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Climatic effects and total factor productivity: econometric evidence for Wisconsin dairy farms

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Abstract

This study exploits temporal and cross-sectional variation in weather and long-run climate trends to investigate their effects on farm-level productivity. Using panel data for a sample of Wisconsin dairy producers, three stochastic production frontier models are estimated and a random parameters approach is chosen as the most desirable, which accounts for stochastic observed and unobserved environmental factors. The estimated coefficients are used to decompose a multiplicative total factor productivity index that accounts for different sources of productivity growth. Annual productivity growth is estimated at 2.16 per cent, driven primarily by technical progress (1.91 per cent per annum). The average per year contribution of the other productivity components is: climate adaptation efforts −0.31 per cent; scale-mix efficiency change +0.13 per cent and technical efficiency +0.05 per cent.

Keywords: dairy farming, climatic effects, stochastic production frontiers, generalised true random effects, random parameters, total factor productivity

1. Introduction

There are growing concerns associated with the impact of climate change on agricultural production and food security at the global (Lobell, Schlenker and Costa-Roberts, 2011; IPCC, 2014; Burke, Hsiang and Miguel, 2015; Dawson, Perryman and Osborne, 2016; FAO, 2017;) and regional levels (Seo and Mendelsohn, 2008; Schlenker and Roberts, 2009; Hughes *et al.*, 2011; Roberts, Schlenker and Eyer, 2013; Burke and Emerick, 2016; Bozzola *et al.*, 2018). Within the United States, there is mounting evidence that damages on

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agricultural production caused by changing temperature and rainfall patterns have increased over the past several years and will continue to do so moving forward (Schlenker and Roberts, 2009; Roberts *et al.*, 2013; Hatfield *et al.*, 2014; Gowda *et al.*, 2018). Notwithstanding, there is evidence that producers continue to seek methods to adapt and moderate some of the negative effects of climate variation (Mendelsohn, Nordhaus and Shaw, 1994; Seo and Mendelsohn, 2008; Di Falco, 2014; Burke and Emerick, 2016; Holden and Quiggin, 2017; Huffman, Jin and Xu, 2018; Ortega-Reig *et al.*, 2018).

The objective of this study is to investigate how changing temperature and precipitation patterns have impacted productivity within the dairy sector in the state of Wisconsin. Wisconsin experiences temperature extremes characterised by cold winters and hot and humid summers. Our identification strategy is predicated on exploiting within-year variations in short-run contemporaneous weather as well as long-run climate trends in order to ascertain how these environmental factors are transmitted to productivity growth. An analysis of short-run weather anomalies will enable us to identify how unanticipated weather shocks impact productivity growth (Kaminski, Kan and Fleischer, 2013; Burke and Emerick, 2016; Njuki, Bravo-Ureta and O'Donnell, 2018). Similarly, an evaluation of long-term temperature trends will enable us to identify the extent to which farmers' adaptive strategies have offset the negative impacts of changing climatic conditions (Deschenes and Greenstone, 2007; Seo and Mendelsohn, 2008; Seo, 2013; Burke and Emerick, 2016).

The dairy sector in Wisconsin provides an ideal setting for investigating the impact of climatic conditions and their subsequent economic outcomes. In addition to experiencing substantial climate variability, Wisconsin is the second largest producer of farm milk, second only to California, and the largest producer of cheese in the United States accounting for 27 per cent of the nation's output (National Agricultural Statistics Service, 2014; Wisconsin Agricultural Statistics Service, 2017). Moreover, in 2012, Wisconsin had 1.28 million dairy cows and was responsible for generating 30.2 billion pounds of milk, generating USD 5.02 billion in farm revenues (Wisconsin Agricultural Statistics Service, 2017). Importantly, over the past several years, the dairy sector across the United States has undergone considerable structural change (MacDonald *et al.*, 2007; Mosheim and Lovell, 2009), and Wisconsin has not been spared these ongoing transformations. For example, in 2002, 54 per cent of Wisconsin's milk production was generated by farms with a herd size of less than 100 cows, and by 2017, this number had dropped to 20.1 per cent (MacDonald *et al.*, 2007). A sizeable 96 per cent of dairy farms in Wisconsin continue to be family owned though the size of such dairy farms has continued to increase (Wisconsin Agricultural Statistics Service, 2017). Falling milk prices, due to competition from other global milk producers (e.g. European Union, India, China, Brazil, Argentina, New Zealand), as well as weather volatility continue to be the sources of concern for dairy producers (Foreign Agricultural Service, 2018).

Figure 1 presents a boxplot of the coefficients of variation of daily maximum temperatures for select counties that illustrate the magnitude of temperature

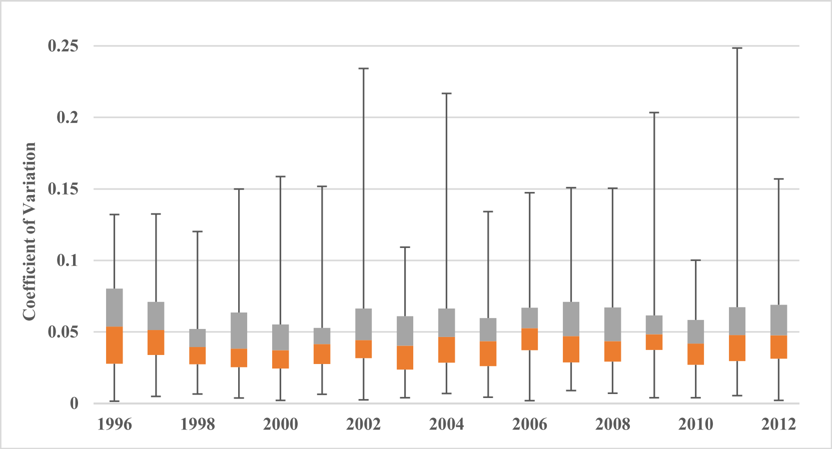

Fig. 1. Coefficient of variation of maximum daily temperatures (June–August).

variability experienced by our sample dairy farmers. These coefficients of variation are obtained by dividing the standard deviations of day-to-day maximum temperatures by their respective means across the various counties in our sample. The boxplot corresponds to the 182 days between June and August, which is the warmest period of the year. It captures the median, the interquartile range, the 25th and 75th percentile, and the outliers. The evidence makes it clear that the dairy farmers in our sample were exposed to substantial day-to-day temperature variability in the upper 75th percentile. This variability is supported by additional evidence indicating that the Wisconsin counties in our sample experienced moderate, severe or extreme drought in 2000, 2002, 2004, 2009 and 2011 (U.S. Drought Monitor, 2018). Furthermore, Figure 2 illustrates 30-year moving averages of temperature for selected counties, which provides evidence that long-run average temperatures have increased over the 1996–2012 period covered in this study.

Several studies have considered various aspects of environmental impacts on the dairy sector. The focus of these studies ranges from the suitability of the temperature–humidity index in measuring heat stress in dairy cows in subtropical environments (Dikmen and Hansen, 2009) to the effects of rising global temperatures in the southeastern region (Mukherjee, Bravo-Ureta, and De Vries, 2013) and the great plains (Mader *et al.*, 2009) of the United States. Other studies have considered the effects of summer heat stress on dairy cows (García-Ispierto *et al.*, 2007; Finger *et al.*, 2018), the dairy sector's contribution to negative externalities and the appropriateness of various measures aimed at regulating the same (Sneeringer and Key, 2011; Njuki and Bravo-Ureta, 2015, 2016). Similarly, some attention has been directed at investigating the relationship between climate and technical efficiency in the dairy industry (Key and Sneeringer, 2014; Qi *et al.*, 2015). In sum, the literature provides evidence indicating that livestock production in general and the dairy sector in particular

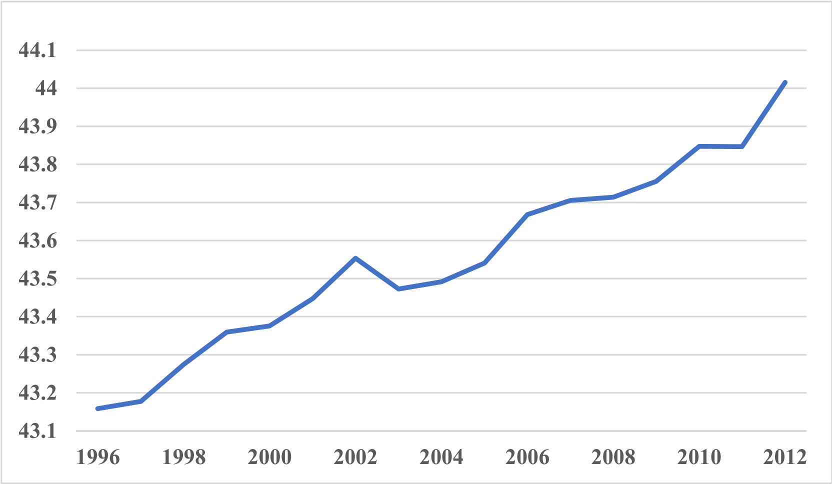

Fig. 2. Temperature normals (1996–2012).

will continue to be impacted by changing climatic conditions, primarily via the availability of feed grain and pastures (Hill *et al.*, 2004; Hatfield *et al.*, 2014), animal health and reproduction, and the distribution and resiliency of livestock parasites and pathogens (Hatfield *et al.*, 2014).

Unfortunately, not much attention has been directed towards investigating and identifying the sources of productivity growth in the dairy sector in the face of climate change. This is a missing link, which we seek to bridge by providing evidence that identifies the sources of productivity growth in the face of a changing climate. We define productivity growth as the rate of change in output relative to the rate of change in inputs. In this study, productivity is measured by constructing a total factor productivity (TFP) index, which is then decomposed into various factors that account for different sources of productivity change, namely: (i) technological change, which is manifested as a shift in the production frontier stemming from technological change; (ii) environmental and scale-and-mix efficiency change that captures economies of scale and the impact of contemporaneous weather anomalies; (iii) climate adaptation, which reflects farmers' efforts at adapting to climate (long-term) temperature trends; (iv) technical efficiency change, which measures the ability of managers to maximise output using given their inputs, technology and environment and (v) statistical noise, which captures unidentified variables that affect productivity. Kneip and Sickles (2012) argue that decomposing productivity change, even with elaborate formulations, is a challenging task and some statistical noise is likely to remain. In addition to providing a comprehensive decomposition of key factors that drive productivity growth, this study contributes important information and analysis that can be used to formulate policies designed to promote productivity in an important farming activity.

2. Climate shifts versus random weather fluctuations

In this study, we make a distinction between random fluctuations in weather and climate shifts. Whereas climate refers to the distribution of outcomes over long intervals (e.g. over several decades), weather refers to a random realisation from a climate distribution. Hence, weather variation refers to shorter run temporal fluctuations in temperature and precipitation within a given geographic area (Dell *et al.*, 2014: 741). The central argument is that a changing climate is causing increases in the intensity and frequency of weather fluctuations, and these fluctuations have a direct biophysical impact on agricultural output (Nelson *et al.*, 2014). Thus, because weather fluctuations constitute unanticipated shocks on output, they are more difficult to address and hence easier to discern using models that utilise panel data (Seo, 2013: 113).

With regard to climate, researchers have proposed a variety of approaches to investigate adaptation due to climate effects, ranging from the 30-year moving averages, known as climate normals, typically used in Ricardian models (Mendelsohn *et al.*, 1994; Seo and Mendelsohn, 2008), to the long-difference approach implemented by Burke and Emerick (2016). Dell, Jones and Olken (2014) argue that any econometric test for adaptation need not require identifying specific adaptation actions, which can be a major challenge, but can instead rely on long-run climatic trends as an indicator.

Climate change may have different impacts than (short-run) weather shocks, and the former may either offset or augment the latter (Dell *et al.*, 2014). In response to climate change, a number of adaptive strategies, including the adjustment of management plans and even policy and institutional regulations, may be implemented over time to reduce the negative effects of weather shocks (Dawson *et al.*, 2016). Depending on the adaptive strategies implemented, weather shocks may have varying impacts on farming (Holden and Quiggin, 2017). A study by Burke and Emerick (2016) exploits variations in climate in order to identify how producers' adaptation strategies might offset weather fluctuations. Their analysis does not find evidence that adaptation has mitigated any of the effects of weather fluctuations.

In dairy farming, short-run effects are associated with the impact of factors such as temperature, precipitation and humidity on milk production. In response, adaptive strategies implemented overtime may include building shade structures, installing cooling systems, changes in feed mixes and switching to breeds better suited to a warmer environment as well as genetic improvement of existing breeds to make them better suited to a changing climate, among others (Bravo-Ureta *et al.*, 2007; Seo and Mendelsohn, 2008; Mukherjee *et al.*, 2013; Key and Sneeringer, 2014). In this study, we utilise the temperature normal (30-year moving average for temperature) to capture the effects of farmers' adaptive strategies and use the term environmental effects to denote the combination of observed and unobserved weather shocks, climate trends and characteristics of the production environment (e.g. topography, soil type).

3. Methodology

First, we make a distinction between the production technology and the characteristics of the production environment. The technology is defined as '... a technique, method or system for transforming inputs into outputs' (O'Donnell, 2016). The production environment, on the other hand, consists of all variables that impact the production process but are beyond the control of the firm. More formally:

$$T^t(z) = \left\{ (x, q) \in \Re_+^{M+N} : x \text{ can produce } q \text{ in environment } z \text{ in period } t \right\} \tag{1}$$

We make additional assumptions in order to ensure that the production technology is regular and can be represented using a period-and-environment specific production frontier (see O'Donnell, 2016: 330). The relationship between the variables in the production technology can be represented more generally as:

$$q_{it} = f^t(x_{it}, z_{it}; \beta, \rho) \exp(v_{it} - u_{it}) \tag{2}$$

where f^t is the function that approximates the production technology, v_{it} measures statistical errors, u_{it} is an output-oriented measure of technical efficiency and subscripts i and t denote firm and period, respectively. As a first step, we investigate the most appropriate approach for modelling how climatic effects are transmitted to productivity growth within a stochastic production frontier framework. The random parameters (RP) approach as well as the generalised true random effects (GTRE) are each examined in turn. In addition, we also test the true random effects (TRE), which is a restricted version of the RP model (Greene, 2005).

3.1. The RP model

The mainstream stochastic production frontier literature assumes that firms in a sample share the same production technology but differ with respect to their levels of technical efficiency. This assumption is likely too restrictive and may lead to inaccurate parameter estimates and misleading efficiency scores (Tsionas, 2002). Firms take up new technologies with considerable lags, and even when they share similar production technologies, they operate in different production environments, and as a result, they are subject to a range of production choices and thus exhibit different levels of productivity. Under the aforementioned scenario, a suitable estimation approach is the use of a RP stochastic production frontier. The randomness in the parameters derives from stochastic variations in environmental variables that are typically unobserved to the researcher (e.g. windspeed, number of frost-free days, soil quality). Following Njuki *et al.* (2018), we partition the vector of environmental variables such that $z = (z_i^*, z_{it}^*, z_{it})$, where z_i^* is an unobserved vector of nonrandom time-invariant environmental variables (e.g. topography, soil type); z_{it}^* is a vector of unobserved random firm and time-varying environmental variables (e.g.

number of frost-free days, wind speed); finally, z_{it} is a vector of observed firm and time-varying environmental variables (e.g. rainfall, temperature). The function that approximates the production technology given the circumstances described here can be specified in logarithmic form as:

$$\ln q_{it} = \alpha_i + \sum_{t=1}^{T} \gamma_t + \sum_{j=1}^{J} \rho_{jit} \ln z_{jit} + \sum_{j=1}^{J} \sum_{l=j}^{J} \rho_{jlit} \ln z_{jit} \ln z_{lit} + \delta_{it} \ln h_{it} + \sum_{m=1}^{M} \beta_{mit} \ln x_{mit} + \phi_c + v_{it} - u_{it} \quad (3)$$

where α_i is a random farm-specific effect that captures unobserved heterogeneity at the farm-level, γ_t are yearly fixed-effects reflecting the rate of technical change, z_{jit} are contemporaneous weather effects, h_{it} captures the effects of long-term climate trends and x_{mit} are conventional inputs. The RP $\rho_{jit} \equiv \rho^j(z^*_{it})$, and $\beta_{mit} \equiv \beta^m(z^*_{it})$ account for the effects of unobserved stochastic firm and time-varying weather variables (see Njuki *et al.*, 2018). Furthermore, we assume that the RP are independent random variables with normal distributions: $\alpha_i \sim N(\mu_\alpha, \sigma^2_\alpha)$, $\rho_{jit} \sim N(\rho_j, \sigma^2_{\rho_j})$ and $\beta_{mit} \sim N(\beta_m, \sigma^2_{\beta_m})$. The component ϕ_c measures the role of county-level heterogeneity such that $\phi_c \equiv \phi^c(z^*_i)$. Finally, the error term is modelled as a two-part component comprising the statistical noise with normal distribution, $v_{it} \sim N(0, \sigma^2_v)$, and the inefficiency component with half-normal distribution, $u_{it} \sim N^+(0, \sigma^2_u)$, respectively (Aigner, Lovell and Schmidt, 1977). Going back to equation (3), we note that if $\sigma^2_{\rho_j} = \sigma^2_{\beta_m} = 0$ for all values of j and m,[1] then all firms share the same production technology but differ with respect to their levels of technical efficiency (Tsionas, 2002).

3.2. The GTRE model

Related studies have decomposed the error structure into persistent and transient components, in addition to a third component capturing statistical noise (e.g. Kumbhakar and Heshmati, 1995). A shortcoming of this last approach is its inability to disentangle unobserved firm-specific effects from persistent and transient inefficiency. Greene (2005) introduced the 'true-fixed' and 'true-random' effects models that go a step further and disentangle unobserved time invariant firm-specific effects from time-varying inefficiency but do not identify persistent inefficiency. More recent studies have gone a step further by incorporating an error structure with four parts, which makes it possible to identify separately, time-invariant unobserved firm-specific effects, persistent inefficiency, transient inefficiency and statistical errors (Colombi *et al.*,

1 The model with $\sigma^2_{\rho_j} = \sigma^2_{\beta_m} = 0$ and $\sigma^2_{\alpha_i} > 0$ gives rise to the true random effects model (see Greene, 2005). We test this assumption and provide a discussion in the results section.

2014; Kumbhakar, Lien and Hardaker, 2014; Tsionas and Kumbhakar, 2014; Filippini and Greene, 2016). This model is known as the Generalised True Random Effects or GTRE.

The GTRE model that approximates the production technology can be written in logarithmic form as:

$$\ln q_{it} = \omega_i + \sum_{t=1}^{T} \gamma_t + \sum_{j=1}^{J} \rho_j \ln z_{jit} + \sum_{j=1}^{J} \sum_{l=j}^{J} \rho_{jl} \ln z_{jit} \ln z_{lit} + \delta \ln h_{it} + \sum_{m=1}^{M} \beta_m \ln x_{mit} + \phi_c + \varepsilon_{it} \quad (4)$$

Following Filippini and Greene (2016), the error structure of the GTRE model consists of two components and four parts. The first component is given by $\omega_i = \xi_i - \eta_i$, where ξ_i and η_i represent time-invariant firm-specific heterogeneity and inefficiency, respectively. Filippini and Greene (2016) indicate that ω_i follows a closed-skew normal distribution with parameters $\kappa = \sigma_\eta/\sigma_\xi$ and $\theta = (\sigma_\xi^2 + \sigma_\eta^2)^{1/2}$. The second component, $\varepsilon_{it} = v_{it} - u_{it}$, where v_{it} and u_{it} captures time-varying statistical errors and inefficiency, respectively. This second component also follows a closed-skew normal distribution with parameters $\lambda = \sigma_u/\sigma_v$ and $\psi = (\sigma_u^2 + \sigma_v^2)^{1/2}$.

4. The TFP index

The estimated coefficients from the preceding stochastic production frontier models (equations (3) and (4)) are used to decompose a productivity index. We define productivity as the rate of change in aggregate output relative to the rate of change in aggregate inputs. Following O'Donnell (2016), the TFP index that measures the productivity of firm i in period t relative to firm k in period s is given by

$$\text{TFPI} = \frac{[Q(q_{it})/X(x_{it})]}{[Q(q_{ks})/X(x_{ks})]} \quad (5)$$

where $Q(.)$ and $X(.)$ are output and input aggregators, respectively. The multiplicative TFP index introduced by O'Donnell (2017) takes on the following form:

$$\text{TFPI}^M(q_{it}, q_{ks}, x_{it}, x_{ks}) = \prod_{n=1}^{N} \left(\frac{q_{nit}}{q_{nks}}\right)^{a_n} \prod_{m=1}^{M} \left(\frac{x_{mks}}{x_{mit}}\right)^{b_m} \quad (6)$$

where $a_1, \ldots a_N$ and $b_1, \ldots b_M$ are nonnegative output and input weights, respectively, that sum to one (O'Donnell, 2017). The stochastic production frontier is the estimated following equation (3), and the estimated parameters are used to construct weights following Njuki *et al.* (2018) such that

$b_m = \hat{\beta}_m / \sum_{k=1}^{M} \hat{\beta}_k$, where $\hat{\beta}_m$ is an estimator of β_m. The resulting multiplicative TFP index decomposes as follows:

$$\mathrm{TFPI}^M(q_{it}, q_{ks}, x_{it}, x_{ks}) = \left[\frac{\exp(\gamma_t)}{\exp(\gamma_s)}\right] \times \left[\left(\frac{\exp(\alpha_i)}{\exp(\alpha_k)}\right)\left(\frac{\exp(\phi_c)}{\exp(\phi_d)}\right)\prod_{j=1}^{J}\left(\frac{z_{jit}^{\rho_{jit}+\sum_{l=j}^{J}\rho_{jlit}\ln z_{lit}}}{z_{jks}^{\rho_{jks}+\sum_{l=j}^{J}\rho_{jlks}\ln z_{lks}}}\right)\prod_{m=1}^{M}\left(\frac{x_{mit}^{\beta_{mit}-b_m}}{x_{mks}^{\beta_{mks}-b_m}}\right)\right] \times \left[\frac{h_{it}^{\delta_{it}}}{h_{ks}^{\delta_{ks}}}\right] \times \left[\frac{\exp(u_{it})}{\exp(u_{ks})}\right] \times \left[\frac{\exp(v_{it})}{\exp(v_{ks})}\right] \quad (7)$$

The index above is used to identify the sources of productivity growth in Wisconsin dairy farms. The first component (inside square brackets) on the right-hand side is an output-oriented technology index (OTI) that captures productivity changes associated with shifts in the production frontier. The second component is the output-oriented environment and scale-mix efficiency index (OESMEI) reflecting changes and differences in productivity growth due to fluctuating environmental factors, economies of scale and farm-level heterogeneity. The third component is the climate adaptation index (CAI) that accounts for farmers' ability to adapt to long-term climate trends. The fourth component is the output-oriented technical efficiency index (OTEI) that measures managerial ability reflected by movements closer to or away from the frontier. Finally, the fifth component is the statistical noise index (SNI), which captures productivity changes for reasons that cannot be identified (O'Donnell 2017).

If $\sigma_{\rho j}^2 = \sigma_{\beta m}^2 = 0$, then the TFP decomposition associated with the parameters estimated from the GTRE model in equation (4) takes on the following form:

$$\mathrm{TFPI}^M(q_{it}, q_{ks}, x_{it}, x_{ks}) = \left[\frac{\exp(\gamma_t)}{\exp(\gamma_s)}\right] \times \left[\left(\frac{\exp(\phi_c)}{\exp(\phi_d)}\right)\prod_{j=1}^{J}\left(\frac{z_{jit}^{\rho_j+\sum_{l=j}^{J}\rho_{jl}\ln z_{lit}}}{z_{jks}^{\rho_j+\sum_{l=j}^{J}\rho_{jl}\ln z_{lks}}}\right)\right] \times \left[\frac{h_{it}}{h_{ks}}\right]^{\delta}\left[\prod_{m=1}^{M}\left(\frac{x_{mit}}{x_{mks}}\right)^{\beta_m-b_m}\right] \times \left[\frac{\exp(\xi_i)}{\exp(\xi_k)}\right] \times \left[\frac{\exp(\eta_i)}{\exp(\eta_k)}\right] \times \left[\frac{\exp(u_{it})}{\exp(u_{ks})}\right] \times \left[\frac{\exp(v_{it})}{\exp(v_{ks})}\right] \quad (8)$$

Similar to the TFP index in equation (7), the first component on the right-hand side of equation (8) is the OTI. The second component is the output-oriented environmental index. The third component is the CAI. The fourth component is the output-oriented scale-and-mix efficiency index (OSEI).

The fifth component is an output-oriented firm-specific index that captures differences in productivity due to time-invariant firm-specific heterogeneity. The sixth component measures output-oriented persistent technical efficiency index (OPEI) that captures differences in productivity changes associated with the persistent part of technical efficiency. The seventh component captures the output-oriented transient technical efficiency index (OTTEI). Finally, the seventh component measures productivity changes due to reasons that cannot be identified.

5. Data

The empirical analysis uses input–output data from Wisconsin dairy farms. The input-output data are obtained from the Agricultural Financial Advisor programme at the University of Wisconsin-Madison Center for Dairy Profitability.[2] For this study, we utilise a balanced panel comprising 53 farms located across 10 counties over a 17-year period going from 1996 to 2012 for a total of 901 observations.

On average, total milk equivalent produced per farm is 1,220 metric tons per year. Milk equivalent units are calculated by dividing total farm income by the average US milk price for the time period in question. The conventional inputs comprise: farm labour, which includes hired labour, paid and unpaid family labour and averaged 6,323 hours per farm per year; concentrate feed, the total quantity of 16 per cent dairy concentrate feed[3] purchased per year; capital cost, which includes depreciation on breeding livestock, machinery, equipment and buildings, and has an average value of USD 78,539 per year per farm; annual animal expense that includes total expenditures on veterinary care and medicine, breeding fees and other livestock expenses; and land used to grow corn silage, an important source of farm produced feed for dairy cows in Wisconsin, averaged 94.5 acres. All monetary figures are expressed in constant 2012 dollars.

Climate and weather variables are obtained from the PRISM climate group, which creates a climate mapping system that generates temperature and precipitation for 4-by-4 km grid cells within each county in the data set, and come from ground weather stations as well as satellite information in order to account for the effects of elevation, temperature inversion and shoreline proximity (Daly *et al.*, 2008, 2015). The weather variables used in this study comprise cumulative precipitation over the spring (March–May) and summer (June–August) growing seasons, the standard deviations of average maximum temperatures during the warmest months (June–August) and the standard deviations of average minimum temperatures during the coldest months (December–February). The standard deviations of maximum and minimum temperatures are incorporated into the model to capture contemporaneous

2 https://cdp.wisc.edu

3 16 per cent concentrate refers to the percentage of protein content in the feed.

Table 1. Descriptive statistics of variables

Variable	Mean	Standard deviation	Minimum	Maximum
Milk equivalent (metric tons)	1,219.74	1,502.77	141.96	18,543.20
Conventional inputs				
Cows (heads)	98.52	98.56	20.50	1,162.00
Capital ($)	78,538.51	98,501.55	464.71	1,196,189.00
Labour (hours)	6,322.63	6,450.05	1,297.76	69,686.05
Concentrate feed (metric tons)	616.08	907.19	10.83	8,694.76
Animal expenses ($)	35,194.36	53,391.81	283.31	642,433.30
Corn silage (acres)	94.59	106.32	0.00	635.00
Climatic variables				
Spring precipitation (mm)	282.56	79.50	111.13	519.17
Summer precipitation (mm)	241.81	72.39	103.12	581.66
Standard deviation of average minimum temperature (December–February)	5.06	2.11	0.62	10.16
Standard deviation of average maximum temperature (June–August)	3.00	1.29	0.60	5.55
Temperature normals (Fahrenheit)	45.15	1.50	39.84	46.60

temperature shocks and anomalies (Kaminski *et al.*, 2013; Njuki *et al.*, 2018). Finally, the temperature climate normal is included as an indicator of the effectiveness of adaptive strategies in offsetting the negative effects of weather shocks (Mendelsohn *et al.*, 2007; Seo and Mendelsohn, 2008; Seo, 2013; Dell, Jones and Olken, 2014). Descriptive statistics of the data used in this study are illustrated in Table 1.

6. Results and analysis

The RP and GTRE models (equations (3) and (4)) are estimated using simulated maximum likelihood methods implemented with LIMDEP (Greene, 2016). We also estimate the TRE model (Greene, 2005), where $\sigma^2_{\rho j} = \sigma^2_{\beta m} = 0$ and $\sigma^2_{\alpha_i} > 0$; thus, it is nested within the RP model. All estimated coefficients and corresponding standard errors are reported in Table 2. Preliminary statistical tests are conducted in order to select the model to be used for the TFP measurement and decomposition. A likelihood ratio test is conducted to contrast the null hypothesis that $H_0 : \sigma^2_{\rho_j} = \sigma^2_{\beta_m} = 0$ for the values of j and m against the alternative hypotheses $H_A : \sigma^2_{\rho_j}$ and $\sigma^2_{\beta_m} > 0$. The restricted and unrestricted log-likelihood values for the RP and TRE models with chi-squared distribution and 16 degrees of freedom are 595.0 and 790.4,

Table 2. Coefficient estimates of random parameters, generalised true random effects and true random effects models

Parameter/variable		Random parameters model		Generalised true random effects model		True random effects	
		Estimate	SE	Estimate	SE	Estimate	SE
μ_α	Constant	0.0797***	0.0038	−0.0907***	0.0260	−0.0282	0.0251
β_1	Cows	0.6491***	0.0041	0.7101***	0.0195	0.7077***	0.0194
β_2	Labour	0.0378***	0.0029	0.0194	0.0191	0.0200	0.0187
β_3	Capital	0.0749***	0.0008	0.0422***	0.0052	0.0424***	0.0051
β_4	Animal expenses	0.0645***	0.0010	0.0350***	0.0065	0.0357***	0.0064
β_5	Concentrate feed	0.1614***	0.0013	0.1213***	0.0089	0.1206***	0.0086
β_6	Corn silage area	0.0050***	0.0002	0.0027***	0.0009	0.0027***	0.0008
σ_{μ_α}	Constant	0.0411***	0.0006	0.1102***	0.0048	0.1130***	0.0044
σ_{β_1}	Cows	0.0091***	0.0012				
σ_{β_2}	Labour	0.0135***	0.0009				
σ_{β_3}	Capital	0.0145***	0.0004				
σ_{β_4}	Animal expenses	0.0316***	0.0006				
σ_{β_5}	Concentrate feed	0.0053***	0.0005				
σ_{β_6}	Corn silage area	0.0041***	0.0006				
ρ_1	Spring precipitation	0.0091***	0.0020	−0.0098	0.0131	−0.0105	0.0130
ρ_{11}	Spring precipitation square	0.1537***	0.0106	0.1014*	0.0615	0.0976	0.0606
ρ_2	Summer precipitation	−0.0199***	0.0021	−0.0124	0.0163	−0.0105	0.0156
ρ_{22}	Summer precipitation square	−0.0753***	0.0102	−0.0681	0.0682	−0.0601	0.0659
ρ_3	Minimum temperature standard deviation	−0.0216***	0.0013	−0.0117	0.0092	−0.0109	0.0089

Continued

Table 2. Continued

Parameter/variable		Random parameters model		Generalised true random effects model		True random effects	
		Estimate	SE	Estimate	SE	Estimate	SE
ρ_{33}	Minimum temperature standard deviation square	0.0001	0.0044	−0.0076	0.0316	−0.0078	0.0312
ρ_4	Maximum temperature standard deviation	−0.0153***	0.0015	−0.0375***	0.0114	−0.0352***	0.0112
ρ_{44}	Maximum temperature standard deviation square	−0.0493***	0.0036	−0.0990***	0.0236	−0.0932***	0.0234
ρ_{42}	Maximum temperature standard deviation × summer precipitation	0.2538***	0.0081	0.1920**	0.0792	0.1919**	0.0772
δ_1	Temperature normals	−0.1870***	0.0231	−0.4463***	0.1150	−0.5398***	0.1102
σ_{ρ_1}	Spring precipitation	0.1406***	0.0019				
$\sigma_{\rho_{11}}$	Spring precipitation square	0.0949***	0.0075				
σ_{ρ_2}	Summer precipitation	0.0332***	0.0017				
$\sigma_{\rho_{22}}$	Summer precipitation square	0.0504***	0.0068				
σ_{ρ_3}	Winter standard deviation	0.0182***	0.0010				
$\sigma_{\rho_{33}}$	Winter standard deviation square	0.0458***	0.0033				
σ_{ρ_4}	Summer standard deviation	0.0213***	0.0009				
$\sigma_{\rho_{44}}$	Summer standard deviation square	0.0162***	0.0016				
$\sigma_{\rho_{24}}$	Maximum temperature standard deviation × summer precipitation	0.1074***	0.0064				
σ_{δ_1}	Temperature normals	0.2553***	0.0208				
ϕ_1	Brown	−0.0153***	0.0029	−0.0394**	0.0173	−0.0421**	0.0169
ϕ_2	Calumet	−0.0506***	0.0029	−0.0177	0.0167	−0.0502***	0.0162
ϕ_3	Clark	−0.0367***	0.0044	−0.1016***	0.0309	−0.1475***	0.0295
ϕ_4	Fond du Lac	−0.0453***	0.0024	−0.0006	0.0139	−0.0341**	0.0133

Continued

Table 2. Continued

Parameter/variable		Random parameters model Estimate	SE	Generalised true random effects model Estimate	SE	True random effects Estimate	SE
ϕ_5	Manitowoc	−0.1428***	0.0033	−0.1158***	0.0217	−0.1190***	0.0211
ϕ_6	Oneida	−0.1756***	0.0045	−0.0904***	0.0290	−0.0842***	0.0286
ϕ_7	Ozaukee	−0.0616***	0.0027	−0.0497***	0.0150	−0.0833***	0.0147
ϕ_8	Price	−0.2505***	0.0062	−0.2787***	0.0300	−0.2796***	0.0286
ϕ_9	Taylor	−0.0323***	0.0034	−0.0328	0.0217	−0.0731***	0.0203
γ_1	1997	0.0642***	0.0028	0.0814**	0.0346	0.0815**	0.0347
γ_2	1998	0.0327***	0.0027	0.0584	0.0363	0.0582	0.0354
γ_3	1999	0.1190***	0.0027	0.1626***	0.0324	0.1624***	0.0319
γ_4	2000	0.0553***	0.0035	0.1241***	0.0268	0.1240***	0.0265
γ_5	2001	−0.0053	0.0035	0.0545*	0.0328	0.0543*	0.0324
γ_6	2002	0.1103***	0.0039	0.1718***	0.0324	0.1711***	0.0320
γ_7	2003	0.1951***	0.0036	0.2635***	0.0291	0.2631***	0.0288
γ_8	2004	0.0201***	0.0034	0.1037***	0.0298	0.1036***	0.0289
γ_9	2005	0.1028***	0.0037	0.1845***	0.0311	0.1845***	0.0300
γ_{10}	2006	0.2368***	0.0038	0.2941***	0.0282	0.2937***	0.0274
γ_{11}	2007	0.0641***	0.0036	0.1416***	0.0309	0.1414***	0.0306
γ_{12}	2008	0.1234***	0.0035	0.2071***	0.0292	0.2070***	0.0292
γ_{13}	2009	0.2677***	0.0036	0.3098***	0.0275	0.3098***	0.0269
γ_{14}	2010	0.1707***	0.0038	0.2345***	0.0233	0.2346***	0.0231
γ_{15}	2011	0.1782***	0.0038	0.2302***	0.0329	0.2305***	0.0320
γ_{16}	2012	0.3029***	0.0037	0.3554***	0.0301	0.3559***	0.0295
	log likelihood function	595.00		792.33		790.40	
	$\overline{u}_{it}$	0.927		0.865		0.919	
	$\overline{\eta}_i$			0.937			
	λ	0.1789***	0.0039	1.3372***	0.2847	1.3537***	0.27629
	κ			0.0392	0.5290		

***,**,* indicate significance at the 1%, 5%, and 10% level.

respectively, with a p value of 0.000. Because the alternative hypothesis is one-sided, the distribution of the likelihood ratio statistic is a mixture of chi-squared distributions and the critical values are obtained from Kodde and Palm (1986). Thus, we reject the TRE model in favour of the RP model. Moreover, the statistical significance of the coefficient estimates of σ_{β_m} in Table 2 is an indication that the β_m parameters do vary across firms and time periods.

We test for the presence of transient (time-varying) inefficiency effects across the models, where $H_0 : \lambda = 0$ and the alternative is $H_A : \lambda > 0$. The test statistic is $z = \tilde{\lambda}/se(\tilde{\lambda}) \sim N(0, 1)$, where $\tilde{\lambda} = (\sigma_u/\sigma_v)$ is the maximum likelihood estimator for λ and $se(\tilde{\lambda})$ is the reported standard error (Coelli, 1995; Coelli *et al.*, 2005). The test-statistics are: $z = (0.179/0.004) = 44.75$ for the RP model; $(1.337/0.284) = 4.71$ for the GTRE model and $(1.354/0.276) = 4.91$ for the TRE model. These test-statistics are all greater than the corresponding critical value $z_{0.95} = 1.96$; hence, we reject the null hypothesis that there are no transient (time-varying) inefficiency effects.

We also test for the presence of persistent (time-invariant) inefficiency where the null hypothesis is $H_0 : \kappa = 0$ and the alternative is $H_A : \kappa > 0$. The test statistic is $z = \tilde{\kappa}/se(\tilde{\kappa}) \sim N(0, 1)$, where $\tilde{\kappa} = (\sigma_\eta/\sigma_\xi)$ is the maximum likelihood estimator for κ and $se(\tilde{\kappa})$ is the corresponding standard error. The estimates shown in Table 2 indicate that the test-statistic $z = (0.039/0.529) = 0.73$, which is less that the critical value $z_{0.95} = 1.96$. So, we fail to reject the null hypothesis that there are no persistent (time-invariant) inefficiency effects; therefore, unless noted otherwise, the estimates from the RP model are the ones we refer to in the rest of this section.

The parameter estimates from the RP model for the conventional inputs, i.e. cows, labour, capital, commercial feed, animal and corn silage area can be interpreted as partial elasticities. The output elasticity of herd size, β_1, indicates that a one-per cent increase in the number of cows raises output by 0.64 per cent, revealing that this is the key contributor to increased milk output. A Wald test for the null hypothesis (H_0) of constant returns to scale generates a chi-squared test statistic of 80.77 and p value of 0.000. Therefore, we reject the null hypothesis of constant returns to scale. The returns to scale, which is given as the sum of the partial elasticities of the conventional inputs, $\sum_m \hat{\beta}_m = 0.99$, revealing slightly decreasing returns to scale. Furthermore, the parameter estimates of the conventional inputs are nonnegative and significantly different from zero, thus satisfying the property of strong disposability of inputs from production theory. In the absence of average prices or value shares, these partial elasticities can be used to compute the nonnegative weights used to construct the indexes in equation (7).

Parameter estimates of the weather variables, ρ_j, are reported in Table 2. An initial exploratory analysis indicates that the use of quadratic and interaction terms for the weather variables provides the most statistically robust results. As indicated in the data section, the weather variables included are a mix of cumulative precipitation during the spring (March–May) and summer (June–August) growing season, the standard deviation of average maximum temperatures during the warmest months of the year (June–August), the standard deviation of average minimum temperatures during the coldest months of the year (December–February) and the temperature normal. The standard deviations of average maximum and minimum temperatures capture the marginal effects of weather volatility and anomalies on dairy production. The temperature normal can be interpreted as an indicator of climate adaptation efforts in response to warmer patterns (e.g. Mendelsohn *et al.*, 2007).

Our results reveal that spring precipitation and its quadratic term have had a strictly increasing positive and statistically significant impact on dairy production. On the other hand, summer precipitation has had a negative and statistically significant effect on dairy production. Its quadratic term reveals that this effect is strictly decreasing. The marginal effects of the standard deviations of maximum temperatures (i.e. June–August) and minimum temperatures (i.e. December–February) are both negative and statistically different from zero. This is an indicator that exposure to temperature volatility, regardless of whether this takes place in the winter or in the summer, has negative impacts on dairy production. However, the interaction between the standard deviation of maximum average temperatures and summer precipitation reveals that marginal increases in precipitation during the summer months (i.e. June and August) may offset some of the negative effects of summer temperature volatility.

Finally, the estimated output elasticity for the temperature normal is negative and statistically significant, revealing that long-run average temperature intensification has not been offset by adaptation efforts in our sample of Wisconsin dairy farmers. An alternative interpretation is that, net of any adaptations by the typical farmer in our sample, a one standard deviation rise above the temperature normal, which amounts to 1.5°F, reduces dairy output for the average farm by 20.1 metric tons per year.[4] Given that output per cow for the average farm was 12.38 metric tons per year, this is equivalent, ceteris paribus, to an annual reduction in the herd size for the average farm of 1.6 cows.

Following Baltagi and Griffin (1988) and Triebs and Kumbhakar (2013), we model technical change using time fixed-effects. This is an appropriate alternative to a regular time-trend that results in a constant rate of technical change. We note that the estimates for the time fixed effects, γ_t, in Table 2 do in fact reveal considerable variation over time. Furthermore, we incorporate county-level fixed effects in order to account for unobserved characteristics of the production environment (e.g. soil type and topography). A likelihood ratio test is conducted to evaluate the null hypothesis, $H_0 : \phi_c = 0$, in which case county-level fixed effects do not belong in the model, against the alternative hypothesis, $H_0 : \phi_c \neq 0$. The test generates a likelihood ratio test statistic of 63.58 with a p value = 0.000, which leads to the rejection of the null hypothesis that county-level fixed effects do not belong in the model.

4 This value is the product of the estimated parameter for temperature normals ($\hat{\rho}_5$), its standard deviation (σ_{z_5}) and the mean output ($\overline{\mu}_y$), divided by 17, which is the length of the panel.

Table 3. TFPI and associated index numbers

Farm ID	Year	TFPI	TI	OTEI	OESMEI	CAI	SNI
1	1996	1.000	1.000	1.000	1.000	1.000	1.000
1	1997	1.351	1.066	1.005	0.741	0.625	1.701
1	1998	1.162	1.033	1.007	0.784	0.649	1.423
1	2010	1.412	1.186	1.012	0.750	0.817	1.569
1	2011	1.343	1.195	1.000	0.753	0.920	1.493
1	2012	2.072	1.354	1.006	0.829	0.843	1.836
12	1996	0.827	1.000	0.977	0.869	0.751	0.974
12	1997	1.143	1.066	0.906	0.676	0.604	1.751
12	1998	1.021	1.033	0.953	0.766	0.724	1.353
12	2010	1.790	1.186	0.968	0.743	0.802	2.096
12	2011	1.520	1.195	0.988	0.952	0.957	1.351
12	2012	1.578	1.354	0.902	0.932	0.792	1.386
34	1996	1.009	1.000	0.947	0.950	0.931	1.121
34	1997	1.143	1.066	1.005	0.587	0.935	1.819
34	1998	1.057	1.033	0.966	0.361	0.592	2.934
34	2010	1.337	1.186	1.004	0.849	0.779	1.322
34	2011	1.302	1.195	0.976	1.020	1.090	1.094
34	2012	1.769	1.354	1.014	0.837	0.775	1.539
47	1996	1.144	1.000	0.987	0.588	0.839	1.970
47	1997	1.162	1.066	0.994	0.657	0.847	1.669
47	1998	1.125	1.033	0.984	0.544	0.811	2.032
47	2010	1.615	1.186	0.999	0.569	0.709	2.394
47	2011	1.278	1.195	0.968	0.577	0.618	1.914
47	2012	1.114	1.354	0.999	0.539	0.700	1.527

Finally, technical efficiency, an indicator that has been widely used in the literature to assess dairy farm performance (Kumbhakar, Ghosh and McGuckin, 1991; Ahmad and Bravo-Ureta, 1995, 1996; Kumbhakar and Heshmati, 1995; Moreira and Bravo-Ureta, 2009; Sipiläinen, Kumbhakar and Lien, 2014; Sauer and Latacz-Lohmann, 2015) ranged between 66.6 and 96.0 per cent with an average of 92.2 per cent for our sample dairy farms.

6.1. Productivity analysis

The estimated parameters from the RP SPF in equation (3), (α_i, γ_t, β_{mit}, ρ_{jit}, δ_{it}, ϕ_c), are used to decompose the TFP index in equation (7) in order to identify the various sources of TFP growth, namely: OTI; output-oriented environmental and scale-mix efficiency index (OESMEI); CAI; OTEI and the SNI. As indicated above, all indexes compare the productivity of farm i in period t, which is the reference farm, against the productivity farm k in period s, which

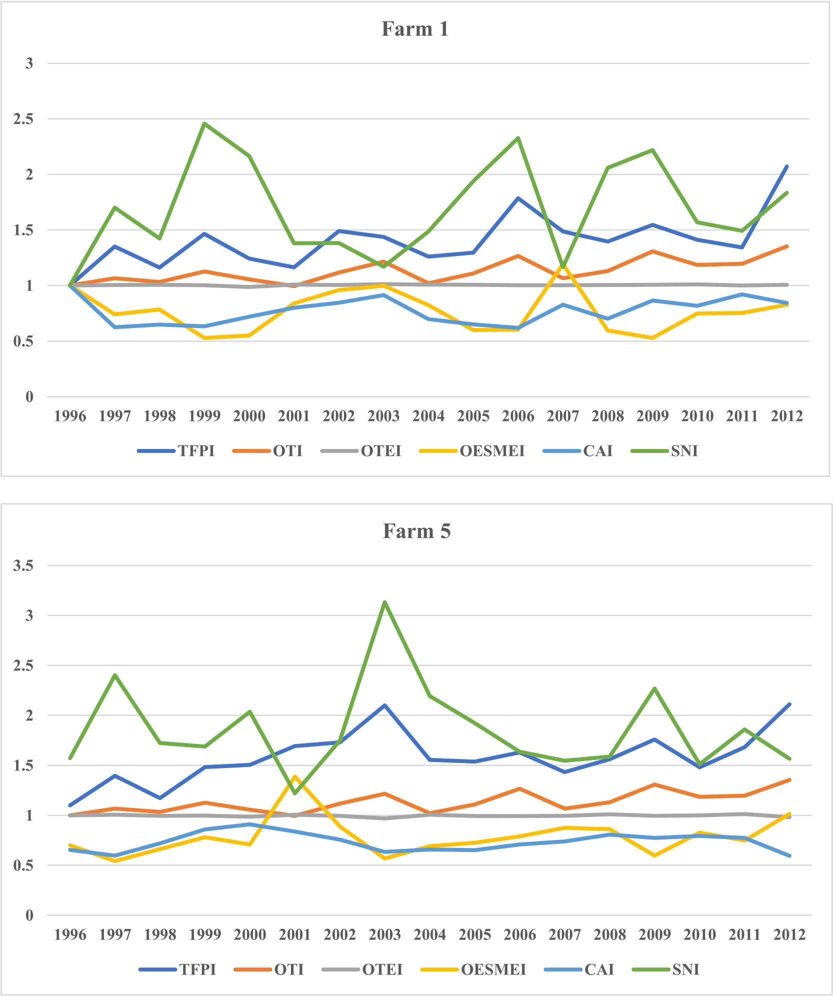

Fig. 3. TFP and its associated indexes (see Farm 1, 1996–2012).

is the comparison farm. To illustrate how these indexes are generated, we report TFP indexes and their components for the first and last three years of the sample for select farms, 1, 12, 34 and 47 in Table 3.[5] For example, the sixth row in Table 3, indicates TFPI for Farm 1, was 2.07 in 2012 revealing that TFP increased at an annual average rate of 4.65 per cent.[6] In Figure 3, we illustrate

5 Farm 1 represents the reference vector against which all other farms are compared.

6 These numbers are calculated in the following manner: Table 3 shows that TFPI in Farm 1 in 1996 and 2012 is 1.000 and 2.072, respectively. Thus, the year-to-year growth rate in TFPI is calculated as $(2.072/1.000)^{1/(2012-1996)} - 1 = 4.65$ per cent. In other words, if we compound 1.0 at a rate of 4.65 per cent per annum, we obtain 2.072.

Table 4. TFPI decomposition and its components using random parameters model

Farm ID	%ΔTFPI	%ΔTI	%ΔOTEI	%ΔOESMEI	%ΔCAI	%ΔSNI
1	4.658	1.911	0.039	−1.169	−1.062	3.869
2	3.044	1.911	0.810	0.811	−0.337	−0.508
3	6.044	1.911	0.251	0.154	−8.798	3.635
4	4.059	1.911	0.121	1.896	−1.613	0.087
5	4.150	1.911	−0.120	2.341	−0.589	−0.021
6	0.704	1.911	−0.139	7.281	3.394	−7.763
7	1.729	1.911	−0.412	4.149	0.582	−3.759
8	−2.608	1.911	−0.033	0.856	−2.635	−5.215
9	1.733	1.911	−0.060	1.005	0.435	−1.108
10	2.724	1.911	0.064	−1.177	−1.802	1.932
11	3.914	1.911	0.777	1.581	1.755	−0.396
12	4.120	1.911	−0.497	0.443	0.332	2.225
13	1.013	1.911	−0.139	−0.720	−0.539	−0.023
14	0.533	1.911	0.018	−0.473	−0.376	−0.902
15	1.921	1.911	0.101	0.582	0.160	−0.669
16	3.154	1.911	−0.047	0.061	0.012	1.205
17	2.230	1.911	−0.553	0.877	0.584	−0.005
18	0.845	1.911	−0.481	−0.713	−1.733	0.146
19	1.267	1.911	0.068	−0.534	−0.209	−0.165
20	2.198	1.911	−0.421	−0.204	−1.129	0.912
21	0.700	1.911	−0.048	0.931	−0.752	−2.053
22	1.781	1.911	−0.096	0.091	0.841	−0.123
23	3.009	1.911	−0.040	−0.528	0.863	1.655
24	1.816	1.911	−0.226	−1.149	−0.557	1.297
25	0.733	1.911	−0.450	−0.383	−0.470	−0.327
26	1.634	1.911	−0.421	−0.953	−0.351	1.113
27	3.045	1.911	−0.185	−1.162	0.675	2.491
28	1.750	1.911	0.035	0.274	0.609	−0.467
29	2.953	1.911	0.031	−1.081	0.467	2.094
30	1.159	1.911	−0.115	−2.733	−0.158	2.169
31	0.007	1.911	0.030	−0.530	−0.040	−1.375
32	2.731	1.911	0.009	−2.883	−1.067	3.788
33	2.598	1.911	0.026	−2.053	0.494	2.758
34	3.572	1.911	0.431	−0.789	−1.144	1.998
35	5.675	1.911	−0.138	−0.142	−1.463	3.984
36	3.740	1.911	−0.059	2.861	0.675	−0.979
37	2.298	1.911	−0.148	−1.347	−0.443	1.900
38	1.787	1.911	0.070	−1.387	0.361	1.213
39	2.257	1.911	0.083	−0.766	0.515	1.030
40	1.074	1.911	0.022	−2.580	−0.639	1.783
41	2.198	1.911	0.314	−2.167	−0.007	2.182

Continued

Table 4. Continued

Farm ID	%ΔTFPI	%ΔTI	%ΔOTEI	%ΔOESMEI	%ΔCAI	%ΔSNI
42	2.741	1.911	0.057	−0.523	−0.057	1.285
43	1.450	1.911	0.000	−0.725	0.392	0.274
44	2.625	1.911	−0.060	3.924	1.793	−3.044
45	1.743	1.911	−0.057	−0.512	−0.518	0.407
46	2.172	1.911	−0.280	0.564	−1.319	−0.025
47	−0.166	1.911	0.077	−0.542	−1.131	−1.579
48	2.181	1.911	0.135	0.868	−0.515	−0.732
49	2.205	1.911	−0.394	1.798	0.134	−1.093
50	0.175	1.911	−0.257	2.102	0.499	−3.479
51	1.407	1.911	−0.175	−0.912	−0.664	0.597
52	1.443	1.911	0.129	0.624	0.110	−1.204
53	2.516	1.911	−0.243	1.566	−0.288	−0.716
Arithmetic average	2.159	1.911	−0.049	0.128	−0.316	0.194

Table 5. Comparison of TFPI decomposition for RPM, GTRE and TRE models

	Random parameters model	Generalised true random effects	True random effects
%ΔTFPI	2.159	2.260	2.260
%ΔTI	1.911	2.246	2.249
%ΔOTEI-SR	−0.049	−0.040	−0.040
%ΔOTEI-LR		−0.024	
%ΔOESMEI	0.128	−0.296	−0.244
%ΔCAI	−0.316	−0.050	−0.061
%ΔSNI	0.194	0.399	0.320

the evolution of TFPI and its associated indexes across representative farms. We observe that TFP was generally on an upward trend and that this growth was primarily driven by the OTI.

Our findings indicate that productivity growth (%ΔTFP), for the entire sample and time period, averaged 2.16 per cent. The primary driver behind this growth was technical progress, captured by the percentage change in output-oriented technological index (%ΔOTI), which averaged 1.91 per cent per annum. The percentage change in output-oriented environmental and scale-mix efficiency index (%ΔOESMEI), which measures fluctuations in TFP due to economies of scale as well as observed and unobserved environmental factors, increased at an average rate of 0.13 per cent per annum. The percentage change in TFP due to climate adaptation efforts (%ΔCAI) declined at an average rate of 0.31 per cent per annum. Fluctuations in TFP associated with shifts towards and away from the frontier due to managerial abilities (%ΔOTEI) declined at an average rate of 0.05 per cent per annum. Finally, the SNI (%Δ SNI) that captures fluctuations in TFP due to unidentified factors averaged 0.19 per cent. Table 4 reports year-to-year TFP average growth rates and its components for all the farms in our sample. In addition, in Table 5, we provide a summary comparison of TFP growth rates and its components across the three models i.e. RP, GTRE and TRE.

7. Concluding remarks

This study contributes to the literature by investigating how weather volatility and climate change are transmitted to productivity growth in dairy production across a sample of Wisconsin dairy farms. We estimate a RP stochastic production frontier, and the resulting parameter estimates are used to decompose a TFP index into five components: output-oriented technical index (OTI), which captures productivity changes due to shifts in the production frontier; OESMEI, which measures productivity changes associated with weather anomalies, climate indicators and economies of scale; CAI, which captures adaptation efforts due to long-term climate trends; OTEI, which captures movements towards and away from the frontier associated with managerial abilities and a SNI that reflects productivity changes for reasons that remain unidentified. This article also contributes to the literature by exploring the suitability of alternative modelling approaches such as RP and the recently introduced GTRE. The GTRE model makes it possible to evaluate both transient and persistent technical efficiency levels while also addressing unobserved time-invariant farm-level heterogeneity. On the other hand, the RP approach allows us to account for the stochastic nature of unobserved environmental effects as well as variations in production technologies across farms.

Wisconsin dairy farming provides an ideal setting for investigating environmental effects and their subsequent economic outcomes given the role that this productive sector plays in the state and the extreme temperatures, both hot and cold that it experiences in summer and winter. Wisconsin is the second largest milk producer in the United States, second only to California, and the largest producer of cheese globally. In addition, dairy production is the single largest agricultural sector in the state contributing approximately USD 5.02 billion in revenue to farm households. Furthermore, though the typical dairy farm in Wisconsin continues to be family-owned, such farms have undergone significant growth in size. Thus, any negative effects due to weather anomalies and climate effects are likely to have far-reaching consequences. Our findings indicate that productivity growth averaged 2.16 per cent per annum and that this growth was primarily driven by technical progress that rose at an average rate of 1.91 per cent per annum. Technical efficiency declined by an average of 0.05 per cent, fluctuations due to economies of scale and observed and unobserved weather factors contributed to 0.13 per cent per annum increase in productivity, and fluctuations following long-term climate trends, in spite of adaptation efforts, resulted in a 0.31 per cent decline in TFP per annum. Furthermore, we find evidence that a one standard deviation shift in long-run average temperatures (i.e. 30-year moving averages) reduces dairy output for the average farm by 20.1 metric tons per year. This is equivalent to a decrease in the average herd size by 1.6 cows per year. It is noteworthy that farm business record data, such as what we use in this study, although non-random, are of high quality and enable the undertaking of detailed analyses as the one presented in this paper. Moreover, this type of data are prevalent in developed economies, including the United States, Australia, New Zealand and Europe, and have been used to undertake a number of informative production economic analyses of dairy farming (Bravo-Ureta and Wall, 2019). Although our estimation results are drawn from a particular setting, dairy operations are universally impacted by weather and climate and this study provides new analysis on this important issue.

The decomposition of TFP into its associated components may assist in highlighting areas where policy-makers and stakeholders can target economic policy and public resources in order to be most effective at raising productivity growth. For example, in our findings, technological progress is a key driver in explaining productivity change. Thus, resources directed towards providing technical know-how, such as investments in research and development increase the potential for productivity growth. Similarly, our results on the range of technical efficiency across these farms of between 66.6 and 96.0 per cent provide evidence that some farms do lag behind. Hence, identifying these farms and directing efforts towards providing education and training may improve management efficiency, which could raise their technical efficiency. Last, our finding that both observed and unobserved climatic factors substantially impact dairy farm productivity implies that moderating the negative effects of climate either through education and training or by direct action that slows down the pace of global warming may ameliorate the negative environmental effects on productivity experienced by dairy farmers.

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