Received: 18 August 2021 | Accepted: 10 December 2023

DOI: 10.1111/1467-8489.12553

ORIGINAL ARTICLE

The Australian Journal of Agricultural and Resource Economics AARES

The role of hired labour on technical efficiency in an expanding dairy sector: The case of Ireland

Luis Garcia-Covarrubias[1] | Doris Läpple[2] | Emma Dillon[3] | Fiona Thorne[3]

[1]JE Cairnes School of Business and Economics, University of Galway, Galway, Ireland

[2]Economics of Sustainable Agri-Food Systems, Department of Agricultural Economics and Rural Development, Faculty of Agricultural Sciences, University of Göttingen, Göttingen, Germany

[3]Rural Economy and Development Programme, Athenry, Ireland

Correspondence
Luis Garcia-Covarrubias, Department of Economics, J.E. Cairnes School of Business & Economics, University of Galway, 49 Upper Newcastle, Galway, H91 YK8V, Ireland.
Email: luis.garcia@universityofgalway.ie

Funding information
Teagasc

Abstract

The 2015 EU milk quota abolition initiated considerable expansion in the dairy sector. This expansion has increased the demand for additional labour in some EU countries, most significantly in Ireland. This paper explores the role of hired labour on Irish dairy farms' technical efficiency (TE). We use a detailed farm-level panel data set of a representative sample from 2000 to 2018. To estimate transient, persistent, and overall TE over time, we apply a 4-component stochastic frontier model. Our findings show significant variation in TE scores over the period. We also control for endogeneity to obtain marginal effects of hired labour on TE. The results reveal that hired labour has a significant yet small, positive effect on farms' TE. Our findings suggest that the effect of hired labour on TE is larger for small and medium-sized farms. This effect is larger when herd size increases.

KEYWORDS

dairy, efficiency, labour, production economics, transient and persistent efficiency

JEL CLASSIFICATION

D00, C01, Q10, Q12, Z22

1 | INTRODUCTION

The European dairy sector has experienced significant structural change initiated by the abolition of milk quotas in 2015. While some countries experienced contraction of their dairy sector, for example Bulgaria and Romania, other member states have expanded their milk production, most significantly the Netherlands and Ireland (Augère-Granier, 2018; EU-FADN, 2018). Understandably, these differing developments in overall dairy production across countries have led to changes in labour demand on individual farms due to adjustments in production (Kelly et al., 2020; Kimhi, 2009).

Ireland is one of the countries that has experienced significant growth in its dairy sector initiated by the EU milk quota abolition. Specifically, between 2008 and 2018, the volume of milk produced has increased by over 50% (CSO, 2020). As the majority of dairy farms in Ireland are family farms (i.e., 99%) (EuroStat, 2018), a significant concern arises from the mismatch of increasing herd size and labour availability (Deming et al., 2018; Kelly et al., 2020). Indeed, the increase in herd size and labour on dairy farms has been quite uneven (Dillon et al., 2019; Kelly et al., 2020). Average herd size increased by 47% but total labour hours only by 16% between 2008 and 2018 (Donnellan et al., 2020). This may suggest that additional labour is required to achieve sustainable growth, as studies reveal high stress levels due to increased workload by Irish dairy farmers (Brennan et al., 2022; Kelly et al., 2020). Although family labour may be a temporary relief to labour shortages, the structural change leading to significant growth in average herd size requires additional non-family labour (Kelly et al., 2020; Thorne et al., 2017). Often, when farms grow, family labour is used more intensively first, but for continued expansion, farms need additional hired labour to meet the increasing workload (Blanc et al., 2008).

Irish dairy farming is characterised by a spring calving pasture based system, due to a mild and rainy climate in Ireland suitable for growing grass for most of the year. While this gives the Irish dairy sector a comparative advantage in producing milk (Läpple & Hennessy, 2012; Thorne et al., 2017), the downside of such a production system is an uneven demand for labour throughout the year. Demand for labour peaks from February to June when calving and breeding takes place (Dillon et al., 2019). These months represent half of the annual workload on Irish dairy farms (Deming et al., 2018; Dillon et al., 2019), and make sourcing additional labour more challenging.

Thus, due to the significant production expansion coupled with seasonal production, the role of hired labour (i.e., permanent and seasonal) has become crucial. However, an additional challenge relates to sourcing workers that have adequate skills to conduct the required tasks on the farm. Anecdotal evidence suggests that it is not easy to source such labour, but some programmes exist to facilitate access (Kelly et al., 2017). This challenge also relates to technology improvements (Kelly et al., 2020; Kimhi, 2009). For instance, investment in machinery, livestock and buildings on dairy farms increased on average by 36% from 2008 to 2018 (Dillon et al., 2019). On top of the general challenge of labour availability, the need for skilled labour has become an extra hurdle for dairy farmers.

In addition, farmers can be hesitant to hire labour. For instance, in 2018, only 11% of dairy farmers stated that they plan to hire extra labour within the next 5 years (Dillon et al., 2019). However, 34% of farmers plan to expand their production in the same period, but only 7% of those who plan to expand their production also plan to hire more labour. Exploring this data in more detail reveals that most farmers (i.e., 71%) also have no plans to invest in labour-saving technologies. This data suggests that farmers are reluctant to hire additional labour. This decision may be driven by the belief that family labour is more suitable for their farm. This belief goes hand in hand with anecdotal evidence suggesting a reluctance to delegate work to non-family labour on the farm. Given that the increased workload associated with larger herds has become a significant source of stress for Irish farmers (Brennan et al., 2022; Kelly et al., 2020), indicates that this is a topic that needs urgent attention. Therefore, in this paper, we explore the role of hired labour on technical efficiency on Irish dairy farms.

The literature highlights the importance of hired labour in estimating farms' technical efficiency (TE) (Devadoss & Luckstead, 2018; Kostov et al., 2019). However, very few studies focus on the direct role of hired labour on TE, but rather focus on other determinants of TE, e.g., off-farm work, farm size, subsidies, or direct costs (e.g., Carroll et al., 2011; Martinez-Cillero et al., 2019; Wollni &

Brümmer, 2012). This paper explores the role of hired labour on farms' TE in a family farming context. We consider it important to address the role of hired labour on TE. Since TE is about "doing things right", a positive role of hired labour on farms TE may suggest that hired labour is suitably skilled and equipped to improve farm efficiency (Kostov et al., 2019). This result would indicate that hired labour can assist in meeting some of the challenges posed by production expansion in the aftermath of milk quota abolition and assist in reducing farmers' hesitancy towards hiring labour.

In our analysis, we use a representative panel data sample of Irish dairy farms from 2000 to 2018. The period under investigation includes a significant agricultural policy change, i.e., milk quota abolition, which led to increased production, larger farms, and higher demand for additional labour. Therefore, it is essential to acknowledge the relevance of time when estimating the role of hired labour on TE.

Since TE may have short (i.e., transient) and long-run (i.e., persistent) components over a long period, splitting the efficiency term according to a farms' transient and persistent TE may also have important policy implications. For example, consideration could be given to when TE is associated with (unobserved) management, which is assumed to be time-invariant. Consequently, TE will also be time-invariant, at least in part. More realistically, if we assume management changes over time, it will have a time-invariant and a time-varying component. If TE is associated with management, we have a situation in which TE has a time-invariant and a time-varying component (Tsionas & Kumbhakar, 2014). This illustrates time-invariant and varying determinants that influence farms' TE (Lai & Kumbhakar, 2018; Tsionas & Kumbhakar, 2014). Recognising this difference, we estimate transient and persistent TE for Irish dairy farms considering the importance of time and the time-varying property of hired labour in TE estimation. Finally, we analyse dairy farms' TE during three distinct stages of EU milk quota abolition since the difference in TE scores can result in varying policy implications over a long period. These relate to the quota (2000–2007), soft landing (2008–2014), and post-quota periods (2015–2018).

This paper offers two explicit contributions to the existing literature. First, we explore the effect of hired labour on TE in a predominantly family farming context, which has —to the best of our knowledge— not been explicitly studied before. As outlined above, the significant structural change initiated by EU milk quota abolition led to increased demand for hired labour. However, due to uncertainty about sourcing and quality of hired labour, the effect on farm economic efficiency is unknown at present. This study aims to fill this knowledge gap. Second, on the methodological side, following Lien et al. (2018), we apply a state-of-the-art stochastic frontier (SF) model that accounts for endogeneity, a problem frequently disregarded in the SF literature (Badunenko & Kumbhakar, 2017; Lai & Kumbhakar, 2018). This enables us to get consistent estimates of all parameters that we report.

The paper proceeds as follows. The following section provides background information about the Irish dairy sector—Section 3 reviews relevant literature on labour and TE in agricultural economics and transient and persistent TE literature. Section 4 describes the methodology, while Section 5 explains the data and the empirical specification. Section 6 presents and discusses the results, while Section 7 offers concluding remarks.

2 | BACKGROUND

Due to the temperate climate in Ireland, the Irish dairy sector is a pasture-based production system, which allows for the outdoor grazing of cows for most of the year (Läpple & Hennessy, 2012). This competitive advantage makes Irish dairy farms the second-lowest cash-cost production system in the EU, surpassed only by Belgium (Kelly et al., 2020; Thorne et al., 2017). Against this backdrop, the Irish dairy sector experienced significant change initiated by EU milk quota abolition.

The EU milk quota system was introduced in 1984 and constrained milk production growth for over 30 years. The European Common Agricultural Policy (CAP) Mid-Term Review discussed abolishing EU milk quotas in 2003. However, it took until the 2008 CAP Health Check to confirm its abolition in 2015. Thus, the elimination of milk quota was a gradual process. For instance, the EU implemented increases in milk quota of 1 to 1.5% annually between 2008 and 2014 (known as the soft landing period). In 2008, the Irish government set a target to increase milk production volume by 50% by 2020 compared to the 2007–2009 base (Kelly et al., 2020; Läpple & Hennessy, 2012). The Irish dairy sector exceeded this target 2 years ahead of time in 2018 (Kelly et al., 2020).

Needless to say, this major growth in milk production initiated significant changes at the individual farm level that posed challenges to farmers. Due to these recent adjustments in the dairy industry, one of the main challenges for the predominantly family farm dairy sector is the availability of skilled labour (Kelly et al., 2020). To overcome this problem, some programmes have been implemented to facilitate farmers' access to hired labour (Kelly et al., 2017). For instance, Farm Relief Services (FRS) is a farmer-owned cooperative that provides skilled labour to meet farmers' labour requirements (FRS, 2020). In addition, the Macra Land Mobility Service (MLMS), a farmer collaborative enterprise, aims to ease increased workload on dairy farms (MLMS, 2021). Labour shortages are seen as a major stress factor (Kelly et al., 2017) and, despite these programmes, in 2018, around 36% of dairy farms did not employ hired labour (Donnellan et al., 2020).

3 | LITERATURE

3.1 | Labour and TE in agricultural economics

While TE in agriculture has received significant attention in the literature (e.g., Aigner et al., 1977; Battese & Coelli, 1992; Martinez Cillero et al., 2021; Sabasi et al., 2019), few studies examine the role of hired labour on TE. One aspect of the literature focuses on contrasting farms' TE between family and corporate farms, i.e., those managed by hired labour (Kostov et al., 2018). Empirical studies often neglect the direct role of hired labour in family farms' TE. Kloss and Petrick (2018) analyse hired and family labour productivity in panel data across eight EU countries. Their results suggest that hired labour is more productive than family labour in countries characterised by family farms, i.e., France, West Germany, and Poland (Kloss & Petrick, 2018). They find the opposite result in the UK sample. This conflicting result may be due to the prevalence in the UK of smaller farms where farmers supervise paid and unpaid labour (Kloss & Petrick, 2018). In a cross-sectional sample, Kostov et al. (2019) analyse the comparative TE of family and corporate farms in four EU countries, i.e., the Czech Republic, Hungary, Romania and Spain. Their findings suggest that family farms have higher TE due to better motivation and lower management costs. However, if family labour involvement is low, family farms do not compare favourably to corporate farms' TE. Also, their results suggest that insufficient managerial capabilities limit family farms' output potential (Kostov et al., 2018, 2019). Hence, from these studies, the specific role of hired labour on farms' TE remains ambiguous.

In a slightly different context, several studies explore the role of labour allocation decisions on farms' TE. For instance, on US dairy farms, studies find a negative and significant correlation between off-farm work and TE (Fernandez-Cornejo et al., 2007; Sabasi et al., 2019). However, in a sample of Slovenian dairy farms, the results of Bojnec and Ferto (2013) suggest the opposite correlation. Using a sample of Spanish dairy farms, Alvarez et al. (2008) conclude that farms with labour-saving technologies are closer to their production frontier.

Several studies explored TE on Irish dairy farms. For example, Kelly et al. (2012) and Kelly et al. (2013) used a representative sample of farms to calculate TE and found TE scores between 76%–83%. Factors such as breeding season length, milk quality, discussion group membership, and soil quality are associated with TE. Moreover, high labour intensity correlates with optimal scale. Carroll et al. (2011) apply SFA to a panel of a representative sample of Irish dairy farms and show that efficiency levels correlate with extension use, soil quality, farm size, and the level of dairy specialisation. Bradfield et al. (2021) estimate an SFA for a cross-section of Irish dairy farms from 2014 to explore the correlation of land fragmentation with TE. They found an average TE score of 91% for dairy farms in their sample. Higher TE levels correlate with increased parcel area, reduced travel distances, contact with advisory services, and intensive practices (Bradfield et al., 2021). Similarly, in a large panel (1975–2012), Gillespie (2015) applied SFA and found that Irish dairy farms have been efficient over the observed 40 years. In summary, previous studies find that Irish dairy farms are highly technically efficient.

3.2 | Transient and persistent TE

Transient and persistent TE was first introduced by Kumbhakar and Heshmati (1995). However, the authors neglected firm effects and assumed that the time-invariant component is due to persistent TE (Agasisti & Gralka, 2019). This drawback was solved by Colombi et al. (2014), Kumbhakar et al. (2014), and Tsionas and Kumbhakar (2014). They developed a novel approach that resulted in a four-way error component model, i.e., latent heterogeneity of firms, transient and persistent TE, and random shocks. The model is known as the homoscedastic Generalised True Random Effects (GTRE) (Tsionas & Kumbhakar, 2014).

Since the development of the persistent and transient TE model, only a few empirical applications are available in the agricultural economics literature. For example, Kumbhakar et al. (2014) apply the model to a panel data set of Norwegian grain farms. They benchmark the model to previous panel SFA approaches, finding that efficiency results are sensitive to model specifications. The variability of the results demonstrates the difficulty in 'correctly' measuring efficiencies (Kumbhakar et al., 2014: p. 335). They suggest that the model selection for the empirical estimation of TE scores should rely on a comprehensive understanding of the data's institutional and production environment (Badunenko & Kumbhakar, 2016; Kumbhakar et al., 2014).

Following transient and persistent TE, Badunenko and Kumbhakar (2016) use, among other panel sets, the Spanish dairy farm data from Alvarez et al. (2008). They find that not accounting for transient and persistent TE leads to an underestimate of overall TE. Additionally, they show that persistent and transient TE are more accurate in data sets where the time series is small and the number of firms is large. Another example is Pisulewski and Marzec (2019) who analyse a panel of Polish crop farms. They conclude that agricultural policy should focus on factors assumed to influence transient inefficiencies, e.g., adopting new technologies, managerial skills, grants and subsidies, or seasonal hired labour. These applications, along with the GTRE model's estimation through a one-step maximum likelihood approach in Filippini and Greene (2016), have the drawback that only unobservable factors determine transient and persistent TE.

3.3 | Endogeneity in transient and persistent TE models

SFA endogeneity is a common problem when determining TE terms (Baležentis & Sun, 2020; Battese & Coelli, 1995; Lai & Kumbhakar, 2018). However, in the standard GTRE model, endogeneity of TE components is not considered due to the assumptions of homoscedasticity in the error term. Therefore, transforming the homoscedastic composed error term in the GTRE model to heteroscedastic is the key to address the endogeneity in the model. Not addressing endogeneity in the GTRE model leads to biased output elasticities in the production function, an underestimation of TE scores, and the impossibility of specifying efficiency drivers (Lai & Kumbhakar, 2018; Lien et al., 2018). This shortcoming was solved by Badunenko and Kumbhakar (2017), Lai and Kumbhakar (2018), Lien et al. (2018), and Baležentis and Sun (2020).

Badunenko and Kumbhakar (2017) apply a heteroscedastic GTRE to a sample of Indian financial banks. Their model is a one-step maximum likelihood approach to allow TE's determinants. Lai and Kumbhakar (2018) propose a one-step approach to specify inefficiency determinants to a dataset of U.S. power plants. Within the agricultural economics literature, Lien et al. (2018) propose a multi-step approach to specify a heteroscedastic GTRE model that allows for determinants of transient TE. They apply the model to a sample of Norwegian crop-producing farms. The main advantage of the multi-step approach of Lien et al. (2018) is that the production parameter estimates are not biased by distributional assumptions which are central to a one-step procedure. Finally, another method to address endogeneity in the GTRE model is the approach taken by Baležentis and Sun (2020). They apply a semi-parametric framework using an input distance function method, which represents the frontier (Levinsohn & Petrin, 2003; Shee & Stefanou, 2015), and transform the composed error term as a function of environmental variables in a Lithuanian dairy farms sample.

In the empirical analysis below, we focus on the role of hired labour on farms' transient TE. To do so, we address the endogeneity between inputs and the GTRE's error term to estimate the marginal effects of hired labour in transient TE (Lien et al., 2018). This allow us to explore the relationship between hired labour and dairy farms' TE in a predominantly family farming context.

4 | METHODOLOGY

SFA is a widely implemented frontier estimation method to obtain TE measures. However, in SFA endogeneity arises when inputs are also determinants of TE (Kumbhakar & Lovell, 2003; Kumbhakar et al., 2015), but this problem is often ignored in TE analyses (Lai & Kumbhakar, 2018; Lien et al., 2018). We address this problem by estimating a GTRE model (Kumbhakar et al., 2014) that controls for endogeneity between inputs and TE drivers following a method outlined by Lien et al. (2018). By doing so we estimate the latent heterogeneity of Irish dairy farms, as well as transient, persistent, and overall TE scores. We also estimate the corresponding marginal effects of transient TE's determinants following Wang and Schmidt (2002) and Wang (2005).

4.1 | GTRE addressing endogeneity

The Lien et al. (2018) method is an updated version of Kumbhakar et al. (2014) homoscedastic GTRE model. In the approach of Lien et al. (2018) the transient technical inefficiency (i.e., the flip side of TE) component is not homoscedastic. Its mean and variance are a function of inefficiency determinants that are time-variant (Musau et al., 2021). Thus, the transient inefficiency component becomes heteroscedastic using the Lien et al. (2018) approach. We keep the distributional assumptions of the persistent inefficiency term and random shocks as homoscedastic.

Following Kumbhakar et al. (2014), we define a Cobb–Douglas (CD) production function as follows[1]:

[1]The CD production function has some limitations regarding its strong assumption on the constant returns to scale and constant elasticity of factor substitution. A translog production function may be preferred if there is a need to relax the assumptions of constant returns to scale and constant elasticity of substitution. Therefore, we also estimated a translog production function, a more flexible functional form (Kumbhakar, 1990; Kumbhakar et al., 2015). However, the translog function model did not produce converged results. Moreover, the GTRE heteroscedastic model we apply assume constant returns to scale (Lien et al., 2018); therefore, the CD function is the best production alternative.

$$y_{it} = \sum_{j=1}^{X} \left(\beta_{ji} x_{jit}\right) + A_{it}, \tag{1}$$

where y_{it} is output for farm i in time t. X is the number if inputs, x_{jit} is the input j for farm i at time t. for the production function ($i.e.,\sum_{j=1}^{X}\left(\beta_{ij}x_{jit}\right)$). The composed error term (A_{it}) includes the latent heterogeneity of farms, persistent and transient inefficiency, and random shocks. The GTRE model by Kumbhakar et al. (2014) is homoscedastic; that is, all the A_{it} components are assumed to be random, independent, and identically distributed (i.e., *iid*) (Colombi et al., 2014; Filippini & Greene, 2016).

As mentioned, endogeneity in the GTRE model is resolved by transforming the composite error term from homoscedastic to heteroscedastic. The Lien et al. (2018) approach resolves this endogeneity in two main steps. First, the approach focuses on the assumptions related to the production function specification that builds the frontier allowing for efficiency drivers in the composed error term. Second, it focuses on the empirical specification of the production function using a semiparametric approach (Lien et al., 2018; Musau et al., 2021; Skevas & Skevas, 2021).

4.1.1 | Production function assumption and composed error term

To allow for determinants of technical inefficiency, Lien et al. (2018) propose a multi-step approach where the transient technical inefficiency term is a function of time variant observable determinants. Following Lien et al. (2018), we rewrite Equation (1) as:

$$\tilde{y}_{it} = \beta_0' + \sum_{j=2}^{J} \beta_j' \tilde{x}_{jit} + A_{it}, \tag{2}$$

where $\tilde{y}_{it} = \ln\left(\frac{y_{it}}{x_{1it}}\right)$ is the natural logarithm of the ratio of the dependent variable for the *ith* farm in time t and input x_1. $\tilde{x}_{jit} = \ln\left(x_{jit}/x_{1it}\right)$, $j = 2, \ldots, J$ is the natural logarithm for the ratio of each input in the production function to input x_1, β_0' is a parameter to be estimated. And A_{it} is the estimated error term that includes four components (i.e., latent heterogeneity of farms, transient and persistent inefficiency, and random shocks).

A fundamental assumption of the Lien et al. (2018) model is that producers maximise the return to outlay (i.e., total revenue divided by total cost). In this way, everything that may affect the error term of the equation will affect the independent side of the equation by the same magnitude allowing both inputs and outputs to be correlated with the composed error term (i.e., inefficiency and random shocks) (Lien et al., 2018; Musau et al., 2021; Skevas & Skevas, 2021). In addition, the Lien et al. (2018) approach by construction assumes degree one homogeneity in the production function.[2]

The standardisation carried out to $\sum_{j=1}^{X}\left(\beta_{ji}x_{jit}\right)$ in Equation (1) by input x_1 allows the modified regressors ($\tilde{x}_{jit}$) in Equation (2) to be independent from the composed error term (A_{it}). In other words, any random element of A_{it} that is correlated with some element from $\tilde{x}_{jit}$ affects the output variable and input ratios in Equation (2) ($i.e.,\tilde{y}_{it};\tilde{x}_{jit}$) by the same magnitude; therefore, the input ratios ($\tilde{x}_{jit}$) are now independent from A_{it}. Therefore, the production function in Equation (2) is homogeneous of degree 1 in inputs (Lien et al., 2018; Musau et al., 2021).

The assumption that farmers maximise return to outlay is a common simplifying assumption in economic models. Although this assumption has its advantages, as any other

[2]This degree 1 homogeneity means that the returns to scale are constant by model construction (Lien et al., 2018).

economic behavioural assumption (i.e., product/profit maximisation), it may not capture the full range of factors influencing farmers' decisions (Brown et al., 2021; Weersink & Fulton, 2020).[3] In practice, Irish dairy farmers have diverse objectives, including risk aversion, non-pecuniary goals, and sustainability considerations (Balaine et al., 2023; Howley et al., 2014; Loughrey et al., 2015). Therefore, this assumption should be viewed as a simplification that facilitates analysis rather than a comprehensive representation of farmers' decision-making behaviour.

4.1.2 | Non-parametric approach for the GTRE model

We use Equation (2) to obtain the parameters from the GTRE model as follows:

$$\widetilde{y}_{it} = \beta_0' + \sum_{j=2}^{J} \beta_j' \widetilde{x}_{jit} + \beta_t' t + b_i - \eta_i + v_{it} - u_{it} \tag{3}$$

where the error term A_{it} in Equation (1) is disentangled in four components in Equation (3). The component b_i is the latent heterogeneity of farms assumed to be and $E(b_i) = 0$ with constant variance σ_b^2. η_i represents persistent inefficiency assumed to be *iid* $N^+\left(0, \sigma_\eta^2\right)$. v_{it} captures the random shocks (i.e., *iid* $N\left(0, \sigma_v^2\right)$), u_{it} is the transient inefficiency component, and $\beta_t t$ is a time trend to observe technical change. Then, we follow the distributional assumptions by Lien et al. (2018) on the transient inefficiency term:

$$\widetilde{y}_{it} = \beta_0' + \sum_{j=2}^{J} \beta_j' \widetilde{x}_{jit} + \beta_t' t + b_i - \eta_i + v_{it} - u_{it}\left(Z_{it}\right) \tag{4}$$

where Z_{it} are the determinants of transient inefficiency. In this way, the transient inefficiency term is no longer assumed to be a random *iid* term, as it is now expressed as a function of a vector Z_{it} of K observable determinants. To empirically resolve the endogeneity between the transient inefficiency term $u_{it}\left(Z_{it}\right)$ and inputs$\widehat{X}_{jit}$, we reformulate Equation (4) into a partial linear model for random effects panel data where the random shocks v_{it} are assumed to have zero-mean and constant variance (Lien et al., 2018; Musau et al., 2021) as follows:

$$\widetilde{y}_{it} = \left[\beta_0' - \alpha - g\left(Z_{it}\right)\right] + \beta' \widetilde{x}_{jit} + \left[b_i - \left(\eta_i - \alpha\right)\right] + \left[v_{it} - \left(u_{it}\left(Z_{it}\right) - g\left(Z_{it}\right)\right)\right] \tag{5}$$

The term $\alpha = E\left(\eta_i\right)$ is assumed to be *iid*, while $g\left(Z_{it}\right) = E\left(u_{it}\left(Z_{it}\right)\right) \geq 0$ is the expected mean

of the transient inefficiency term, and $\beta' \widetilde{x}_{jit}$ includes $\sum_{j=2}^{J} \beta_j \widehat{X}_{jit}$ and $\beta_t t$ from Equation (4). For simplicity, we rewrite Equation (5) as:

$$\widetilde{y}_{it} = h\left(Z_{it}\right) + \beta' \widetilde{x}_{jit} + \alpha_i + \varepsilon_{it} \tag{6}$$

where $h\left(Z_{it}\right) = \left[\beta_0 - \alpha - g\left(Z_{it}\right)\right]$, $\alpha_i = b_i - \left(\eta_i - \alpha\right)$ and $\varepsilon_{it} = v_{it} - \left[u_{it}\left(Z_{it}\right) - g\left(Z_{it}\right)\right]$. Therefore, $E\left(\alpha_i\right) = 0$ *and* $E\left(\varepsilon_{it}\right) = 0$. We estimate the parametric component $\beta' \widetilde{x}_{jit}$ as in Robinson (1988),

[3]Some advantages of assuming farmers maximise return to outlay are: the assumption of maximising return to outlay aligns with the profit incentive, which is a fundamental concept in economic theory. By focusing on return to outlay, models can implicitly incorporate risk considerations without explicitly adding complex risk preferences (e.g., Lien et al., 2006; Loughrey et al., 2015). Moreover, in the short run, farmers may have fixed inputs or limited flexibility in adjusting their operations which is relevant to the estimation of transient inefficiency determinants. Under these circumstances, maximising return to outlay may be a more realistic assumption than maximising long-term profits, which would require adjustments to multiple input where farmers may not have complete information about market conditions, costs, or demand elasticity (Mas-Colell et al., 1995).

Lien et al. (2018), and Musau et al. (2021) taking the conditional expectation on each side of Equation (6) subject to Z_{it}:

$$E\left(\%\tilde{y}_{it} | Z_{it}\right) = E\left(\left(h\left(Z_{it}\right) + \beta' \widetilde{x}_{jit} + \alpha_i + \varepsilon_{it}\right) | Z_{it}\right)$$

Since $E\left(\alpha_i | Z_{it}\right) = 0$ and $E\left(\varepsilon_{it} | Z_{it}\right) = 0$, then:

$$E\left(\%\tilde{y}_{it} | Z_{it}\right) = h\left(Z_{it}\right) + \beta' E\left(\%\tilde{x}_{jit} | Z_{it}\right) \tag{7}$$

Consequently, we subtract (7) from (5) to obtain:

$$y^*_{it} = \beta' x^*_{jit} + \beta_t t + \alpha_i + \varepsilon_{it} \tag{8}$$

where $y^*_{it} = \widetilde{y}_{it} - E\left(\%\tilde{y}_{it} | Z_{it}\right)$ and $x^*_{jit} = \widetilde{x}_{jit} - E\left(\%\tilde{x}_{jit} | Z_{it}\right)$. To obtain the conditional means (i.e., $E\left(\%\tilde{y}_{it} | Z_{it}\right)$ and $E\left(\%\tilde{x}_{jit} | Z_{it}\right)$) as a function of vector Z_{it}, we estimate Equation (8) by means of a nonparametric local kernel regression using the *npregress* command included in Stata®16. Therefore, Equation (8) allows for determinants of transient inefficiency while dealing with the problem of endogeneity in inputs (Lien et al., 2018). Furthermore, the Lien et al. (2018) approach provides consistent estimates of β' regardless of the distribution of error components α_i and ε_{it} which we use in the following steps to estimate persistent and transient inefficiency (Baltagi, 2008; Lien et al., 2018). Therefore, the two-step semiparametric approach proposed by Lien et al. (2018) can be seen as a non-parametric 2SLS method that addresses the endogeneity between using inputs as efficiency drivers in the GTRE model.

4.2 | Estimates of inefficiency and TE

4.2.1 | Persistent inefficiency and persistent TE

Due to data limitations regarding time invariant observable determinants in our panel data set, we keep the homoscedastic distributional assumptions of the persistent technical inefficiency term. We use the predicted values of α_i assuming that the latent heterogeneity of farms $\left(b_i\right)$ is *iid* $N\left(0, \sigma^2_b\right)$ and the persistent inefficiency term $\left(\eta_i\right)$ is *iid* $N^+\left(0, \sigma^2_\eta\right)$ (Colombi et al., 2014; Filippini & Greene, 2016; Kumbhakar et al., 2014). Then, we estimate:

$$\alpha_i = \alpha + b_i - \eta_i \tag{9}$$

Using the standard SF model for pooled data and the maximum likelihood procedure proposed by Jondrow et al. (1982), we obtain the predicted values of persistent technical inefficiency. Therefore, we can estimate persistent TE (PTE) as $PTE = \exp\left(-\eta_i\right)$.

4.2.2 | Estimates of transient technical inefficiency, transient TE, overall TE and marginal effects

To estimate the transient technical inefficiency ($u_{it}\left(Z_{it}\right)$) in Equation (4) we use the predicted values of ε_{it} obtained from (8):

$$\varepsilon_{it} = g\left(Z_{it}\right) + v_{it} - u_{it}\left(Z_{it}\right) \tag{10}$$

We assume v_{it} is *iid* $N\left(0, \sigma_v^2\right)$, and $u_{it}\left(Z_{it}\right) \sim N^{+}\left(0, \sigma_u^2\left(Z_{it}\right)\right)$ which means $E\left(u_{it}\left(Z_{it}\right)\right) = \sqrt{\frac{2}{\pi\sigma_u}}\left(Z_{it}\right) \equiv g\left(Z_{it}\right)$. We estimate Equation (10) by the SFA technique (Jondrow et al., 1982; Kumbhakar, 1990; Kumbhakar et al., 2014) treating ε_{it} as the dependent variable and $g\left(Z_{it}\right)$ as regressors. Since $g\left(Z_{it}\right)$ has no new parameters other than those in the variance of u_{it}, we need to make sure that the exact relationship between $g\left(Z_{it}\right)$ and the variance of $u_{it}\left(Z_{it}\right)$ is maintained in estimating the model (Lien et al., 2018). To do so, and to make it non-negative, $\sigma_u^2\left(Z_{it}\right)$ is parameterized as $\exp\left(w'_{uit}Z_{\mathrm{it}}\right)$. The term w' is a vector parameter to be estimated (Lien et al., 2018). Therefore, we obtain the estimates for transient technical inefficiency and we compute the transient TE (TTE) as $TTE = \exp\left(-u_{it}\left(Z_{it}\right)\right)$. Finally, we obtain the overall TE (OTE) from the product of PTE and TTE, i.e., $OTE = PTE * TTE$.

Given the half-normal distribution of the transient inefficiency term $\left(i.e., u_{it}\left(Z_{it}\right) \sim N^{+}\left(0,\ \sigma_u^2\left(Z_{it}\right)\right)\right)$ and the parameterization of its variance $\left(i.e., \sigma_u^2\left(Z_{it}\right) = \exp\left(w_u Z_{it}{}'\right)\right)$, we compute the marginal effect of the kth variable of Z_{it} on $E\left(u_{it}\left(Z_{it}\right)\right)$ as:

$$\frac{\partial E\left(u_{it}\left(Z_{it}\right)\right)}{\partial Z\left[k\right]} = w_u\left[k\right]\frac{\sigma_u\left(Z_{it}\right)}{2}\left[\frac{\phi(0)}{\Phi(0)}\right] = w_u\left[k\right]\ \sigma_u\left(Z_{it}\right)\phi(0) \tag{11}$$

where ϕ and Φ are the probability density and cumulative distribution functions of a standard normal variable, respectively. The term $\phi(0)$ is approximately 0.3989 (Kumbhakar et al., 2015; p. 72), and $w_u\left[k\right]$ is the estimated coefficient of the kth variable of Z_{it}. Therefore, the assumptions of Lien et al. (2018) for the transient technical inefficiency term create similar marginal effects to the Caudill and Ford (1993); Caudill et al. (1995); Hadri (1999) (i.e., CFCFGH) model. Consequently, Lien et al. (2018) and the CFCFGH model assume monotonic marginal effects of the variables determining the inefficiency term (Kumbhakar et al., 2015).[4] We use the *sfpredict* command included in Wang (2005) for Stata®16 to estimate the marginal effects of Z_{it} in the transient technical inefficiency term.

5 | DATA AND EMPIRICAL MODELS

We use an unbalanced panel data set from a representative sample of Irish dairy farms (939 farms and 7420 observations). The data spans from 2000 to 2018 and comes from the Teagasc National Farm Survey (NFS), collected as part of the EU Farm Accountancy Data Network (FADN).

The NFS is published on an annual basis since 1972. Approximately 900 farms are surveyed by a professional data collection team annually, representing a farming population of about 92,000 farms. This analysis restricts the data to specialised dairy farms, which results in approximately 390 observations per year. Beyond standard farm accountancy measures, the Teagasc NFS also captures farm labour through self-reported hours and work units, calculated on an annual basis. Farm labour is divided into paid, i.e., any hired labour, and unpaid, i.e., family labour.

5.1 | Hired labour hours

The role of hired labour on farms' TE is of main interest in this analysis. Data on labour refers to both seasonal and permanent hired labour reported on an annual basis by the farmer. Table 1 illustrates the development of hired labour on Irish dairy farms from 2000 to 2018.

[4]Monotonicity of marginal effects means that the sign (i.e., positive or negative) of the marginal effect remains the same for all the observations in the dataset (Wang & Schmidt, 2002).

TABLE 1 Hired labour hours on Irish dairy farms 2000–2018.

(1) Year	(2) Farms	(3) Hired labour hours (farms that hire labour).	(4) Hired labour in average working units (AWU)	(5) % of farms with no hired labour	(6) Hired labour share
2000	486	512 (806.96)	0.42	35.18%	10.96%
2001	535	475.57 (786.22)	0.39	37.94%	9.92%
2002	490	457.94 (758.95)	0.38	36.53%	10.25%
2003	501	474.76 (778.01)	0.39	36.92%	10.41%
2004	465	499.84 (837.9)	0.42	41.29%	9.91%
2005	440	467.49 (787.12)	0.42	43.41%	9.99%
2006	408	459.65 (730.1)	0.40	41.42%	10.44%
2007	377	501.47 (739.06)	0.42	38.72%	11.16%
2008	362	534.85 (794.3)	0.44	38.39%	11.44%
2009	345	457.66 (746.34)	0.42	42.02%	10.16%
2010	335	518.16 (829.93)	0.44	39.71%	10.87%
2011	347	579.65 (783.54)	0.48	39.48%	12.3%
2012	342	506.21 (710.24)	0.45	39.18%	11.82%
2013	342	548.57 (806.73)	0.45	37.42%	11.67%
2014	342	503.81 (728.47)	0.41	32.74%	11.78%
2015	335	511.09 (756.42)	0.41	34.62%	11.47%
2016	328	572.55 (810.82)	0.46	34.75%	12.27%
2017	315	666.15 (912.68)	0.51	33.01%	13.23%
2018	325	738.91 (979.52)	0.55	36.00%	14.10%
All years	390	520.5 (796.21)	0.43	37.93%	11.13%

Source: Teagasc NFS data. (3) Mean and standard deviations in parentheses. (4) An AWU represents 1800 hours a year, and one AWU is capped at 1800 hours even if a person works more than 1800 hours. People under 18 years of age are allocated the following labour-unit equivalents: 16 to 18 years = 0.75 AWU and 14 to 16 years = 0.50 AWU. Labour variables weighted by a dairy specialisation factor.

The data indicates that Irish dairy farms utilise on average 520 hours of hired labour per year across the time period examined (i.e., Column 3). The average has increased during the post-quota period (2015–2018), particularly during 2017 and 2018. During the quota years and soft-landing phase, hired labour hours remained stable, with few exceptions: 2002, 2005, 2006 and 2009 where the proportion of hired labour was low. This is a likely consequence of the milk quota, and, in 2009, low milk prices caused a drop in milk supply (Dillon et al., 2019). Across all years examined, farms that hire labour have an average of just 0.43 AWU (i.e., Column 4). All of the above indicates that despite a significant increase, the proportion of farms utilising hired labour remains relatively low. Column (4) also demonstrates the increase in labour required i.e., hired labour expressed in AWUs have increased to 55% AWU in 2018 compared to the 41% figure in 2015. This increase is understandable given the strong growth in milk production experienced post-quota (CSO, 2020). However, Column (5) shows that a non-trivial percentage of farms do not hire labour in the period (i.e., 38% on an annual average). Also, 2005, 2006 (i.e., milk quota) and 2009 (i.e., soft-landing and economic recession) showed the highest percentage of farms with no hired labour (see Column 5). In Column (6), we can see that hired labour represents 11% of the total labour hours over the period, emphasising the prevalence of family farming (reflected in the unpaid family labour component) in an Irish context. However, we observe an increase in the ratio of hired labour to 13% and 14% in 2017 and 2018.

Table 2 presents descriptive statistics for several variables relevant to Irish dairy production in the sample from 2000 to 2018.

In Table 2, milk output describes total milk produced by the average dairy farm in hundreds of euros. Capital comprises machinery, buildings, and livestock as follows: the aggregated value of machinery and buildings and the value of the dairy herd, calculated according to the end of year valuation based on a replacement cost methodology. This approach acknowledges the capital input as both a flow of income and a stock (Ros, 2013). In this way, we obtain unbiased output elasticities for the capital input (Martinez-Cillero et al., 2019). Labour accounts for total labour input on the entire farm, including unpaid and paid labour. Miscellaneous inputs are direct costs incurred in dairy production, such as concentrates, fertiliser, purchased seeds, building repairs, livestock expenses, veterinary and artificial insemination expenses, farm insurance, advisory fees, among others. Land is based on dairy forage area in hectares.

Herd size is the average number of cows in the dairy herd over a 12-month period. Herd expansion is the average annual growth rate of herd size in the period. Farms with herd expansion is the average percentage of farms with a positive herd growth rate per annum. Detailed yearly statistics of the variables in Table 2 are included in Table S1 in the Appendix S1. Finally, all monetary values are deflated using Irish national price indices (with the base year 2015) taken from the Irish Central Statistics Office (CSO, 2020). In addition, we weight farms' inputs (i.e., capital and labour) by a specialisation factor (i.e., gross dairy output as a proportion of gross farm output) (Kelly et al., 2013), as dairy farms can use inputs to produce other outputs (e.g., crops, sheep, livestock, calves) and the data does not provide enterprise specific breakdowns for capital and labour.

TABLE 2 Relevant descriptive statistics Irish dairy farms 2000–2018.

Variable	Description	Mean	Min	Max
Milk output	Total milk output in hundreds of euros	1576.28 (836.42)	6.70	6963.77
Capital	Machinery, buildings, and livestock in hundreds of euros	1650.82 (1281.98)	21.06	12,214
Labour	Paid and unpaid self-reported annual hours on the farm	1956.19 (950.11)	13.98	8685.18
Miscellaneous inputs	Direct costs incurred in dairy production in euros	522.93 (398.11)	1.96	4272.25
Land	Dairy forage area in hectares	61.24 (34.26)	3.70	281.40
Herd size	Average annual herd size by farm	61.15 (38.15)	1	318.42
Herd expansion	Average annual growth rate of herd size in the period	2.11% (12.8%)	−97%	154%
Farms in herd expansion	Percentage of farms with herd growth rate above zero	65.16%	55.48%	80.3%

Source: Teagasc NFS data from 2000 to 2018. All monetary variables deflated by agricultural price indices (CSO, 2020; base year 2015). Standard deviations in parentheses. The output value can indeed be measured in Euros (Dillon et al., 2019) and subsequently subjected to logarithmic application, similar to other variables in the model (e.g., Lien et al., 2018). In 2018, the EUR to AUD exchange rate stood at 1.61 AUD, while the EUR to USD rate was 1.14 USD. The exchange rate from AUD to USD was 0.70 USD (Available online at www.xe.com, last accessed December 2023).

5.2 | Empirical specification

We apply the heteroscedastic GTRE model by Lien et al. (2018) described in Section 4. For the dependent variable specified in Equations (2) to (8) of Section 4 (i.e., $\widetilde{y}_{it}$; y^*_{it}), we use the natural logarithm of milk output measured in constant euros. The vector of inputs (i.e., $\widetilde{x}_{jit}$; x^*_{jit}) used in these equations includes capital, labour, miscellaneous inputs, and land. The GTRE model by Lien et al. (2018) allows to any input in the production function to be used as the numeraire. As specified in Equation (2) in Section 4, we use land as the numeraire input $\left(x_1\right)$ and applied natural logarithms to all the inputs included in vectors $\widetilde{x}_{jit}$ and x^*_{jit}.

Using the estimated parameters in Equation (8) we compute the following output elasticities (Equation 12), and technical change (i.e., Equation 13) as follows:

$$\frac{\partial y^*_{it}}{\partial x^*_{jit}} = \beta'_j x^*_{jit}, j = 2, \ \ldots \ , J \tag{12}$$

$$\frac{\partial y^*_{it}}{\partial t} = \beta'_t \tag{13}$$

5.3 | Determinants of transient technical inefficiency

For the empirical specification of technical inefficiency determinants (Z_{it}) in Equations (4–8), we use the annual hired labour hours, the herd size and the interaction term of hired labour and herd size. We applied the log-transformation suggested by Cameron and Trivedi (2010) to Z_{it} to avoid losing information due to the number of farms that do not hire labour annually. The log-transformation consists in approximating a gamma constant to the zero values in the sample to keep the logistic distribution of the variables. To obtain the marginal inefficiency effects by Wang and Schmidt (2002) described in Section 4.1, we use the Stata® code introduced by Wang (2005).

6 | RESULTS AND DISCUSSION

6.1 | Production function

We begin our results with the output elasticities, technical change and returns to scale reported in Table 3.

First, all the output elasticities are positively and significantly correlated with output. Due to the transformation of the variables to control for endogeneity between inputs and the composed error term (see Section 4), we can interpret the output elasticities of capital, labour, and miscellaneous inputs in terms of percentage changes per hectare per farm. Also, the modelling approach specified in Equations (3–9) that included hired labour as a determinant of transient inefficiency implies that the output elasticity for labour is a proxy for unpaid labour, i.e., family labour. At 1.4% per year on average, the estimate of technical change is also statistically significant and positive. These findings are similar to previous output elasticities for Irish dairy farms and technical change estimates reported by Gillespie (2015) and Bradfield et al. (2021). Therefore, we can confirm that technical change is an important element for productivity improvements on Irish dairy farms.

TABLE 3 Output elasticities, technical change and returns to scale.

	(1)
Milk output	Coefficients
Capital	0.201***
	(0.009)
Labour	0.111***
	(0.008)
Miscellaneous inputs	0.603***
	(0.009)
Land *(calc.)*	0.085
Technical change	0.014***
	(0.001)
Region[a]	0.107 (0.301)
Returns to scale	1.00
Constant	−0.146***
	(0.007)
Observations	7420
Number of farms	939

Note: *** $p < 0.01$.

[a]None of the regional dummies are statistically significant. Standard errors in parentheses.

6.2 | Overall, transient and persistent TE scores

Table 4 includes the estimates of average overall, transient, and persistent TE scores for the years 2000 to 2018. We also report the TE scores from the homoscedastic GTRE (Kumbhakar et al., 2014) as a robustness analysis.

The results confirm that not addressing endogeneity in a GTRE model may lead to an underestimation of TE scores, which is in line with findings by Lai and Kumbhakar (2018) and Lien et al. (2018). Table 4 shows that in our analysis, this underestimation is around 3.5% of farms' overall TE from 2000 to 2018 (see Columns 1 and 2). In Column 2, overall TE is 0.79, which suggests that Irish dairy farms are highly efficient. As such, our results are consistent with the findings of Geary et al. (2012), Kelly et al. (2013), Gillespie (2015) and Bradfield et al. (2021) who all report average TE of Irish dairy farms above 70%. Additionally, average transient and persistent TE scores are very similar for Irish dairy farms (i.e., 88.4% and 88%, respectively). This result suggests that, on average, Irish dairy farm production is highly efficient in the short (i.e., transient) and long run (i.e., persistent).

In Figure 1, we show the development of transient, persistent, and overall TE over the observation period.

During the milk quota period (2000–2008), we observe an increasing trend of transient TE that remains close to its persistent trend (i.e., persistent TE). In 2008, the EU initiated the soft-landing period (2008–2014) in preparation for a deregulated market in 2015 (Läpple & Hennessy, 2012). Figure 1 displays that transient TE shows greater variation in the soft-landing period. This may be caused by the high volatility in dairy markets due to the international recession during this time (i.e., 2008–2011), and dairy farmers' adaptation processes towards the milk quota abolition. There is a considerable dip in transient TE in 2013 that recovers in

TABLE 4 Average overall, transient and persistent TE scores.

Efficiency	(1) Homoscedastic GTRE	(2) Heteroscedastic GTRE addressing endogeneity
Overall TE	0.755	0.791
	(0.091)	(0.072)
Transient TE	0.876	0.884
	(0.065)	(0.059)
Persistent TE	0.861	0.88
	(0.077)	(0.061)
Observations	7420	7420
Number of farms	939	939

Note: Standard deviations in parentheses. As a robustness check, we estimated the heteroscedastic GTRE model in a balanced panel subsample of Irish dairy farms (Farms: 132; N: 2508). The results confirm that the high TE scores of Irish dairy farms are consistent with the unbalanced panel (see Table S2 in Appendix S2). The results form Table S3 also confirm that larger farms hold in average higher TE scores (Bradfield et al., 2021; Garcia-Covarrubias et al., 2023).

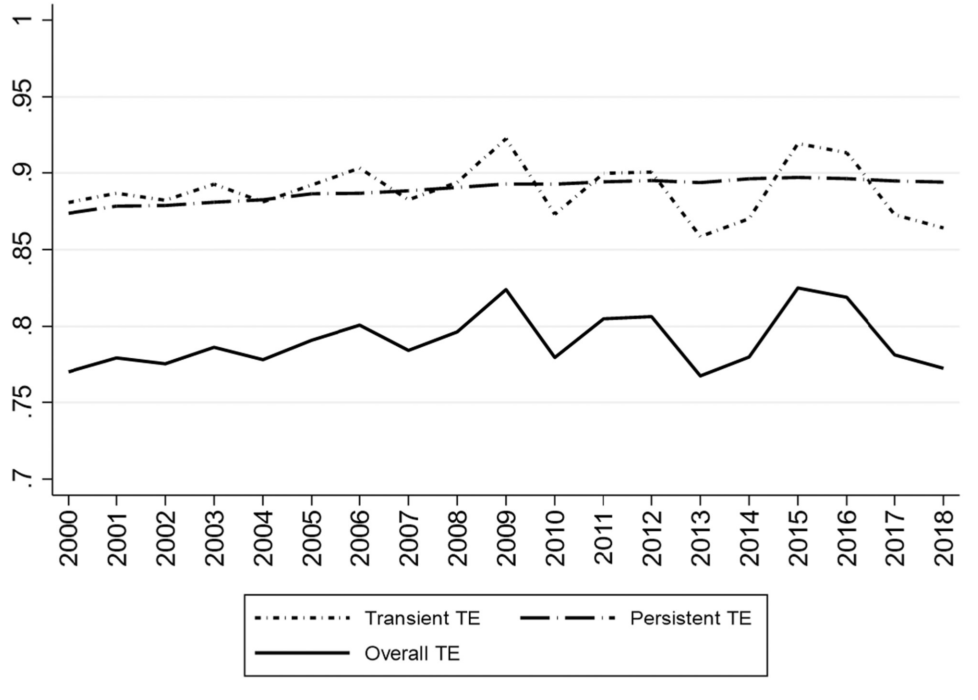

FIGURE 1 Development of transient, persistent and overall TE on Irish dairy farms (2000–2018). Estimates from SF model by Lien et al. (2018) applied to Teagasc NFS panel data 2000–2018.

the following year. This may partly be due to the uptake of new technologies by farmers since, in 2013 and 2014, significant investments have been made in the Irish dairy sector initiated by private sector and government grants (Promar-International, 2018; Donnellan et al., 2020; Kelly et al., 2020).

During the post-quota period (2015–2018), we observe a growing trend of transient TE from 2015 to 2017, which reverses in 2018. This dip in TE can be related to adverse weather that affected agricultural production (and costs) in 2018, with a significantly negative impact on Irish farm incomes (Dillon et al., 2019).

Finally, it is important to note that observed variation in persistent TE scores' is due to the unbalanced panel dataset. In other words, for each farm, persistent TE is constant and the small variation on persistent TE over time is due to a different set of observations each year.

6.3 | Marginal effect of hired labour on transient technical inefficiency

In the last part of our analysis, we focus on the marginal effect of hired labour on transient technical inefficiency, presented in Table 5.

Since the coefficients in column 2 of Table 5 do not have a direct interpretation, we report the marginal effects of hired labour, herd size, and the interaction term on TE in column 3. The result shows that, on average, a 1% increase in hired labour has a diminishing marginal effect of −0.0046% on transient technical inefficiency.[5] To put this in context, a 1% increase in hired labour is 5.2 hours per year, which explains the small economic significance of our coefficient estimate.

Similarly, for a 1% increase in herd size, there is a decreasing marginal effect of −0.0039% on technical inefficiency. That is, as the farm size increases, the technical inefficiency of the farms decreases (Bradfield et al., 2021; Gaviglio et al., 2021; Kelly et al., 2020). The interaction term for hired labour and herd size has a positive sign. This result implies two things: first, as hired labour and herd size increase, technical inefficiency decreases, and the combined effect of hired labour and herd size makes the effect of hired labour on technical inefficiency stronger. In other words, our results provide evidence that hiring labour and expanding the farm size and decreases farm inefficiency.

Second, the coefficients in Table 5 present the effect of hired labour and herd size on technical inefficiency; therefore, the effect on TE is the opposite. Consequently, our findings suggest that hired labour has a significant yet small effect on increasing TE of Irish dairy farms.

In the following figures, we explore this effect in more detail. In Figure 2, we show the marginal effects of hired labour on TE (i.e., *y-axis*) by hired labour share (i.e., *x-axis*).

TABLE 5 Marginal effects of hired labour on technical inefficiency.

(1)	(2)	(3)
Variable	**Coefficient**	**Marginal effect of hired labour**
Hired labour	−0.557 (0.72)	−0.0046***
Herd size	−0.472 (0.03)	−0.0039***
Hired labour and herd size	0.053 (0.01)	0.0004***
Wald Chi^2	2126.52***	

Note: Standard errors in parentheses. As a robustness check, we estimated the marginal effects of the determinants of technical inefficiency in a balanced subsampled panel of Irish dairy farms (Farms: 132: N: 2508). The results confirm the robustness of the marginal effects of hired labour and herd size in the unbalanced panel (see Table S3 in Appendix S1). The results from Table S3 also confirm that the effect of hired labour is of less magnitude in larger farms with higher TE scores. *** $p<0.01$.

[5]As a robustness check, we estimate the effect of the share of hired labour on TE (not reported here). The results suggest that the magnitude of the effect of hired labour share is similar to the effect of hired labour hours in TE (i.e., −0.0042%). The share of hired labour effect on TE can increase two-fold: an increase in hours of hired labour and a reduction in hours of family labour. Therefore, these similar results confirm that the increase in TE is due to hired labour hours.

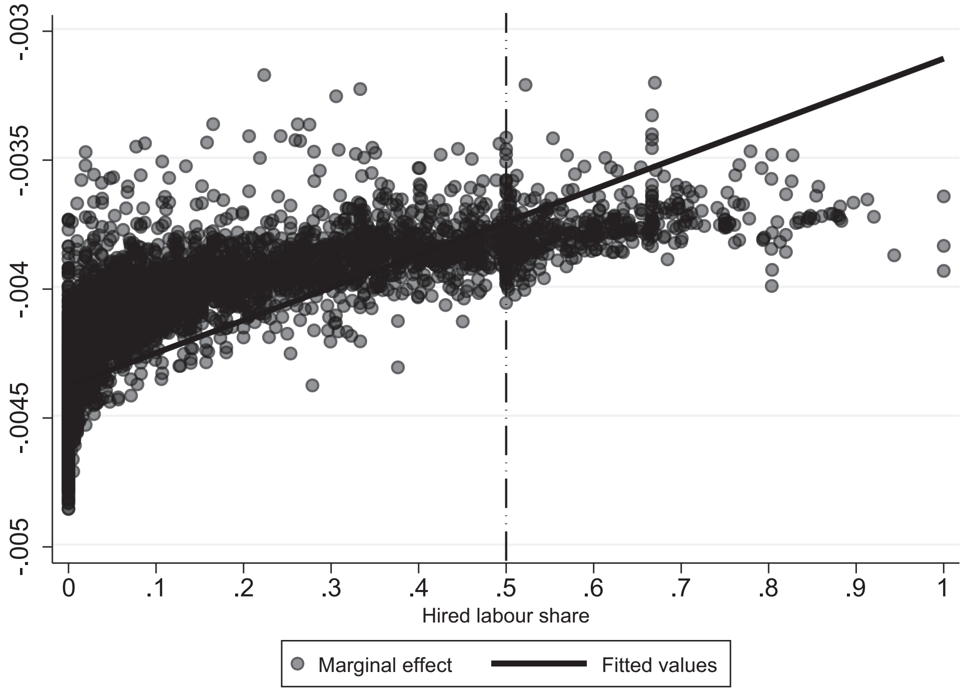

FIGURE 2 Scatter plot of marginal effects of hired labour on transient technical inefficiency. Results from Lien et al. (2018) marginal effects. The dash-dot line represents 50% of hired labour share.

For ease of interpretation, we place a linear fit over the marginal effect of hired labour and the variable included in Figure 2 to show the marginal effects. We also tried a quadratic and cubic relationship, but it does not fit the data well. Our results suggest that the effect of hired labour on transient technical inefficiency is negative regardless of hired labour share's level. However, when the hired labour share increases, the marginal effect of hired labour declines. For instance, if a farm's hired labour share is below 50%, the effect on technical inefficiency will be more extensive than at higher levels of hired labour share (see Figure 2). Since 95% of farms in the sample report less than 50% of hired labour share, most dairy farms will reduce their technical inefficiency by a larger magnitude by hiring extra labour.

Next, we explore how the effect of hired labour varies with herd size. The findings are shown in Figure 3.

The results from Figure 3 indicate that most farms cluster at a herd size of less than 80 cows. This is the case since herd size distribution is positively skewed. For most years in the sample, the average herd size is below 80 cows (see Table S1 in Appendix S1). As small and medium-sized farms tend to have lower hired labour hours working on the farm, the marginal effect of hired labour on technical inefficiency is larger than the average figure (i.e., > -0.0046). In other words, marginally increasing hired labour has a more extensive effect on technical inefficiency when compared to larger farms with higher hired labour hours. This result implies that the acquisition of additional hired labour on larger farms (>80 cows) has a moderate lower impact in terms of reducing technical inefficiency. Therefore, the effect of hired labour on technical inefficiency is marginally more extensive on small and medium-sized farms.

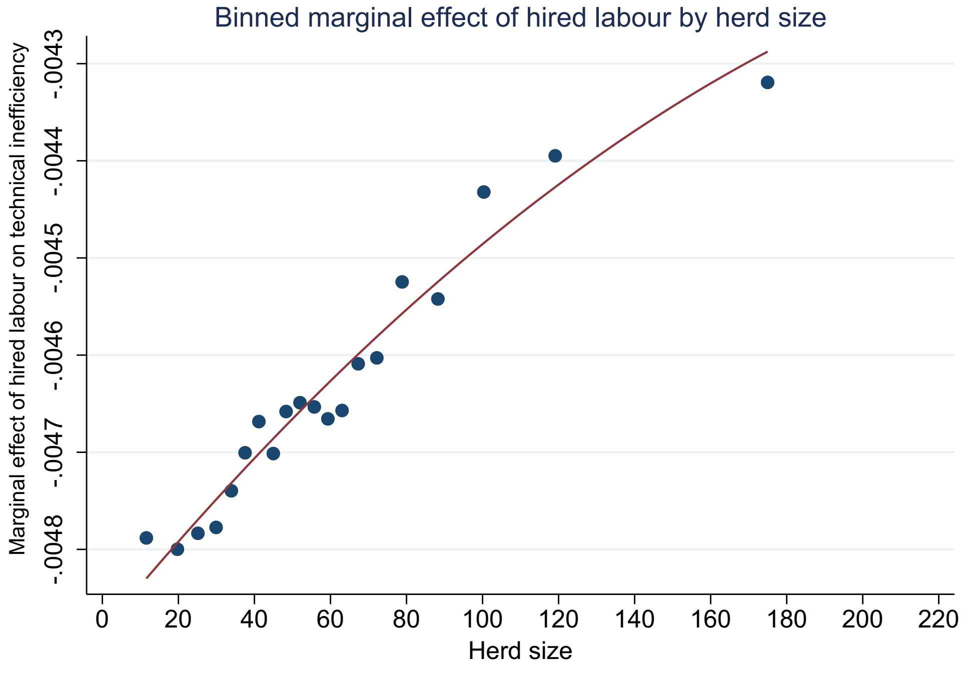

FIGURE 3 Binned scatter plots of marginal effects of hired labour on TE by herd size and herd expansion. Results from Lien et al. (2018) marginal effects. [Colour figure can be viewed at wileyonlinelibrary.com]

7 | CONCLUSION

The EU milk quota abolition created significant opportunities and challenges for the European dairy sector. One such challenge relates to increased labour demand on farms that expanded production, particularly on farms with seasonal production—in this context, sourcing hired labour is an additional hurdle for dairy farmers, which becomes crucial to understanding farm efficiency.

This paper assessed the role of hired labour on Irish dairy farms' technical efficiency (TE). We used representative farm-level panel data for the years 2000 to 2018. We applied a GTRE model that accounts for endogeneity in inputs and decomposes TE into transient and persistent TE scores. We also estimated the marginal effects of hired labour on transient TE.

Consistent with the literature, we find that Irish dairy farms are technically efficient. Specifically, average TE of Irish dairy farms is 79%, 88% and 88% for overall, transient and persistent TE, respectively. The technical change estimation result confirms its importance for Irish dairy production (i.e., 1.4% annually). If we do not control for endogeneity, the efficiency scores are biased by approximately 3%, which is consistent with findings from Lai and Kumbhakar (2018) and Lien et al. (2018).

In addition, our findings show that hired labour has a positive effect on Irish dairy farms' TE, and as such suggest that hired labour assists in increasing dairy farms' TE. However, the analysis indicates that relatively smaller farms (i.e., <80 cows) benefit more from hiring labour. We conclude that there are two main reasons for this. First, farms of smaller size have a lower hired labour share (i.e., 6% compared to 27% for smaller and larger farms, respectively), and second, small farms generally tend to be less efficient (Bradfield et al., 2021; Carroll et al., 2011). Therefore, it is easier to increase TE on these farms.

Furthermore, most dairy farms have little hired labour (i.e., 95% of farms have less than a 50% share of hired labour). However, in 2018, the average herd size in the sample was 88 cows, and TE scores for smaller and larger farms are, on average, 74% and 79% (see Table S1 in Appendix S1). Moreover, the majority of dairy farms in the period cluster below 80 cows in average (see Figure 3). These figures suggest that the marginal effect of hired labour on TE is at its highest point for the majority of Irish dairy farms. Therefore, there is considerable potential for farm TE improvement based on expanding hired labour.

Our findings also suggest that the marginal effect of hired labour increases to a small degree as herd size expands (see Table 5). Intuitively, as herd size expands, so too does the total labour input, increasing the reliance on hired labour and thus total labour costs (Kelly et al., 2020; Kimhi, 2009). Therefore, it is generally accepted that in order to manage the increasing workload on expanding farms, additional hired labour will be required as it is not sustainable in the long term for the farmer or family labour to absorb it. In relation to the recommendation by Anderson (2020) and Kelly et al. (2020) that larger and expanding farms should utilise hired labour where available, our findings confirm this suggestion—although, our analysis suggests that the positive effects of hired labour on TE are more evident on smaller farms.

The findings from our study have important practical and policy implications. The suggestion that small and medium-sized farms should increase their share of hired labour may be surprising as farmers generally aim to minimise labour costs, especially those involved in a smaller, family-run operation.[6] However, as Anderson (2020) and Kelly et al. (2020), we consider it a good general practice to treat labour costs as a standard running cost for the farm, similar to fertiliser or feed. Therefore, our findings suggest that policy should expand programs that facilitate access and communicate the benefits of hired labour to all farms.

This suggestion is important as many dairy farmers may still be reluctant to hire additional labour due to concerns that it may reduce farm efficiency. This reluctance may be mitigated by circulating information regarding the relationship between hired labour and farm efficiency through extension agents such as Teagasc, the Farm Relief Services (FRS), the Macra Land Mobility Service (MLMS) programmes, and through Teagasc's social media strategy. In this way, our findings should give farmers the confidence that hired labour is suitable for increasing the TE on their farm while easing the workload.

This paper is one of the first that directly assesses the effect of hired labour on farms TE. We find a positive and significant effect of hired labour on farms' TE—yet the effect is small in economic terms. However, whether or not this TE increase will be enough to offset the increase in labour cost requires an input-oriented analysis is worth further investigation. Our finding of the positive impact of hired labour on TE is likely to also apply to other farms in developed countries, as many farms also heavily rely on family labour. However, it is important to keep in mind that our study is based on spring calving dairy production with a very seasonal labour demand.

One limitation inherent in self-reported hours, as utilised in FADN data, is the potential for measurement inaccuracies, especially concerning farm labour (Charmes, 2020; Fall & Magnac, 2004). Family labour is challenging to quantify precisely due to its unpaid nature, informal contributions and varying definitions of work (Almeida & Bravo-Ureta, 2019; Kelly et al., 2020). Similarly, the accuracy of reporting hired labour can be compromised, as seen in some EU countries where seasonal labour may be under-reported to evade taxes, which might not be a significant source of concern in Ireland because Teagasc NFS accounts for casual hired labour (Dell'Anno & Davidescu, 2019; Dillon et al., 2022; Kelly et al., 2020). However, potentially biased reporting in total labour hours can introduce inaccuracies in the analysis (Fall & Magnac, 2004; Loughrey & Hennessy, 2014).

[6]The labour cost is also variable due to factors other than farm size, e.g., the farm's location, as it may be more challenging to obtain such labour in some regions (Loughrey & Hennessy, 2016).

In this sense, this paper recognises the need for a more detailed task-specific data collection of farm labour to consider the potential impact of measurement errors on the reported economic significance of hired labour. Although most agricultural studies that explore labour input on farms are also based on aggregated numbers (e.g., Blanc et al., 2008; Bradfield et al., 2021; Kostov et al., 2018), the potential for systematic biased reporting of on-farm labour hours could be countered using the time-use methodology. Using such a methodology for future research may aid in informing more specific best practices on the farm and providing precise evidence-based recommendations to contribute to policy changes (Charmes, 2020; Tocco et al., 2012).

ACKNOWLEDGEMENTS

The authors gratefully acknowledge funding from the Teagasc Walsh Scholarship Postgraduate Scheme granted by Teagasc the Agriculture and Food Authority in Ireland. Open access funding provided by IReL.

DATA AVAILABILITY STATEMENT

The data supporting this study's findings are provided by Teagasc—the Agriculture and Food Development Authority in Ireland. Restrictions apply to the availability of these data, which were used under license for this study. For further information about licenses to this data, please email Teagasc at info@teagasc.ie.

ORCID

Luis Garcia-Covarrubias https://orcid.org/0000-0003-0157-9811

REFERENCES

Agasisti, T. & Gralka, S. (2019) The transient and persistent efficiency of Italian and German universities: a stochastic frontier analysis. *Applied Economics*, 51(46), 5012–5030.

Aigner, D., Lovell, C. & Schmidt, P. (1977) Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1), 21–37.

Almeida, A.N. & Bravo-Ureta, B.E. (2019) Agricultural productivity, shadow wages and off-farm labor decisions in Nicaragua. *Economic Systems*, 43(1), 99–110.

Alvarez, A., Del Corral, J., Solís, D. & Pérez, J. (2008) Does intensification improve the economic efficiency of dairy farms? *Journal of Dairy Science*, 91(9), 3693–3698.

Anderson, C. (2020) *Dairy farm labour, working smarter not harder*. Lakeland dairies, Teagasc. (Online). Available from: https://www.teagasc.ie/media/website/publications/2020/dairy-farm-labour-lakeland-teagasc-collaboration.pdf [Accessed 9 March 2022].

Augère-Granier, M.L. (2018) *The EU dairy sector: Main features, challenges and prospects*. EU Briefing European Parliamentary Research Service. 1941 (89) 3 (Online). Available from: http://www.europarl.europa.eu/regdata/etudes/brie/2018/630345/eprs_bri(2018)630345_en.pdf [Accessed 18 May 2020].

Badunenko, O. & Kumbhakar, S. (2016) When, where and how to estimate persistent and transient efficiency in stochastic frontier panel data models. *European Journal of Operational Research*, 255(1), 272–287.

Badunenko, O. & Kumbhakar, S. (2017) Economies of scale, technical change and persistent and time-varying cost efficiency in Indian banking: do ownership, regulation and heterogeneity matter? *European Journal of Operational Research*, 260(2), 789–803.

Balaine, L., Läpple, D., Dillon, E.J. & Buckley, C. (2023) Extension and management pathways for enhanced farm sustainability: evidence from Irish dairy farms. *European Review of Agricultural Economics*, 50(2), 810–850.

Baležentis, T. & Sun, K. (2020) Measurement of technical inefficiency and total factor productivity growth: a semiparametric stochastic input distance frontier approach and the case of Lithuanian dairy farms. *European Journal of Operational Research*, 285(3), 1174–1188.

Baltagi, B. (2008) Forecasting with panel data. *Journal of Forecasting*, 27(2), 153–173.

Battese, G. & Coelli, T. (1992) Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. *Journal of Productivity Analysis*, 3(1/2), 153–169.

Battese, G. & Coelli, T. (1995) A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, 20(2), 325–332.

Blanc, M., Cahuzac, E., Elyakime, B. & Tahar, G. (2008) Demand for on-farm permanent hired labour on family holdings. *European Review of Agricultural Economics*, 35(4), 493–518.

Bojnec, Š. & Ferto, I. (2013). Farm income sources, farm size and farm technical efficiency in Slovenia, *Post-Communist Economies* 25(3), 343–356.

Bradfield, T., Butler, R., Dillon, E., Hennessy, T. & Kilgarriff, P. (2021) The effect of land fragmentation on the technical inefficiency of dairy farms. *Journal of Agricultural Economics*, 72(2), 486–499.

Brennan, M., Hennessy, T., Meredith, D. & Dillon, E. (2022) Weather, workload and money: determining and evaluating sources of stress for farmers in Ireland. *Journal of Agromedicine*, 27(2), 132–142.

Brown, C., Kovács, E., Herzon, I., Villamayor-Tomas, S., Albizua, A., Galanaki, A. et al. (2021) Simplistic understandings of farmer motivations could undermine the environmental potential of the common agricultural policy. *Land Use Policy*, 101, 105136.

Cameron, A.C. & Trivedi, P.K. (2010) *Microeconometrics using Stata*, Vol. 2. College Station, TX: Stata Press.

Carroll, J., Newman, C. & Thorne, F. (2011) A comparison of stochastic frontier approaches for estimating technical inefficiency and Total factor productivity. *Applied Economics*, 43(27), 4007–4019.

Caudill, S. & Ford, J. (1993) Biases in frontier estimation due to heteroscedasticity. *Economics Letters*, 41(1), 17–20.

Caudill, S., Ford, J. & Gropper, D. (1995) Frontier estimation and firm-specific inefficiency measures in the presence of heteroscedasticity. *Journal of Business & Economic Statistics*, 13(1), 105–111.

Central Statistics Office CSO. (2020) *Agriculture – manufacturing milk prices*. (Online). Available from: https://www.cso.ie/multiquicktables/quicktables.aspx?id=ajm07 [Accessed 14 June 2021].

Charmes, J. (2020) *Measuring time use: an assessment of issues and challenges in conducting time-use surveys with special emphasis on developing countries*. Methodological Inconsistencies, Harmonization Strategies, and Revised Designs. Available from: https://data.unwomen.org/publications/measuring-time-use-assessment-issues-and-challenges-conducting-time-use-surveys

Colombi, R., Kumbhakar, S., Martini, G. & Vittadini, G. (2014) Closed-skew normality in stochastic Frontiers with individual effects and long/short-run efficiency. *Journal of Productivity Analysis*, 42(2), 123–136.

Dell'Anno, R. & Davidescu, A. (2019) Estimating shadow economy and tax evasion in Romania. A comparison by different estimation approaches. *Economic Analysis and Policy*, 63, 130–149.

Deming, J., Gleeson, D., O'Dwyer, T., Kinsella, J. & O'Brien, B. (2018) Measuring labour input on pasture-based dairy farms using a smartphone. *Journal of Dairy Science*, 101(10), 9527–9543.

Devadoss, S. & Luckstead, J. (2018) US immigration policies and dynamics of cross-border workforce in agriculture. *The World Economy*, 41(9), 2389–2413.

Dillon, E., Moran, B., Lennon, J. & Donnellan, T. (2019) *Teagasc national farm survey 2018 results*. (Online). Available from: https://www.teagasc.ie/publications/2019/teagasc-national-farm-survey-2018-results.php [Accessed 18 February 2021].

Dillon, E., Moran, B., Lennon, J. & Donnellan, T. (2022) *Teagasc national farm survey 2021 results* (online). Available from: https://www.teagasc.ie/publications/2022/teagasc-national-farmsurvey-2021.php

Donnellan, T., Moran, B., Lennon, J. & Dillon, E. (2020). *Teagasc national farm survey 2019 results*. Available from: https://www.teagasc.ie/media/website/publications/2020/teagasc-national-farm-survey-2019.pdf [Accessed 22 February 2022].

European Commission – EU-FADN. (2018) *EU dairy farms report based on 2016 FADN data*. (Online). Available from: https://ec.europa.eu/agriculture/rica/pdf/dairy_report_2016.pdf [Accessed 2 March 2021].

Eurostat. (2018) *Farms and farmland in the European Union – statistics* (Eurostat: Brussels). (Online) Available from: https://ec.europa.eu/eurostat/statistics-explained/index.php/farms_and_farmland_in_the_european_union_-_statistics#cite_note-1 [Accessed 16 May 2021).

Fall, M. & Magnac, T. (2004) How valuable is on-farm work to farmers? *American Journal of Agricultural Economics*, 86, 267–281.

Farm Relief Services, FRS. (2020) *Expert farm services*. (Online). Available from: https://Frsfarmreliefservices.Ie/ [Accessed 24 October 2022].

Fernandez-Cornejo, J., Mishra, A.K., Nehring, R.F., Hendricks, C., Southern, M. & Gregory, A. (2007) *Off-farm income, technology adoption, and farm economic performance. off-farm income, technology adoption, and farm economic performance*. Report, University Of Minnesota. (Online). Available from: http://libgate.library.nuigalway.ie/login?url=https://ageconsearch.umn.edu/record/7234/ [Accessed 17 January 2022].

Filippini, M. & Greene, W. (2016) Persistent and transient productive inefficiency: a maximum simulated likelihood approach. *Journal of Productivity Analysis*, 45(2), 187–196.

Garcia-Covarrubias, L., Läpple, D., Dillon, E. & Thorne, F. (2023) Automation and efficiency: a latent class analysis of Irish dairy farms. *Q Open*, 3(1), qoad015.

Gaviglio, A., Filippini, R., Madau, F., Marescotti, M. & Demartini, E. (2021) Technical efficiency and productivity of farms: a periurban case study analysis. *Agricultural and Food Economics*, 9(1), 1–18.

Geary, U., Lopez-Villalobos, N., Begley, N., Mccoy, F., O'Brien, B., O'Grady, L. et al. (2012) Estimating the effect of mastitis on the profitability of Irish dairy farms. *Journal of Dairy Science*, 95(7), 3662–3673.

Gillespie, P. & National University of Ireland, Galway. College of business, public policy law. (2015) Theses. Cairnes school of business economics. Theses. "Dairy and grassland economics in an era of possible expansion" (National University of Ireland, Galway, thesis 12090). Galway: National University of Ireland, Galway.

Hadri, K. (1999) Estimation of a doubly heteroscedastic stochastic frontier cost function. *Journal of Business & Economic Statistics*, 17(3), 359–363.

Howley, P., Dillon, E. & Hennessy, T. (2014) It's not all about the money: understanding Farmers' labour allocation choices. *Agriculture and Human Values*, 31(2), 261–271.

Jondrow, J., Knox Lovell, C., Materov, I. & Schmidt, P. (1982) On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, 19(2), 233–238.

Kelly, E., Shalloo, L., Geary, U., Kinsella, A., Thorne, F. & Wallace, M. (2013) An analysis of the factors associated with technical and scale efficiency of Irish dairy farms. *International Journal of Agricultural Management*, 2(3), 149.

Kelly, E., Shalloo, L., Geary, U., Kinsella, A. & Wallace, M. (2012) Application of data envelopment analysis to measure technical efficiency on a sample of Irish dairy farms. *Irish Journal of Agricultural and Food Research*, 51(1), 63–77.

Kelly, P., Shalloo, L., O'Dwyer, T., Beecher, M., Horan, B., French, P. et al. (2017) *The people in dairy project: a report on the future people requirements of Irish dairy farming to support sustainable and profitable dairy expansion*. Moorepark, Fermoy, Co. Cork. (Online). Available from: https://www.teagasc.ie/media/website/publications/2017/the-people-in-dairy-project.pdf [Accessed 14 May 2021].

Kelly, P., Shalloo, L., Wallace, M. & Dillon, P. (2020) The Irish dairy industry – recent history and strategy, current state and future challenges. *International Journal of Dairy Technology*, 73(2), 309–323.

Kimhi, A. (2009) Demand for on-farm permanent hired labour on family holdings: a comment. *European Review of Agricultural Economics*, 36(3), 447–452.

Kloss, M. & Petrick, M. (2018) *The productivity of family and hired labour in EU arable farming* (No. 174). Discussion Paper. Leibniz Institute of Agricultural Development in Transition Economies (IAMO), Halle (Saale).

Kostov, P., Davidova, S. & Bailey, A. (2018) Effect of family labour on output of farms in selected EU member states: a nonparametric quantile regression approach. *European Review of Agricultural Economics*, 45(3), 367–395.

Kostov, P., Davidova, S. & Bailey, A. (2019) Comparative efficiency of family and corporate farms: does family labour matter? *Journal of Agricultural Economics*, 70(1), 101–115.

Kumbhakar, S. (1990) Production Frontiers, panel data, and time-varying technical inefficiency. *Journal of Econometrics*, 46(1), 201–211.

Kumbhakar, S. & Heshmati, A. (1995) Efficiency measurement in Swedish dairy farms: an application of rotating panel data, 1976-88. *American Journal of Agricultural Economics*, 77(3), 660–674.

Kumbhakar, S.C., Lien, G. & Hardaker, J.B. (2014) Technical efficiency in competing panel data models: a study of Norwegian grain farming. *Journal of Productivity Analysis*, 41(2), 321–337.

Kumbhakar, S.C. & Lovell, C.K. (2003). *Stochastic frontier analysis*. Cambridge: Cambridge University Press.

Kumbhakar, S.C., Wang, H. & Horncastle, A.P. (2015) *A Practitioner's guide to stochastic frontier analysis using Stata*. Cambridge: Cambridge University Press.

Lai, H. & Kumbhakar, S. (2018) Endogeneity in panel data stochastic frontier model with determinants of persistent and transient inefficiency. *Economics Letters*, 162, 5–9.

Läpple, D. & Hennessy, T. (2012) The capacity to expand Milk production in Ireland following the removal of Milk quotas. *Irish Journal of Agricultural and Food Research*, 51(1), 1–11.

Levinsohn, J. & Petrin, A. (2003) Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies*, 70(2), 317–341.

Lien, G., Flaten, O., Jervell, A.M., Ebbesvik, M., Koesling, M. & Valle, P.S. (2006) Management and risk characteristics of part-time and full-time farmers in Norway. *Applied Economic Perspectives and Policy*, 28(1), 111–131.

Lien, G., Kumbhakar, S. & Alem, H. (2018) Endogeneity, heterogeneity, and determinants of inefficiency in Norwegian crop-producing farms. *International Journal of Production Economics*, 201, 53–61.

Loughrey, J. & Hennessy, T. (2014) Hidden underemployment among Irish farm holders 2002-2011. *Applied Economics*, 46(26), 3180–3192.

Loughrey, J. & Hennessy, T. (2016) Farm income variability and off-farm employment in Ireland. *Agricultural Finance Review*, 76(3), 378–401.

Loughrey, J., Thorne, F., Kinsella, A., Hennessy, T., O'Donoghue, C. & Vollenweider, X. (2015) Market risk management and the demand for forward contracts among Irish dairy farmers. *International Journal of Agricultural Management*, 4(1029–2017-1510), 173–180.

Macra Land Mobility Service. (2021) *Macra na ferime*. (Online). Available from: https://landmobility.ie/collaborative-farming/ [Accessed 15 September 2021].

Martinez-Cillero, M., Thorne, F., Wallace, M. & Breen, J. (2019) Technology heterogeneity and policy change in farm-level efficiency analysis: an application to the Irish beef sector. *European Review of Agricultural Economics*, 46(2), 193–214.

Martinez Cillero, M., Wallace, M., Thorne, F. & Breen, J. (2021) Analyzing the impact of subsidies on beef production efficiency in selected European Union countries. A stochastic metafrontier approach. *American Journal of Agricultural Economics*, 103(5), 1903–1923.

Mas-Colell, A., Whinston, M.D. & Green, J.R. (1995) *Microeconomic theory*, Vol. 1. New York: Oxford University Press.

Musau, A., Kumbhakar, S.C., Mydland, Ø. & Lien, G. (2021) Determinants of allocative and technical inefficiency in stochastic frontier models: an analysis of Norwegian electricity distribution firms. *European Journal of Operational Research*, 288(3), 983–991.

Pisulewski, A. & Marzec, J. (2019) Heterogeneity, transient and persistent technical efficiency of polish crop farms. *Spanish Journal of Agricultural Research (SJAR)*, 17(1), e0106.

Promar-International. (2018) *UK catching up on processor investment*. (Online). Available from: https://dairy.ahdb.org.uk/news/news-articles/april-2018/uk-catching-up-on-processor-investment/#.xh-jlmn7s70 [Accessed on April 20, 2021].

Robinson, P. (1988) Root-N-consistent semiparametric regression. *Econometrica*, 56(4), 931–954.

Ros, J. (2013) *Rethinking economic development, growth, and institutions*. Oxford: Oxford University Press.

Sabasi, D., Shumway, C. & Astill, G. (2019) Off-farm work and technical efficiency on U.S. dairies. *Agricultural Economics*, 50(4), 379–393.

Shee, A. & Stefanou, S. (2015) Endogeneity corrected stochastic production frontier and technical efficiency. *American Journal of Agricultural Economics*, 97(3), 939–952.

Skevas, I. & Skevas, T. (2021) A generalized true random-effects model with spatially autocorrelated persistent and transient inefficiency. *European Journal of Operational Research*, 293(3), 1131–1142.

Thorne, F., Gillespie, P.R., Donnellan, T., Hanrahan, K., Kinsella, A. & Läpple, D. (2017) *The competitiveness of Irish agriculture. Report*. Dublin, Ireland: Teagasc.

Tocco, B., Davidova, S. & Bailey, A. (2012) *Key issues in agricultural labour markets: a review of major studies and project reports on agriculture and rural labour markets*. IDEAS Working Paper Series from RePEc, 2012.

Tsionas, E. & Kumbhakar, S. (2014) Firm heterogeneity, persistent and transient technical inefficiency: a generalized true random-effects model. *Journal of Applied Econometrics (Chichester, England)*, 29(1), 110–132.

Wang, H. (2005) *Stata code for 'heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model*. (online). Available from: http://homepage.ntu.edu.tw/~wangh/ [Accessed 17 March 2022].

Wang, H.J. & Schmidt, P. (2002) One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *Journal of Productivity Analysis*, 18(2), 129–144.

Weersink, A. & Fulton, M. (2020) Limits to profit maximization as a guide to behavior change. *Applied Economic Perspectives and Policy*, 42(1), 67–79.

Wollni, M. & Brümmer, B. (2012) Productive efficiency of specialty and conventional coffee farmers in Costa Rica: accounting for technological heterogeneity and self-selection. *Food Policy*, 37(1), 67–76.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Garcia-Covarrubias, L., Läpple, D., Dillon, E. & Thorne, F. (2024) The role of hired labour on technical efficiency in an expanding dairy sector: The case of Ireland. *Australian Journal of Agricultural and Resource Economics*, 68, 437–459. Available from: https://doi.org/10.1111/1467-8489.12553