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Examining the Relationship between Social Inefficiency and Financial Performance. Evidence from Wisconsin Dairy Farms

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Abstract: Although social sustainability is an important component of sustainable agricultural production, little research has been conducted to assess social sustainability performance at the farm level. This study measures farmers' social sustainability performance using (in)efficiency measures derived from a non-parametric dynamic directional distance function approach. It further examines the relationship between social (in)efficiency and financial performance measured by profitability, which is crucial to understand the financial impact of engaging in socially responsible activities. The empirical application focuses on a sample of Wisconsin dairy farms over the period 2007–2017. Results show that sample farms could have (decreased/)increased their social (in)efficiency by an average of 14%. Social (in)efficiency was found to be (negatively/)positively related to farm profitability, implying that social objectives can be achieved in tandem with economic goals.

Keywords: social inefficiency; social sustainability; financial performance; data envelopment analysis; dairy farms

1. Introduction

Sustainable farming is not only limited to sustaining the economic viability of farm operations and protecting the natural environment under which farms operate. It also involves achieving social sustainability or responsibility goals such as promoting animal well-being and improving the quality of life of farmers, farm workers, and society [1,2]. Although social sustainability is an important component of the overall sustainability of a farm, little is known about social sustainability performance at the farm-level.

One way to measure farmers' social sustainability performance is to use the tools available in the efficiency and productivity literature. These tools allow researchers to treat socially responsible activities as part of the firm's production process. This is a desirable feature, as the adoption of socially responsible activities, such as practices to promote animal well-being, can affect production costs and the value of marketed items [3]. While a great deal of efficiency studies has measured farmers' technical (or economic) and environmental (in)efficiency (see, e.g., [4–6], among others), much less attention has been devoted to the measurement of farm social (in)efficiency. Notably, the studies by [7,8] are the only two studies to date that have assessed farmers' social (in)efficiency (more social (in)efficiency studies exist in sectors other than farming, such as the corporate industry (see, e.g., [9–11]).

To measure social (in)efficiency, social sustainability indicators need to be identified and evaluated. In a review of agricultural sustainability indicators, [12] classified social sustainability indicators into two main categories: (a) indicators that are related to the well-being of the farm community (i.e., farmers and their families), and (b) indicators

that are "related to society's demands, depending on its values and concerns, which are constantly changing", as emphasized by [13] (p. 315). Indicators in the first category include, among others, farmers' education, working conditions (measured, for example, by working time), and physical and psychological well-being indicators such as the physical health of farmers and workers, social involvement, feeling of independence, family access to infrastructure and services, and gender equality. The second category includes indicators such as contribution to employment, acceptable agricultural practices, quality of products, intergenerational continuity in agriculture, and heritage and aesthetic values. Other important indicators in this second category can be constructed based on the degree of farmers' engagement in social farming activities, such as employing vulnerable and disadvantaged people (e.g., disabled people, drug addicts, children in problem families, long-term unemployed people), providing services in support of psychological, medical, and rehabilitation therapies (e.g., pet-therapy and hippotherapy), participating in projects aiming at promoting environmental and food education, and providing services for the local community (e.g., participating in local markets) [14–17]. As is obvious, many of the social indicators included in the two aforementioned categories are qualitative and subjective in nature, which makes their quantification challenging [12]. Social sustainability indicators are also found in the Corporate Social Responsibility (CSR) literature. CSR indicators that are commonly agreed upon in the CSR literature as important to consider include employment quality, neighborhood and society, future generations, customer responsibility, and human rights [18,19]. Employment quality can be quantified, for example, using measures such as the value of employee benefits, expenditures for employee training [19], and occupational accidents and diseases [20,21]. Indicators related to neighborhood and society include, among others, the number of employees, firm expenditures on family support, and the number of female and disabled workers [19]. Future generation indicators include variables like the number of trainees and the investment in R&D and capital assets. Customer responsibility involves producing value-added and high-quality goods and using complete, consistent, and accurate product labels. Finally, variables related to human rights include the use of child or forced labor, the violation of the freedom of association, etc. Once such social sustainability indicators are available, they can be used as outputs or inputs in (in)efficiency or productivity models. For example, [7,8] used workers' injuries, farmers' satisfaction, and the perceived contribution of their farms to society as (socially desirable) outputs to production, while farmers' working conditions were used as an input to production.

Measuring farmers' social (in)efficiency can give a sense of how a farm is performing in terms of social responsibility, provide a benchmark relative to its peers, and help farmers assess the potential for social efficiency improvement. For a farm to become more socially efficient, greater involvement in socially responsible activities is needed. Such involvement may, on the one hand, increase production costs [22] and, on the other hand, result in significant managerial [23] and financial benefits [24] for the farm. With economics often playing an important, if not the most important, role in farmers' decision-making [25], information on the relation between social efficiency improvement and financial performance could help farmers understand the impact of investing on socially responsible practices on economic outcomes. Such information could, in turn, help farmers determine whether to invest in socially responsible activities or not. There is, however, no empirical evidence on the relation between farmers' social (in)efficiency and financial performance yet, and this study attempts to fill this gap in knowledge. Some evidence on the relation between farm-level social and financial performance is provided by studies that have developed and compared absolute, and not relative as social inefficiency is, measures of economic, social, and environmental sustainability [26–29]. The results of these studies are mixed with some studies that found that social and economic objectives compete with each other [26,27], and others reporting the opposite result [28,29]. While the farm-level studies exploring the relation between social sustainability performance and financial performance are limited, this relationship has been studied more extensively in the corporate context. In a

recent second-order meta-analysis of the relation between corporate social/environmental performance (CSP) and corporate financial performance (CFP), [30] reviewed 25 previous meta-analyses encompassing almost two thousand primary studies and found a highly significant and positive effect on the CSP-CFP relation. The authors also found that the relation is positive regardless of whether firms focus on social or environmental aspects.

To this end, the goal of this study is to measure farmers' social (in)efficiency and assess its effect on farm financial performance. In doing so, it adds to the limited knowledge base on these issues. This work differs from existing farm-level social (in)efficiency studies [7,8] in two ways. First, it measures farmers' social (in)efficiency with respect to employment quality. Second, it models farm (in)efficiency in a dynamic context which accounts for adjustment costs associated with investments in quasi-fixed assets. Ignoring such adjustment costs have been shown to lead to an overestimation of inefficiency [11]. By linking financial and social sustainability performance, this study creates useful information for decision-making related to the engagement in socially responsible activities.

The remainder of this paper is structured as follows. The next section presents the methods used to model farmers' social inefficiency and its relation to farm financial performance. Section 3 presents the data used in this study and discusses empirical issues. Results are presented in Section 4, and conclusions are drawn in Section 5.

2. Methods

2.1. Dynamic Inefficiency Model

Consider a sample of n dairy farms ($i = 1, \ldots, n$) which produce an output y from Q variables inputs, C fixed inputs, a quasi-fixed input K with its associated gross investment I, and a socially responsible input s. Let $y \in R_+$, $x \in R_+^Q$, $L \in R_+^C$, $K \in R_+$, $I \in R_+$, and $s \in R_+$. The production technology of dairy farms in year t can be mathematically characterized by the technology set Ψ_t:

$$\Psi_t = \left\{ (x_t, L_t, K_t, I_t, s_t, y_t) \in R_+^Q \times R_+^C \times R_+ \times R_+ \times R_+ : \; x_t, L_t, K_t, I_t, s_t \; can \; produce \; y_t \right\} \quad (1)$$

It is assumed that Ψ satisfies the standard regularity conditions, such as closedness, convexity, no free lunch, and strong input and output disposability [31]. Given that Ψ is not very helpful from an empirical perspective, it can be expressed by a function representation that is computationally accessible and carries the same assumptions as Ψ. The function chosen here, which provides a primal characterization of Ψ, is the dynamic directional distance function (DDF), defined as

$$\overrightarrow{D}(x, L, K, I, s, y; \; g_y, -g_x, g_I, g_s) = \max_{\beta} [\beta : \; (x, I, s, y) + \beta g \in \Psi] \quad (2)$$

where $g = (g_y, -g_x, g_I, g_s)$ is a directional vector that determines the direction in which $\overrightarrow{D}(\cdot)$ is defined. For notational economy, the time subscript is dropped from Equation (2) and the equations to follow. The dynamic DDF in (2) seeks to simultaneously expand the output, investments, and socially responsible input while contracting the variable inputs. The choice of g is driven by the production technology under investigation. Dairy farmers want to invest more in quasi-fixed inputs, such as machinery and equipment, to improve farm productivity. At the same time, farmers seek to produce the maximum amount of output with the least possible use of variable inputs. As will be discussed in greater detail in the data section, the socially responsible input is defined as the employee benefits a farm offers. It is assumed that dairy farmers want to increase the benefits offered to their employees because (a) WI dairy farmers are competing for competent labor in a tight labor market [32,33], and (b) the provision of increased employee benefits can motivate employees to work harder to achieve farm objectives. The latter reason is in line with the social exchange theory that posits that agents tend to reciprocate when they receive a benefit or favorable treatment from their organization [34,35].

The dynamic DDF in (2) is empirically approximated using data envelopment analysis (DEA). The DEA model of farm i under the assumption of variable returns to scale is given by the following linear programming problem:

$$\vec{D}(x, L, K, I, s, y; \, g_y, -g_x, g_I, g_s) = \max_{\beta_y, \beta_s, \beta_I, \beta_x, \lambda} \{\beta_y + \beta_s + \beta_I + \beta_x\} \tag{3}$$

$$s.t.$$

$$\sum_{i=1}^{I} \lambda_i y_i \geq y_i + \beta_y g_y$$
$$\sum_{i=1}^{I} \lambda_i s_i \geq s_i + \beta_s g_s$$
$$\sum_{i=1}^{I} \lambda_i (I_i - \delta_i K_i) \geq I_i + \beta_I g_I - \delta_i K_i$$
$$\sum_{i=1}^{I} \lambda_i x_{iq} \leq x_{iq} - \beta_{x_q} g_{x_q}, \, q = 1, \dots, Q$$
$$\sum_{i=1}^{I} \lambda_i L_{ic} \leq L_{ic}, \, c = 1, \dots, C$$
$$\sum_{i=1}^{I} \lambda_i = 1$$
$$\lambda_i \geq 0, \, i = 1, \dots, n$$

where $\beta_y, \beta_s, \beta_I$, and β_x are vectors of inefficiency scores of output, socially responsible input, investments, and variable inputs, respectively. The λ_i are the farm weights or intensity variables that define the best practice frontier. The δ_i are the depreciation rates associated with the quasi-fixed input K; as a result, $I_i - \delta_i K_i$ represents net investments. The net investment constraint (i.e., third constraint in (3)) is the one that introduces the dynamics in the model above. This constraint ensures that the technology set accounts for adjustment costs (e.g., search costs for new capital), which are generally assumed to increase with the level of investment. To account for technological change, macroeconomic effects, and changes in the regulatory environment, Equation (3) is estimated separately for each year of data.

In line with [36], the directional vectors, except for g_I, are set equal to the observed values of the corresponding farm-specific variables (i.e., $g_y = y_i, g_s = s_i, g_{x_q} = x_{iq}$). This allows one to interpret inefficiency scores as a percentage of inefficiency. Regarding the directional vector of investments, because investment is highly heterogeneous across the sample farms, g_I was set equal to 20% of the capital stock (i.e., $g_I = 0.2 \times K_i$), which is in line with previous studies (see, e.g., [37]). As a result, investment inefficiency should be interpreted relative to this vector. Moreover, such a vector allows zero values of investment to be accounted for in the estimation [38].

It is worth mentioning here that the DEA model (i.e., Equation (3)) used in the inefficiency analysis avoids some of the pitfalls associated with using parametric techniques for measuring inefficiency (e.g., biases stemming from specifying a functional form of the production frontier). Another advantage of DEA, and more specifically the non-radial slack-based DDF in Equation (3), is that, unlike stochastic frontier models, it enables the calculation of output and input-specific inefficiency scores, allowing for non-proportional changes in inputs and outputs. This feature is important here because our goal is to measure socially responsible input inefficiency, without the need to assume equiproportionate changes in inputs and outputs. However, DEA does not account for statistical noise and is sensitive to the presence of outliers (details about how this study has dealt with the detection and removal of outliers are provided in Section 3).

2.2. Panel Data Regression Analysis of the Effect of Social Inefficiency on Farm Financial Performance

After computing the socially responsible input inefficiency (β_s, hereafter termed social inefficiency) for each farm in the sample, a panel data regression is used to examine how such inefficiency affects farm finances. The panel data model takes the following form:

$$\pi_{it} = \gamma_0 + z'_{it}\gamma + \beta_{sit}\theta + \alpha_i + u_{it} \tag{4}$$

where π is farm financial performance measured by profitability, z_{it} is a vector of control variables that may affect farm profitability, γ_0 (the intercept), γ, and θ are parameters to

be estimated. The α_i term captures the time invariant unobserved heterogeneity between farmers (e.g., managerial ability, motivation, etc.). To determine whether α_i are best treated as fixed or random effects, the Hausman test was used. The u_{it} term is an error term, which is assumed to be homoscedastic and serially uncorrelated. Multiple regression models similar to the one presented above have been used to assess the effect of socioeconomic factors, such as the adoption of recombinant bovine somatotropin [39,40] and discussion group membership [41], on dairy farm profitability.

The effect of social inefficiency on farm financial performance is an empirical question. On the one hand, higher social inefficiency, which implies less expenditures on employee benefits, can increase profits through cost savings. On the other hand, higher social inefficiency can decrease farm profitability through a decrease in labor productivity. For example, providing less employee benefits may decrease workers' motivation to perform their tasks well, leading to a lower output. Another reason why a negative effect of social inefficiency on farm profitability might be observed is that providing less employee benefits may decrease farmers' ability to retain employees, leading to increased recruitment and training costs. Based on interviews with dairy managers in Wisconsin, [33] reports that employee turnover on dairy farms is the biggest cost related to human resource management. This cost is not negligible, with estimates valuing it at a minimum of $2000 to $3000 per employee leaving the dairy operation [33].

At this point, it is worth discussing two issues related to the estimation of Equation (4). First, if profitability and social inefficiency are determined at the same time, the use of social inefficiency as an explanatory variable in Equation (4) may cause a simultaneity bias. As the WI employment law mandates farm employers to disclose in writing the terms and conditions of employment (including employee benefits such as insurance, food, etc.) to workers at the time of recruitment [42], social inefficiency, which is calculated based on employee benefits, and farm profitability are not simultaneously determined. Moreover, as will be seen in the next section, employee benefits do not include benefits that are likely to vary considerably with profitability (e.g., cash bonuses), implying that a simultaneity bias is unlikely to be a concern in this study. Second, the well-known problem of serial correlation among non-parametrically derived efficiency scores [43] is not a problem when estimating Equation (4). This is because, unlike in a second-stage truncated regression of inefficiency determinants where bootstrap is used to correct the serial correlation problem, we use inefficiency scores as an explanatory variable in a model that aims to explain variation in farm profitability and, as a result, the error terms of the estimated equation are not serially correlated. Therefore, there is no need to use a bootstrap technique to estimate Equation (4). This has been recognized in other studies in which nonparametrically derived efficiency scores have been used as an explanatory variable in regression analysis and no bootstrapping has been applied [37,44].

3. Data and Empirical Issues

The empirical application uses panel data of specialized dairy farms in Wisconsin for the years 2007–2017. Wisconsin is in the north-central part of the United States and, in 2019, was the second largest milk producing state in the country, representing 14% of the national milk production [45]. Dairy production was the most important agricultural activity in the state of Wisconsin in 2019, with milk sales totaling $5.7 billion. The data used in this study are provided by the University of Wisconsin–Madison Center for Dairy Profitability and consist of detailed financial statements and performance measures of dairy farms participating in the Agricultural Financial Advisor program. This program allows participating farms (or their advisors) to benchmark their performance against that of other dairies and then identify and adopt the best practice. The initial sample contained 4641 observations of dairy farms. Of the initial data set, 1236 observations were removed because they did not have any non-dependent labor expenses recorded. These farms employed only family labor and, therefore, did not report non-dependent employee benefits, which are necessary for calculating a farm's social inefficiency. Of the

remaining observations, 314 were dropped because they reported zero non-dependent employee benefits. For those observations, it was impossible to determine whether the non-dependent employee benefits were added to the labor expense or were not provided at all (Vanderlin, J., personal communication, 15 July 2020). Observations were also dropped if they had missing data on any of the relevant variables (*n* = 70). Finally, the [46] super-efficiency method was employed to identify and remove the outliers in the data (*n* = 1370). This was done because DEA is particularly sensitive to outliers which can substantially affect the estimated best practice frontier. Unlike DEA, the super-efficiency approach excludes each observation from its own reference set. In line with [46], the cut-off level of 1.2 was used to detect outliers. Observations with performance scores above 1.2 were eliminated from the sample. These restrictions resulted in a final sample of 1651 observations, with 423 distinct farms over the study period. Farms remained in the sample for four years, on average.

The DEA model distinguishes one output, two variable inputs, one quasi-fixed input with its corresponding gross investment, two fixed inputs, and a socially responsible input. The output is the sum of all receipts from the sale of milk, meat, and crops. The two variable inputs are feed expenses and other expenses (e.g., energy payments, contract work payments, crop-specific costs, etc.). The quasi-fixed input is capital, which consists of the beginning-of-the-year value of machinery, equipment, and buildings. As in other studies that have modeled the performance of dairy farms using DEA [47–49], livestock units were not used as separate (quasi-fixed) input to keep the DEA model empirically tractable. To allow for adjustment costs in capital allocation, gross investments in capital assets are considered. Annual gross investment is defined as the end-of-the-year value of capital minus the beginning-of-the-year capital value, plus the depreciation value of capital in the same year. Fixed inputs include land and labor. Land is measured in acres and includes both own and rented land. Labor is the deductible cash money paid to dependent and non-dependent employees. It includes wages, incentives, bonuses, vacation pay, sick pay, etc. Finally, the socially responsible input is defined as the value of non-cash benefits a farm offers to its non-dependent employees. These benefits include medical insurance, retirement contributions, uniforms, food, housing, transportation, etc. The output variable and all monetary inputs were transformed into implicit quantity indices by computing the ratio of value to its corresponding price index (or Törngvist price index in the case of the aggregate output and inputs), with 2010 being the base year. Price indices were retrieved from the National Agricultural Statistics Service [50].

Farm profitability, which is the dependent variable in Equation (4), is defined on a per cow basis as the difference between total farm receipts and total farm expenses. The control variables specified in the z vector of Equation (4) are selected based on data availability and previous research on dairy farmers' profitability [39–41] and include the following: government payments, non-farm income, number of heads, debt-to-asset ratio, and regional dummies. Government payments include all farm government payments received by farmers—not just those related to dairy farming. Non-farm income is the income generated through off-farm employment. Number of heads, which is a measure of farm size, is defined as the number of cows a farm possesses in the beginning of the year, *t*. Finally, debt-to-asset ratio is defined as a farmer's total liabilities normalized by the value of total assets. Regional dummies include North, South, and Central and capture region-specific influences such as infrastructure, soil quality, etc. Descriptive statistics for all the variables employed in this study are shown in Table 1.

Table 1. Descriptive statistics of the study variables (*n* = 1651) for the period 2007–2017.

Variable.	Unit	Mean	Std. Dev.
Output	$1000	1790.174	2184.813
Feed	$1000	488.276	731.102
Other variable inputs	$1000	771.084	925.611
Land	acres	709.654	554.098
Labor	$1000	174.499	224.095
Capital	$1000	800.061	1284.790
Net investment	$1000	50.470	343.664
Depreciation	$1000	191.327	253.864
Employee benefits	$1000	33.252	39.040
Farm profit	$/cow	583.161	808.525
Number of head	count	330.040	400.151
Debt-to-asset ratio	ratio	0.333	0.254
Non-farm income	$1000	18.109	63.165
Government payments	$1000	20.316	26.629
South	(0/1)	0.207	0.405
North	(0/1)	0.748	0.434
Central	(0/1)	0.041	0.197

Sample farmers had an average of $1.8 million in annual sales. Their average herd size was 330 cows, which is more than double the average herd size of WI dairy farms in 2017 (i.e., 142 cows) [51]. Feed costs with an average of almost $500 thousand per year, accounted (on average) for around 53% of the sample farmers' total annual production expenses (i.e., feed costs, expenses on other variable inputs, and employee wages and benefits). Farmers in this sample had, on average, about $800 thousand worth of capital, and their average annual net investment on capital assets was $50 thousand. The same farmers spent annually, on average, about $33 thousand on employee benefits, which accounted for around 16% of total labor costs (i.e., wages and benefits). Figure 1 shows the evolution of the average value of employee benefits of the sample farms during the 2007–2017 period. The mean value of employee benefits almost doubled during this period, from $26,175 in 2007 to $48,581 in 2017. The sharpest increase is observed for the 2014–2017 period. Competition for labor in a tight labor market coupled with relatively high employee turnover rates may explain these findings [32,33]. As [33] notes, the rural workforce has declined in most Wisconsin counties, and immigrant labor is now fully employed. As a result, competition for labor has increased, and Wisconsin dairy farmers (who face relatively high employee turnover rates [33]) have become more creative in terms of recruitment and retention strategies. One of these strategies may be increasing employee benefits. Finally, the average annual profitability of the sample farms was $583 per cow. The same farms earned an off-farm and subsidy income of $18 and $20 thousand, respectively, and most of them were in Northern Wisconsin.
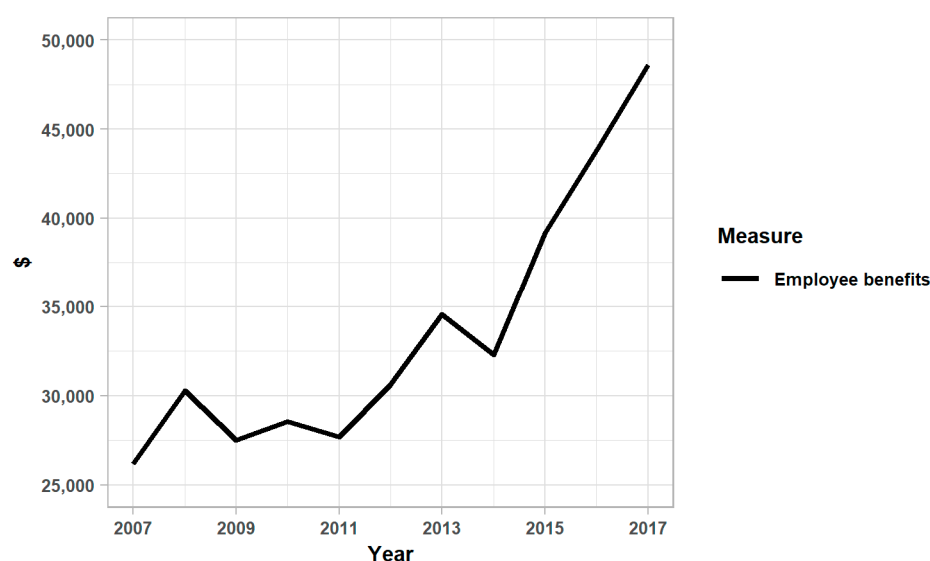
Figure 1. Mean employee benefits of the sample farms for the period 2007–2017.

4. Results and Discussion

4.1. Dynamic Inefficiency Estimates

Table 2 presents the sample farms' average output dynamic inefficiency and the dynamic inefficiencies associated with each input. Average inefficiency scores are presented for each sample year, as well as over all years. Results show that, over the entire study period, sample farms could have increased their output, investments, and socially responsible input by an average of 1.1%, 73.2% (3.66 × 0.2 × 100), and 13.9%, respectively, while reducing their feed and other variable input costs by 3% and 3.6%, respectively. The high average values of dynamic investment inefficiency (i.e., average scores between 1.8 and 5 over the different years) reflect the heterogeneity of the investment variable. The fact that some sample farms choose not to invest or invest little in farm capital assets while others invest heavily in such assets may explain some of the large investment inefficiency scores.

Table 2. Average dynamic inefficiency estimates of the sample farms, 2007–2017.

Year	Output	Feed	Other Variable Inputs	Investments	Socially Responsible Input
2007	0.008	0.032	0.008	2.490	0.121
2008	0.003	0.040	0.022	4.644	0.153
2009	0.017	0.067	0.038	4.088	0.205
2010	0.003	0.018	0.052	3.438	0.107
2011	0.003	0.030	0.029	1.825	0.189
2012	0.004	0.018	0.049	4.147	0.107
2013	0.005	0.010	0.032	4.071	0.092
2014	0.018	0.010	0.037	2.472	0.094
2015	0.062	0.051	0.079	3.555	0.147
2016	0.000	0.020	0.029	5.011	0.122
2017	0.002	0.030	0.022	4.521	0.197
2007–2017	0.011	0.030	0.036	3.660	0.139

Figure 2 shows histograms for the different types of dynamic inefficiency. All histograms exhibit the typical right skewed pattern. Most of the farms have low or zero dynamic inefficiency, whereas no or very few farms have very high inefficiency. Regarding social inefficiency, 131 observations have inefficiency scores over 0.5. These farms would need to expand their employee benefits significantly to reach the best practice frontier.
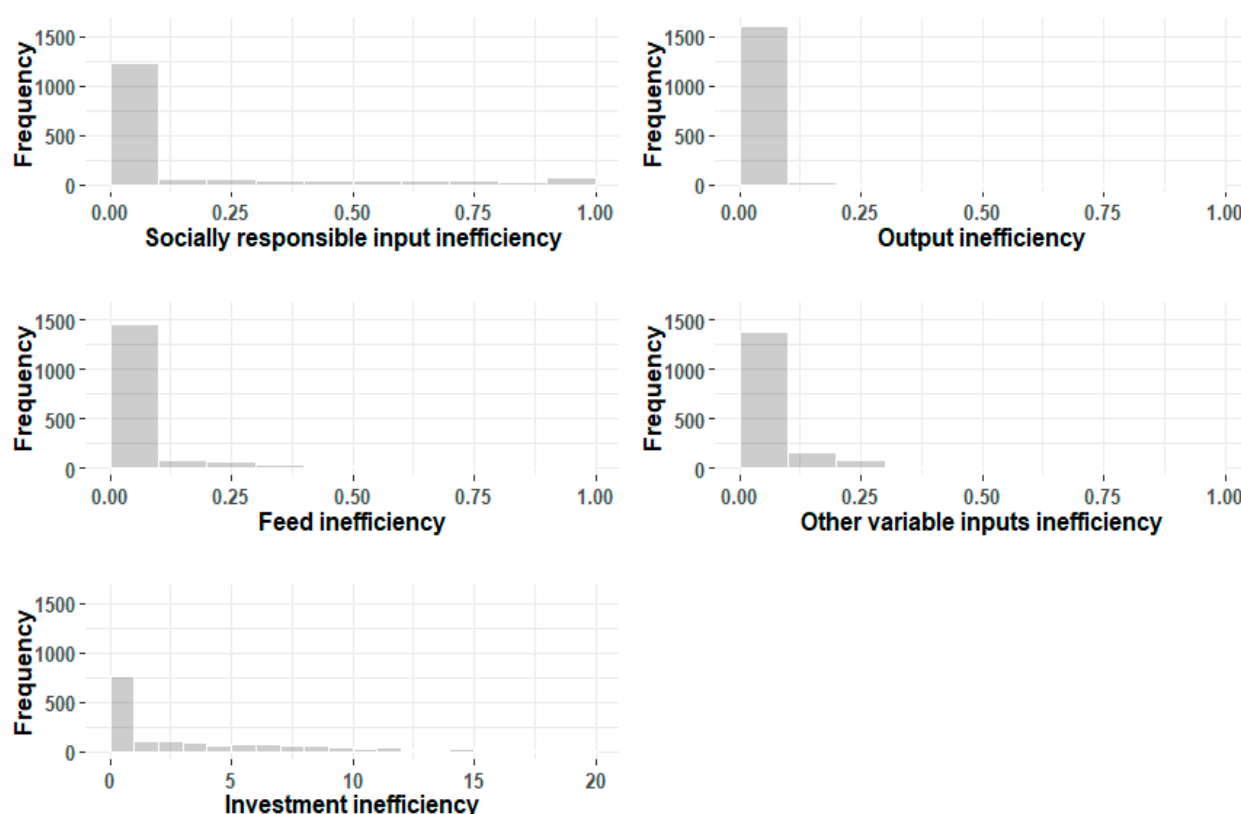
Figure 2. Histograms for the different dynamic inefficiency scores of the sample farms over the 2007–2017 period.

The number and percentage of efficient and inefficient farms in each input and output are shown in Table 3. With 58% of the farms being inefficient in the investment dimension, investment in capital assets is the largest source of inefficiency for the farms under investigation. The second and third largest sources of inefficiency are the socially responsible input and other variable inputs, with 29% and 27% of the sample farms being inefficient, respectively. These results are in line with the findings in Table 2.

Table 3. Efficient and inefficient farms across the different inefficiency dimensions.

	Inefficient Farms		Efficient Farms	
	Count	**%**	**Count**	**%**
Output	123	7	1528	93
Feed	307	19	1344	81
Other variable inputs	438	27	1213	73
Investments	965	58	686	42
Socially responsible input	481	29	1170	71
Output and all inputs	976	59	675	41

A comparison of our inefficiency results with those of previous inefficiency studies in Wisconsin dairy farming should be made with caution due to differences in methods and periods of study. For example, [52–55] reported an (average) output inefficiency of Wisconsin dairy farms in the range of 6–14%, which is higher than the respective value found in the present study. These studies used stochastic frontier analysis to compute inefficiency, and, unlike our study, did not account for production dynamics and farmers' engagement in socially responsible activities. In another study from Wisconsin dairy farming, [49] used DEA to compute the dynamic overall, and not output and input-specific (as in the present study), technical inefficiency and found it to be 12%, on average.

4.2. The Effect of Social Inefficiency and Control Factors on Farm Profitability

Table 4 presents the results of the panel data regression of profitability on social inefficiency and control variables. The Hausman test failed to reject the null hypothesis (that a random-effects model was consistent) at the 5% level, implying that the random-effects model was the preferred specification. Therefore, the results presented in Table 4 are those of the random-effects model. Results suggest that socially inefficient farms are less profitable. More specifically, it was found that an increase in farmers' social inefficiency by one percent led, on average, to a $153 decrease in farm profit per cow. A possible explanation for this finding is that farm workers are less motivated to perform their tasks efficiently when the farm invests less in socially responsible employment practices. Decreased labor productivity can, in turn, increase farm operation costs and even result in lower output yields and prices, all of which reduce farm profitability. For example, a poor implementation of hygienic practices, such as the proper cleaning of milking equipment and washing the milkers' hands, may increase mastitis infection in dairy herds. This, in turn, may translate into higher expenditures for drugs and veterinary services, milk yield losses, and price penalties imposed by milk buyers. Another potential explanation for the negative effect of social inefficiency on farm profitability is that more socially irresponsible farms are less able to maintain skilled labor and thus have higher employee turnover costs (e.g., the cost of hiring and training new workers). The same magnitude of coefficient (and significance level) is obtained when using social efficiency (i.e., $1 - \beta_{sit}$) instead of inefficiency in the panel data regression of profit. However, the sign of the respective estimate is reversed (see Appendix A, Table A1), meaning that a higher social efficiency increases farm profitability. This result implies that improving farm employees' welfare by providing more employment benefits can improve farm finances. It further suggests that financial and social objectives are not in conflict with each other but can be achieved simultaneously. This implication is in agreement with findings by [28] for dairy and tillage farms in Ireland, and by [29] for vegetable family farms in southeast Spain.

Table 4. Results of the random-effects panel regression of the determinants of farm profitability.

	Coefficient	Standard Error
Social inefficiency	−153.407 **	66.186
Number of head	−0.043	0.075
Debt-to-asset ratio	−898.576 ***	97.925
Non-farm income	−0.764 ***	0.285
Government payments	−4.289 ***	0.720
South	−256.583 **	124.378
North	−267.106 **	114.61
t	−15.184 **	6.069
t^2	−11.409 ***	2.065
_cons	1357.776 ***	119.327
Wald X^2	203.030 ***	-

Note: The dependent variable is profit per cow. t denotes a time trend. ***, and ** denote that the coefficient is significant at the 1%, and 5% level, respectively.

Regarding the impact of the control variables on farm profitability, higher debt-to-asset ratio, increased off-farm income, and a higher amount of government payments received all decrease farm profitability. More indebted farms may be unable to access further credit when it is needed [56,57], especially in response to new economic and technological conditions, resulting in missed investment opportunities that could have improved farm economic performance. On the other hand, higher debt is often indicative of farms that have recently borrowed to invest in new farm technologies that increase farm productivity. The former effect dominated in the present case. Moving to the effect of off-farm income, a higher off-farm income may imply less time for farming activities, which may lead to inefficiencies in production. Moreover, as [58] pointed out, spending less time on the farm may cause farmers to fall behind with new agricultural technologies and miss out

on innovations that can improve farm performance. Regarding the negative effect of government payments on profit, farmers receiving higher amounts of such payments may substitute market income with subsidy income and invest less effort in improving farm productivity and profitability [6]. The number of heads, a farm size indicator, was found to have a statistically insignificant effect on profitability. This result contrasts with previous studies that report a positive and statistically significant association between herd size and profitability [40,41]. The results of the regional dummy variables show that the sample farms located in southern and northern Wisconsin were less profitable than the sample farms located in central Wisconsin. Finally, farm profitability was found to decrease with time, but at a decreasing rate.

5. Conclusions

This study extends the literature on the measurement of farm social (in)efficiency by computing farmers' social inefficiency with respect to their contribution to socially responsible employment practices. This contribution is measured as the value of employee benefits provided to non-dependent workers. A nonparametric dynamic directional distance function approach accounting for adjustment costs in quasi-fixed inputs was used to model social inefficiency along with technical input and output inefficiency. After computing farms' social inefficiency, a panel data regression was used to examine the relationship between social inefficiency (and control factors) and farm financial performance, measured by profitability. The empirical application focuses on a sample of Wisconsin dairy farms observed during the period 2007–2017.

The results show that the average social inefficiency of the sample farms was about 14%, implying that these farms could have become more socially efficient or responsible had they increased their non-wage contributions to non-dependent employees by 14%, on average. Increasing employee benefits will not only help sample farmers to become more socially efficient but may also help them to recruit and retain employees, leading to decreased turnover costs, which are known to be significant in Wisconsin dairy farming. Results further show that social inefficiency was not the main source of dynamic inefficiency for the sample farms. Most dynamic inefficiency was observed in capital-related investment and is attributed to large differences in investment strategies of the sample farms.

The findings of the panel data regression model show that an increase in social (in)efficiency is associated with (lower/)higher farm profitability. Workers reciprocating a rise in employee benefits with increased effort may explain such a finding. This argument is in line with the social exchange theory, which argues that when an employer provides a benefit or reward to its employees, the latter will reciprocate by devoting more effort for the benefit of the employer. Improving farms' overall sustainability requires meeting economic, environmental, and social goals simultaneously. By showing that higher social efficiency is related to higher farm profitability, this study demonstrates that farmers can meet social sustainability goals without compromising their financial performance.

This research on social (in)efficiency assessment and its relation to profitability has focused on a single state and a single type of farming. Future research could extend this work by exploring whether similar results would be observed in different states or countries where cultural, social, and economic differences can affect farmers' engagement in socially responsible practices, and different types of farms.

Appendix A

Table A1. Results of the random-effects panel regression of the determinants of farm profitability-social efficiency as a determinant of profitability.

	Estimate	Standard Error
Social efficiency	153.407 **	66.186
Number of head	−0.043	0.075
Debt-to-asset ratio	−898.576 ***	97.925
Non-farm income	−0.764 ***	0.285
Government payments	−4.289 ***	0.72
South	−256.583 **	124.378
North	−267.106 **	114.61
t	−15.184 **	6.069
t^2	−11.409 ***	2.065
_cons	1204.369 ***	133.62
Wald X^2	203.03 ***	

Note: The dependent variable is profit per cow. t denotes a time trend. ***, and ** denote that the coefficient is significant at the 1%, and 5% level, respectively.

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