7**	319.1
2007	72.2	144.3	237.7	105.1	48.6	**607.9**	302.2
2008	71.3	142.3	235.3	105.9	46.9	**601.6**	303.3
2009	67.7	125.7	241.7	115.0	58.4	**608.7**	295.9
2010	67.1	125.1	239.3	117.1	56.7	**605.3**	295.7
2011	66.0	123.3	238.1	115.2	55.1	**597.7**	295.8
2012	53.8	110.1	225.1	142.1	76.6	**607.7**	295.6
2013	58.0	106.0	225.1	145.6	75.4	**610.1**	298.7
2014	57.0	107.8	225.0	143.6	78.6	**612.0**	296.9
2015	43.7	85.8	202.1	156.1	98.1	**585.9**	287.2
2016	49.9	86.4	199.5	152.1	98.9	**586.8**	291.4
2017	55.7	86.8	197.6	148.1	98.3	**586.5**	295.6
2018	43.4	75.9	171.4	146.4	133.0	**570.0**	270.7
2019	42.6	77.4	173.8	146.5	129.7	**569.9**	270.6
2020	41.4	76.2	174.7	143.9	126.5	**562.7**	268.6
2021	39.9	75.0	174.0	141.6	127.7	**558.3**	268.3

Source: Own calculation based on FADN data; EU-FADN – European Commission



Source: Own calculation based on FADN data; EU-FADN – European Commission

Figure 1 Evolution of the total labour force by economic size (1,000 AWU – France)

As also shown in Figure 1, the agricultural labour force in the three smaller size classes declined steadily over the 2004–2021 period (–48%, –54% and –31% for the below-50 k€ of SO, the 50–100 k€ of SO, and the 100–250 k€ of SO categories, respectively), while that in the two larger size classes increased (+38% and +190% for the 250–500 k€ of SO and the above-500 k€ of SO categories, respectively). However, the increase recorded in the top two economic size classes did not offset the decrease in the bottom three, so that total agricultural labour fell from 637,500 AWU in 2004 to 558,300 AWU in 2021 – at a slightly slower pace than farm numbers (–12% over 18 years, or on average annual rate of –0.8%).

3.2. Markov chain model

Each year, the population of N agents is partitioned into a finite number K of exhaustive and mutually exclusive categories defined over a dependent variable, which may be quantitative (e.g., economic or physical size) or categorical (e.g., legal status or type of farming).

Assuming that agents move from one category to another from one year to the next according to a stochastic Markov chain process, the number $n_k(t+1)$ of agents in category k at time $t+1$ is obtained as:

$$n_k(t+1) = \sum_{j=1}^{K} p_{j,k}(t) n_j(t) \tag{1}$$

where $n_j(t)$ is the number of agents in category j at time t, and $p_{j,k}(t)$ is the probability of moving from category j to category k between t and $t+1$. Being probabilities, the $p_{j,k}(t)$ must jointly satisfy the following non-negativity and adding-up-to-unity constraints:

$$p_{j,k}(t) \geq 0 \tag{2}$$

and

$$\textstyle\sum_{k=1}^{K} p_{j,k}(t) = 1 \tag{3}$$

for all j, k an t.[5]

Under this framework, all agents in category j at time t share the same probability of moving to category k in the next time period $t+1$.

At the individual agent level, let the indicator variable $y_i(t)$ represent the state of agent i at time t; it equals j if agent i is in category j at time t. The transition probability $p_{j,k}(t)$ then writes:

$$p_{j,k}(t) = P(y_i(t) = k | y_i(t-1) = j) \tag{4}$$

If $p_{j,k}(t)$ is assumed constant over time – that is $p_{j,k}(t) = p_{j,k}$ whatever t – the model is said to be stationary. If, on the contrary, $p_{j,k}(t)$ varies over time, the model is said to be non-stationary. In the latter case, the time-varying transition probabilities may be modelled as a function of a set of exogenous variables:

$$p_{j,k}(t) = P\big(y_i(t) = k \big| y_i(t-1) = j, \boldsymbol{X}_i(t-1)\big) \tag{5}$$

where $\boldsymbol{X}_i(t-1)$ is a vector of L explanatory variables characterising agent i at time $t-1$, including a constant.

[5] Note that constraints (2) and (3) together imply that $p_{j,k}(t) \leq 1 \quad \forall j,k,t$.

Among the various possible specifications,[6] we model $p_{j,k}(t)$ as a multinomial logit:

$$p_{j,k}(t) = P\big(y_i(t) = k \big| y_i(t-1) = j, \boldsymbol{X}_i(t-1)\big) = \frac{\exp\left(\boldsymbol{\beta}'_{j,k}\boldsymbol{X}_i(t-1)\right)}{\sum_{l=1}^{K}\exp\left(\boldsymbol{\beta}'_{j,l}\boldsymbol{X}_i(t-1)\right)} \tag{6}$$

where $\boldsymbol{\beta}_{j,k}$ is a vector of L parameters specific to each transition from category j to category k.

This specification ensures that both the non-negativity and adding-up-to-unity constraints hold for all $p_{j,k}(t)$. For identification purposes, we further impose that $\boldsymbol{\beta}_{j,j} = \boldsymbol{0}_L$ for all j, where $\boldsymbol{0}_L$ is a vector of zeros.

Finally, to account for possible entries and exits, an additional state denoted $k = 0$ is introduced, bringing the total number of states to $K + 1$. As a consequence:

- On the exit side, $y_i(t) = 0$ is simply an additional category that agents in any initial category $j = 1$ to K may transition into, so that the summing-up-to-unity constraint (3) must be rewritten as $\sum_{k=0}^{K} p_{j,k}(t) = 1$ for all $j = 1$ to K;
- On the entry side, $\boldsymbol{X}_i(t-1)$ is unobserved regardless of the entry category $j = 1$ to K; only $\boldsymbol{X}_i(t)$ is observed, and the transition from state $y_i(t-1) = 0$ to state $y_i(t) = 0$ is not likewise unobserved.[7] Consequently, $p_{0,k}(t)$ must be defined slightly differently from Equation (5) as $p_{0,k}(t) = P\big(y_i(t) = k \big| y_i(t-1) = 0, \boldsymbol{X}_i(t)\big)\ \forall k = 1, \dots, K$. Its interpretation also differs accordingly: $p_{0,k}(t)$ is not an "entry probability" *per se*, but rather the probability of being in category $k = 1, \dots, K$ conditional on having entered between $t-1$ and t and exhibiting characteristics $\boldsymbol{X}_i(t)$ (upon entry). In this case, the summing-up-to-unity constraint remains unchanged ($\sum_{k=1}^{K} p_{0,k}(t) = 1$) and, in Equation (6), any category $k = 1, \dots, K$ may serve as the reference category for identification purposes.

3.3. Transition data preparation

The main challenge in using FADN data to estimate a MCM is to account for farm entries and exits, as these data do not readily allow such transitions to be measured directly: farms may enter or leave the sample simply because they begin or cease participating in the survey, rather than because they actually start or discontinue operations (Gocht et al., 2012). The strategy adopted therefore consists in making use of the year-specific weights attached to each farm in the FADN sample to infer entry and exit flows.

Let denote w_{it} the extrapolating factor attached to farm i in year t. Three cases need to be considered, depending on whether a farm observed in the sample in a given year t: i) remained in the sample in the following year $t + 1$; ii) was no longer observed in the following year $t + 1$; or iii) had not been observed in the preceding year $t - 1$.

i) In the first case, it has to be further considered whether the farm's extrapolating factor remained unchanged, increased, or decreased between year t and year $t + 1$:

- if $w_{it+1} = w_{it}$, we infer that the w_{it} farms represented by sample farm i during t continued farming during $t + 1$;

[6] This point will be discussed further in Section 5.

[7] In practice, this would correspond to farms "that could have entered but did not" or "that entered during t but exited immediately". In both cases, such situations are not – and cannot be – observed in the FADN.

- if $w_{it+1} > w_{it}$, we assume that the w_{it} farms represented by sample farm i during t continued farming during $t + 1$, and that $\Delta w^{+}_{it,t+1} = w_{it+1} - w_{it}$ farms sharing the same characteristics as farm i started business between t and $t + 1$;
- if $w_{it+1} < w_{it}$, we assume that only w_{it+1} farms represented by sample farm i during t continued farming during $t + 1$, and that $\Delta w^{-}_{it,t+1} = w_{it} - w_{it+1}$ farms present during t and sharing the same characteristics as farm i ceased operations between t and $t + 1$.

ii) In the second case, it is assumed that the w_{it} farms represented by sample farm i during t ceased operations between t and $t + 1$, which is equivalent to setting $w_{it+1} = 0$ and $\Delta w^{-}_{it,t+1} = w_{it}$.

iii) In the third case, it is assumed that the w_{it} farms represented by sample farm i during t started business between $t - 1$ and t, which is equivalent to setting $w_{it-1} = 0$ and $\Delta w^{+}_{it-1,t} = w_{it}$.

Finally, since the database is both left- and right-censored, farms present in the sample in 2004 – the first year of observation – must not be interpreted as having entered between 2003 and 2004; similarly, farms still present in the sample in 2021 – the last year of observation – must not be interpreted as being about to exit between 2021 and 2022.

Based on these rules, the FADN database is restructured to reflect the observed weight variations, by duplicating sample farms where necessary and adjusting their extrapolating factors accordingly.Table 3 provides three illustrative examples of this restructuring.

Table 3 Three examples of how the FADN database is rearranged to reflect entries and exits

id	year	wgt
XXX	2012	5.15
XXX	2013	9.57
XXX	2014	6.70
XXX	2015	12.57
XXX	2016	14.67
XXX	2017	12.57
YYY	2020	5.00
YYY	2021	5.00
ZZZ	2004	5.71
ZZZ	2005	15.00
ZZZ	2006	7.06
...	...	...

a) Original data

id	year_L	year	wgt_L	wgt	stay	entry	exit
XXX	2011	2012	.	5.15	0	1	0
XXX	2012	2013	5.15	5.15	1	0	0
XXX	2012	2013	.	4.42	0	1	0
XXX	2013	2014	6.70	6.70	1	0	0
XXX	2013	2014	2.87	.	0	0	1
XXX	2014	2015	6.70	6.70	1	0	0
XXX	2014	2015	.	5.87	0	1	0
XXX	2015	2016	12.57	12.57	1	0	0
XXX	2015	2016	.	2.10	0	1	0
XXX	2016	2017	12.57	12.57	1	0	0
XXX	2016	2017	2.10	.	0	0	1
XXX	2017	2018	12.57	.	0	0	1
YYY	2019	2020	.	5.00	0	1	0
YYY	2020	2021	5.00	5.00	1	0	0
ZZZ	2004	2005	5.71	5.71	1	0	0
ZZZ	2004	2005	.	9.29	0	1	0
ZZZ	2005	2006	7.06	7.06	1	0	0
ZZZ	2005	2006	7.94	.	0	0	1
...	...	...	...	...	...	...	...

b) Restructured data

Source: Own calculation based on FADN data; EU-FADN – European Commission

Panel a) shows to an excerpt of the initial database, where *id* denotes the unique farm identifier, *year* denotes the year of observation and *wgt* denotes the corresponding extrapolating factor. According to this panel:

- farm 'XXX' was observed in the sample between 2012 and 2017;
- farm 'YYY' was first observed in 2020 and was still present in the sample in the last year of observation, 2021;
- farm 'ZZZ' was in the sample from the very beginning (2004) and remained for at least three years.

Panel b) presents the database restructured according to the assumptions set out above. Five new variables are introduced: *year_L* denotes the one-year lag of the observation year; *wgt_L* denotes the extrapolating factor to be considered in the lagged year; and *stay*, *entry*, and *exit* are dummy variables taking the value 1 if the farm remained in, entered, or exited the sample between *year_L* and *year*, respectively, and 0 otherwise.

Consider first farm 'XXX':

- Since it is observed for the first time in 2012, which is not the first year of the panel, a number of farms corresponding to its weight for 2012 are assumed to have started business between 2011 and 2012; accordingly, *wgt_L* is set to missing and *entry* is set to 1.
- The original database shows that farm 'XXX' remained in the sample in 2013, but that its extrapolating factor increased from 5.15 to 9.57. Under our rules, this means that 5.15 farms similar to 'XXX' continued operations between 2012 and 2013 and that, simultaneously, 9.57 – 5.15 = 4.42 similar farms started operations over the same period. Accordingly, the 'XXX' observation for 2013 is duplicated: the first copy reflects the 5.15 continuing farms (*wgt_L* and *wgt* both take the value 5.15, and *stay* is set to 1), and the second reflects the 4.42 new farms (*wgt_L* is set to missing, *wgt* takes the value 4.42, and *entry* is set to 1).
- For 2014, the original database shows that 'XXX' was again present but that its extrapolating factor decreased from 9.57 to 6.70. Under our rules, this means that 6.70 out of the initial 9.57 similar farms continued operations between 2013 and 2014, while 9.57 – 6.70 = 2.87 similar farms ceased operations over the same period. Accordingly, the 'XXX' observation for 2014 is duplicated: the first copy reflects the 6.70 continuing farms (*wgt_L* and *wgt* both take the value 6.70, and *stay* is set to 1), and the second reflects the 2.87 exiting farms (*wgt_L* takes the value 2.87, *wgt* is set to missing, and *exit* is set to 1).
- The same reasoning applies through to 2017, the last year in which farm 'XXX' was observed. Since this is not the last year of the panel, a new copy of 'XXX' is created to reflect that 12.57 similar farms ceased operations between 2017 and 2018 (*year_L* takes the value 2017, *year* takes the value 2018, *wgt_L* takes the value 12.57, *wgt* is set to missing, and *exit* is set to 1).

Farm 'YYY' is more straightforward: first observed in 2020, it remains in the sample in 2021 – the last year of the panel – with its extrapolating factor unchanged between the two years. The entry rule is therefore applied for 2020 and the continuation rule for 2020–2021; no exit is created for 2022, as doing so would be misleading.

Finally, farm 'ZZZ' is already present in 2004 and is subsequently observed in the following years with a changing extrapolating factor. No artificial entry is therefore created for 2004, and the same rules as for farm 'XXX' are applied in subsequent years.

Alongside this restructuring, care must be taken to ensure that the variables characterising each sample farm are updated consistently. This applies to both the dependent variables reflecting the current and former farm category, and the explanatory variables pertaining to the former period (for standard category and exit transitions) and the current period (for entry transitions).

4. RESULTS

4.1. Contingency matrix and stationary model

The method described above was applied to the French FADN data introduced in Section 3.1 to study the annual labour force transitions across five economic size categories plus one entry/exit category over the 2004–2021 period.

The restructured database allows the overall contingency matrix to be derived directly, by summing the weight variable pre-multiplied by the labour variable across all observed AWU transitions from one year to the next (Table 4). For instance:

- of the 1,024,503 observations recorded in the below-50 k€ of SO size category over the 2004-2020 period: 596,755 remained in the same size category the following year (i.e., between 2005 and 2021); 66,662 enlarged sufficiently to move up to the 50–100 k€ of SO category; 2,821 moved up to the 100–250 k€ of SO category; 124 moved up to the 250–500 k€ of SO category; none reached the above-500 k€ of SO category; and 358,141 ceased operations (as defined by our exit rule);
- similarly, among the 988,218 recorded in the below-50 k€ of SO size category over the 2005–2021 period: 596,755 were already in the same category the preceding year (i.e., between 2004 and 2020); 51,497 shrank enough to move down from the 50–100 k€ of SO category; 2,953 did so from the 100–250 k€ of SO category; 509 came from the 250–500 k€ of SO category; 109 came from the above-500 k€ of SO category; and 336,395 entered operations directly in the below-50 k€ of SO category during the 2005–2021 period (as defined by our entry rule).

Table 4 Contingency matrix for the overall period (transitions from 2004-2020 to 2005-2021)

Initial category	Final category						
	< 50 k€	50–100 k€	100–250 k€	250–500 k€	≥ 500 k€	exit	Total
< 50 k€	**596,755**	66,662	2,821	124	0	358,141	**1,024,503**
50–100 k€	51,497	**1,308,386**	131,682	1,730	977	468,215	**1,962,487**
100–250 k€	2,953	79,983	**2,750,952**	178,824	5,109	716,515	**3,734,336**
250–500 k€	509	2,881	93,585	**1,586,059**	99,722	410,643	**2,193,399**
≥ 500 k€	109	302	3,135	50,229	**992,432**	270,504	**1,316,711**
entry	336,395	416,813	673,872	415,543	302,178		**2,144,801**
total	**988,218**	**1,875,027**	**3,656,047**	**2,232,509**	**1,400,418**	**2,224,018**	**12,376,237**

Source: Own calculation based on FADN data; EU-FADN – European Commission

The same reasoning applies to the other size categories, both horizontally and vertically. In total, the number of observed transitions amounts to 12,376,237, of which 2,224,018 are exits and 2,144,801 are entries. This overall excess of exits over entries is consistent with the decline in total AWU documented in Table 2 and Figure 1. The contingency matrix also accurately reproduces the net change in total labour force for each size category, with exits outnumbering entries for the three smaller economic size categories and vice versa for the two larger ones.

The contingency matrix can be used to derive the average annual transition probability matrix by dividing each cell by its corresponding row total (Table 5). This probability matrix corresponds to the stationary MCM – that is, the $p_{j,k}(t)$ used in Equation (1) with $p_{j,k}(t) = p_{j,k} \;\; \forall t$. For instance, a farm in the below-50 k€ of SO in a given year has a 58.2% probability of remaining in the same category the following year, a 35.0% probability of ceasing operations, a 6.5% probability of enlarging sufficiently to move up to the 50–100 k€ of SO category, and so on. Similarly, a farm entering operations in a given year has a 15.7% probability of doing so in the below-50 k€ of SO category, a 19.4% probability in the 50–100 k€ of SO, and so on.

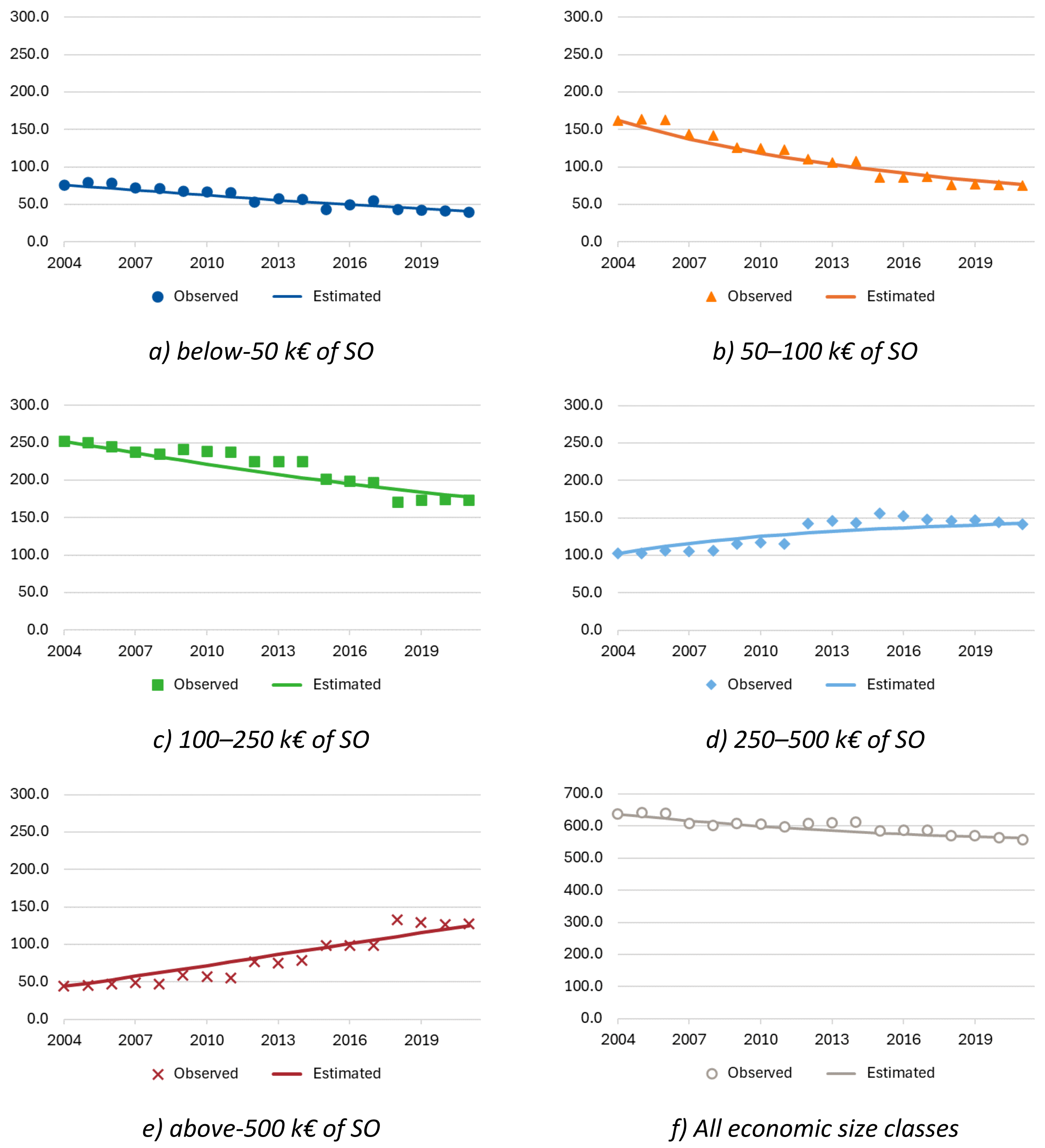
Compared with much of the existing literature (Tonini and Jongeneel, 2009), entry and exit probabilities appear overestimated, while the probabilities of remaining in the same initial economic size class (i.e., the diagonal elements of the transition probability matrix) appear underestimated. This was not unexpected: as noted above, the adopted method cannot fully disentangle genuine entries and exits from sample entries and exits. Nevertheless, Figure 2 shows that, from a statistical standpoint, accounting for the implicit entries and exits embedded in the variations in extrapolating factors for farms that remain in the sample from year to year makes it possible to accurately replicate the evolution of AWU numbers by economic size classes (panel a to e) and in aggregate (panel f) from the estimated stationary transition matrix.[8]

Table 5 Stationary annual transition probability matrix

Initial category	Final category					
	< 50 k€	50–100 k€	100–250 k€	250–500 k€	≥ 500 k€	exit
< 50 k€	**58.2%**	6.5%	0.3%	0.0%	0.0%	35.0%
50–100 k€	2.6%	**66.7%**	6.7%	0.1%	0.0%	23.9%
100–250 k€	0.1%	2.1%	**73.7%**	4.8%	0.1%	19.2%
250–500 k€	0.0%	0.1%	4.3%	**72.3%**	4.5%	18.7%
≥ 500 k€	0.0%	0.0%	0.2%	3.8%	**75.4%**	20.5%
entry	15.7%	19.4%	31.4%	19.4%	14.1%	

Source: Own calculation based on FADN data; EU-FADN – European Commission

[8] Figure 2 was obtained by iteratively applying the stationary annual transition probability matrix reported in Table 5 to the 2004 data through to 2021, with the exception of entries. Following Piet and Saint-Cyr (2018), the number of entries for each size category observed in the contingency matrix reported in Table 4 was divided by the total initial number of observations in the same category to obtain a 'true' entry probability, from which a 'net-entry' probability was derived by subtracting the corresponding exit probability. For instance, the 336,395 entries in the below-50 k€ of SO represent 32.8% of the total 1,024,503 initial observations in that category, yielding a net entry probability of 32.8% – 35.0% = –2.2%. Similarly, the 302,178 entries in the above-500 k€ of SO represent 22.9% of the 1,316,711 initial observations in that category, yielding a net entry probability of 22.9% – 20.5% = +2.4%.



Source: Own calculation based on FADN data; EU-FADN – European Commission

Figure 2 Stationary model fit to the observed data (1,000 AWU – France)

4.2. Non-stationary model

4.2.1. Explanatory variables

As explained in Section 3.2, estimating a non-stationary MCM requires specifying a set of explanatory variables that may drive the evolution of transition probabilities.

Drawing on the literature and an analysis of correlations among candidate variables in the FADN database, the following potential drivers were selected:

- the legal status of the farm, defined as a dummy variable taking value 1 for companies and 0 otherwise (variable LEGAL in the FADN database, denoted *legal* hereafter);
- the total utilised agricultural area of the farm (SE025, denoted *uaato*);
- the ratio of unpaid to total labour (SE015/SE010, denoted *shfwu*);
- family farm income per unpaid labour unit (SE430, denoted *ffinc*);
- the debt ratio of the farm, defined as total liabilities divided by total assets (SE485/SE436, denoted *debtr*);
- total first-pillar CAP payments per total labour unit (SE606/SE010, denoted *sub1p*);
- total second-pillar CAP payments per total labour unit (SE624/SE010, denoted *sub2p*).

The last two variables are the policy measures whose impact on total agricultural employment we seek to assess.

Table 6 reports descriptive statistics for these variables over the entire study period, as well as for the economic size of French commercial farms from which the dependent categorical size variable was constructed.

Table 6 Descriptive statistics for selected variables (2004-2021)

Variable	Label	Unit	Mean	St. dev.
ecosz	Economic size	1,000€ of SO/farm	177.7	210.0
legal	Legal status (1: company; 0: otherwise)	0/1	0.220	0.414
uaato	Total utilised agricultural area	ha/farm	86.92	75.33
shfwu	Unpaid labour / total labour	FWU/AWU	0.851	0.241
ffinc	Family farm income / unpaid labour	1,000€/FWU	27.3	78.4
debtr	Debt ratio (total liabilities / total assets)	%	40.2	49.8
sub1p	Total 1st pillar payments / total labour	1,000€/AWU	16.3	14.0
sub2p	Total 2nd pillar payments / total labour	1,000€/AWU	2.5	4.5

Source: Own calculation based on FADN data; EU-FADN – European Commission

Table 7 further shows that, overall, the selected explanatory variables exhibit low pairwise correlations (below 0.25 in absolute value),[9] with the exception of first-pillar CAP payments per total labour unit, which is notably correlated with both total utilised agricultural area and the ratio of unpaid to total

[9] The correlations displayed in Table 7 were computed prior to the database restructuring to reflect entries and exits. The values differ slightly after restructuring, but the signs and magnitudes remain similar.

labour. This is unsurprising: first-pillar CAP payments are granted primarily on a per-hectare basis, and utilised agricultural area is itself fairly correlated with the unpaid labour force.

Table 7 Correlation matrix for the selected explanatory variables (2004-2021)[9]

Variable	legal	uaato	shfwu	ffinc	debtr	sub1p
uaato	0.1575					
shfwu	-0.1254	0.1333				
ffinc	0.0657	0.0391	-0.1709			
debtr	0.0741	0.0151	-0.0960	-0.0452		
sub1p	-0.0658	0.6010	0.3944	0.0324	-0.0222	
sub2p	0.0449	0.1875	0.2467	-0.0495	-0.0808	0.1840

Source: Own calculation based on FADN data; EU-FADN – European Commission

4.2.2. Non-stationary transition probability matrix and elasticities

The detailed results of the multinomial logit estimations underlying the non-stationary MCM are reported in Table A2 of the Appendix. As these coefficients are not straightforwardly interpretable, they are not discussed here. Instead, this section reports the non-stationary transition probability matrix and the corresponding probability elasticities derived from the estimation results.

First, Table 8 shows that, evaluated at the means of the explanatory variables based on Equation (6), the estimated non-stationary transition probabilities differ little, if at all, from their stationary counterparts reported in Table 5.

Table 8 Estimated average non-stationary annual transition probability matrix

Initial category	Final category					
	< 50 k€	50–100 k€	100–250 k€	250–500 k€	≥ 500 k€	exit
< 50 k€	**0.583*** (0.007)**	0.065*** (0.002)	0.003*** (0.001)	0.000** (0.000)	-	0.349*** (0.007)
50–100 k€	0.026*** (0.001)	**0.667*** (0.003)**	0.067*** (0.002)	0.001*** (0.000)	0.000** (0.000)	0.238*** (0.003)
100–250 k€	0.001*** (0.000)	0.021*** (0.001)	**0.737*** (0.002)**	0.048*** (0.001)	0.001*** (0.000)	0.192*** (0.002)
250–500 k€	0.000** (0.000)	0.001*** (0.000)	0.043*** (0.001)	**0.723*** (0.003)**	0.045*** (0.002)	0.187*** (0.003)
≥ 500 k€	0.000 (0.000)	0.000* (0.000)	0.002*** (0.001)	0.038*** (0.002)	**0.754*** (0.006)**	0.205*** (0.006)
entries	0.157*** (0.003)	0.194*** (0.003)	0.314*** (0.003)	0.194*** (0.003)	0.141*** (0.003)	

Note: standard errors in parenthesis; ***, ** and * denotes significance at the 1%, 5% and 10% level, respectively.

Source: Own calculation based on FADN data; EU-FADN – European Commission

Table 9 Transition probability elasticities

Initial category	Final category					
	< 50 k€	50–100 k€	100–250 k€	250–500 k€	≥ 500 k€	exit
< 50 k€	**0.001 (0.015)**	0.230*** (0.039)	-0.100 (0.362)	0.729*** (0.241)	-	-0.057** (0.029)
50–100 k€	0.167** (0.085)	**0.014* (0.007)**	0.036 (0.030)	-0.477 (0.368)	-1.618 (1.144)	-0.073*** (0.021)
100–250 k€	0.743*** (0.127)	0.556*** (0.043)	**0.032*** (0.005)**	-0.373*** (0.043)	-0.108 (0.334)	-0.101*** (0.019)
250–500 k€	0.632*** (0.099)	0.478*** (0.109)	0.405*** (0.035)	**0.006 (0.007)**	-0.478*** (0.092)	-0.035 (0.025)
≥ 500 k€	0.885*** (0.343)	0.303*** (0.064)	0.273*** (0.045)	0.218*** (0.027)	**-0.036*** (0.011)**	0.047 (0.031)
entries	0.487*** (0.047)	0.489*** (0.030)	0.085*** (0.022)	-0.404*** (0.029)	-1.350*** (0.172)	

a) with respect to 1st pillar CAP payments

Initial category	Final category					
	< 50 k€	50–100 k€	100–250 k€	250–500 k€	≥ 500 k€	exit
< 50 k€	**0.035*** (0.006)**	-0.088*** (0.025)	-0.979*** (0.343)	-0.037 (0.268)	-	-0.054*** (0.015)
50–100 k€	0.054** (0.026)	**0.029*** (0.002)**	-0.140*** (0.017)	-0.408 (0.260)	-4.922 (3.918)	-0.069*** (0.009)
100–250 k€	0.139** (0.061)	0.111*** (0.010)	**0.011*** (0.001)**	-0.210*** (0.017)	-0.109 (0.204)	-0.030*** (0.005)
250–500 k€	-0.313 (0.372)	0.013 (0.068)	0.035*** (0.008)	**0.003** (0.001)**	-0.111*** (0.019)	-0.006 (0.005)
≥ 500 k€	-30.305*** (8.553)	0.027** (0.011)	-0.059 (0.070)	0.013* (0.007)	**0.002* (0.001)**	-0.014** (0.007)
entries	0.234*** (0.008)	0.126*** (0.005)	-0.097*** (0.007)	-0.328*** (0.013)	-0.562*** (0.039)	

b) with respect to 2nd pillar CAP payments

Note: standard errors in parenthesis; ***, ** and * denotes significance at the 1%, 5% and 10% level, respectively.

Source: Own calculation based on FADN data; EU-FADN – European Commission

Second, long-run probability elasticities may be derived following Zepeda (1995a) and Saint-Cyr (2022) for each of the selected explanatory variables. These elasticities measure the relative impact – expressed as a percentage change – of a 1% increase in the variable of interest, evaluated at its mean, on each transition probability in the matrix. Table 9 reports such elasticities for the two policy variables, namely first-pillar (panel a) and second-pillar (panel b) CAP payments.

With regard to year-to-year size category transitions, it appears that, with a few exceptions, both payment types: i) increase the probability of remaining in the initial size category; ii) increase the probability of moving to a smaller size category; and iii) decrease the probability of moving to a larger size category. Both payment types also tend to reduce the probability of exiting across all size categories, although this effect is not statistically significant in a few cases. At the same time, they tend to increase the probability of entering at smaller size categories and, correspondingly, to decrease it at larger ones. The turning point lies between the 100–250 k€ of SO and 250–500 k€ of SO categories for first-pillar payments, and between the 50–100 k€ of SO and 100–250 k€ of SO categories for second-pillar payments.

4.2.3. Structure elasticities

Based on the previous probability elasticity results, both types of CAP payments would be expected to exert an overall positive impact on AWU numbers, particularly in the smaller size categories. This is indeed the conclusion that emerges from the structures elasticities reported in Table 10, which measure the relative change in the number of AWU induced by a 1% increase in the variable of interest, evaluated at its mean, within each economic size category and in aggregate (Zepeda 1995a; Saint-Cyr, 2022).

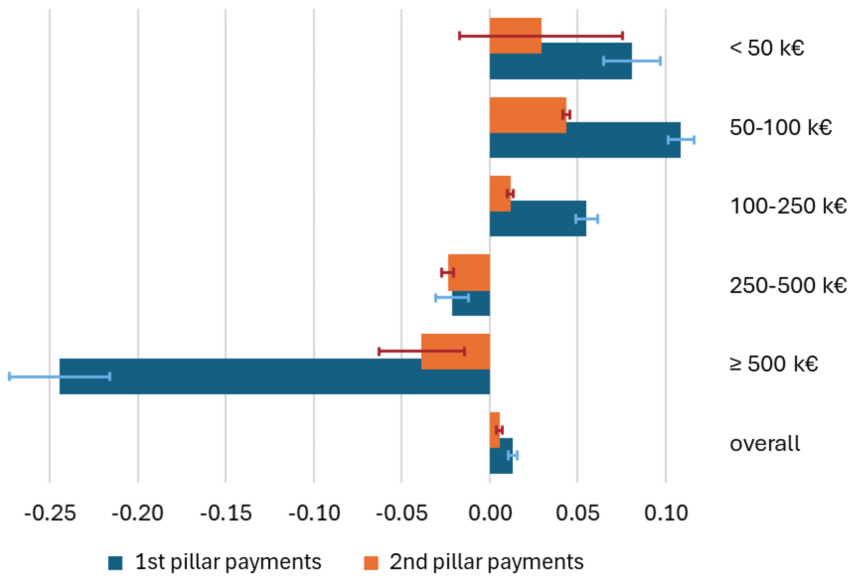
It first appears that both payment types have a positive and, in most cases, statistically significant long-run impact on AWU numbers in smaller economic size categories (up to 250 k€ of SO), while their impact is significantly negative in the larger categories (250 k€ of SO or more).

Table 10 Structure elasticities

Variable	< 50 k€	50–100 k€	100–250 k€	250–500 k€	≥ 500 k€	overall
sub1p	0.081*** (0.016)	0.109*** (0.008)	0.055*** (0.006)	-0.021** (0.009)	-0.244*** (0.028)	**0.013*** (0.003)**
sub2p	0.029 (0.046)	0.044*** (0.002)	0.012*** (0.002)	-0.024*** (0.003)	-0.039 (0.024)	**0.006*** (0.002)**

Note: standard errors in parenthesis; ***, ** and * denotes significance at the 1%, 5% and 10% level, respectively.

Source: Own calculation based on FADN data; EU-FADN – European Commission



Note: error bars represent ± 1 standard error intervals.

Source: Own calculation based on FADN data; EU-FADN – European Commission

Figure 3 Structure elasticities by economic size

Second, the overall long-run impact of both payment types, though modest, is positive and significant, amounting to 0.013 for first-pillar payments and 0.006 for second-pillar payments. Moreover, the impact of first-pillar payments is at least twice as large as that of second-pillar payments across all economic size categories but one (the 250-500k€ of SO category) and in aggregate (see also Figure 3). Taken together, this means that a 1% increase in first-pillar CAP payments would result in a 0.013% increase in total AWU, while an equivalent 1% increase in second-pillar payments would yield a smaller increase of 0.006%. It should be recalled from Table 6, however, that a 1% increase in first-pillar payments corresponds to an average of +163€ per AWU, whereas a similar 1% increase in second-pillar payments corresponds to only +25€ per AWU on average. This implies that the impact of a €1 increase in second-pillar payments per AWU is in fact approximately three times larger than that of an equivalent increase in first-pillar payments per AWU. In other words, under a constant budget assumption, second-pillar payments appear more efficient than first-pillar payments in sustaining agricultural employment.

5. DISCUSSION

Although, as noted above, the FADN sampling strategy is not primarily designed to capture genuine farms entries and exits fully, the proposed method and derived results demonstrate that making judicious use of variations in extrapolating factors is an effective way to accurately replicate the evolution of farm and AWU numbers as well as their drivers. The resulting structure elasticities are therefore considered to reliably capture the impact of the studied policy variables on these numbers. Moreover, a key advantage of the proposed method is that, unlike much of the previous literature on farm structural change using an MCM approach, it allows explanatory variables to be evaluated at the individual farm level rather than only at the aggregate (typically national, or at best local) level. Saint-Cyr (2022) is, again, a notable exception.

Taken together, our results indicate that, in France, increasing either type of subsidies would have a positive effect on farm numbers and agricultural employment, primarily by supporting labour in farms of smaller economic size. Indeed, both payment types are found to exert a positive and, in most cases, statistically significant long-run impact on farm and AWU numbers in the smaller economic size categories (up to 250 k€ of SO), while their long-run impact is significantly negative in the larger categories (250 k€ of SO or more). This is consistent with previous findings which, using different approaches, showed that CAP payments help sustain agricultural labour (Olper et al., 2012; Lillemets et al., 2022). Other studies however suggest that this positive effect is context-dependent (Psaltopoulos et al., 2006; Schuh et al., 2016; Vigani et al., 2019; Garrone et al., 2019). The MCM approach developed here will therefore be applied to FADN data from other EU Member States to assess the robustness and consistency of the results obtained for France.

This research can be extended in several directions. A first methodological question concerns the MCM specification as a multinomial logit. Storm et al. (2015) argue that when the dependent categorical variable is an ordinal variable – as is the case when using a 'size' variable, since the underlying variable is actually continuous – an ordered logit specification should be preferred. We acknowledge that the argument is valid, but the question of how to handle entries and exits remains. On the exit side, it is debatable whether exit can legitimately be treated as the 'smallest' size category. A two-step nested logit approach could offer an effective solution: the first step would consist of a binary logistic selection model (exit vs. remain), and the second step would be implemented as an ordered logit (capturing the magnitude of the transition conditional on having remained). On the entry side, however, since entry is modelled here as the probability of being in a given size category conditional on having entered, the use of an ordered logit seems less warranted, and retaining a multinomial logit specification may be preferable.

Second, it could be worth exploring an alternative approach to handling changes in extrapolating factors. In the present study, a decline in a farm's weight is interpreted as reflecting the exit of a corresponding number of similar farms. However, when associated with a transition to another size category, such a variation could alternatively be interpreted as that number of farms remaining in the initial category, while the rest actually transition to the new one. A similar reasoning could be applied to revisit the treatment of entries when extrapolating factors increase. Revising the transition rules along these alternative assumptions could help mitigate the overestimation of entry and exit probabilities and the underestimation of the diagonal no-change probabilities.

Third, additional explanatory variables could be incorporated into the non-stationary MCM specification, either as further controls or as additional variables of interest. Drawing on the existing MCM literature, such variables could pertain to the individual farm level or to higher levels of aggregation. At the farm level, additional controls could include the type of farming, indicators of technical efficiency such as yields (Zepeda, 1995a; Stokes, 2006; Zimmermann and Heckelei, 2012; Ben Arfa et al., 2015), farmers' age (Zimmermann and Heckelei, 2012; Saint-Cyr, 2022), or indicators of human capital (Chavas and Magand, 1988). At a more aggregate level, three types of variables could be considered: i) farming condition indicators, such as input-to-output price ratios (Chavas and Magand, 1988; Zepeda, 1995b; Rahelizatovo and Gillespie, 1999; Karantininis, 2002; Stokes, 2006; Ben Arfa et al., 2015), local farmland prices (Stokes, 2006; Saint-Cyr, 2022), or indicators characterising the distribution of surrounding farm structures (Huettel and Margarian, 2009; Zimmermann and Heckelei, 2012); ii) local economic conditions indicators, such as unemployment rates (Zimmermann and Heckelei, 2012), general population dynamics (Zimmermann and Heckelei, 2012), or regional fixed effects (Rahelizatovo and Gillespie, 1999; Storm et al., 2015); and iii) broader economic and/or environmental indicators, such as interest rates (Rahelizatovo and Gillespie, 1999; Karantininis, 2002) or climatic variables (Zepeda, 1995b).

The choice of policy variables necessarily depend on the period under study: Storm et al. (2015) included dummy variables to capture the impact of the MacSharry, Agenda 2000 and Mid-Term Review CAP reforms; Saint-Cyr (2022) did likewise for the Mid-Term Review and 2014 CAP reforms, and also examined the impact of investment subsidies; the effect of milk quotas has been studied by several authors (Tonini and Jongeneel 2009; Huettel and Jongeneel, 2011; Zimmermann and Heckelei 2012; Ben Arfa et al., 2015); and Ben Arfa et al. (2015) further investigated the impact of the young farmer settlement program. In the present context, it could be worthwhile to consider different types of CAP subsidies separately – disaggregating, on the one hand, the various decoupled and coupled first-pillar payment components and, on the other hand, agri-environmental and climate schemes from support to less-favoured areas for second-pillar payments. Additionally, since our primary interest lies in the impact of CAP programmes on employment, it could also be worth examining unpaid and paid labour separately, rather than total labour as a whole as done here.

Finally, among the various limitations of the FADN that have been already identified elsewhere (Gocht et al., 2012; Neuenfeldt and Gocht, 2014), a further avenue for future research would consist in attempting to overcome two closely related ones: the use of SO to define the economic size of farms, and the use of agricultural censuses (AC) and interim Farm Structure Surveys (FSS) to set the extrapolating factors of sample farms. These are, in fact, two sides of the same coin. As explained in Eurostat (2026a), SO is calculated as an average value over a reference period, typically three to five years. Consequently, the measured economic size of a farm may change from one year to the next solely due to an update of the SO coefficients, rather than any change in the underlying physical units (crop hectares or livestock head). One way to address this issue would be to use an alternative variable to measure farm 'size'. Physical units such as hectares or animal numbers are not suitable candidates, as they are not readily comparable across farming types – wine growers, for instance, typically require fewer hectares than arable crop producers to generate an equivalent economic value. An economic or financial variable such as total fixed assets might instead be worth investigating.

The second consequence of computing SO as a multi-year average concerns the stratification of the AC and FSS populations from which FADN sample farms are drawn. Two stratification variables – type of farming and economic size – are closely related to SO: the former through its distribution across crops and livestock, the latter through its total amount. Since AC and FSS are not conducted annually and SO coefficients are not updated every year, the FADN sampling probabilities of farms – and hence their extrapolating factors – do not evolve smoothly over time. This is the so-called 'time-variable vs. time-invariant' SO puzzle (Gocht et al., 2012).[10] It explains why, as evidenced by Figure 1 and Table 2, FADN farm numbers typically display a plateau or step-like pattern over time. To address this issue, Storm et al. (2015) interpolate AC and FSS data between survey years; while effective in practice, this approach has the drawback of introducing data that are not actually observed. An alternative would be to restrict the analysis to FADN data corresponding strictly to AC and FSS years, though this comes with the difficulty that these surveys are not equally spaced in time. Challenging as it may be, resolving this issue would substantially enhance the robustness of an FADN-based MCM approach.

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8. APPENDIX

Table A1 Evolution of farm numbers by economic size categories (1,000 units – France)

year	< 50 k€	50–100 k€	100–250 k€	250–500 k€	≥ 500 k€	Total
2004	61.4	109.6	108.6	28.3	7.1	**315.1**
2005	64.0	110.1	108.5	28.4	7.2	**318.2**
2006	63.6	111.0	108.5	28.5	7.4	**319.1**
2007	59.0	99.1	107.1	29.3	7.7	**302.2**
2008	59.4	99.9	107.1	29.5	7.4	**303.3**
2009	55.0	85.6	111.9	33.8	9.6	**295.9**
2010	53.4	85.9	112.0	34.8	9.7	**295.7**
2011	53.3	86.0	112.0	34.6	9.9	**295.8**
2012	43.4	77.5	114.7	46.1	13.9	**295.6**
2013	47.7	76.7	114.8	45.9	13.7	**298.7**
2014	45.0	77.3	114.8	46.0	13.8	**296.9**
2015	37.7	64.7	111.9	54.0	18.8	**287.2**
2016	40.8	65.7	112.1	53.9	18.9	**291.4**
2017	45.9	65.1	112.0	53.6	18.9	**295.6**
2018	36.6	57.1	100.1	52.6	24.2	**270.7**
2019	36.6	57.0	100.4	52.5	24.1	**270.6**
2020	35.1	57.1	100.3	52.2	23.9	**268.6**
2021	35.0	56.9	100.1	52.2	24.1	**268.3**

Source: Own calculation based on FADN data; EU-FADN – European Commission

Table A2 Detailed results of the estimated non-stationary mlogit model

Final category	Variable	Initial category					
		< 50 k€	50–100 k€	100–250 k€	250–500k€	≥ 500 k€	entry
< 50 k€	legal	(base outcome)	-0.346 (0.166)**	-0.306 (0.399)	-2.125 (1.585)	-22.489 (1.199)***	-1.061 (0.141)***
	uaato		-0.014 (0.002)***	-0.046 (0.005)***	-0.048 (0.018)***	-1.315 (0.157)***	-0.042 (0.001)***
	shfwu		1.188 (0.313)***	3.055 (0.768)***	2.507 (1.308)*	-3.836 (0.910)***	3.335 (0.227)***
	ffinc		-0.012 (0.002)***	-0.013 (0.002)***	-0.003 (0.001)***	0.001 (0.002)	-0.006 (0.004)*
	debtr		-0.233 (0.183)	0.196 (0.099)**	-1.411 (1.359)	0.916 (1.133)	-0.502 (0.258)*
	sub1p		0.011 (0.006)*	0.047 (0.009)***	0.051 (0.008)***	0.171 (0.064)***	0.034 (0.004)***
	sub2p		0.009 (0.009)	0.068 (0.032)**	-0.316 (0.372)	-214.678 (60.589)***	0.185 (0.007)***
	const		-3.384 (0.276)***	-7.174 (0.554)***	-6.425 (1.236)***	-2.946 (1.959)	-1.364 (0.245)***
50–100 k€	legal	0.512 (0.182)***	(base outcome)	-0.306 (0.399)	-1.067 (0.491)**	0.281 (1.318)	-0.523 (0.066)***
	uaato	0.006 (0.001)***		-0.046 (0.005)***	-0.028 (0.007)***	-0.022 (0.013)*	-0.022 (0.001)***
	shfwu	-0.950 (0.237)***		3.055 (0.768)***	1.857 (0.672)***	5.497 (0.862)***	1.643 (0.114)***
	ffinc	0.000 (0.000)		-0.013 (0.002)***	-0.002 (0.001)***	-0.012 (0.002)***	-0.005 (0.001)***
	debtr	0.003 (0.058)		0.196 (0.099)**	0.248 (0.089)***	-6.065 (2.606)**	-0.297 (0.123)**
	sub1p	0.021 (0.004)***		0.047 (0.009)***	0.038 (0.009)***	0.053 (0.010)***	0.035 (0.003)***
	sub2p	-0.038 (0.008)***		0.068 (0.032)**	0.010 (0.068)	0.043 (0.020)**	0.124 (0.006)***
	const	-1.757 (0.225)***		-7.174 (0.554)***	-5.654 (0.623)***	-7.371 (1.647)***	-0.615 (0.122)***
100–250 k€	legal	0.274 (0.607)	0.303 (0.078)***	(base outcome)	-0.246 (0.073)***	-1.147 (0.424)***	(base outcome)
	uaato	0.012 (0.003)***	0.008 (0.001)***		-0.008 (0.001)***	-0.009 (0.002)***	
	shfwu	-2.763 (0.821)***	-0.609 (0.146)***		0.962 (0.141)***	1.411 (0.740)*	
	ffinc	-0.001 (0.001)	0.004 (0.001)***		-0.002 (0.001)**	-0.005 (0.001)***	
	debtr	0.136 (0.068)**	0.204 (0.063)***		0.191 (0.086)**	0.516 (0.745)	
	sub1p	-0.009 (0.034)	0.002 (0.002)		0.032 (0.003)***	0.048 (0.008)***	
	sub2p	-0.313 (0.106)***	-0.057 (0.006)***		0.032 (0.009)***	-0.107 (0.123)	
	const	-3.099 (0.638)***	-2.404 (0.138)***		-2.960 (0.116)***	-5.413 (0.604)***	

Source: Own calculation based on FADN data; EU-FADN – European Commission

Table A2 (continued)

Final category	Variable	Initial category					
		< 50 k€	50–100 k€	100–250 k€	250–500k€	≥ 500 k€	entry
250–500k€	legal	1.524 (0.952)	-0.510 (0.733)	0.479 (0.054)***	(base outcome)	-0.593 (0.124)***	0.706 (0.048)***
	uaato	-0.012 (0.014)	0.001 (0.009)	0.009 (0.000)***		-0.003 (0.001)***	0.012 (0.000)***
	shfwu	0.431 (1.501)	-1.722 (1.246)	-0.958 (0.110)***		0.978 (0.187)***	-1.489 (0.101)***
	ffinc	0.000 (0.001)	0.000 (0.008)	0.003 (0.001)***		-0.003 (0.001)***	0.003 (0.001)***
	debtr	0.169 (0.069)**	0.222 (0.066)***	0.264 (0.061)***		0.292 (0.192)	0.226 (0.114)**
	sub1p	0.068 (0.022)***	-0.036 (0.027)	-0.027 (0.003)***		0.040 (0.005)***	-0.042 (0.003)***
	sub2p	-0.022 (0.083)	-0.148 (0.088)*	-0.117 (0.009)***		0.018 (0.013)	-0.129 (0.008)***
	const	-9.456 (1.34)***	-4.769 (1.063)***	-2.805 (0.096)***		-3.021 (0.156)***	-0.464 (0.111)***
≥ 500 k€	legal		3.540 (1.278)***	1.868 (0.394)***	0.250 (0.086)***	(base outcome)	1.097 (0.086)***
	uaato		0.033 (0.006)***	-0.005 (0.005)	0.005 (0.001)***		0.019 (0.001)***
	shfwu		-7.04 (2.380)***	-4.678 (1.057)***	-0.658 (0.170)***		-2.913 (0.327)***
	ffinc		-0.005 (0.006)	0.002 (0.001)**	0.001 (0.000)**		0.004 (0.001)***
	debtr		0.142 (0.281)	0.336 (0.069)***	0.279 (0.082)***		0.311 (0.154)**
	sub1p		-0.118 (0.083)	-0.009 (0.022)	-0.039 (0.008)***		-0.123 (0.016)***
	sub2p		-1.680 (1.330)	-0.063 (0.108)	-0.114 (0.019)***		-0.260 (0.022)***
	const		-5.615 (0.861)***	-4.646 (0.476)***	-2.812 (0.109)***		-0.511 (0.192)***
exit	legal	0.295 (0.152)*	-0.045 (0.062)	-0.228 (0.031)***	-0.286 (0.042)***	-0.425 (0.074)***	
	uaato	0.000 (0.001)	0.001 (0.001)*	0.001 (0.000)*	0.000 (0.000)	0.000 (0.000)	
	shfwu	-0.390 (0.221)*	-0.322 (0.105)***	-0.186 (0.058)***	-0.080 (0.083)	0.047 (0.196)	
	ffinc	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.000)	-0.001 (0.000)*	0.000 (0.000)	
	debtr	0.068 (0.065)	0.173 (0.060)***	0.203 (0.046)***	0.204 (0.068)***	0.254 (0.118)**	
	sub1p	-0.005 (0.004)	-0.006 (0.002)***	-0.009 (0.002)***	-0.003 (0.003)	0.013 (0.006)**	
	sub2p	-0.027 (0.006)***	-0.033 (0.004)***	-0.022 (0.003)***	-0.009 (0.007)	-0.029 (0.015)**	
	const	-0.066 (0.204)	-0.686 (0.100)***	-1.113 (0.054)***	-1.269 (0.063)***	-1.312 (0.108)***	
Number of observations		13,582	40,393	75,059	35,651	13,986	66,532
Adjusted R^2		0.013	0.019	0.033	0.020	0.025	0.252

Source: Own calculation based on FADN data; EU-FADN – European Commission

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