AgriFood economics centre

WORKING PAPER 2020:2

*Ida Lovén*
*Martin Nordin*

# Are agri-environmental schemes boosting farm survival?

# Is agri-environmental schemes boosting farm survival?

*Ida Lovén*[1] *& Martin Nordin*[2]

## Abstract

A topical policy goal is to design agri-environmental schemes that not only protect the environment but also foster agricultural production. This paper contribute with new knowledge towards this ambition, exploring the role of agri-environmental schemes for farm survival. Employing rich farm-level data on Swedish farms during 2001-2014, we explore farm survival using discrete-time hazard models and finds a significant association between agri-environmental schemes and farm survival. More specifically, the results suggests that participants are more likely to survive than farms without an agri-environmental scheme commitment and more extensive commitments favors increased survival up to a point when the commitment becomes too large in relation to other commitments and resources of the farm. Robustness analysis across subsamples of farms supports the finding that agri-environmental schemes are correlated with survival also for different groups of farms. Together, these results suggests that the agri-environmental schemes are important for farmers, and not only as a means to enable environmental protection. Consequently, this study contributes to policy, underlining the importance to encompass consequences beyond environmental concerns when assessing the overall benefits of the agri-environmental schemes.

**Keywords:** agri-environmental schemes, farm survival, duration analysis, Sweden

[1] Ida.loven@slu.se, AgriFood Economics Centre, Lund University, P.O. Box 730, S-220 07. Lund, Sweden; corresponding author.

[2] martin.nordin@agrifood.lu.se, AgriFood Economics Centre, Lund University, P.O. Box 730, S-220 07. Lund, Sweden.

# Introduction

The trade-off between agricultural production and environmental protection has long been a major policy concern. However, the discussion is now shifting towards how policies are to be designed to foster both the environment and agricultural production, underlining a need to learn more about the interplay between economic and environmental aspects of farming. This paper contribute with new knowledge on the importance of agri-environmental schemes (AESs), exploring their role for farm survival.

AESs are included in the rural development programme and are, according to the European Commission (2020a), elementary for the integration of environmental concerns into the Common Agricultural Policy of the European Union. The aim of the AESs are to encourage farmers to protect and enhance the environment by adopting environmentally-friendly measures that go beyond legal obligations. The Swedish AESs include support for, for example, organic production and the establishment of riparian strips and wetlands that enhance biodiversity and reduce eutrophication.

In EU, about 25% of the utilized agricultural area was under an AESs and expenditure for 2007-2013 was about €23 billion (Science for Environment Policy, 2017). For Sweden, this amounted to 2.1 million hectares supported by agri-environment payments during the same time period (Swedish Board of Agriculture, 2016). The EU payments to the Swedish rural development programme have increased over time (European Commission, 2020b) and the most resent Swedish programme, the 2014–2020 programme, had a total budget of about 4.3 billion euro (Regeringskansliet, 2020). Through the AESs, farmers subscribe to an environmental commitment and are compensated for additional costs and income foregone due to the measures taken.

But how important is this environmental support for farmers' economy and continued operation? Is it only a measure to enable farmers to protect the environment or could it also be a way for farmers to ensure the long-term survival of their farm? Farm survival and farm closures are important not only for individual farmers but also for society at large because it affects food production, land abandonment, land management, and the depopulation of rural areas. A topical policy concern is, therefore, whether environmental goals could coexist with productivity goals to ensure a sustainable and competitive agricultural sector.

AESs could influence farm survival through a variety of mechanisms. Survival increases if the AES contributes to farm profitability. Some farmers will produce environmental services in a profitable manner, while others will not. To start producing environmental services, like when starting a new business, requires both time and effort and farmers, as well as farms, have differing prerequisites to succeed or fail. The effects of AESs could, thus, both boost and hinder survival, via its influence on farm profitability. Another mechanism, favoring survival, arise if AESs are used as a way to diversify the farm business portfolio and function as a survival strategy when the income-generating potential of the main business is weak. Arguably, farmers could use the AESs as a source of extra income to both develop their business and mitigate short term liquidity problems. Previous research supports this argument. For example, interviews with Danish farmers reveal that some farmers apply for environmental support with the intention to exit before the commitment period ends, as the support payments are to be used to improve the farm (i.e., for maintenance, new buildings etc.) and not to foster the environment (Kaltoft and Risgaard, 2006). Taken together, the suggested mechanisms propose that AESs could have uses beyond its original purpose that foster continued farm survival.

Having rich farm-level panel data on the entire population of Swedish farms, we explore farm survival in relation to AESs participation over a time span of fourteen years (2001-2014), the results points to a significant correlation between AESs and the risk of farm closures. More specifically, AESs participants appear more likely to survive compared to farms without an AESs commitment and to increase the commitment appears favorable up to a point when it becomes very large in relation to the size of the farm, in terms of the farm's direct payments (Pillar I of EU's Common Agricultural Policy). Consequently, these findings suggest that the AESs are important for farmers, and not only as a means to enable environmental protection.

The structure of our dataset allows us to employ an empirical strategy that builds on survival analysis, applying a discrete-time proportional hazard panel model with nonparametric duration effects to and account for changes that occur over time and random effects to adjust for farm-level heterogeneity. Environmental change seldom happens overnight and to follow up environmental effect of an AESs could take time, even more so for the economic effects to manifest. Therefore, survival analysis is a useful tool to explore the dynamics behind farm survival as it allows us to model changes over time and, thereby, account for all impacts related to the passing of time, even if the underlying variable causing the impact is unobservable or hard to measure such as risk profiles, attitudes, learning, motivation and ability (Lastra-Bravo et al., 2015, Peerlings and Polman, 2009). Yet, the lack of adequate panel data following farms over time have limited the number of previous studies that apply duration analyses in agricultural economics (Defrancesco et al., 2018). Though papers on farm survival by Key and Roberts (2006) and Key and Roberts (2007a) underlines the contributions of duration analysis, no other study has, as far as we know, previously been published that explicitly focus on effects of AESs participation on farm survival.

Given that AESs participation is unlikely to be random, selection and endogeneity concerns is a challenge when estimating the effect of AESs on farm survival, making it difficult for us to rule out its presence and its potential influence over our results. Selection problems arise as farmers who are forward looking and prone to change are more likely to take on new environmentally-friendly farming techniques and invest in their farm to secure its long term survival than present-oriented peers. Consequently, farms could have differing underlying risk profiles that makes them more or less likely to survive. Arguably, farms faced with an imminent risk of closure are unlikely planning to take on an AESs commitment, suggesting that high-risk farms are selected away from AESs participation. However, it seems equally reasonable to argue that high-risk farms are more likely to use the AESs as an additional source of income when facing a risk of closure, suggesting that high-risk farms are instead selected into the AESs participant group. Thereby, the AESs participants may represent both high- and low-risk farms, as the selection in AESs uptake may operate both to increase or decrease between group heterogeneity in susceptibility to farm closure. Nevertheless, we test for the influence of selection bias by stepwise introducing economic variables likely to have been affected if farmers' abilities or risk profiles systematically differs between groups of farms. Thereby, we show that differences in ability, for example, to earn a profit is not the main mechanism behind the results. Moreover, we run extensive sensitivity tests to show the robustness of our results to different more or less homogeneous subgroups.

## Data, variables, and empirical approach

The firm-level longitudinal dataset that we use originates from Statistics Sweden (SCB) and the Swedish Board of Agriculture. It consists of merged farm-level information on Swedish farms for each year during 2001-2014. Statistics Sweden's Business Register provides us with comprehensive information on the number of employees, industry, and spatial location of all firms in Sweden as well as information about for example, sales, costs, and assets, and other records from income statements and balance sheets reported to the Swedish tax agency. We focus exclusively on the agricultural sector and identify firms in this sector based on the Swedish Standard Industrial Classification (SNI) cooding of the data and combine all firms that operate on a single farm (e.g., if brothers with sole proprietorship manage a farm together) to get farm-level data as decisions concerning the farm are likely made on this level. Then, we add information on direct payments (Pillar I) and AESs payments granted from the CAP including if, when, what type, and how much payments each farm has received.

### Sample and durations

To define duration, i.e., the length of time until a farm exits our dataset, we start by defining our sample by considering all farms identified from Statistics Sweden's Business Register that, during the period 2001-2014, (1) had a farm income registered for at least two years and (2) received a direct payment from the CAP. We excluded 1,644 farms who was present in the data only once as the analysis uses lagged variables and, also, because we cannot know if farms present only in year 2001 have had any AESs commitments prior to the observational window and are to be classified as an AESs farm or not. Farms that never had a direct payment is a relatively small but homogenous group (8,428 farms or about 10 % of the sample) that deviate from farms in general and are unlikely to have an AESs commitment. This way, the sample consists of 68,303 farms. Additionally, we restricted our sample to farms that have non-missing financial information and non-negative AESs payments (as we cannot know if a negative payment indicates that the farmers have returned a wrongly made payment or have failed their commitment) and exclude another 8,137 farms. The final number of farms in our sample is 57,624 with a total of 685,725 observations and an average duration of 11.91 years during the studied period.

This sampling strategy and the fact that our data is collected annually have two implications. First, we have left truncated discretely measured (also called interval-censored) durations as we only know that a closure occurred at some point during the year. Second, a duration is defined as the number of time periods a farm is registered in the data. Time takes positive values, t=1,2,…,14, and a farm duration starts at t=1 and ends at $t=t_i$, either with an exit (i.e., the last year we observe a farm) or with a right-hand censored observation (i.e., those farms which have not yet exit the dataset in 2014 and we do not know how long these durations will turn out to be, all we know is that they will be at least as long as the tracking period). The share of durations that are right-hand censored is about 88 percent of our sample. We account for interval-censoring and adjust for left-truncation in our empirical model to account for bias due to a likely overrepresentation of longer spells as farms entering the study when the sampling begins in 2001 have survived up to this point in time already.[3]

## The AESs

Three five-year AESs programs have been in place during the studied period (2001-2014) and the first one started in 2000, one year prior to the studied period. The design of the programs are similar but their composition of subsidies, their requirements and amounts payable differ somewhat between programs and over time. However, this study does not aim to explore different programs and changes in their design but encompasses AESs as a whole and study effects of participation in general

[3] Another way to handle left truncation is to drop all farms that started before 2001 but then our sample would consist of only relatively new farms and would no longer be representative. As we are studying how AESs relates to farm survival and not survival per see, we choose to use the full sample.

irrespective of type of scheme. Table A1 in the appendix lists the different subsides in the AESs and report uptake and average payments.

We define AESs *participants* as farms having received a payment, irrespective of which part of the program it comes from. Once the farm have received an AESs payment it is defined as an AESs participant, even if the farms leaves the AESs commitment. Thus, n*on-participants are* farms that have not yet entered a commitment along with farms that never attend an AESs during the studied period. In the first time period, 41.53 percent of the farms (n=23,931) are non-participants, while 58.47 percent of the farms (n=33,693) has an AES payment.

To model participation and non-participation this way means that once a farm enters a commitment it remains a participant throughout. Being part of the process of winding up a farm, the decision to exit an AESs or to not renew it as it ends could be endogenous because we do not now when the decision to leave an AESs is taken, if it is before or after deciding whether or not to close the farm. If the decision to leave an AESs is taken before a potential farm closure the cutback could be part of an attempt to balance the farm business portfolio and the closure, if it happens, should not be attributed to AESs participation. If the decision to leave an AESs instead is taken after the farm decides to close down, it should be counted as part of the closure. Consequently, we risk mixing up the potential effect of non-participation with the potential effect of exiting an AESs commitment if we were to allow farms to return to being non-participants. Still, to interpret the results based on the group of farms that exits or not renew an AESs as it ends is problematic. Even if we continue to count them as participants, why we will perform the analysis both with and without this group.

Next, we define the groups we are to study. We cannot use only the AESs payments as it largely overlaps with the size of the farm. Instead we want to put the AESs payment in relation to farm size. We use the amount of direct payments received from CAP to proxy farm size[4]. Larger farms often have larger AESs support payments if they have a commitment because the direct payment, alike many of the AESs subsidies, are based on hectares of arable land. This proxy works for both animal- and crops farms. By controlling for farm size in the analysis, the grouping will in some meaning mirror the intensity of the AESs commitment. This way, we follow Mishra et al. (2014), who reports that households with reduced intensity of government payments (payments in relation to farm income) more often express an intention to exit farming. To control for farm size is important also to adjust for the fact that larger farms have been found to be more frequent adopters and remainers of environmental programs than smaller farms (Hynes and Garvey, 2009, Läpple, 2010, Wilson and Hart, 2000).

[4] We find a large correlation between the direct payments and hectares of arable land and number of animals, but we only have data on these variables for some years.

For the participants, we calculate the total amount of AESs payments and divide it with the total amount of direct payments received during *all* years of participation. We then form seven groups with varying AESs intensity, ranging from non-participants to participants with AESs payments that are more than 125 percent the amount of the direct payment. The farms in the group *no AES* never has an AESs or will have one later, i.e., the non-participants. The group *AES 1-25* has a total AESs payments that are between 1-25 percent of their total direct payments, the group *AES 26-50* between 26-50 percent, etc. Table 1 shows how the farms are distributed across the groups at the first time period. Thereafter, farms in the no AES group who enter a commitment for the first time (54.43 % of the farms) change to the relevant participation group the year after they enter the commitment (as participation is lagged), while farms that never commit or already are participating remain as they are.

**Table 1.** The number of farms in each group along with descriptive characteristics of payments, number of subsidies, and dropouts from AESs

| **AES grouping** | **No. of farms** | **AESs payments** (mean, SEK) | **Direct payments** (mean, SEK) | **Farms that later leave the AESs** (%) | **No. of years left after leaving the AESs** (mean) | **No. of AES subsidies** (mean) |
|---|---|---|---|---|---|---|
| No AES | 23931 | n.a. | 37205 | 20.24 | 4.23 | n.a. |
| AES 1-25 | 10401 | 21716 | 166895 | 46.50 | 5.73 | 1.31 |
| AES 26-50 | 8416 | 35865 | 99845 | 29.06 | 4.57 | 1.51 |
| AES 51-75 | 5144 | 48587 | 76857 | 27.14 | 4.68 | 1.63 |
| AES 76-100 | 3400 | 68187 | 72256 | 25.88 | 4.54 | 1.73 |
| AES 101-125 | 2157 | 75066 | 64262 | 24.43 | 4.66 | 1.79 |
| AES > 125 | 4175 | 64276 | 32145 | 31.57 | 5.16 | 1.79 |

Table 1 presents also the average number of AESs subsides, AESs payment, direct payment in the groups at t=1 as well as the percentage of farms that will later leave an AESs commitment. The average AESs payment, along with the number of subsidies, is larger the more AESs intense the group is, except for the last group representing the most intense AESs participants. The average amount of direct payment is smallest for the last group: the most intense AESs participants, closely followed by the first group: the non-participants. The highest average direct payment is above SEK 150 000 for the second group: the lowest intensity participants, and then it goes down from there. Both the last and the first groups have relatively small average direct payments.

The share of farms that later will exit or not renew an AESs is it ends varies between groups but is as least 20.24 percent, meaning that dropouts are present in all groups. When leaving a commitment, the farms generally do not immediately close down. On the contrary, they have on average more than four years left before exiting the data set. When exiting, the vast majority of farms, 80 percent, are right censored, i.e., have reached the end of the studied period. The distribution between the participant groups of farms leaving an AESs hardly changes when all farms that are to start an AESs commitment have done so (not shown).

The grouping can be done in alternative ways, as can the definition of AESs participation, but we favor the chosen measures for two main reasons. First, they encompass the fact that leaving an AESs could, as already mentioned, be part of the decision to close the farms. Second, they work irrespective of which subsidy or subsides the farm have and when. This generalizability is important because the access requirements and the amounts payable for some subsidies has changed over time. In addition, different subsidies in the AESs are available only in certain parts of the country, for farms with specific production types, and the size of the payments depend, in part, on the size of the farm (Swedish Board of Agriculture, 2020). Therefore, to have or not to have a specific AESs, or to receive a certain amount of a specific subsidy could mean different things in different parts of the country and between different years. Measures based on the number of subsidies or specific subsides are not general enough to work. Still, we assess an alternative definition, based on the number of subsidies, in the sensitivity analysis. We rule out also alternative measures that put the AESs in relation to sales or some other economic outcome as many of the farms have outcomes close to zero, which would inflate such weighted measure.

## Sample hazard rates and survival

We estimate unadjusted sample hazard functions and the corresponding cumulative survivor functions for the seven AESs groups.[5] Assessing the results suggest that the risk of farm closure differs between the groups and indicates an inverted u-shaped relationship between increasing AESs participation and the likelihood of farm survival. While, the probability of sample survival appear most likely for farms in the AES 26-50 group, it decreases as we move towards the groups with either lesser or more extensive AESs participation. The first and last AESs groups: the non-participants and the most intense participants, are least likely to survive each year given that they have survived up and until that year.

Figure 1 presents results for these three groups, as including all clouds the figure. As already said, the risk of farm closure is lowest among farms in the AES 26-50 group and this period-by-period lower risk cumulates into a substantial difference in survivorship (the long dashed lines), while the risk is higher and survival less likely for farms without an AESs (the short dashed line) or more extensive AESs participation (the solid line). In panel (a), the development of AESs 26-50's

[5] The hazard function depicts the probability of farm closure in a specific period given that the farm has survived until that period and the survival function the probability that a randomly selected farm will 'survive' through each successive time period.

survival is closely followed by the No AES group up and until the third time period. By the last time period, 89.18 percent of the farms in the AES 26-50 group remained active, while only 84.41 percent of the non-participants and 82.53 percent of the farms with the most extensive participants.

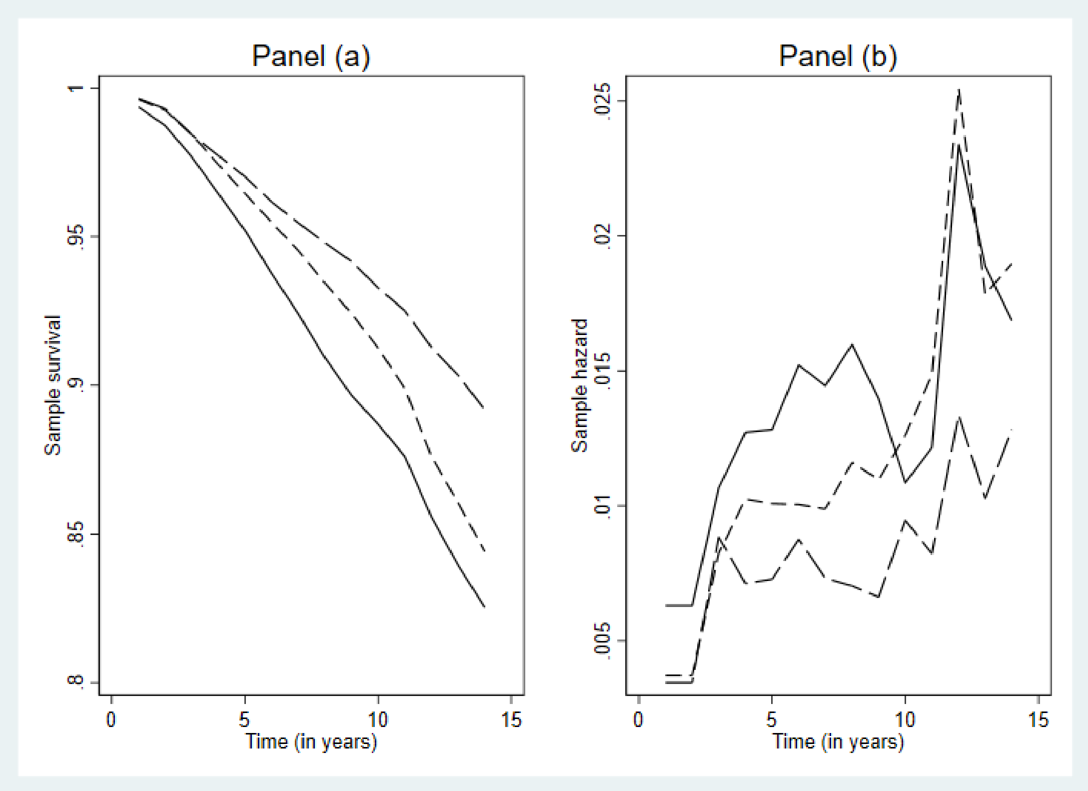


**Figure 1.** Within-group sample survivals (panel a) and sample hazards (panel b) for farms in the No AES group (short dashed line), the AES 26-50 group (long dashed line), and the AES > 125 group (solid line)

The probability of farm closure in panel (b), show upward sloping curves, all peaking at time twelve (occurs in 2012 for 89 % of the farms, or later). The peak in farm closures is probably related to two changes that took place in 2010 and affected which farms that was included in the Swedish Board of Agriculture's farm register. First, the boundaries of the register was lowered to allow smaller firms to be registered, increasing the number of farms. Second, the hectares of agricultural land needed to be eligible for CAP direct payments was raised from two to four hectares of land, instead lowering the number of farms (Swedish Board of Agriculture, 2017). Together, these changes probably lead to a temporary increase in the number of small farms, resulting in a peak of farm exits in our data at time twelve (corresponding to the years 2012-2014) when the effect of the changes have had time to kick in. Confirming that this peak does not threaten to drive our results, Figure A1 in the appendix report similar hazard- and survival curves even after excluding all farms that exit the dataset in 2012, except that the peak at time twelve has turned in to a drop (as should be expected).

The gap between the hazard curves and the differing survival curves could indicate an effect of participation. But remember, it only does so if the farms are comparable in all other aspects apart from their varying AESs intensity. Otherwise, it could be a spurious relationship that causes the patterns in Figure 1 as the curves merely are unadjusted sample hazards. Consequently, it might be something else the grouping captures, besides differing AESs intensities, also contributing to differing survival rates.

The upward sloping hazard curves (and the relatively high cumulative survival rates) stand in contrast to previous findings on firm survival that tells us that the hazard generally drops after some initial hazardous years (Key and Roberts, 2006). Economic theory suggest that successful firms learn and adopt to their surrounding over time, while less successful firms fail in the competition and close down (see, e.g., Jovanovic, 1982). The farms we study, date back to the 1970's and our risk set consists of experienced mature firms who have passed the initial high-risk learning period; therefore, their risk is generally low but increasing as more farm managers approaches retirement. Unfortunately, we do not have data on the age of the farmer, but the sensitivity analysis will later confirm that our results persists when removing farms that enters farming during the studied period.

Consequently, the upward sloping curves are only natural in our setting and also reassuring because downward sloping curves could often be attributed to selection within the groups. Selection causes dropping hazards as high-risk farms, more prone to failure, are the first to fail, and when they leave the risk set, its composition changes in favor of more successful farms. Therefore, as time passes the population is increasingly depleted of those farms most likely to close down, leading to a decrease in the population hazard. Because of this type of *within group selection*, we may, thus, see a decrease in the population hazard even if farms' individual hazards are constant or increasing. However, Figure 1 revealed upward sloping hazards, thereby, contradicting that this type of selection is present in the data. Had ability or differing underlying risk profiles been important drivers of selection within the groups it would likely be present also between the groups, which we argued against in the introduction.

Nevertheless, potential selection *into* the different groups still needs our attention. Firstly because farmers that are prone to take on risks are likely prone also to take on more extensive AESs commitments compared to less risk-prone peers. Secondly, because high-ability farmers are assumingly more able to achieve a balanced AESs setup, they are probably also less likely to leave an AESs commitment than less able peers. If present and ignored, selection into the different AESs groups could be a mechanism causing the participants to have differing sample hazards across the participation intensity groups, why we will return to this issue later.

## Empirical model and covariates

Our empirical strategy builds on survival analysis, to account for the dynamic implications of learning over time and its effect on the survival of the farm. We therefore set out to model the duration of time from farm entry to exit. The discrete nature of our data (the underlying continuous durations are recorded in discrete units) implies that a bivariate discrete-time proportional hazard model for farm *i* at time period *t* can be employed

$$\lambda(X_{it}, AES_i) = \Pr(farm\ closure) = \Pr(T_i < t + 1 | T_i \geq t, X_{it}, AES_i) = F(\beta_1{}'X_{it} + \beta_2{}'AES_i + \alpha_T)$$

Eq 1

where $T_i$ is the end time of a duration. In this model, a unit increase in a covariate is multiplicative with respect to the hazard rate. To be able to estimate the model parameters, we assume a normal distribution for the hazard function and fit Equation 1 with a probit panel data model, as the probit specification have a better fit to our data than logit and cloglog, which also are commonly used. $\alpha_T$ is a function of time that allows the hazard rate to vary across periods. Because the underlying baseline hazard is unknown $\alpha_T$ is modeled as a set of dummy variables identifying the duration periods of each duration spell. These duration effects capture all developments on the farms which are related to the passing of time.

$AES_i$ is the time-invariant category variable that represents our interest groups and allows us to test if the estimated hazard of the participant groups differs from the estimated hazard of the reference group, which we choose to be AES 26-50. This group had the lowest sample hazard, as seen in Figure 1, implying that this could represent the top of a potentially inverted u-shaped relationship with farm survival.

$X_{it}$ is a vector with both time-variant and time-invariant covariates. Table 2 presents the covariates that we have chosen with reference to the existing literature connecting farm-specific factors to farm survival. As a growing body of studies points to similar farm- and operator characteristics as important determinants of both AESs participation and farm survival (see, e.g., Lastra-Bravo et al., 2015, Van Herzele et al., 2013), these control variables operates to control for both their direct influences on survival and the influence that otherwise would be captured by AESs participation variable. We control for location-specific calendar fixed effects as the design of the AESs varies by location and over time. We do this by including fixed effects for location, calendar year, and an interaction between the two. Farm location is measured by 280 municipalities that we group into eleven counties. In addition, the location and calendar-year fixed effects control for all factors that are shared among farms in the same location and for economic fluctuations in the economy common to all farms.

To hinder inferential dilemmas of state and rate dependence, we follow the survival analysis literature and lag all time-variant variables one year. For the first time period, we use imputation as suggested by Singer et al. (2003). To instead drop the first time period does not affect the results (not shown).

We control for farm-specific factors that, at least partly, overlap with farmers' characteristics. Direct payments and direct payments squared, which are highly correlated with the size of the farm measured as number of animals and hectares of arable land, are lagged and measured in SEK. To include these controls are important as we want the AESs grouping to capture varying AESs intensities among equally sized farms and not size itself. The size of the farm influence survival as scale effects implies that larger farms generally use labor more efficiently (Flaten, 2002) and adopt new technologies earlier (Weiss, 1999). Moreover, Key and Roberts (2006) shows that government payments, an income support alike the direct payments, is negatively associated with business failures. Furthermore, we control for the farms primary production (crop, livestock, or mixed determined by a five-digit SNI cod), startup dummies (the year the farm was first registered) and details about the farms' annual economic performance.

**Table 2:** Definition of covariates

| **Variable name** | **Short description** | **Categories or min/max** |
|---|---|---|
| *Demographics* | | |
| Startup year | Dummies indicating year when the farm was founded. | 1971/2013 |
| Type of farm | Time invariant category variable indicating type of production based on five digit SNI codes. | 1 if mainly crops<br>2 if mainly animals<br>3 if mixed<br>4 if other (forest) |
| Location | 280 dummies indicating the municipality where in Sweden the farm is located grouped into eleven counties. | 1/11 |
| Calendar year | Dummies indicating the calendar year when observation registered. | 2001/ 2014 |
| Direct payments | Time variant continuous variable, annual amount direct payments from CAP. Used with a polynomial. | -771,000/11,095,000 SEK |
| *Annual economic outcomes* | | |
| *Step 1* | | |
| Value added | Time variant category variable with equally sized categories ranking the added value of the farms. Added value is the production value minus input costs, excluding costs of capital and labor. | 1 if ≤ 20$^{th}$ percentile<br>2 if 21$^{st}$ - 40$^{th}$ percentile<br>3 if 41$^{st}$ - 60$^{th}$ percentile<br>4 if 61$^{st}$ - 80$^{th}$ percentile<br>5 if ≥ 81$^{st}$ percentile |
| *Step 2* | | |
| Net income | Time variant continuous variable, annual profit or loss. | -77,978/89,660 SEK |
| Return on equity | Time variant continuous variable, net income divided by shareholders' equity. | -1,454/832 |
| Shareholder equity ratio | Time variant continuous variable, total shareholders' equity divided by total assets. | -252/259 |
| Off-farm value added | Time variant continuous variable, annual added value. | -24,004/1,56,995 SEK |
| Off-farm net income | Time variant continuous variable, annual profit or loss. | -40,489/99,580 SEK |

*Note: All monetary values are in SEK (EUR 1 ≈ SEK 10) and deflated using producer price index and 2000 as base year.*

To include control variables related to economic performance could be problematic as it could introduce endogeneity issues that makes the estimates on AESs participation difficult to interpret. We, therefore, add the economic variables to our model specification in a stepwise manner to assess potential changes in the estimates for the AESs groups. Such changes would imply that the variables are correlated, and we would not know if the additional controls reduces bias or effect. However, we will show that the estimates on AESs participation remain robust, thereby, strengthening the interpretation of our results as it suggests that neither bias nor the economic mechanism is driving our results.

The economic variable included in the first step is a category variable capturing the *added value* of farm production. Having explored the linearity assumption of the model specification, we transform the added value variable into five categories to improve the model fit. The categorize are based on a farms outcome in relation to other farms, splitting the sample in five equally sized groups each year, grouping farms given which part of the distribution the farm belongs to. All other economic variables are also lagged and transformed, but using qubic root[6] form.

In the second step, we add the farms *net income*, *return on equity (ROE)*, *shareholder equity ratio*, as well as *added value* and *net income outside of farming*. *Net income* is the annual profit or loss the farm gained from farming or other businesses. *Return on equity (ROE)* is a measure of financial performance calculated by dividing net income by shareholders' equity. Because shareholders' equity is equal to a company's assets minus its debt, ROE could be thought of as the return on net assets. ROE is considered a measure of how effectively management is using a company's assets to create profits. *The shareholder equity ratio* shows how much of the company's assets are funded by equity shares. The ratio, expressed as a percentage, is calculated by dividing total shareholders' equity by total assets of the firm. The ratio reveals how much a company depends on debt and how financially stable it may be in the long run. The groups perform on average equally well on these two measures of economic performance, as shown in Figure 2.

[6] Log transformations does not work with negative or zero values.

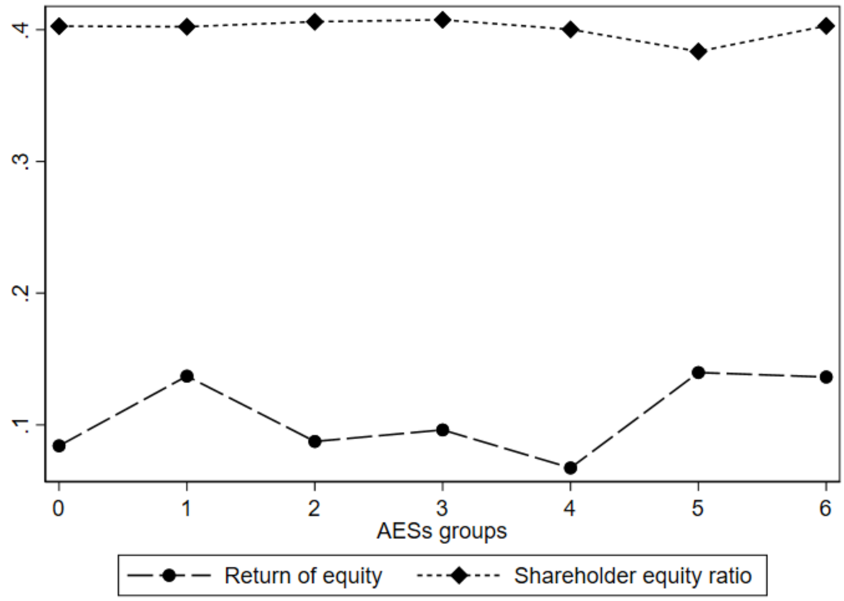


**Figure 2.** Average return of equity and Shareholder equity ratio for all groups ranging from No AES to AES > 125

The dataset does not contain any information about the farmers running the farms, or their families. Therefore, we follow Hess and Persson (2012) and add controls for unobserved heterogeneity ('frailty' in the bio-statistics literature) by including random effects to the model. By incorporating the unobserved heterogeneity factor, our model becomes

$$\lambda = \Phi(\beta_1{}'X_{it} + \beta_2{}'AES_i + \alpha_T + v_i) \qquad \text{Eq 2}$$

where $v_i$ denotes the unobserved heterogeneity factor and is assumed to follow a Gaussian distribution, as it is computationally convenient (Hess and Persson, 2012). The random effects captures any time-invariant homogeneity within a farm that is uncorrelated with the included covariates and, thereby, gives more consistent estimates. Thus, the random effects will capture, for example, systematic differences between the farms with differing age profiles of the farmer as the farmer's age has been found to increase the risk of farm closures when the farmer approaches retirement (Glauben et al., 2009). However, it will not capture any selection effects due to aging farmers as such effects, if present, will be correlated with AESs participation and, thereby, captured by the estimate for the AESs grouping. As the upward sloping sample hazards in Figure 1 revealed a positive duration dependence, we will underestimate the true effect if neglecting unobserved heterogeneity.

# Results

This section presents the results from estimating the probability of farm closures for the different AESs groups. We consider the coefficients from the proportional hazard model that gives the average differences between groups as well as plots of the groups' fitted hazards and survivals.

## Proportional hazards and average differences between the groups

Table 3 presents the coefficient estimates along with their associated standard errors of the discrete-time duration model. Model 1 includes demographic variables and direct payments, Model 2 adds value added, Model 3 includes the full set of economic variables, and Model 4 adds random effects. Model 5 and Model 6 focus on farms remaining active AESs participants and excludes all farms exiting or not renewing their AESs commitment. Model 5 corresponds to Model 3 and Model 6 to Model 4.

Across model specifications, the estimated coefficient on AESs differs significantly from zero, indicating that, ceteris paribus, the AESs groups with more or less intense participation differs from the reference group with an AES commitment that is between 26 and 50 percent of the direct payments. The positive sign of the AESs estimates indicate a higher average risk of farm closure over the studied period. As we move across the AESs grouping, the change in the estimates suggest a tilted u-shaped relationship with the risk of farm closures. Figure 3 shows how the estimates from model 3 becomes smaller as they approach the reference group and grows afterwards. Notice also that the shape of the u becomes more even when excluding farms that quits their AESs (model 5). Contrasting the estimates of Model 3 and Model 5, the estimate for non-participants increases in size when focusing on active participants, while the estimates for the other AESs groups remains more similar. This finding reveals that the associations are stable within the participants group but changes towards farms without an AESS. We will return to discuss implications of this finding towards the end of the results section when discussing the interpretation of the overall findings of the analysis.

**Table 3.** Estimated coefficients from the discrete-time proportional hazards duration model

| | (1) Model 1 | (2) Model 2 | (3) Model 3 | (4) Model 4 | (5) Model 5 | (6) Model 6 |
|---|---|---|---|---|---|---|
| *AESs* | | | | | | |
| No AES | $0.0690^{***}$ | $0.0593^{***}$ | $0.0591^{***}$ | $0.0633^{***}$ | $0.290^{***}$ | $0.293^{***}$ |
| | (0.0162) | (0.0161) | (0.0165) | (0.0175) | (0.0225) | (0.0233) |
| AES 1-25 | $0.0488^{***}$ | $0.0484^{***}$ | $0.0525^{***}$ | $0.0535^{***}$ | $0.0649^{**}$ | $0.0646^{**}$ |
| | (0.0159) | (0.0160) | (0.0164) | (0.0171) | (0.0259) | (0.0259) |
| AES 26-50 | Ref. | Ref. | Ref. | Ref. | Ref. | Ref. |
| AES 51-75 | $0.0339^{*}$ | $0.0334^{*}$ | $0.0345^{*}$ | $0.0364^{*}$ | $0.0496^{*}$ | $0.0497^{*}$ |
| | (0.0191) | (0.0192) | (0.0196) | (0.0205) | (0.0288) | (0.0290) |
| AES 76-100 | $0.0552^{**}$ | $0.0593^{***}$ | $0.0578^{**}$ | $0.0600^{**}$ | $0.0609^{*}$ | $0.0600^{*}$ |
| | (0.0219) | (0.0221) | (0.0226) | (0.0237) | (0.0332) | (0.0336) |
| AES 101-125 | $0.117^{***}$ | $0.122^{***}$ | $0.120^{***}$ | $0.125^{***}$ | $0.157^{***}$ | $0.159^{***}$ |
| | (0.0249) | (0.0250) | (0.0256) | (0.0275) | (0.0365) | (0.0369) |
| AES > 125 | $0.228^{***}$ | $0.228^{***}$ | $0.213^{***}$ | $0.222^{***}$ | $0.238^{***}$ | $0.239^{***}$ |
| | (0.0188) | (0.0189) | (0.0193) | (0.0235) | (0.0287) | (0.0294) |
| *Covariates* | | | | | | |
| Demographics | Yes | Yes | Yes | Yes[a] | Yes | Yes[a] |
| Direct payments | Yes | Yes | Yes | Yes | Yes | Yes |
| *Economic outcomes* | | | | | | |
| Step 1 | No | Yes | Yes | Yes | Yes | Yes |
| Step 2 | No | No | Yes | Yes | Yes | Yes |
| Random effects | No | No | No | Yes | No | Yes |
| / lnsig2u | | | | $-2.988^{**}$ | | $-4.351^{**}$ |
| | | | | (1.239) | | (2.105) |
| No. of observations | 685725 | 685725 | 645037 | 645037 | 456160 | 456339 |
| No. of farms | | | | 57624 | | 41378 |
| Log L | -34332.0 | -34072.6 | -32463.8 | -32590.5 | -18209.0 | -18322.2 |
| rho | | | | 0.0480 | | 0.0127 |

*Note: Robust clustered standard errors in parentheses, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$. The demographics include fixed effects for time, startup year, type of farm, and location-specific calendar year. [a] No location-specific calendar year effects, only separate location effects and calendar year effects. Direct payments includes direct payments in SEK and direct payments squared. Economic outcomes in step 1 includes categories of value added, and step 2 adds net income, return on equity, shareholder equity ratio, off-farm value added, and off-farm net income (defined in table 2).*

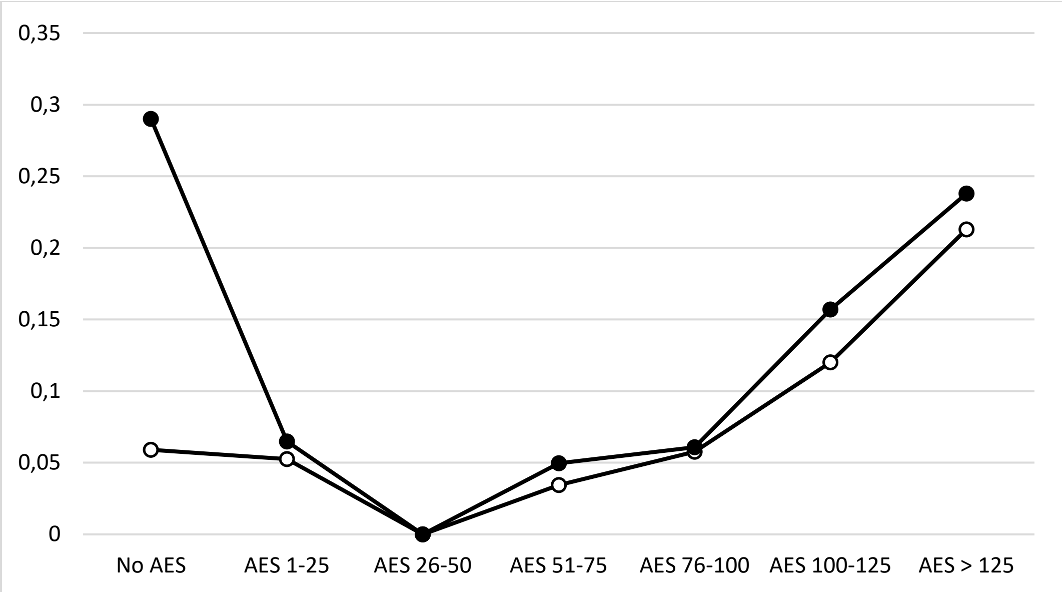


**Figure 3.** The coefficients for all farms from model 3 (hollow circles) and active participants from model 5 (filled circles)

## Fitted hazards and survival

Given that the magnitude of the estimate, i.e., the risk differential, is difficult to interpret as it is measured on the standard normal scale (the coefficients are Φ hazards)[7], we calculate and plot the fitted hazards and the corresponding cumulative survival for the AESs groups. To predict the hazards and cumulative survival curves, we use seven hypothetical farms, one from each group, and give them, apart from AESs participation, the same set of characteristics—middle sized crop farms, started in 1996, located in Sothern Sweden, with zero random effect, and mean annual value of direct payments and economic outcomes. We apply the results from both model 3 and 5. Figure 4 holds the resulting estimated hazards for all farms (model 3) in panel (a) and for active AESs participants (model 5) in panel (b). Again, we present the results for groups representing the bottom, AES 26-50, and two endpoints, of the u-shaped relationship, no AES and AES > 125, as we did for the unadjusted sample hazards in Figure 1.

[7] The estimated coefficients are to be interpreted such that a 1 unit increase in the variable will raise the z-score of Pr(Y=1) by the coefficient value.

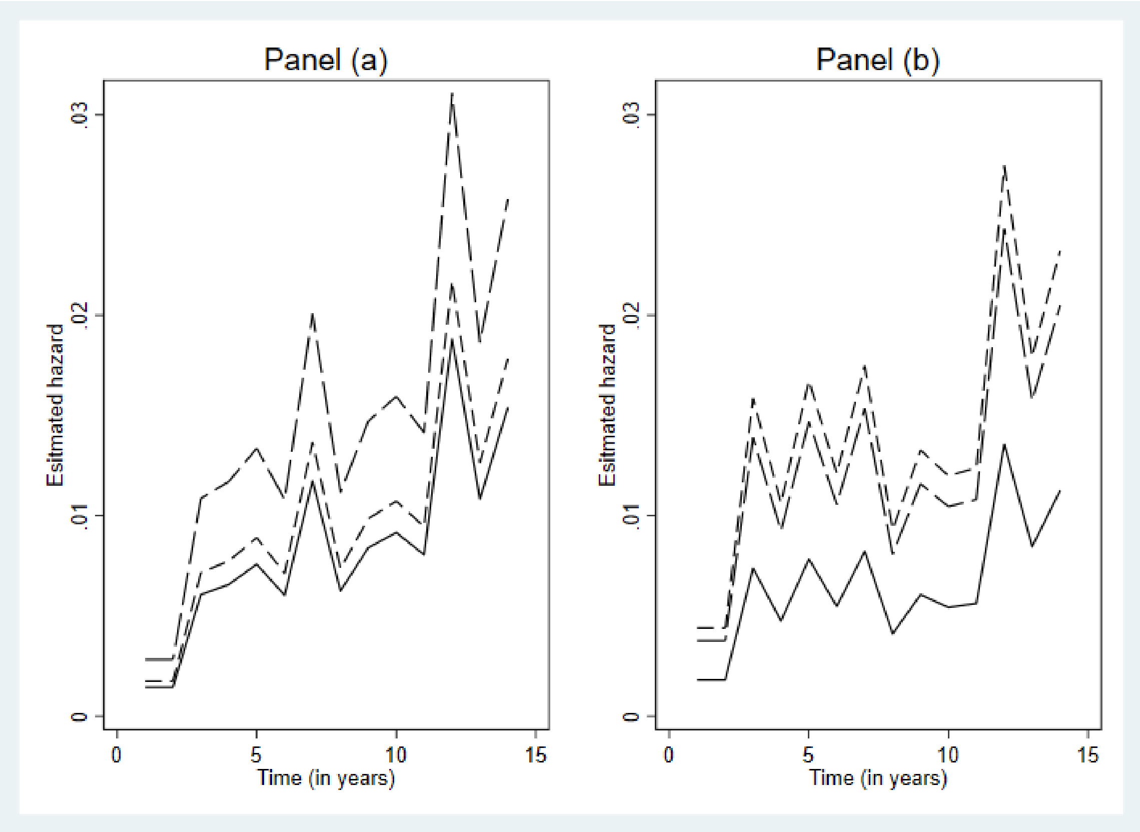


**Figure 4:** Fitted hazard functions for the full sample of all farms (panel a) and active participants (panel b), which are hypothetical crop farms located in southern parts of Sweden for farms in the No AES group (short dashed line), the AES 26-50 group (solid line), and the AES > 125 group (long dashed line)

Overall, the estimated hazards of farm closure, though less than three percent throughout, are increasing over time and are, everything else equal, lowest for farms in the AES 26-50 group as shown previously also for the unadjusted sample hazards (Figure 1).[8] Contrasting the results in the two panels reveals that the curve for non-participants changes from being close to the AES 26-50 group to laying at the top, above the AES >125 group. Because the gap between the two participants groups (AES 26-50 and AES > 125) remains the same, the only change in association occurs between participants and non-participants, as indicated already by the estimated coefficients. The gap between the hazard curves depicts differences in the estimated risk of farm closure between the groups, why this change is to be expected if AESs participation indeed favors farm survival. The change could, however, also be driven by farms leaving their AESs commitment as a part of winding up their business as we do not now when the decision to leave an AESs is taken in relation to the decision to close the farm.

Before turning to the probability of survival, notice also that the shape of the hazard is somewhat flatter for active AESs participants than for all farms, suggesting that the excluded group of

[8] Because the proportional hazards model expresses the linear effect of the predictor on Φ hazard, we cannot say anything about the stability of the effect over time using graphs plotted on the raw hazard scale as in Figure 4. The sample hazards in Figure 1 were not proportional but varied freely over time.

farms leaving the AESs commitment generally are more prone to close their farm than farms that remains in a commitment throughout the studied period. Unfortunately, as already discussed, we do not know if this difference should be attributed to AESs participation or not.

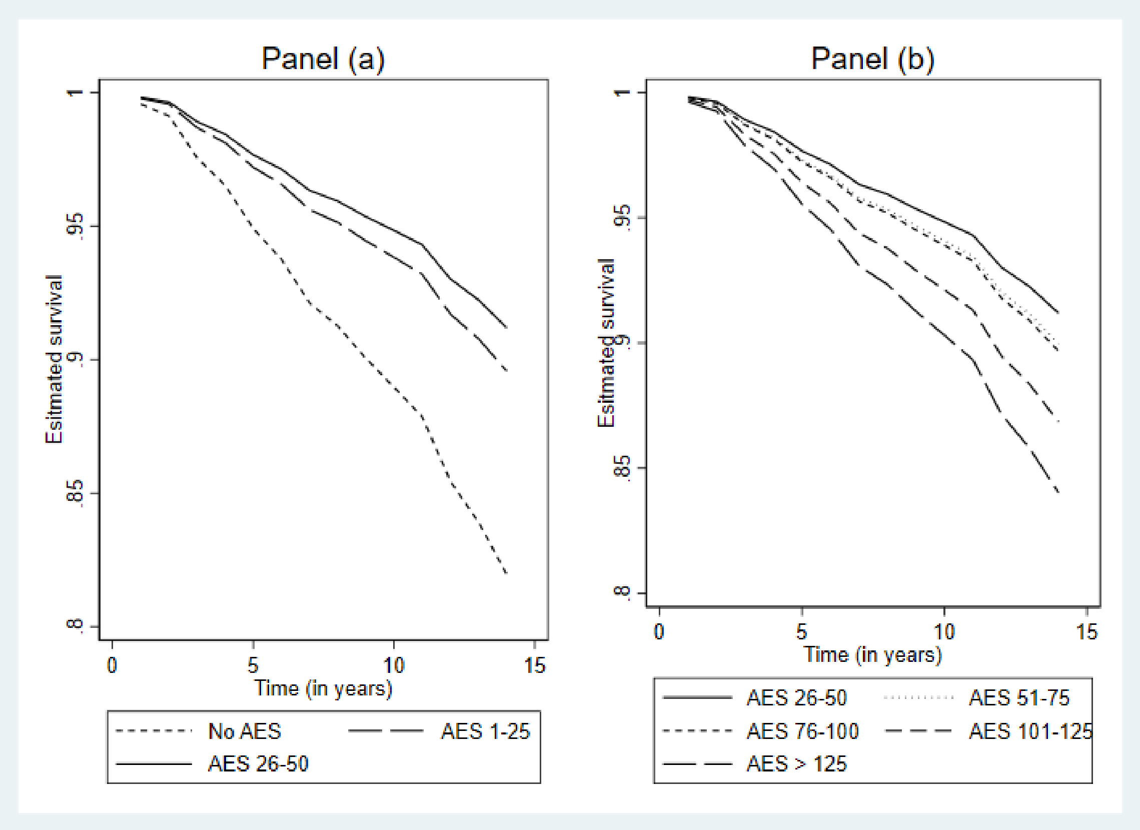


**Figure 5.** Fitted survival based on the sample of active participants calculated for hypothetical crop farms located in southern parts of Sweden for the three low-end groups of the AES intensity scale in Panel (a) and the five high-end groups in Panel (b).

Moving on with the active participants (the corresponding figure for all farms are available in the Appendix, Figure A2), Figure 5 presents the fitted survival curves for all groups, showing how the period-by-period hazard differences cumulate into differences in survival between the groups. Panel (a) shows the curves for farms up and until group AES 26-50 and panel (b) repeats the curve for group AES 26-50 along with those for the groups with more extensive AES participation. After five years, 96.66 percent of the farms in the AES 26-50 group remains in business, in comparison to 94.90 percent of the non-participants and 95.53 percent of the AES > 125 group. By the end of the tenth year, 94.83 percent of the AES 26-50 group remains in business, while only 88.96 percent of the non-participants and 90.30 of the AES > 125 group. Taking the complement of these percentages, 5.17 percent of the AES 26-50 group has closed down, and as many as 11.04 (9.70) percent of the non-participants (AES > 125 group). After fourteen years, the percentage of farm closures is 18.03 (15.98) percent for farms without a commitment (AES > 125 group) but only 8.81 percent for the AES 26-50 group. Consequently, the closure rate for the AES 26-50 is less than half the size of the rate for non-participants, pointing towards a rather large difference in survival between the high survival AESs participants and farms without an AESs commitment.

Looking instead at the groups closest to the AES 26-50 group, that is the AES 1-25, AES 51-75, and AES 76-100, reveals that about 10 percent of all three groups have closed at the end of the studied period, thus their likelihood of survival is only slightly lower than for the AES 26-50 group. Finally, when comparing the likelihood of survival of the non-participants to the six participation groups, we find that farms without a commitment have a significantly higher risk of farm closure than all other groups (see Table A3 in the appendix).

Together these results shows that farms with an AESs commitment have a higher survival than farms without a commitment, possibly implying that AESs participation contributes to survival. Similarly, Mishra et al. (2014) reports that farm households' stated intention to exit farming is linked to government payments, so that households with reduced intensity of government payments (payments in relation to farm income) are more likely to exit farming. But, we also find that too large commitment could be less favorable. This finding seems reasonable as having a balanced portfolio of AESs in relation to other farm commitments and resources ought to favor continued farm survival better than a more extensive AESs. Likewise, a relatively small AESs commitment ought to be less effective than a balanced portfolio to improve farm survival. However, it still remains to explore whether these results actually imply an effect of AESs participation or if they could be driven solely by selection.

## The influence of the farms' economic outcomes and the random effects

Returning to the estimated coefficients (Table 3, Columns 1-3) the fact that the sign and magnitude of the estimate for AESs groups are relatively stable between specifications with and without the economic covariates indicates robustness. The economic outcomes have only a small correlation with continued survival and the effect of AESs participation. If farms with some specific favorable set of characteristics are selected into a specific AESs group, we would expect the controls for economic outcomes to have a more profound impact on the estimated effect of AESs participation. This is so even if the controls for direct payments to some extent could be capturing similar "size effects" as economic variables does. Using lagged economic variables, we only account for past economic performance. Still, these controls aim to capture long-term changes to the farms profitability, why some correlation, if present, ought to have appeared in the tests also for lagged outcomes. Consequently, the influence on AESs participation from past economic performance are not signaling that selection are at play.

When contrasting results from Equation 1 and Equation 2 (Table 3, Columns 3-4 and Columns 5-6), with and without random effects, the magnitude of the estimated effects increases slightly, as expected when we add controls for random effects given the positive duration dependence shown by the sample hazards in Figure 1.[9] However, the models with random effects takes a very long time to estimate and will not converge with location-specific calendar year fixed effects, why we move on to the sensitivity analysis without controlling for random effects. This decision is supported by a non-significant likelihood ratio test (not shown), indicating that the panel-level variance component might be unimportant as the test cannot reject that rho (i.e., the proportion of the total variance contributed by the panel-level variance component) is zero.

Taken together, our results for AESs participation appear to be robust across model specifications. Remember that when excluding farms that leaves their AESs commitment, the associations within the AESs participation group remains stable but changes compared to non-participants. Consequently, to exclude these farms does not affect the interpretation within participants, but merely between participants and non-participants. Thereby, confirming the robustness of the results within the participant groups and increases the association with non-participants as it should if participation indeed fosters survival. Though we cannot rule out that farms leave their AESs as part of winding up their business.

Still, the analysis indicates that AESs are favorable, even if too excessive commitments could be counterproductive, as indicated by the higher risk of farm closure among the two groups with largest commitments in relation to farm size. Either due to some unknown difference in risk (selection) or as an effect of the AESs if farms with strong environmental commitments either overinvest or take on unprofitable commitments.

Even if our results so far appear to be robust across specifications with and without controls for the covariates most likely to be related to selection, the sensitivity analysis will dig deeper into the robustness of results for different subsamples.

## Sensitivity tests

We test the robustness of the results to alternative definitions of AESs participation and to specific subsidies in the AESs. We also limit the analysis to subsamples of farms with certain characteristics to assess the potential for selection bias in our main analysis. For simplicity and to speed up the calculations, all sensitivity tests are for active participants and specified as Model 5 in Table 3, and it is to this model we compare the results of the sensitivity tests. Because the corresponding results for

[9] The increase is also due to a scaling effect.

all farms (Model 3) lead to similar interpretations of our main results, they are presented in the appendix only (see Table A3-A4[10]).

## The definition of AESs participation and specific AESs subsidies

Table 4 reports the results of sensitive test were AESs participation is defined based on the lagged number of subsidies the farm have each year. The finding of the test is in line with the main results showing a lower risk of farm closure for participants compared to farms without an AESs commitment. Furthermore, the results implies that the risk decreases with increasing number of commitments.

**Table 4.** Estimated coefficients based on the sample of active AESs participants for sub analyses with AESs participation defined by the number of subsidies the farm have

| | (1)<br>Alternative AESs grouping |
|---|---|
| *Number of AESs subsidies* | |
| 0 | Ref. |
| 1 | $-0.153^{***}$ |
| | (0.0184) |
| 2 | $-0.234^{***}$ |
| | (0.0202) |
| 3 | $-0.274^{***}$ |
| | (0.0254) |
| 4 | $-0.364^{***}$ |
| | (0.0421) |
| >4 | $-0.447^{***}$ |
| | (0.0961) |
| *Covariates* | |
| Demographics | Yes |
| Direct payments | Yes |
| *Economic outcomes* | |
| Step 1 | Yes |
| Step 2 | Yes |
| Random effects | No |
| No. of observations | 93585 |
| Log L | -2564.1 |

*Note: Robust clustered standard errors in parentheses, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$*
*The demographics include fixed effects for time, startup year, type of farm, and location-specific calendar year. Direct payments includes direct payments in SEK and direct payments squared. Economic outcomes in step 1 includes categories of value added, and step 2 adds net income, return on equity, shareholder equity ratio, off-farm value added, and off-farm net income (defined in table 2).*

As discussed when presenting the AESs grouping in the data and method section, the alternative definitions are overlapping in some respects, but to have a specific subsidy or a certain number of subsidies could mean different things for different farms depending on their location and timing.

[10] We do not report for the full sample when testing the alternative definition of participation because, being time variant, this definition of participation implies that farms that leave a commitment will be classified as non-participants.

Different subsidies have been available in different parts of the countries and some subsidies have come and gone during the studied period, why we use this definition only as a test to confirm the robustness of our results.

Next Table 5 reports for subsamples that excludes farms that either have one of the most common subsidies in the AESs, i.e., cultivated grasslands, open and varied landscape, and pastures and meadows (column 1), or have the subsidy with the largest subsidy payment, i.e., organic farming (column 2). Either of these could be used strategically to boost farm survival. The two most commonly used subsides is the same in all AESs groups (see Figure A1). They do not require much additional work once received, why they are a relatively low-cost alternative if a farmer seeks an extra source of income to diversity of make improvements on the farm. To shift to organic farming is, in contrast, a demanding process but the market for organic products is growing and may attract farmers to transition (Uematsu and Mishra, 2012).

**Table 5.** Estimated coefficients for the sample of farms focusing on active AESs participants for sub analyses excluding specific AESs subsidies

| | (1)<br>Excl.<br>common subsidies | (2)<br>Excl. largest subsidy payment |
|---|---|---|
| *AESs* | | |
| No AES | -0.0131 | 0.281$^{***}$ |
| | (0.0842) | (0.0272) |
| AES 1-25 | 0.170$^{*}$ | 0.0372 |
| | (0.0985) | (0.0299) |
| AES 26-50 | Ref. | Ref. |
| AES 51-75 | 0.0592 | 0.0625$^{*}$ |
| | (0.136) | (0.0375) |
| AES 76-100 | -0.115 | 0.110$^{**}$ |
| | (0.214) | (0.0467) |
| AES 101-125 | -0.232 | 0.222$^{***}$ |
| | (0.292) | (0.0552) |
| AES > 125 | 0.208 | 0.295$^{***}$ |
| | (0.163) | (0.0411) |
| *Covariates* | | |
| Demographics | Yes | Yes |
| Direct payments | Yes | Yes |
| *Economic outcomes* | | |
| Step 1 | Yes | Yes |
| Step 2 | Yes | Yes |
| Random effects | No | No |
| No. of observations | 119546 | 313199 |
| Log L | -8386.3 | -14393.7 |

*Note: Robust clustered standard errors in parentheses, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$*
*The demographics include fixed effects for time, startup year, type of farm, and location-specific calendar year. Direct payments includes direct payments in SEK and direct payments squared. Economic outcomes in step 1 includes categories of value added, and step 2 adds net income, return on equity, shareholder equity ratio, off-farm value added, and off-farm net income (defined in table 2).*

When excluding the most common subsidies, the estimates for non-participant is no longer significant and close to zero in size. While it still seems better to have a commitment in the AES 26-50 group than in the AES 1-25, the higher risk of farm closures for the most excessive AESs participants is no longer significant. The finding of a weaker association between farms with and without an AESs when excluding the low-cost easy to maintain commitments could perhaps indicate a strategic use of AESs, supporting our argument that the relatively large effect for excessive AESs participation in the main analysis could be overestimated. But as the results are for another sample, it is not possible to determine if this really is the case. The difference could also indicate heterogeneous effects across subsidies in the AESs. The estimates when dropping all farms that have the subsidy in support for organic production changes only marginally; thereby, the associations in the main analysis are not entirely driven by large subsidy payments. At least not when the payments are conditioned on doing large changes on the farm, as often required when converting to organic farming.

## Selection into AESs participation

If selection is at play, farmers who are forward looking and prone to change are more likely to take on new environmentally-friendly farming techniques and invest in their farm to secure its long term survival than present-oriented peers. Consequently such farmers are likely to be overrepresented as AESs participants. To test the robustness of the results, we focus on subgroups of farms possessing some characteristic that in some meaning turns the farm successful to even out potential ability differences between participants and non-participants. Arguably, such characteristics are likely to be expressed as an ability to earn a profit, work the farm full time, and to have had survived already for quite some time. Consequently, we expect the AESs estimates to become weaker in these sub analyses if selection is a main mechanism behind our results.

Table 6 reports the results for, first, the top 25$^{th}$ percentile of the most profitable farms, i.e., farms with an average yearly net income above SEK 168,900 (column 1). Second, farms with an added value above SEK 200,000, which resembles full time farming (column 2). Third, the oldest surviving farms, i.e., subgroup that started before 1985 and survived at least until 2001 (column 3). The results seems robust to selection as the estimates remains similar to the main result. Overall, the risk of farm closure still appear higher for non-participants throughout the subgroups.

**Table 6.** Estimated coefficients for sub analyses of homogenous groups of 'successful' farms taken from the sample of farms focusing on active AESs participants

| | (1) | (2) | (3) |
|---|---|---|---|
| | Net income > SEK 169' | Value added > SEK 200' | Startup year < 1985 |
| *AESs* | | | |
| No AES | 0.316*** | 0.271*** | 0.207*** |
| | (0.0610) | (0.0418) | (0.0458) |
| AES 1-25 | 0.0580 | 0.0416 | 0.0579 |
| | (0.0548) | (0.0412) | (0.0432) |
| AES 26-50 | Ref. | Ref. | Ref. |
| AES 51-75 | -0.0358 | -0.0239 | 0.0134 |
| | (0.0684) | (0.0511) | (0.0527) |
| AES 76-100 | 0.0568 | 0.0219 | 0.0858 |
| | (0.0747) | (0.0571) | (0.0594) |
| AES 101-125 | 0.208*** | 0.0457 | 0.155** |
| | (0.0787) | (0.0686) | (0.0686) |
| AES > 125 | 0.271*** | 0.230*** | 0.212*** |
| | (0.0707) | (0.0540) | (0.0611) |
| *Covariates* | | | |
| Demographics | Yes | Yes | Yes |
| Direct payments | Yes | Yes | Yes |
| *Economic outcomes* | | | |
| Step 1 | Yes | Yes | Yes |
| Step 2 | Yes | Yes | Yes |
| Random effects | No | No | No |
| No. of observations | 93585 | 159106 | 98152 |
| Log L | -2564.1 | -4924.2 | -4408.5 |

*Note: Robust clustered standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*
*The demographics include fixed effects for time, startup year, type of farm, and location-specific calendar year. Direct payments includes direct payments in SEK and direct payments squared. Economic outcomes in step 1 includes categories of value added, and step 2 adds net income, return on equity, shareholder equity ratio, off-farm value added, and off-farm net income (defined in table 2).*

# Discussion and conclusions

This study, aimed at estimating farm survival, scrutinized the role of agri-environmental schemes to investigate differences in survival over time between farms with varying intensities of their agri-environmental commitment. We find significant positive associations between participation in agri-environmental schemes and farm survival, and the stability of our results indicate that participation fosters continued farms survival. Though, it could be problematic if the balance of the agri-environmental commitments in relation to other commitments on the farm tips towards too extensive commitments.

We cannot rule out that selection could affect which farms that commits to an AESs. However, our combined results indicate a robustness that, at least partly, mitigates such concerns. Rather than being entirely driven by selection, we argue that the effect is more likely to be overestimated. To commit to an AESs could be part of a larger change on the farm. Such as when a younger generation takes over. Or, as a strategy to improve the farm, diversifying it or providing a source of extra income to finances investments and balance liquidity fluctuations. If so, it is difficult to disentangle how much of the estimate that represents a direct effect of the AESs and how much that is due to the change inducing an increased AESs participation, implying either overestimation or selection.

The results are in line with previous findings on general income subsidies to farmers. Findings from, for example, Mishra et al. (2014), Key and Roberts (2007b) and Key and Roberts (2006) implicate that government program payments reduce or slow down the exit rates of farmers. Mishra et al. (2014) explain that the extra income increases the farm's 'staying power', thus, enabling farms, who otherwise would have closed down, to stay active. If this is true also in our setting, farmers that leave their agri-environmental commitment will at the same time lose staying-power and consequently increase their risk of farm closure.

While we conclude that participation in agri-environmental schemes is indicative of a higher likelihood of continued farming, an explanation why is not readily apparent. Having explored the influence of economic outcomes, increased profitability is not the main mechanism behind the association as the results are robust to a large set of variables capturing the farms' economic performance. However, these controls aims to capture long-term changes to the farms profitability, whereas, they are not necessarily detailed enough to capture effects of an increased staying power. The subsidy is set to cover the costs of the agri-environmental service and if this approximation equals the costs on the farm it will not affect the farms operating profits, at least not directly. Yet, on the margin, it could still contribute to the farm's staying power as it could, for example, finance urgent improvements on the farm or even out short-term liquidity fluctuations.

Given that participation in agri-environmental schemes is unlikely to be random, we had to tackle selection and endogeneity concerns when estimating the associations between agri-environmental schemes and farm survival and we cannot rule out that selection is biasing our results. Tests speak against high-performing farms being selected into agri-environmental schemes (Table 6), thereby, driving the estimated effect. Likewise does the shown robustness to economic variables (Table 3). We also test the robustness to alternative definitions of participation (Table 4) and to specific subsidies in the agri-environmental schemes (Table 5). Again, these tests support the main message of our results and leads us to conclude that the estimates are unlikely to be entirely driven by selection. Still, it is difficult to disentangle whether the associations represents true effects, overestimations and/or selection, limiting the casual interpretation of our results.

Having followed the entire population of Swedish farms trough 2001-2014 using rich farm-level register data from the Swedish authorities, a strength of our study is that the results stem from reliable detailed annual data. Another strength is that the data allowed us to apply a discrete-time survival model, a probit model with random effects. Thereby, we could control for the time-dynamics that is likely to be correlated with both continued participation in an agri-environmental scheme and farm survival. To control for duration effects are important given that economic theory emphasize the importance of learning, networking and other such processes that evolve over time. However, as our data set does not contain information on the farmers running the farms, we are not able to account specifically for the farmers' age, family situation, retirement decisions, education, motivation and other such farmer characteristics to further explain the mechanisms behind the effect. Still, our approach enabled us to, at least partly, pick up the potential influence of these factors on survival through the applied estimation strategy.

Together, the findings in this study suggest that the agri-environmental schemes could be important for farmers, not only as a means to enable environmental protection but also to foster farm survival. Therefore, we urge future research to continue to dig into the selection problems and underlying mechanisms to assess if the associations found in this study could be attributed to true effects of agri-environmental schemes.

Being able to boost survival would be an important merit of the agri-environmental schemes for the farms that commit and possibly also for policymakers, offering them a means to attract farms to engage in environmental services. Thereby, we contribute with promising insight to farmers and policymakers wanting to aid future farming as well as the production of environmental services, underlining the importance to encompass consequences beyond environmental concerns when assessing the overall benefits of the agri-environmental schemes. However, some caution is warranted as much work remains to establish the effects and which mechanisms that dominate. Such documentation is needed if we are to discuss policy design. For example, if the effect of agri-environmental schemes operates via an increased staying power, as our results suggests, it might be unwise to use environmental support to promote increased productivity. This is so, because it is likely to be an inefficient alternative to policies directly aimed towards increasing productivity if productivity is the main goal. In addition, an increased staying power due to the agri-environmental schemes could have adverse productivity effects, enabling less productive farms to stay in business, thereby, counteracting structural change and also crowding out more productive new entrants as the farmland is limited.

# Appendix

**Table A1.** Subsidies in the AESs, uptake among farms with an AESs and average payment if payed, pooling all years

| Subsidies | Average uptake (%) | Average payment if payed (SEK) |
|---|---|---|
| Catch crops and no autumn tillage (2001-2014) | 10.91 | 24,600 |
| Grassed buffer zones (2001-2014) | 5.25 | 7,600 |
| Wetlands (2001-2014) | 1.72 | 13,800 |
| Organic production (2001-2014) | 19.99 | 46,600 |
| Environmental protection measures, e.g., soil mapping, crop production plans, and nutrient balances (2001-2014) | 1.80 | 15,600 |
| Cultivated grassland (2001-2002, 2007-2014), open and varied landscape (2001-2014) | 59.82 | 20,900 |
| Culturally significant landscape elements (2001-2014) | 18.86 | 19,500 |
| Pastures and meadows (2001-2014) | 43.97 | 28,500 |

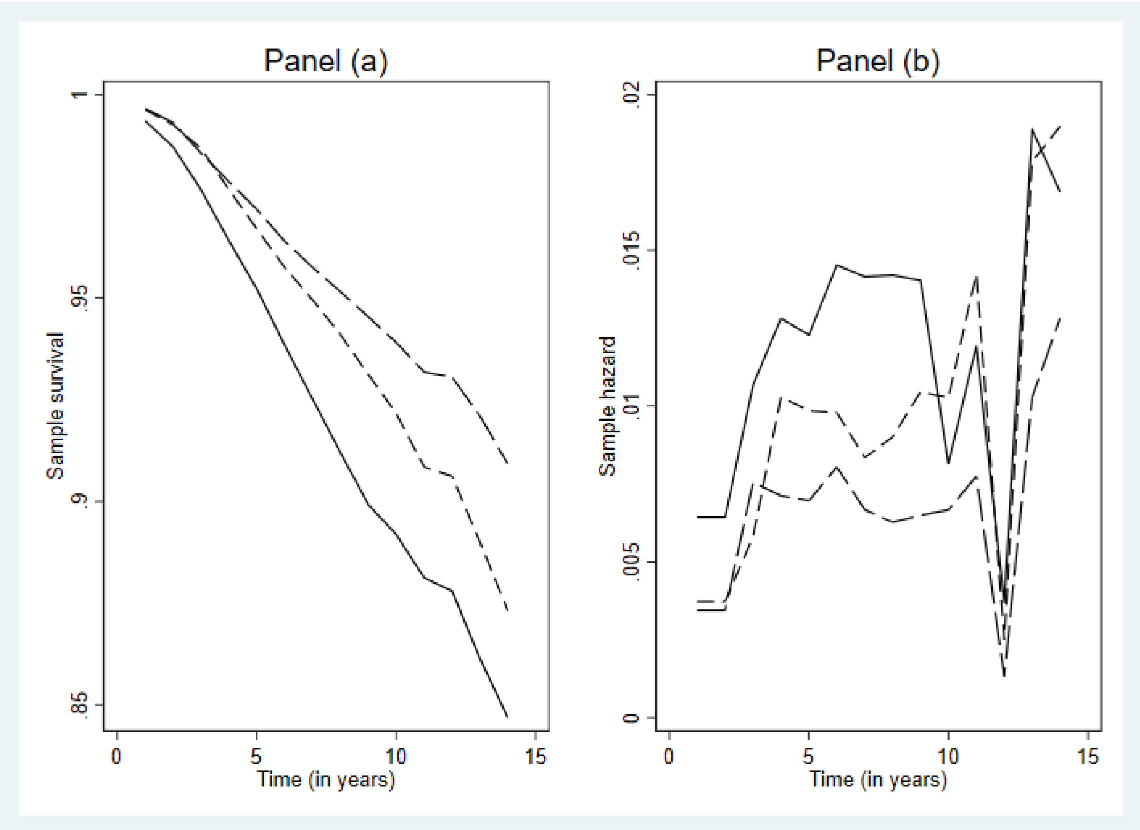


**Figure A1. Figure 1.** Within-group sample survivals (panel a) and sample hazards (panel b) for farms in the No AES group (short dashed line), the AES 26-50 group (long dashed line), and the AES > 125 group (solid line), excluding farms that exits the dataset in year 2012

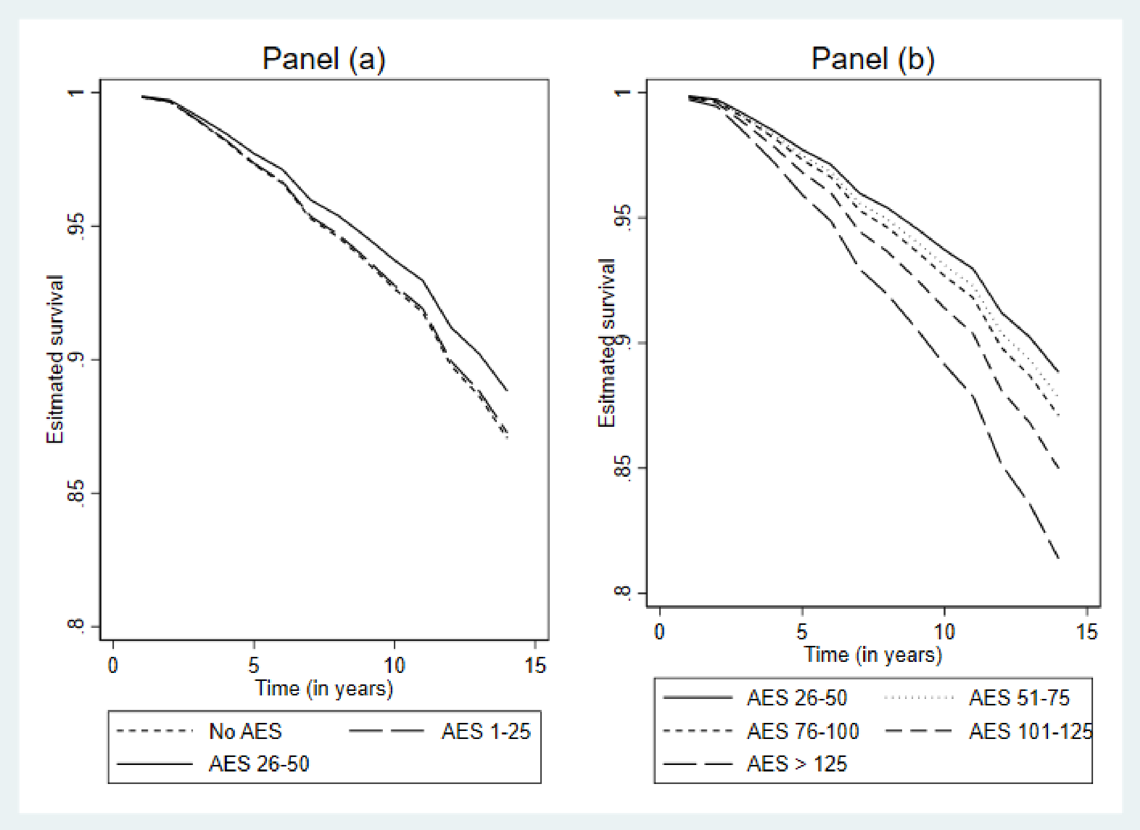


**Figure A2.** Fitted survival based on the full sample of all farms and are calculated for hypothetical crop farms located in southern parts of Sweden for the three low-end groups of the AES intensity scale in Panel (a) and the five high-end groups in Panel (b).

**Table A2.** Estimated coefficients from the discrete-time proportional hazards duration model in Table 3 but with No AES as the reference category

| | (1) All farms (model 3) | (2) Active participants (Model 5) |
|---|---|---|
| *AESs* | | |
| No AES | Ref. | Ref. |
| AES 1-25 | -0.00660 | -0.225*** |
| | (0.0154) | (0.0224) |
| AES 26-50 | -0.0591*** | -0.290*** |
| | (0.0165) | (0.0225) |
| AES 51-75 | -0.0246 | -0.240*** |
| | (0.0188) | (0.0256) |
| AES 76-100 | -0.00136 | -0.229*** |
| | (0.0219) | (0.0305) |
| AES 101-125 | 0.0611** | -0.133*** |
| | (0.0250) | (0.0341) |
| AES > 125 | 0.154*** | -0.0521** |
| | (0.0181) | (0.0251) |
| *Covariates* | | |
| Demographics | Yes | Yes |
| Direct payments | Yes | Yes |
| *Economic outcomes* | | |
| Step 1 | Yes | Yes |
| Step 2 | Yes | Yes |
| Random effects | No | No |
| No. of observations | 645037 | 456160 |
| Log L | -32463.8 | -18209.0 |

*Note: Robust clustered standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*
*The demographics include fixed effects for time, startup year, type of farm, and location-specific calendar year. Direct payments includes direct payments in SEK and direct payments squared. Economic outcomes in step 1 includes categories of value added, and step 2 adds net income, return on equity, shareholder equity ratio, off-farm value added, and off-farm net income (defined in table 2).*

**Table A3.** Estimated coefficients from sub analyses excluding specific AESs subsidies from the full sample of all farms

| | (1)<br>Excl.<br>common subsidies | (2)<br>Excl.<br>largest subsidy payment |
|---|---|---|
| *AESs* | | |
| No AES | 0.0372 | 0.0495** |
| | (0.0396) | (0.0196) |
| AES 1-25 | 0.0169 | 0.0282 |
| | (0.0438) | (0.0192) |
| AES 26-50 | Ref. | Ref. |
| AES 51-75 | 0.0976 | 0.0251 |
| | (0.0708) | (0.0262) |
| AES 76-100 | 0.0137 | 0.0927*** |
| | (0.105) | (0.0320) |
| AES 101-125 | 0.0325 | 0.201*** |
| | (0.151) | (0.0376) |
| AES > 125 | 0.203** | 0.240*** |
| | (0.0861) | (0.0274) |
| *Covariates* | | |
| Demographics | Yes | Yes |
| Direct payments | Yes | Yes |
| *Economic outcomes* | | |
| Step 1 | Yes | Yes |
| Step 2 | Yes | Yes |
| Random effects | No | No |
| No. of observations | 162298 | 439515 |
| Log L | -10609.8 | -23800.2 |

*Note: Robust clustered standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*
*The demographics include fixed effects for time, startup year, type of farm, and location-specific calendar year. Direct payments includes direct payments in SEK and direct payments squared. Economic outcomes in step 1 includes categories of value added, and step 2 adds net income, return on equity, shareholder equity ratio, off-farm value added, and off-farm net income (defined in table 2).*

**Table A4.** Estimated coefficients for sub analyses of homogenous groups of 'successful' farms taken from the full sample of all farms

| | (1)<br>Net income > SEK 160' | (2)<br>Value added > SEK 200' | (3)<br>Startup year < 1985 |
|---|---|---|---|
| *AESs* | | | |
| No AES | $0.111^{**}$ | $0.0860^{**}$ | 0.0556 |
| | (0.0490) | (0.0342) | (0.0348) |
| AES 1-25 | $0.0746^{*}$ | $0.0632^{**}$ | $0.0487^{*}$ |
| | (0.0387) | (0.0295) | (0.0288) |
| AES 26-50 | Ref. | Ref. | Ref. |
| AES 51-75 | -0.0437 | -0.0289 | 0.0143 |
| | (0.0510) | (0.0389) | (0.0371) |
| AES 76-100 | -0.00871 | -0.0104 | 0.0275 |
| | (0.0585) | (0.0451) | (0.0446) |
| AES 101-125 | $0.136^{**}$ | -0.00205 | $0.111^{**}$ |
| | (0.0624) | (0.0532) | (0.0514) |
| AES > 125 | $0.223^{***}$ | $0.204^{***}$ | $0.227^{***}$ |
| | (0.0523) | (0.0400) | (0.0410) |
| *Covariates* | | | |
| Demographics | Yes | Yes | Yes |
| Direct payments | Yes | Yes | Yes |
| *Economic outcomes* | | | |
| Step 1 | Yes | Yes | Yes |
| Step 2 | Yes | Yes | Yes |
| Random effects | No | No | No |
| No. of observations | 144640 | 223377 | 154126 |
| Log L | -4576.0 | -8239.0 | -8492.9 |

*Note: Robust clustered standard errors in parentheses,* $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$
*The demographics include fixed effects for time, startup year, type of farm, and location-specific calendar year. Direct payments includes direct payments in SEK and direct payments squared. Economic outcomes in step 1 includes categories of value added, and step 2 adds net income, return on equity, shareholder equity ratio, off-farm value added, and off-farm net income (defined in table 2).*

## References


DEFRANCESCO, E., GATTO, P. & MOZZATO, D. 2018. To leave or not to leave? Understanding determinants of farmers' choices to remain in or abandon agri-environmental schemes. *Land Use Policy,* 76**,** 460-470.

EUROPEAN COMMISSION. 2020a. *Agriculture and rural development* [Online]. Available: https://ec.europa.eu/agriculture/envir_en [Accessed 22 Jan 2020].

EUROPEAN COMMISSION. 2020b. *Annual EU budget payments (The European agricultural fund for rural development) made by programme period* [Online]. Available: https://cohesiondata.ec.europa.eu/EU-Level/Annual-EU-budget-payments-EUR-made-by-programme-pe/h85u-sjcv [Accessed].

FLATEN, O. 2002. Alternative rates of structural change in Norwegian dairy farming: impacts on costs of production and rural employment. *Journal of Rural Studies,* 18**,** 429-441.

GLAUBEN, T., PETRICK, M., TIETJE, H. & WEISS, C. 2009. Probability and timing of succession or closure in family firms: a switching regression analysis of farm households in Germany. *Applied Economics,* 41**,** 45-54.

HESS, W. & PERSSON, M. 2012. The duration of trade revisited. *Empirical Economics,* 43**,** 1083-1107.

HYNES, S. & GARVEY, E. 2009. Modelling Farmers' Participation in an Agri-environmental Scheme using Panel Data: An Application to the Rural Environment Protection Scheme in Ireland. *Journal of Agricultural Economics,* 60**,** 546-562.

JOVANOVIC, B. 1982. Selection and the Evolution of Industry. *Econometrica: Journal of the Econometric Society***,** 649-670.

KALTOFT, P. & RISGAARD, M. 2006. Has organic farming modernized itself out of business?-Reverting to conventional methods in Denmark. *In:* HOLT, G. & REED, M. (eds.) *Sociological perspectives of organic agriculture: From pioneer to policy.* CABI.

KEY, N. D. & ROBERTS, M. J. 2006. Government Payments and Farm Business Survival. *American Journal of Agricultural Economics,* 88**,** 382-392.

KEY, N. D. & ROBERTS, M. J. 2007a. *Commodity payments, farm business survival, and farm size growth*, US Department of Agriculture, Economic Research Service.

KEY, N. D. & ROBERTS, M. J. 2007b. Do Government Payments Influence Farm Size and Survival? *Journal of Agricultural and Resource Economics,* 32**,** 330-348.

LASTRA-BRAVO, X. B., HUBBARD, C., GARROD, G. & TOLÓN-BECERRA, A. 2015. What drives farmers' participation in EU agri-environmental schemes?: Results from a qualitative meta-analysis. *Environmental Science & Policy,* 54**,** 1-9.

LÄPPLE, D. 2010. Adoption and Abandonment of Organic Farming: An Empirical Investigation of the Irish Drystock Sector. *Journal of Agricultural Economics,* 61**,** 697-714.

MISHRA, A. K., FANNIN, J. M. & JOO, H. 2014. Off-Farm Work, Intensity of Government Payments, and Farm Exits: Evidence from a National Survey in the United States. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie,* 62**,** 283-306.

PEERLINGS, J. & POLMAN, N. 2009. Farm choice between agri-environmental contracts in the European Union. *Journal of Environmental Planning and Management,* 52**,** 593-612.

REGERINGSKANSLIET. 2020. *A rural development programme for Sweden* [Online]. Available: https://www.regeringen.se/informationsmaterial/2015/12/a-rural-development-programme-for-sweden/ [Accessed 28 Jan 2020].

SCIENCE FOR ENVIRONMENT POLICY 2017. Agri-environmental schemes: how to enhance the agriculture-environment relationship. Bristol: Issue produced for the European Commission DG Environment by the Science Communication Unit.

SINGER, J. D., WILLETT, J. B. & WILLETT, J. B. 2003. *Applied longitudinal data analysis: Modeling change and event occurrence*, Oxford university press.

SWEDISH BOARD OF AGRICULTURE 2016. Landsbygdsprogram för Sverige år 2007–2013 – Årsrapport 2015 och slutrapport för programmet.

SWEDISH BOARD OF AGRICULTURE 2017. Jordbruksmarkens användning 2017 - Slutlig statistik (Use of agricultural land 2017 - Final statistics). *Statistikt meddelande JO 10 SM 1703.*

SWEDISH BOARD OF AGRICULTURE. 2020. *Landsbygdsprogrammet* [Online]. Available: https://nya.jordbruksverket.se/stod/programmen-som-finansierar-stoden/landsbygdsprogrammet [Accessed 28 Jan 2020].

UEMATSU, H. & MISHRA, A. K. 2012. Organic farmers or conventional farmers: Where's the money? *Ecological Economics,* 78**,** 55-62.

VAN HERZELE, A., GOBIN, A., VAN GOSSUM, P., ACOSTA, L., WAAS, T., DENDONCKER, N. & HENRY DE FRAHAN, B. 2013. Effort for money? Farmers' rationale for participation in agri-environment measures with different implementation complexity. *Journal of Environmental Management,* 131**,** 110-120.

WEISS, C. R. 1999. Farm growth and survival: econometric evidence for individual farms in Upper Austria. *American journal of agricultural economics,* 81**,** 103-116.

WILSON, G. A. & HART, K. 2000. Financial Imperative or Conservation Concern? EU Farmers' Motivations for Participation in Voluntary Agri-Environmental Schemes. *Environment and Planning A: Economy and Space,* 32**,** 2161-2185.

## About AgriFood Economics Centre

AgriFood Economics Centre provides economic expertise in the fields of food, agriculture, fishing and rural development. The Centre is a cooperation for applied research between the Swedish University of Agricultural Sciences (SLU) and Lund University. The aim is to supply government bodies with a solid scientific foundation supporting strategic and long-term policy choices.

Publications can be ordered free of charge from **www.agrifood.se**

AgriFood Economics Centre
PO Box 7080
SE-220 07 Lund
SWEDEN

www.agrifood.se
mail: info@agrifood.se

AgriFood
economics centre