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Eco-efficiency in Swedish dairy farms

- incorporating sustainability into the measure of eco-efficiency

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Abstract

This thesis introduces a novel method to incorporate absolute values of GHG emissions into the measure of eco-efficiency. The aim is to assess eco-efficiency in Swedish dairy farms and adjusting the scores towards a threshold of absolute levels of GHG emissions using the proposed method. The Swedish target of net-zero emissions in 2045 is used to specify the threshold of GHG emissions. The secondary objective of this thesis is to test for exogenous variables correlating with eco-efficiency using OLS-regression. The empirical application is on Swedish dairy farms using FADN data from 2016. I use a data envelopment analysis (DEA) to assess eco-efficiency considering the environmental pressures nutrients and contribution to global warming. When assessing eco-efficiency, the result is that Swedish dairy farms are inefficient with a mean-efficiency of 0.33 among conventional farms and 0.56 among organic farms. Adjusting the scores towards absolute levels of GHG emissions increase the farms' mean-efficiency. Using an environmental target as a threshold when computing efficiency indicates whether the units in the sample reach the environmental target or not. Comparing the unadjusted and adjusted efficiency-scores using a Spearman rank test shows a high similarity between the unadjusted- and adjusted scores. Testing for exogenous variables correlating with efficiency shows that the intensity of farming correlates significantly with both the adjusted and unadjusted eco-efficiency in both conventional- and organic farms. Thus, the policy-recommendation is to increase the intensity of farming in order to increase eco-efficiency. The correlation between eco-efficiency and some other exogenous variables tested for, such as the number of livestock-units and subsidies, differs between the unadjusted and adjusted efficiency scores. This result indicates that the effect of policies aiming to increase eco-efficiency can differ whether considering absolute environmental damages in the measure or not. Differences in scores and correlates with eco-efficiency before and after the adjustment points to the contribution of this thesis.

Sammanfattning

I och med växande miljöproblem har relevansen av eko-effektivitet som ett sätt att bedöma sektorers eller regioners miljöpåverkan ökat. En brist i bedömningen av eko-effektivitet är dock att måttet inte tar hänsyn till absoluta nivåer av utsläpp när effektiviteten av en enhet bedöms. Detta innebär att utsläpp och andra skador på miljön tillåts att kompenseras av ekonomisk vinst. Denna uppsats bemöter denna kritik genom att inkludera absoluta utsläpp av växthusgaser i bedömningen av eko-effektivitet. Uppsatsen bidrar till att utveckla eko-effektivitetesmåttet genom att justera effektivitetspoängen till absoluta utsläpp efter att en poäng för varje enhet beräknats. I denna uppsats appliceras metoden på svenska mjölkgårdar.

För att genomföra effektivitetsanalysen används FADN data från 2015 och 2016. Effektiviteten beräknas genom en metod introducerad av Kuosmanen och Kortelainen (2005) där en DEA (data envelopment analysis) används för att generera en effektivitetspoäng för varje enhet, i detta fallet för varje gård. Denna metod definierar eko-effektivitet som ekonomisk inkomst delat med skadan på miljön orsakad av varje gård. I denna uppsats uppskattas skadan på miljön genom variablerna konsumtion av bränsle och värme samt konsumtionen av gödningsmedel.

Absoluta nivåer av växthusgasutsläpp som effektivitetspoängen justeras mot beräknas genom att använda miljömålet att Sverige ska ha netto-noll utsläpp 2045. Om utsläppsmålet ska nås genom en linjär procentuell minskning motsvarar detta en minskning på 1,7% per år. Denna siffra, tillsammans med två andra liknande scenarion, används för att justera effektivitetspoängen till absoluta nivåer av utsläpp. Effektivitetspoängen innan och efter justeringen mot absoluta nivåer jämförs med hjälp av ett Spearmans rangkorrelation som visar på att de två måtten är mycket lika.

I ett andra steg av analysen genomfördes en stegvis OLS-regression där variabler med potentiell korrelation med eko-effektivitet testades. Resultatet från regressionen är att en högre intensitet i produktionen korrelerar med en högre eko-effektivitet. Detta indikerar att styrmedel som höjer intensiteten också ökar eko-effektiviteten. Ett annat resultat är att justeringen av effektiviteten ändrar hur de exogena variablerna korrelerar med eko-effektiviteten. Detta visar på att styrmedel som syftar till att öka eko-effektiviteten kan missa viktiga aspekter om denna inte justeras i och med att dessa inte nödvändigtvis minskar utsläppen.

Abbreviations

DEA – Data envelopment analysis
EE – Eco-efficiency
GHG – Greenhouse gases
LU – Livestock-units
OLS – Ordinary least squares

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1 Introduction

Unsustainable agricultural practices are a considerable concern to policymakers both nationally and internationally. On an international level, the agricultural sector caused 26 per cent of the global greenhouse gas (GHG) emissions between 2006 and 2016 and thereby being one of the most significant contributors to climate change (FAO, 2018). Climate change, in turn, changing the prospects for food production (ibid). Of these international GHG emissions from agriculture, livestock production, including dairy, cause the most significant part (IPCC, 2019). Internationally, agriculture is the largest emitter of nitrogen, phosphorus and pesticides contributing to water pollution and global warming (FAO, 2015). On the other hand, agriculture could contribute positively to the environment by increasing biodiversity in fields and open landscapes. Furthermore, it contributes to society by providing food, income for farmers and attracting people to rural areas. A framework often used to illustrate to what extent human activities can damage the planet without catastrophic events occurring is the nine planetary boundaries (Steffen et al. 2015). Internationally, agriculture challenges the planetary boundary of climate change by emitting GHG. It also challenges the planetary boundary of biochemical flows by emitting nitrogen and phosphorous. Further, agriculture has the potential to contribute positively to the boundary of biodiversity by providing habitat for species when managed sustainably (Swedish board of agriculture, 2019a). This implies that if the agricultural sector could act within the planetary boundaries, its practices could become sustainable. The 13th UN sustainable development goals state that more action is required in mitigating emissions internationally (UN, 2019). Nationally in Sweden, the target is to have net-zero emissions of GHG in 2045 (The Swedish government, 2019. p.29), which is a more ambitious target compared to the long-term EU strategy which aims for net-zero emissions in 2050 (European parliament, 2019). To reach the national target of net-zero emissions of GHG, the Swedish government has set the sub-target to decrease emissions by 40 per cent in 2020 compared to the levels of 1990 (The Swedish government, 2019. p.30).

As environmental issues have grown more urgent, an increasing amount of literature has focused on assessing the environmental impact of industries and firms, where eco-efficiency is a standard method (Zhou et al. 2017). Previous research has assessed eco-efficiency of industries and firms on both micro- and macro levels. The measure captures the ability to produce output with the smallest relative damage on the environment as possible and is frequently applied to the agricultural sector. One advantage of assessing eco-efficiency lies in that it shows how much the included environmental pressures could be reduced while maintaining value-added. Generally, research has assessed eco-efficiency within one sector or region. When assessing micro-level eco-efficiency, the purpose is to create optimality at a macro-level to reach the environmental quality and economic development that society seeks (Huppes et al. 2005).

Nonetheless, measuring eco-efficiency does miss out on some crucial aspects making the measure less accurate. One of these aspects relates to sustainability, where farms can classify as eco-efficient without considering the absolute levels of emissions. This shortcoming indicates that the agriculture can emit at a level where its accumulated emissions contribute to breaching the planetary boundaries, without this being reflected in the efficiency-score. This makes the measure too narrow because it, as previously stated, only considers the relative levels of value-added and environmental pressures while omitting the absolute levels. Only considering relative measures indicates that firms can compensate damages to the environment with high economic yield, which is inconsistent with not breaching the planetary boundaries (Steffen et al. 2015). Previous attempts to include sustainability into the measure of eco-efficiency are to determine the allocation of emissions through a sustainability value-added

(Figge et al. 2004) or by defining a sustainability set (Kusomanen and Kortelainen, 2005). Nevertheless, these expositions are unsatisfactory since they do not set an absolute level of environmental damages allowed without breaching the planetary boundaries. The concept of including absolute levels of environmental pressures in the measure of eco-efficiency is central for the measure to be relevant also in future studies when environmental problems become more pressing. To date, there have been no attempts to include sustainability into the measure of eco-efficiency by incorporating absolute levels of environmental damages.

In Sweden, around 13 per cent of total greenhouse gas emissions come from the agricultural sector, mainly from keeping livestock (Swedish board of agriculture, 2018). Keeping livestock cause emissions from the animals intrinsically. It also contributes to emissions outside farms from producing and transporting the feed (ibid). Agriculture also uses fossil fuels in its practices as propellants for the machines and heating for the buildings. Apart from emitting GHG, manure from livestock and the usage of fertilizers when growing feed contributes to overfertilization damaging the nearby environment (Swedish board of agriculture, 2019b). Swedish dairy farming is intensive in its production and together with Denmark, Estonia, Finland, and Portugal it has one of the highest annual yields of milk per cow within the EU (Augère-Granier, 2018). As a part of reaching the climate objective, Hjerpe (2012) on behalf of the Swedish board of agriculture points out the need for more efficient use of resources and energy within the agriculture. This thesis aims to contribute to this by assessing the eco-efficiency in Swedish dairy farms.

The objective of this thesis is to assess eco-efficiency and adjusting the efficiency-scores towards a threshold of absolute levels of GHG emissions. This thesis is, to my knowledge, the first study to incorporate an adjustment towards absolute emissions in the measure of eco-efficiency. The adjustment states that emissions are only allowed below a certain level in order to not breaching the planetary boundary of climate change, sanctioning farms emitting above the threshold with lower efficiency-scores. To assess eco-efficiency, the environmental indicators used are the consumption of fossil fuels and nutrients. The secondary objective of this thesis is to find reasons behind the potential eco-inefficiency to get information on how to increase efficiency. This thesis assesses eco-efficiency in Swedish dairy-farms adjusting the scores to observe whether the farms act within the planetary boundary of climate change and global warming. Thus, the aim of this thesis is twofold: to assess eco-efficiency using a novel method incorporating absolute levels of GHG emissions and to find reasons behind potential inefficiency. The research questions of this thesis are:

- How eco-efficient are Swedish dairy farms?
- What are the reasons behind potential eco-inefficiency?

The questions are answered using a two-stage approach, assessing the eco-efficiency in the first stage and testing for potential reasons behind the inefficiency in the second stage. Incorporating sustainability when measuring eco-efficiency has been discussed in previous literature but not attempted since the value of the carrying capacity of the environment is difficult, if not impossible, to find. This thesis makes use of the environmental target that Sweden aims to be independent of fossil fuels and have net-zero emissions in 2045 to proxy the sustainable level of GHG emissions. More precisely, the analysis uses the sub-target of a 40 per cent decrease of GHG-emissions between 1990 and 2020. This target of emissions reduction is used to compute the adjustment of the scores in the model indicating whether the farm is on a path of achieving sustainability regarding net-zero emissions in 2045 or not. The data used for assessing eco-efficiency is cross-sectional data of Swedish dairy farms from the farm accountancy data network (FADN). The data are from 2016, which is the most recent data currently available.

The FADN dataset provides information to be used for both the economic and environmental variables required to calculate eco-efficiency as well as the variables used to test for the reasons behind potential inefficiency.

This thesis introduces a new addition to the model showing how one aspect of sustainability could be incorporated into the measure of eco-efficiency. The thesis adds to the field of research that uses data envelopment analysis (DEA) to assess eco-efficiency adding to the model developed by Kuosmanen and Kortelainen (2005). The model is further developed by adjusting the efficiency-scores considering how much GHG a farm emits in absolute terms. Using absolute levels of GHG emissions to adjust the efficiency-scores is the main contribution that this thesis offers to the field of research. To my knowledge, no previous research has incorporated absolute levels of environmental pressures into the measure of eco-efficiency. By assessing eco-efficiency and the reasons behind it, this thesis also provides policy implications of how to increase efficiency and decrease emissions of greenhouse gases in the sample of Swedish dairy farms.

2 Literature review and conceptual framework

2.1 Literature review

As environmental issues have become more pressing, economic research has produced more literature on eco-efficiency. When assessing efficiency using DEA, it is common to use a two-stage approach, assessing efficiency in the first stage and the reasons behind potential inefficiency in the second stage (Zhou et al. 2017). For the first stage, previous research exhibits two prominent ways of modelling environmental damages when assessing eco-efficiency. A vast literature assessing environmental performance has modelled damages, such as emissions or waste, as undesirable outputs or inputs which firms should seek to minimize (Tyteca, 1996). One of the first papers using DEA to assess environmental performance was Färe et al. (1989), who suggested an asymmetric treatment of desirable and undesirable outputs where desirable outputs were weakly disposable. The same authors later developed an index of environmental performance by decomposing productivity into an environmental- and a productive index (Färe et al. 1996). These previous methods assessed technical-efficiency and eco-efficiency simultaneously. The definition of eco-efficiency as the ratio of economic value-added and environmental pressures as suggested by Kuosmanen and Kortelainen (2005) takes a more ecologically oriented view assessing eco-efficiency independently.

Kuosmanen and Kortelainen (2005) measured eco-efficiency using a DEA approach. The authors added to the research on eco-efficiency by considering environmental pressures rather than bad outputs or bad inputs as done in previous papers. Environmental pressures are variables such as global warming potential or acidification where each pressure can contain several indicators (Kuosmanen and Kortelainen, 2005). The authors aggregate the environmental pressures to a single environmental damage index using a DEA approach to determine the weights (ibid). In their work, Kuosmanen and Kortelainen (2005) touch upon the issue of incorporating sustainability into the eco-efficiency measure. However, they conclude that it is difficult to set a specified maximum level of damages. The difficulties in finding a maximum level of damages are since environmental carrying-capacities are dependent on interactions between the environment and human activity (ibid).

Eco-efficiency has many areas of application. The most common, according to recent meta-studies, is the agricultural sector (Emrouznejad and Yang, 2018; Zhou et al. 2017). The following papers provide an overview of the previous research of eco-efficiency applied to agriculture using environmental pressures as proposed by Kuosmanen and Kortelainen (2005). Picazo-Tadeo et al. (2011) used this approach when measuring eco-efficiency in agriculture in the Spanish Campos county. The authors developed the method further to measure pressure-specific eco-efficiency by computing the pressure- and value added-slacks. The authors calculated the slacks after having assessed an eco-efficiency score for each farm (Picazo-Tadeo et al. 2011). The main finding was that the eco-inefficiency did not differ much between the different environmental pressures (Picazo-Tadeo et al. 2011). Gómez-Limón et al. (2011) made use of distance functions decomposing the eco-efficiency measure into managerial- and program inefficiency when studying Andalusian olive farms. The authors projected two frontiers for the two inefficiencies and found that inefficiency is high regarding management. The authors also found that there is a high correlation between eco-inefficiency and technical inefficiency (Gómez-Limón et al. 2011). In 2012 Picazo-Tadeo et al. contributed further to the research by using directional distance functions to assess eco-efficiency. This method provided several measurements, for example, pressure specific measures. The method also showed how much the environmental pressures could be contracted and value-added expanded simultaneously (Picazo-Tadeo et al. 2012). The results were in line with previous research and showed that for the sample of olive-growing farms in Spain, inefficiency did not differ much when comparing the environmental pressures (Picazo-Tadeo et al. 2012). A more recent paper using this DEA method with environmental pressures is Urdiales et al. (2016). The authors aim to explain eco-efficiency using socio-economic variables. The study concluded that younger farmers and farmers expecting to continue their business for a long time exhibits higher eco-efficiency (Urdiales et al. 2016). Eco-efficiency can also relate to economic performance, where Jan et al. (2012) analysed the relationship between environmental and economic performance. The authors found a positive correlation between environmental and economic performance in Swiss dairy farms.

Research that has previously investigated how to include sustainability into the eco-efficiency measure is Figge et al. (2004). The authors developed a sustainable value-added to include a benchmark of a maximum amount of emissions allowed. Through this, sustainability could be achieved at a macro level. Figge et al. (2004) defined the benchmark as the ratio of GDP and environmental impacts created. The method determines how to allocate the right to damage among firms, given a certain amount of damages possible to sustain at a macro level (Figge et al. 2004). By discussing the allocation of emissions between firms, this method also addresses a rebound effect. A rebound effect can arise where improved eco-efficiency leads to increased production and increased damages in absolute terms (ibid). Figge et al. (2004) emphasize the allocation of the right to emit but does not deal with how to set an absolute level of emissions that can be sustained.

These papers are the foundation on which this thesis is built. The current thesis takes the measure of eco-efficiency one step further by including absolute measures of one environmental pressure. It also makes use of previous research regarding what determinants of eco-efficiency to test for in the second stage of the analysis. An absolute level of emissions per farm in the sample is set, which separates the contribution of this thesis from the contribution of Figge et al. (2004).

2.2 The model

This thesis assesses eco-efficiency following the model by Kuosmanen and Kortelainen (2005). After having computed the efficiency-scores, the thesis adds to the method by adjusting the efficiency relative to an environmental target. Eco-efficiency is first assessed following the approach suggested by Kuosmanen and Kortelainen (2005) and the scores are thereafter adjusted towards an absolute level of GHG emissions. By adjusting the scores, the novelty of this thesis incorporates the absolute levels of one environmental pressure into the measure of eco-efficiency.

The adjustment of the efficiency-scores specifies that a farm cannot obtain full eco-efficiency if the environmental pressure of contribution to global warming exceeds a certain threshold-value specified for each farm. After having maximized the efficiency-score for each farm, the scores are adjusted towards the threshold. The adjusted scores reflect how each farm meets the environmental target of GHG emissions, disregarding the level of value-added. If the method had implemented the adjustment in the same stage as computing the efficiency, farms not meeting the environmental targets would have gotten an efficiency-score of zero. By adjusting the scores after having calculated the eco-efficiency, the scores are reduced or increased proportionally to how each farm meets the environmental target. The adjustment is applied to the computed eco-efficiency score, increasing or decreasing the score relative to how the farm meets the threshold.

When computing eco-efficiency, Kuosmanen and Kortelainen (2005) suggests the usage of a DEA-approach. An advantage of using DEA is that it does not require any subjective specification of the aggregation of weights (ibid). The advantage of not requiring any subjective weighting is that this minimizes misspecifications of the model. In the model, eco-efficiency is defined as the ratio of economic value-added and environmental pressures. Mathematically defined for the nth farm, this is expressed as $EE_n = V_n / D(Z_n)$ where V_n is the value-added for farm n. The environmental pressures are added according to the function $D(Z) = w_1 Z_1 + w_2 Z_2 + \cdots + w_M Z_M$ where Z_m is the environmental pressure m and w_m is the weight assigned to that environmental pressure. Each environmental pressure can contain several variables. For example, different sources of GHG emissions can all be included in the environmental pressure of climate change as CO_2 equivalents (Kuosmanen and Kortelainen, 2005). The weights are determined using DEA to maximize the relationship between value-added and environmental pressures. Each farm gets weights specified individually to obtain the highest efficiency score possible. Maximizing the eco-efficiency for farm n requires linearity in terms of the weights, w_m. A simple linear problem is obtained by taking the inverse of the eco-efficiency problem where weights are generated to optimize efficiency. Following Kuosmanen and Kortelainen (2005) the inverse of the maximization problem is:

$$min_w EE_n^{-1} = w_1 \frac{Z_{n1}}{V_n} + w_2 \frac{Z_{n2}}{V_n} + \cdots + w_M \frac{Z_{nM}}{V_n}$$

$$s.t.\ \frac{1}{V_1}(w_1 Z_{11} + w_2 Z_{12} + \cdots + w_M Z_{1M}) \geq 1$$

$$\vdots \qquad (1)$$

$$\frac{1}{V_N}(w_1 Z_{N1} + w_2 Z_{N2} + \cdots + w_M Z_{NM}) \geq 1$$

$$w_1, w_2, \dots, w_M \geq 0$$

The constraints specify that the eco-efficiency for farm n is optimized concerning all other farms in the sample. Additionally, weights are restricted to be positive, generating efficiency-scores between zero and one. The solution to this problem specifies weights for the nth farm. The efficiency score of farm n is obtained by taking the inverse of the solution to equation (1). This model is particularly useful when studying several sources of emissions contributing to the same environmental pressure (Kuosmanen and Kortelainen, 2005). The aggregation of different sources of emissions to environmental pressures results in fewer environmental damages to weigh. It also prohibits the possibility of damages contributing to the same pressure to receive different weights when determining the efficiency score. For example, the pressure contribution to global warming receives one weight, even if it consists of several indicators.

The novelty of this thesis is to adjust the efficiency-score so that farms cannot be fully efficient if breaching the planetary boundary of climate change. If a farm contributes more to global warming than what is consistent with the environmental targets, this reflects as a lowered efficiency-score. The threshold value is denoted Z_n and is measured in the same units as the environmental pressure that it adjusts. Its value is specified individually for each farm and is elaborated on further in the method-section of this thesis. This approach offers an intuitive adjustment of the efficiency-score relative to a threshold of emissions. It also follows previous papers in first computing and then adjusting the efficiency score such as Picazo-Tadeo et al. (2011) when calculating pressure-specific slacks.

This method implements the adjustment by multiplying each farm's efficiency-score by how much the actual value of the environmental pressure differs from the targeted value. If the actual level of the environmental pressure exceeds the threshold value, the efficiency score is decreased proportionally to the excess. Similarly, if the actual level of the environmental pressure is smaller than the threshold value, the efficiency-score is increased proportionally. This approach provides for an intuitive adjustment of the eco-efficiency to the absolute environmental pressure. The adjustment is thus formulated as:

$$EE_n * \frac{Z_n}{Z_{n1}} \leq 1 \quad (2)$$

Where Z_{n1} is the adjusted environmental pressure and Z_n is the threshold for farm n. Adjusting the efficiency-scores to absolute levels of one environmental pressure is new to this field of research. By adding this to the eco-efficiency score, absolute levels of the environmental pressure are implemented. The above implementation of the adjustment is similar to what is done by Picazo-Tadeo et al. (2011) when calculating slacks. The slacks were calculated after generating the efficiency-score as specified by Kuosmanen and Kortelainen (2005) (ibid). While slacks show how to decrease the environmental pressures or increase value-added while maintaining the efficiency score, the contribution formulated for this thesis shows a proportional change in eco-efficiency corresponding to how well the firm meet the restriction. If $Z_{n1} > Z_n$ the efficiency-score of the n^{th} farm will be reduced. If the opposite holds the efficiency-score is increased.

By adjusting the efficiency-scores, damages on the environment by contribution to global warming cannot be compensated by high economic yield. The notion of not breaching the planetary boundary of climate change are thus incorporated into the measure of eco-efficiency.

3 Method

3.1 Data description

The data used for this thesis is farm-level data of Swedish dairy farms from 2016 from the farm accountancy data network (FADN). FADN is the most comprehensive farm-level data available and contains information on costs and incomes for Swedish farms. The FADN data is an EU initiative, the purpose of which is to evaluate the impacts of the common agricultural policy (CAP). The data also contains a vast number of indicators for incomes, costs and specialization of agriculture in the EU. The Swedish board of agriculture collects the FADN-data for Sweden. Previous research has used the FADN to assess eco-efficiency (see, for example, Jan et al. 2012, Reinhard et al. 1999).

To be able to assess eco-efficiency, economic value-added and environmental pressures need to be defined. This thesis uses the FADN standard results to define farm net value-added as the gross farm income minus depreciation. The net value-added considers profit from all output from farms subtracting the intermediate consumption. Value-added also include taxes. The definition does not include wages, as this is just a transaction of assets from the farm to the worker creating a net-zero benefit to society, which is also considered as a benefit of using value-added (Kuosmanen and Kortelainen, 2005).

Farms with a negative value-added were omitted from the analysis since they, due to the construction of the linear problem, all receive an inverse efficiency-score of zero.[1] Due to this, five farms were omitted from the analysis. Since only five farms were excluded for having a negative value-added, the potential selection-bias due to this is not a major concern for this study.

The following section presents and discusses the environmental pressures and external variables included in this thesis. An overview of all variables used is presented in table 1.

3.1.1 Environmental pressures

The environmental pressures accounted for in this analysis follows from previous research. Urdiales et al. (2016) divided the environmental pressures into two categories: contribution to global warming and nutrients, a division which this thesis will adapt. Since there are no data on the actual emissions from each farm available in the FADN dataset, the emissions of GHG and nutrients are proxied by other variables presented in this chapter. As the FADN dataset concerns farms' accounting, the variables are measured as expenditures, making the available units Swedish crowns (SEK) rather than consumed quantities.

The contribution to global warming is proxied by the expenditure on fuels (motor fuels and lubricants) and heating. The consumption of fossil fuels is related to CO_2-emissions, assuming all fossil fuels bought are used. However, the data does not account for renewable- and fossil fuels separately. Swedish dairy farms consume a mixture of fossil- and renewable fuels which is not possible to distinguish with this data. According to the Swedish energy agency, diesel fuels formed the most significant part of energy usage in agriculture in 2015 and 2016 (Swedish energy agency, 2019). The usage of diesel fuels exceeded the usage of biofuels by almost ten thousand GWh during both years (ibid). Between 2015 and 2016, the consumption of diesel fuels increased by 18 thousand GWh while the consumption of biofuels increased by 93

[1] The restriction $(w_{GHG}Z_{1GHG} + w_{Nu}Z_{1Nu}) \geq V_1$ generates the weights to be zero if $V_1 \leq 0$. This minimizes EE^{-1} to zero for all farms with a value-added smaller or equal to zero corresponding to $EE = infinity$.

thousand GWh (ibid). It is therefore likely that some increased spending on fuels visible in the data is due to increased spending on biofuels.

In this thesis, the assumption is that higher expenditures on fuels indicate more emissions contributing negatively to the environmental pressure of contribution to global warming. This assumption is not entirely consistent with reality since farms, as previously stated, can increase their spending on fuels by using more renewable energy. Farms already using only renewable fuels are not possible to distinguish. One group of farms where this is especially problematic are certified organic farms acting under different regulations than conventional farms. One example of the difference between these two types of farms is where the Swedish cooperative and milk-producer Arla managed to advertise their organic products as having net-zero emissions in 2019 (Arla, 2019). Because of this, the analysis mainly consists of a separate assessment of efficiency in conventional- and organic farms. A variable distinguishes the organic farms in the FADN dataset identifying whether the farm uses organic practices or not. Farms not using any certified organic production methods at all are classed as conventional.

To reach the target of decreasing emissions by 40 per cent between 1990 and 2020, the efficiency by which all fuels are used must increase while the usage of fossil fuels decreases to zero (Royal Swedish Academy of engineering sciences, 2019. p.37). A transition also needs to be made towards using more electricity rather than fuels to reach the environmental goals (ibid). This indicates that the expenditure on fuels, renewable and fossil, need to decrease for the environmental target to be reached. Urdiales et al. (2016) used data on emissions of CO_2 to measure this environmental pressure. Picazo-Tadeo et al. (2011) did not have information about the actual emissions and used the ratio of energy inputs and energy outputs times the land to get an energy ratio to use as an environmental variable. Due to data restrictions, this thesis will only use the expenditure on energy inputs to measure the contribution to global warming rather than considering energy output as in previous research.

The other environmental pressure, nutrients, causes damages on the nearby environment. The damages of using nutrients are mainly overfertilization, but it also emits CO_2 in its production. The consumption of nutrients is used to proxy for the emissions on each farm. The emissions of nutrients are closely linked to how they are managed (Swedish board of agriculture, 2019b). Thus, the consumption is not linearly related to the expenditure. Even though the management of the nutrients matter, using expenditures as an environmental indicator is motivated since the consumption of nutrients need to decrease over time. The reason why the consumption of nutrients needs to decrease relates to the target of net-zero emissions since nutrients emit CO_2 and nitrous oxide when manufactured (Swedish board of agriculture, 2020). Urdiales et al. (2016) used the difference between the inflows and outflows of nutrients at farms to see how much of the nutrients leak into the nearby environment. However, for this thesis, only information about the consumption of nutrients is available. The consumption of nutrients provides an approximation of the emissions. As not all dairy farms use nutrients in their practices, for example, if not growing any crops, only the farms with consumption of nutrients are used in the analysis. Due to this, 86 farms were omitted. Descriptive statics of the environmental pressures is presented in Table 1, together with the exogenous variables presented in the next chapter.

A problem arising from only including the indicators mentioned above of environmental pressures is that it fails to account for all emissions produced by dairy farms. As mentioned, this thesis does not account for the emissions intrinsically caused by keeping animals. Furthermore, the largest source of GHG emissions from agriculture occurs from keeping animals and growing plants where the most substantial part of GHG gases emitted are methane and nitrous oxide (Swedish board of agriculture, 2018). Agriculture also decreases the pressure of global warming by storing carbon in its crops and pasture (ibid). These aspects are not included in this thesis since it would complicate the adjustment of emissions of GHG and due to data availability. By only including emissions of GHG through fossil fuel usage, the adjustment made in the model reflects the environmental objective of net-zero emissions of GHG. Another issue is that expenditures on fuels, heating and nutrients are used rather than the actual emissions. Not considering the actual emissions might make the results less accurate, but it does not affect the main contribution of this thesis, which is to add to the method by adjusting the efficiency-scores to the environmental target.

3.1.2 Exogenous variables

The second stage of the analysis tests exogenous variables to assess what indicators are associated with the computed eco-efficiency scores. The variables tested for this purpose are farm size, the intensity of farming, labour per livestock-unit and four kinds of subsidies. The subsidies are national dairy subsidy, environmental subsidy, payment for young farmers and farm payment. These are variables that previous research has used in the second stage DEA and that could indicate how to shape future policies to improve efficiency and reduce CO_2 emissions. The variables have also been chosen due to availability considerations.

Picazo-Tadeo et al. (2011) previously tested the association between farm size and efficiency, measuring farm size as the farm surface area. The size of the farm was found not to affect eco-efficiency in the sample of Spanish farms (ibid). Even though farm size was found not to affect eco-efficiency according to Picazo-Tadeo et al. (2011), it is included in this thesis. Farm size is relevant to include due to the various size of Swedish dairy farms, and the policy implications it could have if the size of the farm was found to influence eco-efficiency. The farm size is measured as the livestock-units per farm rather than hectares of arable land. Measuring farm size in livestock-units is appropriate since it is the number of animals rather than the size of the land that determines dairy production. The intensity of farming was tested by Gómez-Limón et al. (2011) as produced kg of output divided by the hectare of the farm. The authors assessed the intensity of farming to influence eco-efficiency positively up to a certain point (Gómez-Limón et al. 2011). The intensity of farming is defined as the real output divided by the livestock-units of the farm (real output per livestock-unit). Labour is labour hours per livestock-unit and could if it is shown to affect eco-efficiency, provide some important policy implications. Authors previously testing for subsidies received are Picazo-Tadeo et al. (2011) and Gómez-Limón et al. (2011). These previous papers found a positive correlation between eco-efficiency and CAP subsidies. These abovementioned explanatory variables are interesting from a policy point of view where the result can guide future policies aiming to improve eco-efficiency and decrease emissions. As mentioned, the variables used are presented in Table 1.

Table 1: Descriptive statics for 263 Swedish dairy farms included in the analysis. Data from FADN. 91 farms are removed from the original sample due to the usage of zero nutrients or a negative value-added.

VARIABLE		MEAN	SD	MIN	MAX
VALUE-ADDED	Net value-added (SEK)	1 771 997	2 348 416	15 055	23 152 730
ENVIRONMENTAL DAMAGES					
CONTRIBUTION TO GLOBAL WARMING	Expenses on fuels (SEK)	166 655	213 459.7	916	2 554 993

	Expenses on heating (SEK)	7 049	23 769.94	0	214 106
NUTRIENTS	Expenses on nutrients (SEK)	126 050	150 923.7	1 529	1 420 566
ECO-EFFICIENCY DETERMINANTS	Farm size (LU)	52.72	63.03743	1.22	678.52
	Intensity of farming (output per LU)	60 918	15 737.55	24 768	135 974
	Labour hours per livestock unit (hrs)	196.48	155.0917	34.21	1 803.28
	National dairy subsidy (SEK)	70 892	243 770.6	0	2 135 166
	Environmental subsidy (SEK)	67 194	157,526.5	0	1 911 252
	Payments for young farmers (SEK)	2 388	10 341.6	0	50 088
	Farm payment (SEK)	224,234	223,774.6	20,894	2,252,562

3.2 Adjustment of the eco-efficiency score

The efficiency-scores are adjusted using absolute levels of the environmental pressure contribution to global warming. In order to compute the adjustment, this thesis uses the target that Sweden should have net-zero emissions in 2045, and after that; negative emissions (The Swedish government, 2019). As a part of this target, the Swedish government has set a sub-target stating that the emissions in Sweden in 2020 from the non-trading sector, including agriculture, should be 40 per cent lower compared to the levels of 1990 (ibid). This target corresponds to a decrease of 20 million tons of CO_2 equivalents in 2020 compared to the levels of 1990 (Sverigesmiljömål.se, 2019). By using this target, it can be calculated that the average decrease of GHG emission between the years 1990 and 2020 should be 1.72 per cent per year on average.

As the data used for the analysis in this thesis is from 2016, the threshold of emissions is specified relative to the levels of 2015. In order to obtain real values, the expenditures on fuels and heating in 2015 is adjusted to the price-levels of 2016 using a production price-index provided by SCB. The real expenditures in 2015 is calculated using the formula $Expenditures * \frac{index_{2016}}{index_{2015}}$, as suggested by SCB.[2] Descriptive statistics on the real expenditures of fuels and heating in 2015 and 2016 are displayed in Table 2.

[2] The formula with description can be found at: https://www.scb.se/vara-tjanster/scbs-olika-index/att-rakna-med-index/ [2020-04-27]

Table 2: Total consumption of fuels and heating in the sample of dairy farms used in the analysis in 2015 and 2016. The 2015 expenditure is adjusted to the 2016 price-level using data and method from SCB. FADN data.

YEAR	*TOTAL CONSUMPTION OF FUELS (MOTOR FUELS AND LUBRICANTS) AND HEATING (SEK)*	MIN	MAX
2015	50 203 825	6 299	3 340 798
2016	41 247 329	916	2 590 335

Using the sub-target of GHG-emissions mitigation and the available data in the FADN dataset, the adjustment in the model is such that the expenditure on fuels and heating used in 2016 should be 1.72 per cent lower than in 2015. This change corresponds to a linear percentage decrease between 1990 and 2020. Farms with expenditures on fuels below the threshold have the potential of being fully efficient, while farms with expenditures higher than the threshold will obtain lower efficiency scores.

However, the environmental strategy to reach net-zero emissions does not specify that the emissions necessarily need to decrease at a constant percentage rate each year as assumed above. Two additional rates of decrease are tested to account for different scenarios of reduced fuel and heating usage. 1.72 per cent corresponds to a constant percentage decrease, but a decreasing absolute value. Furthermore, a constant absolute decrease and an increasing absolute decrease are tested. An absolute linear decrease corresponds to a decrease of 0.666 tons of CO_2 equivalents per year. Between 2015 and 2016, this corresponds to a decrease of 2 per cent. An accelerating decrease in fuel consumption between 1990 and 2020 is also tested corresponding to a decrease of 2.2 per cent between 2015 and 2016. The three values of the restriction are analysed to provide information on how sensitive the model is to different specifications. These values are presented in Table 3.

Table 3: The calculated values of the restriction of the consumption of fuels and heating

	DECREASE BETWEEN 2015 AND 2016 (PERCENTAGE*)*	DECREASE BETWEEN 2015 AND 2016 (ABSOLUTE VALUES, MILLION TONS)
DECREASING ABSOLUTE REDUCTION (CONSTANT PER CENTAGE DECREASE)	1.7%	0.56
CONSTANT ABSOLUTE REDUCTION (VARYING PERCENTAGE DECREASE)	2%	0.66
INCREASING ABSOLUTE REDUCTION (INCREASING PERCENTAGE DECREASE)	2.2%	0.77

The estimation of the threshold is arbitrary. It does not consider the fact that farmers can substitute consumed fossil fuels by renewables since this is not accounted for in the data. As previously mentioned, the consumption of fossil fuels exceeded biofuels by almost ten thousand GWh in 2015 and 2016 (Swedish energy agency, 2019). With more precise data on the spending and consumed amount of fossil fuels and renewables, the restriction could be elaborated on further. However, the restriction still provides an estimation of the consumption of fossil fuels. It also contributes to the method of measuring eco-efficiency by using environmental targets.

3.3 Estimating efficiency using a two-stage DEA

In the first stage, eco-efficiency is assessed, and each farm is assigned an efficiency score. The efficiency is estimated using the model by Kuosmanen and Kortelainen (2005) adjusting the scores post estimation. The scores are adjusted considering each farm's emissions of CO_2. In order to assess the contribution of adjusting the scores, the unadjusted and adjusted scores are compared. By running the model with different threshold-values for the adjustment, different strategies of emissions mitigations are considered. These different values provide a sensitivity analysis of the model. In the second stage, potential determinants of eco-efficiency are tested.

3.3.1 The first stage: measuring eco-efficiency

Theoretically, there are several ways to go about incorporating aspects of sustainability in terms of planetary boundaries into the eco-efficiency measure. The reason why this has not been attempted previously is that deciding on the level of damages that can be sustained by the ecosystem is far from trivial. This thesis uses the target of net-zero emissions and its sub-target to decide on the absolute level of damages to incorporate in the model. The threshold is incorporated by adjusting the efficiency-scores. The specified threshold is that the environmental pressure of contribution to global warming cannot exceed 98.3 per cent of the year before, corresponding to a 1.7 percentage decrease. This is calculated individually for each farm. A decrease in emissions by 1.7 per cent is consistent with the environmental target, assuming the strategy is to decrease the consumption of fossil fuels at a constant rate between 1990 and 2020. As discussed in the previous chapter, a 2- and a 2.2 per cent decrease between 2015 and 2016 are also used in the model as a sensitivity analysis.

The environmental pressures are denoted Z_{nGHG} and Z_{nNu} for farm n where n = (1, …, N) are the farms in the sample. GHG denotes the environmental pressure contribution to global warming, and Nu indicates the environmental pressure nutrients. w_{GHG} and w_{Nu} are the weights assigned to each environmental pressure which are determined by solving the linear problem. The inverse of the maximization problem is:

$$
\begin{aligned}
& min_w EE_n^{-1} = w_{GHG}\frac{Z_{nGHG}}{V_n} + w_{Nu}\frac{Z_{nNu}}{V_n} \\
& s.t.\ \frac{1}{V_1}(w_{GHG}Z_{1GHG} + w_{Nu}Z_{1Nu}) \geq 1 \\
& \quad . \\
& \quad . \\
& \frac{1}{V_N}(w_{GHG}Z_{NGHG} + w_{Nu}Z_{NNu}) \geq 1
\end{aligned}
\tag{3}
$$

$$w_{GHG}, w_{Nu} \geq 0$$

When the eco-efficiency score has been computed, the adjustment of absolute levels of GHG emissions is implemented as follows:

$$EE_n * \frac{z_{nGHG2015}*0.983}{z_{nGHG}} \leq 1 \qquad (4)$$

This incorporates one aspect sustainability into the measure of eco-efficiency by prohibiting high net value added to compensate for high emissions of GHG. Farms, to be fully efficient, need to emit at the sustainable level of CO_2-equivalents or less. If $Z_{nGHG} > Z_{nGHG2015} * 0.983$, this indicates that the farm does not reach the environmental target and its efficiency-score is reduced proportionally.

As discussed above, two additional scenarios are tested as the sustainable level compared to the previous year. The alternative specifications are reductions of the eco-efficiency score if $Z_{nGHG} > Z_{nGHG2015}$*0.980 and if $Z_{nGHG} > Z_{nGHG2015}$*0.978 according to the calculations presented in the previous chapter. The higher above the threshold a farm emits, the more it will be penalized in terms of lower efficiency. If the farm is on the threshold, the efficiency-score will remain the same. Farms below the threshold, that have decreased their expenditures on fuels by more than required, are rewarded with a higher efficiency score. Specifying the restriction in this manner allows farms to obtain eco-efficiency scores greater than one. An efficiency-score higher than one will occur if a farm already has an efficiency-score of one and emits below the threshold, or if a farm has decreased its pressure contribution to global warming very significantly. Such a substantial decrease in expenditures on fuels and heating points to some underlying changes within the farm, not accounted for in this analysis. Since an efficiency score above one is not feasible theoretically in this model, the scores above one are normalized to one as indicated in the equation above.

The efficiency-scores are analysed both before and after adding the adjustment. Through this, it is assessed what changes the adjustment brings to the result. Comparing the results also provides information on whether the same farms are efficient before and after adjusting the scores. Using the model with the different values of the threshold shows how sensitive the model is to different assumptions about the sustainable level of emissions. As mentioned, there is one crucial difference among dairy farms in Sweden which could affect the efficiency scores. This difference is whether a farm practises conventional or organic farming. Since efficiency is estimated relative to the other units in the sample, the two kinds of farms are assessed separately. However, to allow for a comparison of the results, all farms' efficiency is also assessed simultaneously.

3.3.2 The second stage: explaining eco-efficiency

In the second stage, exogenous variables correlating with eco-efficiency are identified to find reasons for potential eco-inefficiency. OLS regression is used to assess exogenous variables' relation to eco-efficiency, together with a discussion of the results. Using this method in efficiency-analysis was suggested by Hoff (2006). The benefit of using OLS for the second-stage DEA is that it provides results by using a method understood by most. This makes the results more transparent than if a more complicated method were used (Hoff, 2006). This second-stage is essential since it can provide policy implications of how to increase eco-efficiency among the farms in the sample. Seven exogenous variables are regressed on eco-efficiency in this second stage OLS-estimation. These exogenous variables are as previously mentioned; farm size, the intensity of farming, labour per livestock-unit, environmental subsidies, payment for young farmers, dairy subsidies and farm payment.

There are several ways to model the DEA efficiency scores against exogenous variables. Simar and Wilson (2007) proposed the usage of a truncated double bootstrap method to overcome the problems of serial correlation arising when regressing efficiency scores on determinants in a DEA framework. Several studies have used the method suggested by Simar and Wilson (2007) when assessing exogenous variables' effect on eco-efficiency (see, for example, Urdiales et al. 2016; Picazo-Tadeo et al. 2011). Despite this, the method have been criticised for being too complicated and not robust to other applications (McDonald, 2009). McDonald (2009) argues that an OLS estimation is sufficient in the second stage DEA regressing the efficiency scores on the determinants. Using an OLS estimation also provides results in a less complicated way than suggested by Simar and Wilson (2007). Hoff (2006) advocates for the advantages of using OLS in the second stage DEA as it simplifies the procedure and performs at least as well as more well-specified models. The author concludes that OLS provides more accurate results compared to the commonly used Tobit regression (Hoff, 2006).

Following the arguments by Hoff (2006) and McDonald (2009), this thesis use OLS in the second-stage DEA regressing the efficiency scores on exogenous variables. The OLS regression can be expressed as:

$$EE_n = \alpha + \beta_1 x_{1n} + \cdots + \beta_i x_{in} + u_n \qquad (5)$$

Where EE_n is the efficiency score for farm *n* computed in the first stage. The subscript *i* denotes the exogenous variables included. EE_n is a value between zero and one, namely $0 \leq EE_n \leq 1$. α is the intercept and u_n is the error term with a zero mean and independence from x_{in}. β_i is an OLS coefficient and x_i is one of the exogenous variables tested for. The regression is run stepwise, at first including all the exogenous variables. The variable with least explanatory power is removed and the regression is re-estimated until only variables with significance on eco-efficiency are left in the regression. This procedure is conducted to provide a first glimpse of variables correlating with eco-efficiency in Swedish dairy farms since previous research has presented conflicting results of what variables affect eco-efficiency. The regression is also conducted to examine whether the correlates change when adjusting the efficiency-scores. For these purposes, stepwise regression is appropriate in providing transparent results.

This second stage regression is conducted using both unadjusted- and adjusted efficiency scores. This amounts to four dependent variables included in separate regressions when analysing both the conventional- and organic farms. The adjusted scores used are the main scenario with the threshold of $Z_{nGHG2015} * 0.983$ corresponding to a 1.7 per cent decrease in 2016 compared to 2015. All the exogenous variables are included in their logged form to make patterns more visible and reduce the influence of outliers present in the variables. Logging the variables also prevents effects from differences in size. In order to avoid values of minus infinity, variables containing zeros was scaled up by one. The results of the regressions are compared, and the implications are discussed. It is important to keep in mind that the OLS regression shows a correlation between eco-efficiency and the exogenous variables tested. Thus, no conclusions regarding causality is drawn.

4 Result and discussion

The analysis was conducted using the package lpSolve in R. To compute the linear problem generating the eco-efficiency scores, equation (3) was manually programmed into the software. First, the model was estimated as specified by Kuosmanen and Kortelainen (2005). Secondly, the scores were adjusted using the three different values specifying different paths of emissions-mitigation as stated and discussed in chapter 3.2. The analysis was conducted on farms contributing to both considered environmental pressures: nutrients and contribution to global warming. All farms in the sample had some expenditure on heating and fuels combined, which constitutes the pressure contribution to global warming. The analysis omits farms not using any nutrients in their practices. Furthermore, farms with a negative value-added were omitted from the analysis, as discussed in chapter 3.1. Moreover, the sample was analysed for conventional- and organic farms separately. The organic farms are farms only or partly applying certified organic production methods or transitioning to organic production. Farms classed as conventional are the remaining farms, which are farms not using any certified organic production methods at all. After discarding 91 observations with a zero-value for nutrients and a negative value-added, the sample of conventional farms consisted of 234 units while the sample of organic farms consisted of 29 units. The main analysis assesses conventional- and organic farms separately, but to enable a comparison between the two types of farms the efficiency of all farms was also assessed as one sample. From this common analysis, the conditional-mean efficiency-score for each type of farm, conventional and organic, was derived. In a second stage, an OLS regression was conducted to assess exogenous variables' correlation with the adjusted eco-efficiency scores.

As reviewed by Kuosmanen and Kortelainen (2005), the DEA results are sensitive to the sample as the weights and efficiency-scores are optimised relative to the other included units. The sample-sensitivity indicates that the efficiency-score assigned to each farm depend on which other farms are analysed in the sample. Thus, the measure should be viewed as a ranking rather than scores relevant without context. These aspects are essential to keep in mind when interpreting the results.

In the following section, the results from the first and second stage of the analysis are presented and discussed. In the first stage, the eco-efficiency scores are assessed while the second stage assess how exogenous factors correlate with the efficiency scores. The emphasis of the analysis and discussion is on conventional farms since this category constitutes most of the sample and the majority of Swedish dairy farms.

4.1 Results of eco-efficiency

First, the model is assessed without the adjustment, and the results are discussed. The scores are then adjusted using the environmental target of net-zero emissions in 2045, as discussed in chapter 3.2. The results are compared before and after being adjusted, and the changes in the scores are discussed. A sensitivity analysis is provided by using different values of the threshold. An analysis is also conducted regarding whether the same farms are efficient before and after adjusting the eco-efficiency scores.

4.1.1 Before adjusting the scores

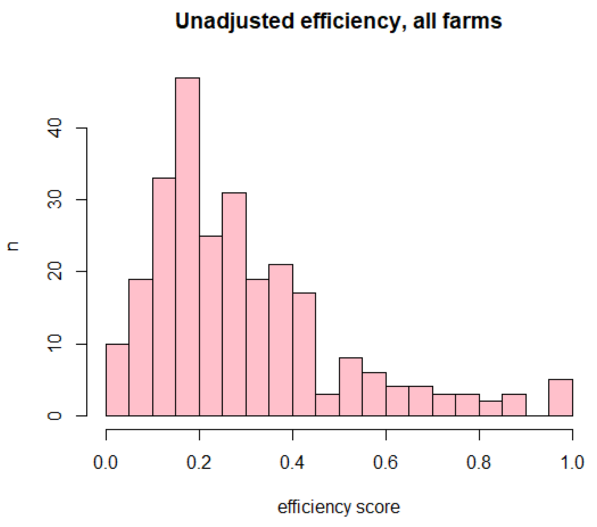
The analysis showed conventional farms to be highly inefficient with a mean efficiency-score of 0.33. The organic farms perform, as expected due to stricter regulations, better with a mean score of 0.56. This result implies that conventional farms could contract their environmental pressures with 67 per cent while maintaining value-added. For organic farms, the corresponding potential decrease in environmental pressures while maintaining value-added is 44 per cent. Among conventional farms, six farms obtained an efficiency-score of 1 indicating full efficiency. Among the organic farms, three farms obtained full efficiency. The lowest score assessed was 0.014 for conventional farms and 0.097 for organic farms. An overview of the results is provided in Table 4.

Table 4: Results of eco-efficiency. The unadjusted EE is estimated with the threshold of a 1.7 percentage decrease compared to the year before. The scores presented in this table are estimated separately for conventional- and organic farms.

		MEAN	SD	MIN	MAX
CONVENTIONAL FARMS *(N=234)*	**Unadjusted EE**	0.32582	0.2188826	0.01394	1.000
	Adjusted EE	0.355794	0.2581718	0.009944	1.000
ORGANIC FARMS *(N=29)*	**Unadjusted EE**	0.56259	0.2742691	0.09656	1.000
	Adjusted EE	0.5760	0.2926023	0.1343	1.000

The linear problem was also solved for all farms simultaneously. This simultaneous assessment was conducted to enable a comparison of the efficiency-scores between conventional- and organic farms. Since efficiency provides a ranking relevant when compared to other units in the sample, a comparison is only feasible for units within the same sample. This assessment provided a mean industry efficiency of 0.29, illustrated as a histogram in figure 1. The conditional mean-efficiency for conventional farms is in this simultaneous assessment 0.27, while the corresponding efficiency for organic farms is 0.51. When assessing all farms simultaneously, organic farms are still performing better than conventional farms with a 0.24 higher mean-efficiency. The distribution of the efficiency-scores for all farms are displayed in figure 1.

Figure 1: Distribution of efficiency scores considering all farms.



The weights also provide valuable information to wherein the inefficiency lies. Since the linear problem assigns weights to each environmental pressure to maximize efficiency, the problem generates lower weights to the pressure where the farm performs the worst. For conventional farms, only 12 farms were assigned a larger weight to the environmental pressure contribution to global warming. That leaves the remaining 222 farms assigning a larger weight to nutrients. This result indicates that all conventional farms except 12 performs better regarding nutrients than the contribution to global warming. For organic farms, the problem generates a somewhat reversed result. Among the organic farms, 24 farms out of 29 assigned the largest weight to contribution to global warming. This result indicates that most of the conventional farms perform better regarding nutrients while the majority of organic farms performs better regarding contribution to global warming.

These results show a significant potential for farms to decrease their environmental pressures while maintaining value-added. Using the descriptive statistics as displayed in table 1 together with the ability to contract the environmental pressures as indicated by the efficiency scores, this result indicates that the average farm theoretically could decrease its expenditures contributing to global warming by 173,704SEK*0.71= 123,329.8SEK**.** Previously, Urdiales et al. (2016) used this calculation method to show the potential reduction of environmental pressures. The corresponding potential decrease in expenditures on nutrients is 89,495.5SEK. This result points to the significant reductions in costs that increasing the eco-efficiency could provide. The result also indicates that for most farms, the most substantial potential for improvement lies in reducing the environmental pressure of contribution to global warming. The results indicate that conventional Swedish dairy farms could contract their usage of fuels mainly, but also nutrients while maintaining value-added.

The result is consistent with previous research since it shows a potential for improvement of efficiency. On the contrary, the result of this thesis displays much higher inefficiency than assessed in previous papers. Urdiales et al. (2016) assessed Spanish dairy farms to be inefficient with a mean efficiency score of 0.632. Picazo-Tadeo et al. (2011) also found similar results with an efficiency score of 0.56 for farms in Spanish Campos County. Jan et al. (2012) found an average eco-efficiency of 0.64 when assessing the eco-efficiency of Swiss dairy farms. Both Urdiales et al. (2016) and Jan et al. (2012) studied dairy-farms and found a mean eco-efficiency of around 0.6, which is much higher than the average of 0.33 found for conventional farms in this thesis. The findings regarding organic farms in this thesis is closer to the results of previous research.

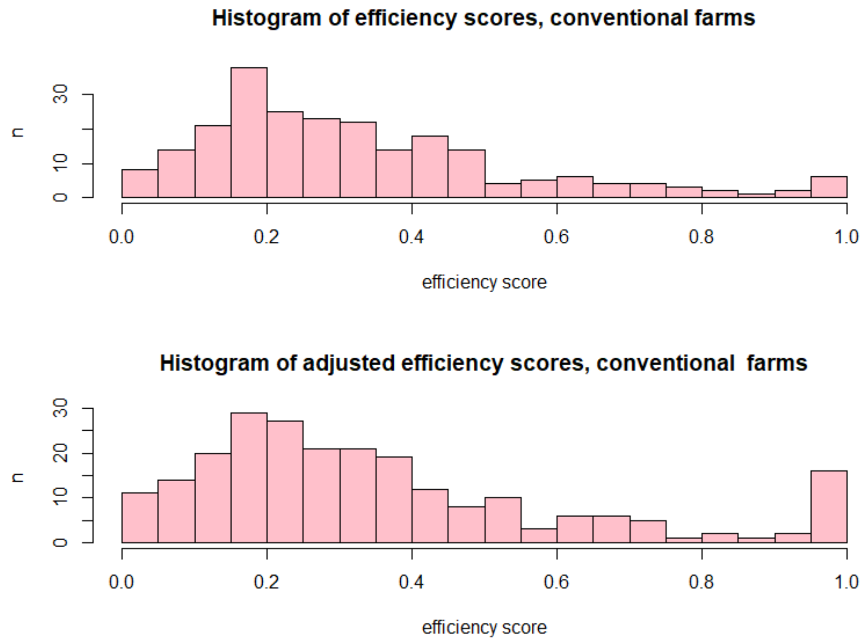
The results of this analysis should be approached with some caution. One apparent reason for the high assessed inefficiency found in this thesis compared to previous research is the data. As discussed in previous chapters, the data used are expenditures on fuels without the possibility to distinguish between renewable- and fossil fuels. Farms using a significant fraction of biofuels are with this data not possible to distinguish. This probably results in higher inefficiency being estimated for farms using a significant fraction of renewable resources. If the FADN would have accounted for the expenditure on renewable- and fossil fuels separately, the results would have been more accurate. By accounting for different types of fuels, the usage of the FADN when assessing eco-efficiency could be increased. As the FADN is such a comprehensive dataset, it is useful when requiring economic variables for the efficiency-analysis. By accounting for expenditures on fossil fuels and renewables separately, the FADN could provide a shared dataset which researchers could use when measuring eco-efficiency in different countries or regions. This would facilitate future research of eco-efficiency. It would also enable making comparisons between years and countries, in turn providing essential policy implications on how to increase eco-efficiency within the EU.

4.1.3 Adjusting the efficiency-scores

The novelty of this thesis is to adjust the efficiency-scores to integrate absolute levels of GHG emissions into the measure of eco-efficiency. After having computed eco-efficiency, the scores were adjusted to the Swedish environmental target of net-zero emissions in 2045. The threshold for the adjustment is a decrease of 1.7 percentage between 2015 and 2016 as the data used in this analysis is from 2016. This threshold corresponds to a linear decrease of 40 per cent between the years 1990 and 2020. This reduction is specified as a sub-target to reach the goal of net-zero emission in 2045 (The Swedish government, 2019. p.30). As a sensitivity analysis, two alternative locusts of decreasing emissions are tested to assess how sensitive the adjustment is to different specifications. The different values used for the restriction is presented in table 3 in chapter 3.

When adjusting the eco-efficiency scores to a decrease of 1.7 percentage in GHG emissions compared to the year before, the mean-efficiency of conventional farms is 0.36. This finding implies that conventional farms increase their mean efficiency-score by 0.03 compared to the unadjusted scores. This result suggests that the sum of all farms' efficiency is higher after adjusting the scores. While some farms lower their efficiency-score, other farms perform relatively better. With the adjustment, the model assesses 15 conventional farms to be fully efficient, compared to the six efficient farms before adjusting the scores. Among the conventional farms, 134 out of the 234 increase their efficiency. By inspecting the histogram of the adjusted efficiency scores, comparing it to the unadjusted scores, it is evident that while a more significant number of farms obtain full efficiency with the adjustment, more farms end up with an adjusted efficiency-score below 0.2 than without the adjustment. This is visible in figure 2, where histograms of before and after adjusting the scores for conventional farms displays the result side-by-side. Thus, there is a slightly higher variance in the adjusted scores compared to the unadjusted scores. This implies that some farms' efficiency has increased while other farms have decreased their efficiency, moving farms further away from the mean. For organic farms, the adjusted mean efficiency-score was 0.58, an increase of 0.02 compared to the unadjusted score.

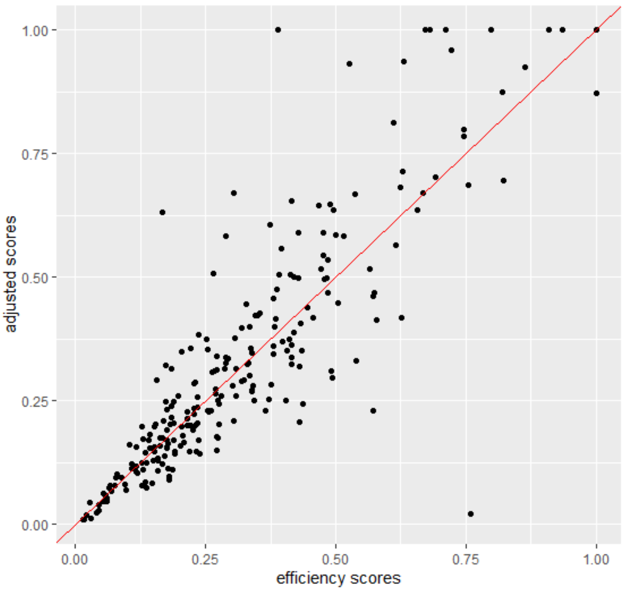
Figure 2: Before and after adjusting the scores for conventional farms.



Conducting a sensitivity analysis by testing the different values of the threshold shows that no significant changes occur from using the different values of the threshold of emissions. The mean efficiency-scores for all tested values are the same, considering the two first decimals. This result shows that the adjustment of the scores is not sensitive to changing the threshold-value slightly. Since precise absolute values of environmental pressures are difficult to specify, this finding points to the advantage of applying this adjustment. Even if the precise value of an environmental threshold is difficult to define, the adjustment could give relevant implications. Using an environmental target as a threshold-value for the adjustment also gives implications whether the units in the sample performs at the level specified in already existing policies. By including an environmental target in the adjustment of the scores, policies aiming to increase eco-efficiency will also increase the ability of firms to meet an environmental target. However, it is possible to use other indicators to calculate the level of the threshold.

One question arising when introducing this adjustment of the efficiency-scores is whether the ranking of the adjusted scores differs compared to before the adjustment. Are the same farms efficient before and after the adjustment? Figure 3 provides an answer to this question. When measuring eco-efficiency without the adjustment, farms can be efficient while having high environmental pressures, if compensating the pressures by high economic yield. Adding the restriction could make even the most efficient farm inefficient since the adjustment does not incorporate value-added when determining which farms meet the threshold and which do not. Figure 3 displays a plot of the relation between the unadjusted and adjusted scores in conventional farms. The adjusted efficiency-scores are plotted on the y-axis while the unadjusted scores are plotted on the x-axis. The red line goes through origo with a slope of 1. Farms above the line perform better with the adjustment, whereas farms below perform worse when adjusting the scores. By inspecting the figure, it is evident that the variance increases with the efficiency scores. Farms with low efficiency also have low adjusted scores while farms with higher efficiency-scores vary more regarding which adjusted efficiency-score they receive. From the figure, it is also evident that the fully efficient farms are not the same in the unadjusted and the adjusted efficiency. Further, farms with low unadjusted efficiency generally also have low adjusted efficiency. By conducting a Spearman rank correlation between the adjusted and unadjusted efficiency scores of conventional farms, it is found that the ranking in the two measures does not differ significantly. The spearman rank coefficient for adjusted and unadjusted scores of conventional farms is 0.87 indicating strong correlation.

Figure 3: The relation between the adjusted- and unadjusted efficiency scores of conventional farms.



Conducting a Spearman rank correlation between the adjusted- and unadjusted efficiency-scores for organic farms yields a similar result with a spearman coefficient of 0.90. This result implies that the adjustment does not contribute to a substantial change in the ranking of farms compared to the unadjusted scores. Conducting Spearman rank correlation tests for unadjusted eco-efficiency and the different thresholds of the adjustment show that the correlation does not change with the different adjustments. Future research applying this adjustment to another issue and sample should replicate this test to assess how much the adjustment changes the efficiency ranking.

4.2 Results of the OLS-regression

Equation (5) illustrates the regression procedure conducted in this chapter. As previously stated, the exogenous variables tested for are the number of livestock-units, the intensity of farming, labour per livestock-unit and four kinds of subsidies. The subsidies included are dairy subsidies, environmental subsidies, payment for young farmers and single farm payments. This second stage regression is run using both unadjusted- and adjusted efficiency scores. The adjusted scores used are the main scenario with the threshold of $Z_{nGHG2015} * 0.983$ corresponding to a 1.7 per cent decrease in 2016 compared to 2015. As adjusted efficiency-scores above one are normalized this might cause censoring issues in the second-stage regression if many farms receive a score above one. However, only thirteen farms are above one in the analysis indicating that the normalization does not pose a major problem to this analysis.

By conducting the stepwise regression removing one variable at the time, exogenous variables correlating with eco-efficiency are identified. It can be concluded that the results differ depending on which efficiency-score is used as dependent variable in the regressions. In conventional farms, the intensity of farming and the number of livestock-units was found to correlate significantly with the adjusted eco-efficiency. For the unadjusted score of conventional farms, the significant variables were the intensity of farming, livestock-units, single farm payment and dairy subsidies. Regarding organic farms, the intensity of farming and labour per livestock-unit was assessed to correlate significantly with eco-efficiency both before and after adjusting the scores. The results of the regressions are displayed in table 5.[3] High F-statistic shows the regression to be significant. A low R-squared, especially for conventional farms, indicate that the included variables do not explain a lot of the variation in the efficiency scores, indicating that there are variables not included in this analysis that could be used to explain eco-efficiency. Collinearity between the variables was tested for, finding a low correlation between most of the variables included in the final regressions. However, a correlation was found in conventional farms between farm payment and livestock-units, with variance inflation factors (VIFs) around five. As collinearity tends to inflate the variance of the regression coefficients of the concerned variables, the coefficients regarding these variables are to be interpreted with caution. No issue of multicollinearity is detected in the variables for organic farms.

[3] Scatterplots of the regressions are available in appendix 2.

Table 5: Average effects of the final OLS and associated p-values with adjusted eco-efficiency or unadjusted eco-efficiency as the dependent variable. The result is obtained from conducting a stepwise regression.

VARIABLES, LOGGED	CONVENTIONAL MARGINAL EFFECT (P-VALUE)		ORGANIC MARGINAL EFFECT (P-VALUE)	
	Adjusted score	Unadjusted score	Adjusted score	Unadjusted score
INTERCEPT	-2.66280 (0.000289 ***)	-1.452192 (0.020177 *)	-5.4849 (0.00109 **)	-4.88212 (0.00174 **)
INTENSITY (OUTPUT/LU)	0.26459 (7.72e-05 ***)	0.219880 (0.000204 ***)	0.6337 (8.06e-05 ***)	0.58446 (9.79e-05 ***)
SINGLE FARM PAYMENT	-	-0.088344 (0.029606 *)	-	-
DAIRY SUBSIDY	-	0.008891 (0.005475 **)	-	-
LABOUR PER LU	-	-	-0.2030 (0.05535 .)	-0.21635 (0.03089 *)
LU	0.03363 (0.050217 .)	0.116594 (0.000359 ***)	-	-
F-STATISTICS	10.03 (6.681e-05***)	8.266 (3.038e-06***)	11.45 (0.0002715***)	11.47 (0.0002687***)
R-SQUARED	0.07987	0.1262	0.4683	0.4687

*'***' indicates significance at the 0.1% level,*
*'**' indicates significance at the 1% level, and*
'.' indicates significance at the 10% level.

Since the exogenous variables are logged, the interpretation of the coefficients presented in Table 5 is that when increasing one of the exogenous variables by one per cent, efficiency is assessed to increase by $\beta_i/100$. The regression conducted on the conventional farms shows that the intensity of farming affects eco-efficiency positively for both the adjusted- and unadjusted scores with similar significance and explanatory power. Apart from the intensity of farming, the number of livestock-units also affects both the adjusted and unadjusted score in conventional farms. However, the significance and correlation between livestock-units and the efficiency score are strongly reduced when adding the adjustment. This reduction in correlation between eco-efficiency and livestock-units is due to the introduction of absolute levels of GHG, where higher economic gain brought by more livestock-units cannot compensate for the damages from not meeting the environmental target. Further, subsidies in the form of single farm payments and dairy subsidies correlate with the unadjusted efficiency-score but are insignificant when adjusting the score. Interestingly, the single farm payment is assessed to decrease eco-efficiency for the unadjusted score in conventional farms. On the other hand, the single farm payment does not significantly affect adjusted eco-efficiency. This result highlights two interesting aspects of the single farm payment scheme; that it affects eco-efficiency negatively and that the effect is lost when considering absolute levels of emissions.

Regarding organic farms, the exogenous variables intensity of farming and labour per livestock-unit are assessed to be significantly correlated with eco-efficiency both when testing the unadjusted- and the adjusted score. The correlation and significance of the variables are barely changed at all when adjusting the scores. The regression estimated labour per livestock-unit to affect eco-efficiency at a 1 per cent significance level for the unadjusted scores, a significance that decreased to 10 per cent when implementing the adjustment. More labour-hours invested in each livestock-unit correlated with lower eco-efficiency. This effect was marginally reduced when adjusting the scores. That is, when aiming to increase eco-efficiency in organic farms, policies could target to decrease the number of labour hours invested in each livestock-unit and to increase the intensity of farming.

Picazo-Tadeo et al. (2011) found environmental subsidies to have a positive impact on eco-efficiency by testing the correlation with Pearson's correlation test. The authors also tested the correlation between CAP-subsidies and eco-efficiency and found a low correlation between the two. On the contrary, Gómez-Limón et al. (2011) found a high positive correlation between CAP-subsidies and eco-efficiency. Thus, it can be concluded that the previous results regarding the effect of subsidies on eco-efficiency differ. The analysis of this thesis shows that the single farm payment and dairy subsidies have a small influence on eco-efficiency among conventional farms before adjusting the scores, but not with the adjustment. Regarding intensity, this too was tested by Gómez-Limón et al. (2011). It was found that intensification increased eco-efficiency since the economic gains from this was higher relative to the increase in environmental pressures (Gómez-Limón et al. 2011). Due to the adjustment of the efficiency-scores towards a threshold of emissions, the loss in environmental pressures cannot be compensated by the economic gain to the same extent as in previous research. This is reflected as the intensity of farming having a smaller impact on efficiency when adjusting the scores, at least for conventional farms. This points to a potential to increase the intensity without increasing the contribution to global warming to the point where it reaches the specified threshold. Picazo-Tadeo et al. (2011) found no correlation between farm-size and efficiency, which is inconsistent with the findings of this thesis where the farm-size (measured by the number of livestock-units) correlates with efficiency for conventional farms. Urdiales et al. (2016) tested socio-economic variables' correlation with eco-efficiency and found that young farmers had higher eco-efficiency compared to older farmers. This thesis had no access to socio-economic variables but used payment to young farmers as one exogenous variable. However, the payment to young farmers was found not to affect the results significantly.

Concluding, most of the exogenous variables tested for correlation with eco-efficiency has some significance in the OLS-model for conventional- and organic farming. Environmental subsidies and payment to young farmers were omitted from the stepwise regression in all cases due to low significance in the correlation with eco-efficiency. The only variable assessed to have a significant effect on all cases was the intensity of farming, which correlated positively with eco-efficiency both before and after adjusting the scores.

Finding the causes of eco-inefficiency has essential policy implications when aiming to decrease emissions while maintaining production and value-added. From the result found in this thesis, increasing the intensity of farms is one way to increase eco-efficiency. This result also holds when adjusting towards absolute levels of GHG emissions. Increasing the intensity of farming as a mean to increase eco-efficiency is especially relevant in organic farms which have a stronger correlation between the intensity of farming and eco-efficiency. However, as the intensity of Swedish dairy farms is already high (Augère-Granier, 2018), it might be difficult and costly to increase the intensity even more. Further, the regression assesses the number of livestock-units to correlate with efficiency in conventional farms, with a decreased effect when adjusting the scores. The decreased effect of the number of livestock-units when adjusting the score is likely a consequence of including absolute levels of GHG emissions since more livestock-units indicate higher emissions of GHG from fuels and heating. Following this, it makes sense that the positive correlation between livestock-units and eco-efficiency should decline when adjusting the efficiency-scores towards a threshold of absolute emissions. Policies aiming to increase the size of farms will thus have a more substantial effect on efficiency when not considering the absolute levels of emissions. Labour per livestock-unit correlates with eco-efficiency in organic farms, but not in conventional farms. Labour per livestock-unit is the only significant variable in the regressions correlating negatively with the efficiency-scores. These findings indicate that when aiming to improve eco-efficiency, policies would not have the same effect on conventional farms as on organic farms. The regression results also show that the exogenous variables correlating with eco-efficiency change when adjusting the scores, implying that some policies might increase eco-efficiency without reducing emissions.

Finding the reasons behind eco-inefficiency is a critical issue for future research to provide policy implications on how to improve eco-efficiency. This thesis found some variables correlating significantly with eco-efficiency, but those were assessed only to explain a small part of the variation in the dependent variable. Urdiales et al. (2016) tested the effects of socio-economic variables on eco-efficiency in Spanish dairy farms and found that young farmers and farmers expecting to continue farming for a long time were more eco-efficient compared to other farmers. Socio-economic- and social variables would be of interest to study in the context of Swedish dairy farms since it would shed more light on possible explanations of eco-efficiency. However, this would require the gathering of new data, which is outside the scope of this study.

5 Conclusion

This thesis aimed to assess eco-efficiency in Swedish dairy farms using a DEA-approach. The novelty of this thesis was to add to the model by including absolute levels of GHG, adjusting the efficiency-scores towards an environmental target. This adjustment incorporates the notion of sustainability into the measure of eco-efficiency, something the measure has been criticised to lack. Thus, the main contribution of this study is the theoretical development of the model. The empirical application was on Swedish dairy farms using the developed model. Assessing eco-efficiency in Swedish dairy farms and adjusting the scores has provided a more in-depth insight into how eco-efficient Swedish dairy farms are. By using an environmental target when adjusting the scores, the result also indicates how Swedish dairy farms meet the environmental target of net-zero emissions in 2045. Testing for different values when adjusting the scores provide a sensitivity analysis of the adjustment. To gain further knowledge in what potentially cause eco-efficiency, exogenous variables were regressed on the efficiency-scores.

When measuring eco-efficiency in Swedish dairy farms using FADN data from 2016, a result of low eco-efficiency is found. Among the conventional farms, the mean-efficiency was 0.33 while the organic farms had a mean-efficiency of 0.59. The result also shows conventional farms to perform better regarding nutrients than contribution to global warming, while the opposite holds for organic farms. The adjusted eco-efficiency scores showed that the mean-efficiency among both conventional- and organic farms increased when adjusting the scores towards absolute levels of GHG emission. This result implies that many farms meet the threshold of decreasing GHG emissions by 1.7 per cent compared to the year before. Testing for the differences between the unadjusted- and adjusted scores using a Spearman rank correlation showed that the ranking did not differ much when comparing the two specifications.

The results found in the second-stage regression indicates that adjusting the scores does change the correlation between the exogenous variables and eco-efficiency. The only exogenous variable correlating significantly with both the unadjusted- and adjusted efficiency for all farms was the intensity of farming. This finding suggests that policies targeted to increase eco-efficiency should aim to increase the intensity of farming. Such a policy would, according to the regression results, have the most notable effect on organic farms, where increasing the intensity of farming might lead to substantial improvements in eco-efficiency. The analysis also implies that a policy increasing the number of livestock-units in a farm would have a larger effect on the unadjusted efficiency-scores than the adjusted in conventional farms. These differences imply that some policies might increase eco-efficiency without reducing emissions. This finding is essential since it shows that policies aiming to increase efficiency will have different impacts depending on whether the measure considers absolute damages or not, pointing to the contribution of adding the adjustment presented in this thesis.

Despite finding variables correlating with efficiency, the question remains what the main determinants of eco-efficiency are. A further study could test for other variables affecting eco-efficiency in Swedish dairy farms, such as farmers' attitudes and socioeconomic features. An important issue for future research is to implement this adjustment in other settings to test its feasibility further.

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Appendix 1: Computing values used for the restriction on CO_2 emissions in the model.

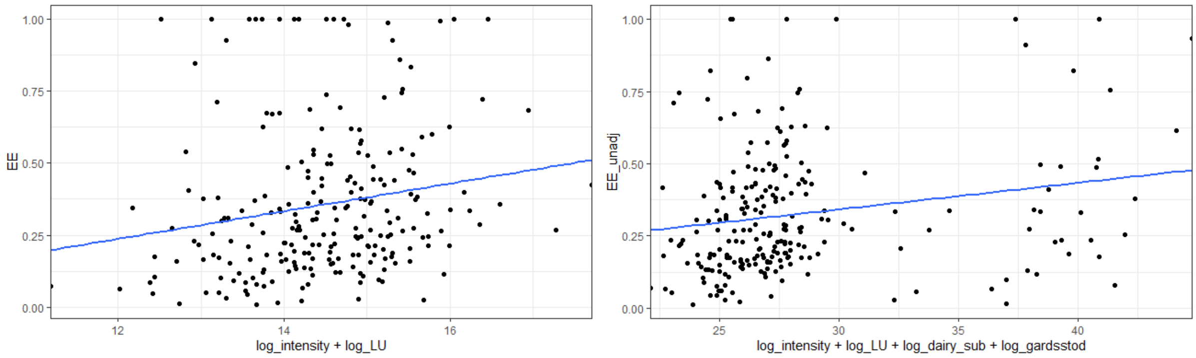
The values were computed using the sub-target that emissions should decrease by 40 per cent between 1990 and 2020 and that this would correspond to a decrease by 20 million tons of CO_2 equivalents (Sverigesmiljömål.se, 2019). If 40 per cent corresponds to 20 million tons between 1990 and 2020, the initial emissions are 50 million tonnes. The targeted emissions in 2020 would be 30 million ton of CO_2 equivalents. The eco-efficiency is assessed using data from 2016, where the adjustment is made regarding the expenditures in 2015. Three different specifications were computed to provide a sensitivity analysis of the model. In the table below, the rate of change is denoted r.

	FORMULA	EXPLANATION
CONSTANT PERCENTAGE DECREASE	$30 = 50 * r^{30}$	$r = 0.9831 \approx 0.983$
CONSTANT ABSOLUTE DECREASE	$\frac{20}{30} = 0.66$ $\frac{32.834}{33.5} = r$	Each year emissions should decrease by 0.66 tonnes, implying going from 33.5 to 32.834 between 2015 and 2016. $r = 0.98012 \approx 0.980$
INCREASING ABSOLUTE- AND PERCENTAGE DECREASE	$\frac{34.11}{34.88} = r$	To obtain a value of increasing decay, the absolute change from the first scenario is reversed. This implies going from 34.88 to 34.11 between 2015 and 2016. $r = 0.9779 \approx 0.978$

Appendix 2: Regression results

In the scatterplots, the eco-efficiency is projected on the y-axis while the various exogenous variables included in the final regressions are plotted on the x-axis. The adjusted efficiency is displayed to the left and the unadjusted efficiency is displayed to the right.

Conventional farms:



Organic farms: