Research Article

Alok Ranjan*, Deep Mukherjee

Assessing the linkage between dairy productivity growth and climatic variability: The case of New York State

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Abstract: Despite the importance of maintaining a high productivity level for the future viability of the dairy sector in the face of changing climate, very few studies have investigated how climatic conditions impact total factor productivity (TFP) growth in dairy farming. In order to bridge this gap in literature, we conducted a TFP decomposition exercise using dairy farm summary records from the New York state which is one of the historically major milk producing regions of the United States. Stochastic frontier models with air temperature, incorporated as an environmental input in an otherwise conventional dairy production function, are estimated using an unbalanced panel of constructed ‘average’ dairy farms of various size-classes covering a sufficiently long time-period. Change in TFP is then decomposed into various components namely technological change, technical efficiency change, and scale efficiency change. Further analysis also establishes that the introduction of average air temperature in the stochastic production frontier soaks what otherwise could be attributed to inefficiency and/or model residual.

Keywords: Dairy, Stochastic frontier, Technical efficiency, Total factor productivity

1 Introduction

Over the course of last two decades, the impact of climate change on farm productivity has emerged as a major research area. While climate change is expected to have a slow, gradual impact on agricultural practices and

decision making by farmers, agricultural productivity in any given short time period depends upon the realization of climatological variables a.k.a. weather in that period. The fact that productivity of dairy cattle is highly sensitive to weather extremes like heat waves can be readily ascertained from dairy science literature originating from different parts of the world. Much of these evidences come from statistical and simulation studies. For example, Solymosi et al. (2010) observe that between 1973 and 2008 the annual number of heat-stress days in Hungary increased at the rate of 4.1 percent per year. Following various climate change scenario simulations, they conclude that at least half of the country would experience on average one additional week of heat stress per year in 2021–2050 as compared to 1961–1990. In order to quantify the impact of heat stress on Italian Holstein dairy cattle, Bernabucci et al. (2014) compile data on test-day records for milk, fat, and protein yields from 484 farms for the period 2001–2007 and combine that animal level data set with climatological data from 35 weather stations. Linear regression analysis indicates that milk yield starts to decline at the daily temperature humidity index (THI) value between 65 and 76. This THI range corresponds to various temperature humidity permutations with temperatures ranging from 21 to 36°C. In the context of the Australian dairy sector, Mayer et al. (1999) analyze long term meteorological data and match that to production data from various sources to find correlation among climatic indices, milk yields, and milk constituents. They also fit a non-linear regression model to daily milk production, using THI, its lag values, and other explanatory variables and find that milk yield declines as THI increases. Hennessy et al. (2016) discuss past and future climate change in Australia, with projections for its eight dairy production regions where the average temperature is expected to increase with more hot extremes and less cold extremes. In order to assess the potential change in favorable dairy production conditions, they assume a temperature threshold of 30°C; beyond which dairy cows experience heat stress.

*Corresponding author: Alok Ranjan, University of Illinois, Urbana-Champaign, Champaign, IL United States, E-mail: alok2@illinois.edu
Deep Mukherjee, Department of Economic Sciences, Indian Institute of Technology Kanpur, Kanpur 208016, UP, India

When dairy farming constitutes a major share of the agro-economy of a region, the value of economic losses due to adverse climatic conditions can be sizeable. However, there is a dearth of analysis regarding this topic based on data generated from actual farm operations. The simulation-based study by St-Pierre et al. (2003) reports significant profitability losses to the United States (US) dairy industry due to the effective temperature conditions being outside the thermal comfort zone of cows. Dairy farming conditions and practices which already show extensive spatial differences within continental US, would be affected differently in various parts of the country due to regional variations in climate change patterns. This calls for localized studies of consequences of changing climate on dairy productivity growth based on farm-level data traversing a sufficiently long time period, but as of today very few studies are available. In recent times, some scholars have adopted econometric modeling techniques to investigate the impact of heat stress on productivity, technical efficiency (an important component of productivity growth) and future profitability of US dairies using farm records. However, the time-span of data employed in these studies is not large.

Mukherjee et al. (2013) analyze the impact of increasing heat stress on dairy farms in Southeastern states of Georgia and Florida which have a relatively hot and humid climate. They utilize an unbalanced panel on dairy farms for the years 1995–2008 and adopt annual mean THI to account for heat stress in dairy cows in a stochastic production frontier (SPF) model to establish a non-linear negative relationship between milk production and THI. Furthermore, they ascertain that the inclusion of the annual mean THI in the SPF regression model soaks what otherwise could be attributed to inefficiency. Key and Sneeringer (2014) utilize the Agriculture Resource Management Survey data for the years 2005 and 2010 on dairies in 24 major dairy producing states and argue that dairy farmers make mitigation decisions based on expectations about future weather. They advocate the use of deviations from expected long-run climatic conditions to study the effect of climate on dairy productivity. More recently, Qi et al. (2015) use seasonal averages for temperature and precipitation in SPF models instead of complex indices to capture the climatic effects and utilize panel data on dairy farms from Wisconsin for 1996–2012. The inclusion of temperature and precipitation variables directly allows for a clear interpretation of climatic effects on dairy productivity. They find that warmer summer months and colder winter months are harmful for milk production. Although it is vital to identify how climatic conditions affect total factor productivity (TFP) growth in

dairy, and this exercise seems to be a natural extension of SPF type studies based on panel data, only one such study (viz. Massaly 2015) is found in the literature review. Likewise, even though a sizable volume of scholarly work exists in the field of agricultural TFP growth analysis, very few incorporate the role of agro-climatic conditions directly. A notable exception is Bachewe (2009) who controls for annual rainfall, land quality, and agro-ecological zones in his study on output growth and inefficiency in the Ethiopian agricultural sector. The current paper aims to contribute to the existing literature by assessing the linkage between temperature and TFP growth.

We chose New York (NY) state as the study area for the following reasons. First, NY is the third major milk producing state in the US, behind California and Wisconsin only. Second, with its relatively cold winter months and mild hot summer months NY is an interesting dairy production region for studying the effects of seasonal temperature as it experiences a wide range of temperatures over a year. Karl et al. (2009) note that since 1970, the annual average temperature in the Northeast US has increased by 2°F, while winter temperatures have gone up almost twice of that. They also state that over the next few decades, average temperature in this region is projected to rise an additional 2.5 to 4°F in winter and 1.5 to 3.5°F in summer. Frumhoff et al. (2007) project that under a higher emissions scenario, the rise in mean summer temperatures might result in milk production reduction by 10–20 percent or more in the Northeast US. This study also reports a decline in milk production ranging from 5 to 15 pounds per cow per day (an 8 to 20 percent decrease) in NY during the unusually hot summer of 2005. Wolfe et al. (2008) corroborate the same in their independently carried out research. Most importantly, the Dairy Farm Business Summary and Analysis (DFBS) project run by the Cornell University's Cooperative Extension has published annual summaries on 'average' dairy farms for more than 50 years, providing an opportunity to study the growth scenario over a sufficiently long time-period. Through this study, we aim to estimate SPF models using DFBS data and use the estimated parameters to decompose TFP change in 'average' dairies of various size. One of the key ideas central to this study is the identification of the impact of seasonal weather outcome on dairy TFP growth.

There are a handful of research papers that study dairy farm efficiency and TFP in the NY state for a number of years. Tauer (1998) uses the DFBS data on 70 dairy farms over 1985–1993 and decomposed dairy productivity growth by employing output distance functions and non-parametric Malmquist Index. He reports that

annual productivity growth rate averages at 2.6 percent over this period and that it is driven mostly by gains in technological advancement. Recently, Massaly (2015) investigates role of climatic effects (average summer temperature, average winter temperature, average summer precipitation, and average winter precipitation) on dairy TFP growth in two traditional dairy regions of the US (Northeast and Midwest). The study uses county level data from the agricultural census for nine years, ranging from 1974 to 2012, on major dairy producing counties in those two regions. The dairy output is constructed by dividing county level dairy sales by milk price received by farmers in the state where that county is located. Most of the input variables are created by multiplying the percentage of dairy sales relative to total agricultural sales of a county with the total input use of the county. Out of 56 selected Northeast region counties, 22 are from the NY state. A Cobb-Douglas production function is defined over cows, machinery and equipment, labor, and commercial feed as conventional inputs along with a linear and quadratic time trend terms and level values for summer and winter average temperatures and total precipitation to estimate a true random effects SPF model. Coefficients from SPF models for winter and summer temperatures are highly significant and exhibit a positive and negative relationship with output, in turn. It is worth noting that, according to some scholars, milk cows are exposed to heat stress when temperature is beyond 30°C (Hennessy et al., 2016). Thus, the negative relationship between milk output and summer temperature, as found by Massaly (2015), is somewhat awkward when the average summer temperature in the Northeast US is about 66°F. Furthermore, Massaly (2015) does not perform the TFP decomposition without climatic variables.

2 Methods

Following dairy science literature, it is reasonable to assume that agro-climatic conditions may impact the shape of the production technology of dairy farms. Hence, these factors should be included directly in the production function. Accordingly, the ‘true’ dairy production frontier to be modeled is $Y = g(X; W)$, where X is a vector of conventional inputs and W is a vector of ‘environmental’ inputs. In this paper we consider atmospheric temperature as the environmental input representing heat stress conditions which is usually omitted in dairy TFP studies. If W plays a significant role in explaining variation in output and is excluded from the model, then the SPF parameter estimates and TFP analysis will be biased. Once W is

included in the production frontier, the derived technical efficiency (TE) scores will be net of climatic conditions. This net efficiency score may be viewed as being indicator of managerial performance. Dairy TFP studies employ either a parametric stochastic frontier approach (e.g. Moreira and Bravo-Ureta, 2016) or a non-parametric data envelopment analysis approach (e.g. Tauer 1998) in order to find the relative importance of TFP components.

This study adopts a SPF approach which incorporates a composite error term in the production function regression equation. The composite error term is the sum of a symmetric normal error and a one-sided error, where the one-sided error term captures technical inefficiency and the symmetric error term accounts for statistical noise. When panel data is available, there are several modeling options to estimate SPF. Pitt and Lee (1981) and Battese and Coelli (1988) offer the first generation panel SPF models to estimate time-invariant TE. Kumbhakar and Lovell (2000) note that the maximum likelihood estimation of these models is structurally alike to the procedure applied to cross-sectional data. In this approach, each data point is treated as a different cross-section unit which is observed for just one time-period. As we have to deal with a highly unbalanced panel data set, we adopt a time-invariant TE type panel SPF model. Ahmad and Bravo-Ureta (1996) apply these types of models to find TE for an unbalanced panel data set on dairy farms located in Vermont. The Battese and Coelli (1988) SPF model is represented as:

$$\ln(Y_{it}) = f(X_{it}, t; \beta) + \varepsilon_{it} \quad (1)$$

$$\varepsilon_{it} = v_{it} - u_{it} \quad (2)$$

$$v_{it} \sim N(0, \sigma_v^2) \quad (3)$$

$$u_{it} \sim N^+(\mu, \sigma_u^2) \quad (4)$$

where subscript i denotes i^{th} cross-sectional unit ($i = 1, 2, \dots, I$), and subscript t denotes t^{th} time-period ($t = 1, 2, \dots, T$); Y_{it} is the output for the i^{th} unit in t^{th} period; X_{it} is a $(1 \times K)$ vector of input variables after logarithmic transformation; t is the time trend that proxies for technical change; β is a corresponding coefficient vector to be estimated; v_{it} is statistical noise assumed to be independently and identically distributed as in equation (3), and u_{it} is a non-negative, independently distributed one-sided error representing inefficiency of the i^{th} unit at t^{th} time-period. If $\mu = 0$ is assumed in equation (4), we get the Pitt and Lee (1981) model. Output-oriented TE which is defined as the ratio of actual output to the maximum possible output (frontier output) for a given input bundle and technology, can then be computed as:

$$TE_{it} = \frac{Y_{it}}{\exp[f(X_{it}, t; \beta) + v_{it}]} = \exp(-u_{it}). \quad (5)$$

Where there are multiple outputs and multiple inputs, multi-factor productivity or TFP is defined as the ratio of aggregate output produced to the aggregate factor inputs. TFP captures how efficiently inputs are utilized and is also a key indicator of competitiveness. Change in TFP occurs via the following pathways: technical change (TC), technical efficiency change (TEC) and scale efficiency change (SEC). TFP change (TFPC) is defined as the output change not explained by input change. For the decomposition of TFPC into its components, there are two popular approaches available in literature. Kumbhakar and Lovell (2003) adopt total differential approach wherein they use just one data point for computing relevant derivatives, while Coelli et al. (2003) adopt an index number approach and the derivatives are computed for both data points. This paper employs Coelli et al. (2003) approach which recommends that the TFPC can be decomposed into its components as follows:

$$\begin{aligned} \ln\left(\frac{TFP_{it}}{TFP_{i(t-1)}}\right) &= \ln\left(\frac{TE_{it}}{TE_{i(t-1)}}\right) + 0.5\left[\frac{\partial f(\cdot)_{it}}{\partial t} + \frac{\partial f(\cdot)_{i(t-1)}}{\partial t}\right] \\ &+ 0.5\sum_{k=1}^K[SF_{i(t-1)}e_{kit(t-1)} + SF_{it}e_{kit}](\ln(X_{kit}) \\ &- \ln(X_{kit(t-1)})) \end{aligned} \quad (6)$$

where the left side of the equation (6) represents change in TFP. The first term on the right-side captures TEC, where TE_{it} is computed as in equation (5). The second term accounts for TC and is computed by obtaining the partial derivative of the frontier equation. The last term in equation (6) measures changes in productivity through scale effects (or, SEC) which identifies the effects of returns to scale on productivity. There, e_{kit} is the partial elasticity for the k^{th} input and SF_{it} refers to scale factor which is computed as

$$SF_{it} = \frac{\sum e_{kit} - 1}{\sum e_{kit}} \quad (7)$$

In this study, we utilize data on dairy farms collected by the DFBS program which is run and managed by the Cornell Cooperative Extension system. The participating farms in the DFBS program are specialized dairies where milk sales represent 80–85 percent of the aggregate annual income received by the dairies. Each year dairies across the state participate in the program to share data on their

farm operations and the DFBS publishes annual reports presenting summary data on ‘average’ farms belonging to different herd-size groups to create benchmarks for the NY dairy industry. However, over the years the DFBS team hasn’t been consistent with the classification of farms to different size groups, perhaps due to rapid intensification in dairy farming and ever-rising average herd size all across the US. For the earlier years, nine herd-size clusters are used to present size-wise summaries of farm records, smallest group being farms with a herd size less than 40. Over the years, the number of herd-size groups in the DFBS dataset is reduced to six, and the smallest group is defined as farms with a herd size smaller than 60 in recent past. The largest herd-size group definition also changes from a collection of farms having more than 150 cows in early 1980s to the set of farms having greater than 300 cows in late 1980s, greater than 600 cows in early 2000s and finally, greater than 900 cows after 2008.

As this paper utilizes size-class summary data, we need to factor in this continuous change in the reported herd-size groups to have as much as possible consistent size-class definition. We propose 12 new farm size-classes based on the DFBS annual reports and to re-organize DFBS data into these many size groups. The reconstructed size-classes are such that farm summary records with similar herd sizes, originally given in DFBS reports, are brought under one new size-class. For instance, the size-class 1 in the constructed dataset corresponds to the herd-sizes less than 40 for the years 1980–1998, less than 50 for 1999–2008 and less than 60 for 2009 and later years. Likewise, size-class 12 comprises of farms with herd sizes larger than 500 for 1998, larger than 600 for 1999–2007 and larger than 900 for later years in our study period. Full re-classification of original size-classes into newly defined 12 size-classes is provided in Table 1. Moreover, as the participation in the DFBS program and data sharing is voluntary, there is no guarantee to have the same set of dairies reporting data every year, and hence the ‘average farm’ in each size-class in each year may be based on a different pool of farms. For this study, an observation from the original DFBS data (from the re-defined size class group 8 in the reorganized data set) is dropped for the year 1980 on account of that data point being an outlier. Accordingly, the compiled data constitutes an unbalanced panel of average dairy farms from 12 size-classes over a period of 35 years (1980–2014) with a total of 283 observations.

Annual reports¹ provide size-group specific averages on milk production, number of milk cows

¹ DFBS annual reports could be downloaded from the webpage <https://dyson.cornell.edu/outreach/extension-bulletins/>

Table 1: Changing definition of size-groups in DFBS data and redefined size groups in the dataset used for analysis

Cross-sectional unit (herd size groups)	Actual herd-size classes used in various DFBS annual reports	Data available for years
1	<40, <50, <60	33
2	40–54	18
3	55–69, 50–74	29
4	70–84	18
5	85–99, 75–99, 60–99	33
6	100–149, 115–129, 100–199	33
7	150–199	21
8	200–249, 200–299	32
9	300–399	9
10	400–599, 300–499, >250	33
11	600–899	7
12	>500, >600, >900	17
Total		283

(X_1), input use, expenditures and receipts on an accrual basis. It provides data for expenditures on grain and concentrate, roughage and expenses on other dairy feeds. We create an input aggregate for purchased feed (X_2) as the total of expenditures on these constituents of dairy feed. These reported expenditures are in nominal dollar values, and thus, are converted to 2014 USD terms by deflating the nominal values using the producer price index for agricultural produce, available from the US Bureau of Economic Analysis. We use two different variables as the third input (X_3) in dairy production function and propose two different SPF models, using them one at a time. Our first choice as the third input is home grown feed and it will provide our Model 1. In addition to the purchased feed, the dairy farms also employ their farmland to produce feed for cows. Annual reports provide data on the area under acreage for corn and hay as well as the respective crop yields (in tons per acre). We use this data to construct a measure of home-grown feed as the total produce of hay and corn (in tons). Our second choice as the third input is labor and it will offer Model 2. Dairies hire workers to run daily operations at farms and may also employ family labor. Effective utilization of all other inputs is carried out by the management and thus it is expected to play a critical role in the production process and influence efficiency (Byma and Tauer, 2010). Annual reports supply data on worker equivalents as well as equivalents of manager employed by farms in each of the size-classes. We create an aggregate input measure of labor as the sum of worker and manager equivalents.

We also estimate two other models, Model 1a and Model 2a, which expand the input set for Model 1 and Model 2 respectively by including environmental inputs. Although several studies have used THI as an indicator of stressful environmental conditions in dairy farming, we choose average temperature as the environmental factor affecting dairy production frontier. One of the reasons behind this choice is likely high correlation between minimum daily air temperature and mean daily dew point temperature which is used to measure humidity in the THI equation used by many researchers (e.g. Mukherjee et al., 2013). In meteorological studies minimum air temperature is often used as a substitute for dew point temperature and the trick works reasonably well except for arid and semi-arid environments (Kimball et al., 1997). Moreover, for many parts of the world, availability of data on dew point temperature for large areas is limited. So, a simpler metric such as mean air temperature would be more universally applicable. Recently, dairy scientists investigated whether THI is the best indicator of heat stress in lactating dairy cows in a subtropical climate region. Dikmen and Hansen (2009) studied the strength of eight versions of THI and dry-bulb temperature (ambient air temperature) to predict the rectal temperature of Holstein cows in north central Florida. Results of their statistical analysis led them to conclude that dry-bulb temperature is nearly as good predictor of heat stress as THI. Therefore, in this paper, mean air temperature is used to represent heat stress factor.

More specifically, we include the temperature for summer and winter months in our estimation of the

production frontier. We use the arithmetic average of June and July temperatures as the representative of summer temperature (W_1) and average of December and January temperatures as the representative of winter temperature (W_2). Data on climatic variables (average monthly temperatures in °F) for the state are obtained from National Oceanic and Atmospheric Administration's (NOAA) National Climatic Data Center (NCDC).² Table 2 shows the descriptive statistics for the all the variables for different time-periods and helps us to examine the overall trend of key variables. As shown in Table 2, the average herd-size of the dairy farms has been consistently increasing over the years. Moreover, the milk yield (milk per cow) has been steadily increasing, indicating the improvements in productivity. These observations are in agreement with other published work on the US dairy industry (e.g. von Keyserlingk et al., 2013).

As we have stated earlier, due to its highly unbalanced nature, the data on dairy farm size-classes is treated as cross-sectional data. The regression model can be represented as a Translog SPF of the form

$$y_{it} = \alpha_0 + \sum_{k=1}^3 \alpha_k x_{kit} + 0.5 \sum_{j=1}^3 \sum_{k=1}^3 \alpha_{jk} x_{kit} x_{jit} + \beta_1 t + 0.5 \beta_2 t^2 + \sum_{s=1}^2 \theta_{1s} w_{st} + 0.5 \sum_{s=1}^2 \theta_{2s} w_{st}^2 + v_{it} - u_{it} \quad (8)$$

where output, conventional and environmental inputs are logarithmically transformed and represented by lower case letters. We include time-trend variables t and t^2 to capture for the effects of Hicks neutral technical change i.e. the frontier shift is independent of the inputs. Following Pitt and Lee (1981), we assume half-normal distribution for the one-sided error term that captures inefficiency across models. We also follow the standard procedure of normalizing the input variables by their geometric mean which facilitates the interpretation of the first-order parameters as partial output elasticities (Coelli et al., 2003). Trend variable is also normalized by their arithmetic mean. The frontier estimation is carried out in STATA software using the programs developed by Kumbhakar et al. (2015). The frontier parameters obtained from four SPF models (Model 1, Model 1a, Model 2 and Model 2a) are then used to compute TFPC and its components following the equations (6) and (7). Model 1 and Model 2 are nested in Model 1a and Model 2a respectively. To test whether including the environmental

inputs significantly improve the model fit, we perform likelihood ratio (LR) test (Coelli et al., 2005).

3 Results

Four SPF models are estimated, and parameter estimates from different models are presented in Table 3. For Model 1, we find that the model fit improves significantly after including temperature inputs i.e. Model 1a. The LR test statistic for this case is 16.2 and is significant at 1% level of significance. Similarly, model fit for Model 2a is better than Model 2. The LR test statistic for this case is 17.0 and is significant at 1% level of significance. Thus, the models with environmental inputs, Model 1a and Model 2a, perform better than Model 1 and Model 2 respectively. For the purposes of brevity, we restrict our detailed analysis of results to models with environmental inputs. The partial output elasticities of conventional inputs to the production process, i.e. the first three 1st order coefficients in equation (8) are positive and significant across model specifications. The number of milk cows is invariably the most important input with a partial elasticity around 0.78 and is highly significant irrespective of the model specification. Thus, at the center of the data, a 1 percent increase in the number of cows causes roughly a 0.78 percent increase in milk production. The next important factor, in terms of partial output elasticity, is purchased feed. Both models 1a and 2a indicate that at the center of the data, milk production grows by approximately 0.22 percent for a 1 percent increase in the purchased feed. These findings are in line with recent literature on SPF studies in the context of US dairy sector (e.g. Mukherjee et al., 2013; Qi et al., 2015). Moreover, the coefficient for home grown feed and labor in are also statistically significant but small in magnitude as per expectation. The elasticity estimates of two common inputs in Model 1a and Model 2a are quite similar and thus are robust to the model specifications. In both these models, the coefficients of quadratic terms of the common inputs are all significant and negative indicating diminishing marginal productivity for these two inputs. The sum of partial output elasticities, called the function coefficient (FC), is the indicator commonly used to measure economies of size in primal models, as used here. Both models exhibit increasing returns to scale at the mean of the data set, as the computed FC values are greater than one. Increasing returns to scale provides the farms with an incentive to increase their scale of operation. This is evident from the steady rise in the herd-size of the farms from Table 2.

² Source: www.ncdc.noaa.gov/cag/

The coefficient on linear term for summer temperature is positive and significant. This implies that at the mean of the data, with an increase in summer air temperature by 1 percent, milk production goes up by about 0.25 percent. Considering that mean summer temperature during our study period is around 68° F which is slightly below the threshold temperature at which heat stress sets in, it can be concluded that modest increases in the summer temperatures could be beneficial for dairy farms in the state. The significant and positive coefficient on second order term for summer temperature suggests that the milk production increases with the rise in summer temperatures. We do not find any significant impact of winter temperature on milk production in the state. The effect of time in Models 1a and 2a is significant in both cases. The annual rate of technical change at the sample mean is to be inferred from the linear coefficient of the trend variable, and that is found to be around 0.7 percent which is relatively low compared with other US dairy SPF studies that use a smooth time trend (e.g., 0.9 percent in Mukherjee et al., 2013). However, the coefficient on the time-squared factor is negative and significant, implying that NY dairy farming sector experiences technical progress but the pace declines with time.

Figure 1 presents the distribution of TE scores using both models (with and without the environmental inputs). It is interesting to note that while Mukherjee et al. (2013) find significant differences in the TE score distributions with and without the environmental input (THI in their case) accommodated in the SPF model specification, we do not observe such stark differences in the TE scores. It could be because of the use of aggregate data in this

study or for the reason that average climatic conditions in NY state are not that adverse for dairy animals. It is also noteworthy that most of the farm size-classes are highly efficient and the mean TE score is around 97 percent which is higher on average than ones attained from farm level SPF studies for dairies operating in 1980s and 1990s in the Northeast US region (e.g., Ahmad and Bravo-Ureta, 1996; Tauer, 1998). However, recent studies based on panel data over constructed ‘average’ dairy farms for various size classes in the Northeast US report similar high TE scores (e.g., Njuki et al., 2016). Moreover, similar to Njuki et al. (2016), we also observe that farm size has no prominent effect on efficiency. Next, we turn to the key issue central to this study viz. to analyze the evolution of TFP, net of environmental influence. The summary of TFPC and its components obtained using equation (6)

Figure 1. Distribution of Technical Efficiency Scores

Table 2: Summary statistics across different time-periods

Year	Milk sold ('000 lbs.)	No. of cows	Purchased feed ('000 USD)	Home grown feed (Tons)	Summer Temperature(°F)	Winter Temperature(°F)
1980–84	1769.9 (1514.0)	115.5 (89.8)	118.5 (98.9)	1837.8 (1673.0)	65.7 (1.1)	21.7 (1.8)
1990–94	2933.6 (3149.2)	154.4 (155.4)	216.2 (231.5)	2381.2 (2532.3)	66.0 (1.76)	24.8 (3.3)
2000–04	6470.5 (7275.6)	294.2 (306.3)	508.3 (575.2)	4638.2 (5100.7)	65.3 (1.0)	23.1 (3.8)
2010–14	13710.8 (12654.7)	548.1 (479.2)	1008.9 (930.9)	9174.9 (8318.5)	67.8 (0.6)	25.6 (2.1)

Note: (i) All input and output variables are measured in ‘per farm’ basis. Arithmetic means of input-output variables are computed including all size-class observations in a specific time period. (ii) Feed expenses are in constant 2014 USD terms. (iii) Standard deviations are given in parentheses.

Source: DFBS and NOAA

Table 3: Estimates from stochastic production frontier estimation

Variables	Model 1	Model 1a	Model 2	Model 2a
$\ln \text{Cows } (x_1)$	0.7931*** (0.0404)	0.7760*** (0.0398)	0.8090*** (0.0453)	0.7787*** (0.0451)
$\ln \text{Purchased Feed } (x_2)$	0.2024*** (0.0283)	0.2162*** (0.0276)	0.2087*** (0.0297)	0.2241*** (0.0292)
$\ln \text{Home Grown Feed } (x_3)$	0.0692*** (0.0233)	0.0707*** (0.0230)		
$\ln \text{Labor } (x_4)$			0.0982** (0.0480)	0.1205*** (0.0469)
x_1^2	-1.7762*** (0.5938)	-1.7036*** (0.5801)	-1.0419*** (0.3409)	-0.9643*** (0.3322)
x_2^2	-0.6606*** (0.1869)	-0.5884*** (0.1853)	-0.6203*** (0.1905)	-0.5450*** (0.1914)
x_3^2	-0.1917 (0.1356)	-0.1803 (0.1383)	-0.1799 (0.5112)	-0.1336 (0.4932)
x_1x_2	1.0939*** (0.3261)	1.0311*** (0.3194)	0.7646*** (0.1957)	0.6986*** (0.1939)
x_1x_3	0.4802* (0.2583)	0.4770* (0.2557)	0.1685 (0.3899)	0.1629 (0.3812)
x_2x_3	-0.2717* (0.1592)	-0.2837* (0.1559)	-0.0384 (0.2466)	-0.0653 (0.2450)
Time (t)	0.0075*** (0.0005)	0.0070*** (0.0005)	0.0069*** (0.0005)	0.0064*** (0.0005)
t^2	-0.0004*** (0.0001)	-0.0003*** (0.0001)	-0.0003*** (0.0001)	-0.0003*** (0.0001)
$\ln \text{Summer Temperature } (w_1)$		0.2517*** (0.0850)		0.2457*** (0.0884)
w_1^2		11.3711** (5.1957)		13.3206** (5.4347)
$\ln \text{Winter Temperature } (w_2)$		0.0103 (0.0152)		0.0083 (0.0152)
w_2^2		-0.2218 (0.1650)		-0.2805* (0.1657)
Constant	0.0491*** (0.0090)	0.0464*** (0.0086)	0.0595*** (0.0071)	0.0593*** (0.0072)
$\ln \sigma_v^2$	-7.1018*** (0.7747)	-7.1057*** (0.6853)	-6.7688*** (0.4565)	-6.6410*** (0.3858)
$\ln \sigma_u^2$	-7.1599*** (0.2937)	-7.2374*** (0.2784)	-7.2366*** (0.2509)	-7.4127*** (0.2738)
Log-likelihood	566.01	574.11	559.04	567.54
Observations (N)	283	283	283	283

Note: (i) Standard errors are in parentheses. (ii) ***1% level of significance, **5% level of significance, *10% level of significance

Table 4: Summary of TFP change using two estimated stochastic frontiers

Data	Variable	Model 1a		Model 2a	
		Mean	Std. dev.	Mean	Std. dev.
1980–2014 N = 271	TFPC	0.760	1.055	0.730	1.526
	TC	0.700	0.322	0.636	0.247
	TEC	0.020	0.954	0.008	1.437
	SEC	0.040	0.428	0.086	0.622
1980–1989 N = 76	TFPC	1.204	0.784	1.131	1.107
	TC	1.091	0.087	0.936	0.067
	TEC	0.076	0.796	0.064	1.173
	SEC	0.036	0.118	0.131	0.354
1990–1999 N = 87	TFPC	0.727	1.223	0.640	1.847
	TC	0.775	0.099	0.693	0.076
	TEC	-0.096	1.074	-0.141	1.631
	SEC	0.048	0.564	0.088	0.775
2000–2009 N = 81	TFPC	0.555	1.009	0.610	1.442
	TC	0.432	0.100	0.429	0.077
	TEC	0.061	1.008	0.096	1.403
	SEC	0.063	0.456	0.085	0.648

and SPF parameter estimates are reported in Table 4. The average TFP growth ranges between 0.73 percent (Model 2a) to 0.76 percent (Model 1a) for the period 1980–2014. As can be seen from the Table 4, technical change is the key driver of the productivity gains as on average it ranges between 0.64 percent (Model 2a) to 0.70 percent (Model 1a). Scale efficiency change is the second most important contributor to TFPC. Technical efficiency change has been rather modest. As it is obvious from Figure 2, TFPC is almost identical across SPF models. However, it is subject to fluctuations over the period under investigation, regardless of the SPF model chosen. In the period 1981–1990, there is a slight decline and subsequently TFP increases at a slow pace. In the next decade, TFP increases in the first year and then decreases sharply in the middle but again rises towards the end. Since 2000, TFPC has become more erratic. In general, comparison of our TFPC numbers with other dairy TFP studies have to be made with caution as many differences in analysis (e.g. time-period, model specification, agro-climatic and policy environment) could lead to dissimilar outcomes. Most comparable figures on TFPC and its components are to be found in Massaly (2015) who finds that the Northeast US

Figure 2. : TFP change from Model 1a and Model 2a

dairy sector experiences a TFP growth of 1.5–2 percent per year during 1974–2012 with TFP growing steadily till 2002, but falling sharply between the period of 2002 and 2007.

Table 4 also provides the decade-wise summary of change in TFP and its components. Mean TFPC has been falling in every decade since the beginning of the study-period. It is interesting to note that, irrespective of model choice, mean TEC is on an average very small and negative

Table 5: Mean TFP change of various size classes using Model 1a and Model 2a

Time	Var.	Small (Size group 3)	Medium (Size group 6)	Large (Size group 8)	Very large (Size group 10)
1980–2014	TFPC	0.721 (0.626)	0.816 (0.818)	0.791 (0.829)	0.681 (0.712)
	TC	0.770 (0.689)	0.698 (0.634)	0.681 (0.621)	0.632 (0.583)
	TEC	-0.050 (-0.081)	0.062 (0.079)	0.022 (0.027)	0.042 (0.049)
	SEC	0.002 (0.017)	0.056 (0.105)	0.089 (0.181)	0.007 (0.080)
	TFPC	1.138 (0.993)	1.252 (1.188)	1.063 (1.142)	1.432 (1.557)
1980–1989	TC	1.100 (0.943)	1.100 (0.943)	1.082 (0.929)	1.065 (0.916)
	TEC	0.035 (0.005)	0.127 (0.173)	-0.087 (-0.069)	0.178 (0.185)
	SEC	0.003 (0.046)	0.025 (0.072)	0.068 (0.282)	0.189 (0.456)
	TFPC	0.579 (0.454)	0.721 (0.571)	0.850 (0.790)	0.568 (0.464)
	TC	0.770 (0.689)	0.770 (0.689)	0.770 (0.689)	0.770 (0.689)
1990–1999	TEC	-0.212 (-0.266)	-0.100 (-0.233)	0.042 (0.029)	-0.175 (-0.245)
	SEC	0.020 (0.031)	0.051 (0.114)	0.037 (0.071)	-0.027 (0.020)
	TFPC	0.463 (0.449)	0.556 (0.640)	0.706 (0.825)	0.498 (0.491)
	TC	0.441 (0.436)	0.424 (0.423)	0.424 (0.423)	0.424 (0.423)
	TEC	0.043 (0.040)	0.052 (0.085)	0.114 (0.171)	0.060 (0.053)
2000–2009	SEC	-0.021 (-0.027)	0.080 (0.132)	0.168 (0.231)	0.015 (0.015)

Note: Particular herd size classes according to Table 1 are given in parentheses in first row.

Mean TFP change from Model 2a are in parentheses

in the 1990s. It is noteworthy that Tauer (1998) also reports that TEC averages -0.8 percent for 70 NY dairies over the period 1985–1993. Perhaps dairy farms had attained such a high efficiency around the early 1990s that it has been difficult to maintain that level in all the coming years. Subsequently we investigate whether TFP growth experience has been uniform across various size-classes. Following Njuki et al. (2016), we define dairies having less than 90 cows as ‘small’, farms with herd size between 90 and 149 as ‘medium’, farms with herd size between 150 and 299 as ‘large’, and dairies having more than 300 cows as ‘very large’. The herd size groups that fit well with this classification are size-clusters no. 3 (small), no. 6 (medium), no. 8 (large), and no. 10 (very large) defined in Table 1. Figure 3 depicts the change in TFPC for these four size classes and Table 5 displays the corresponding mean TFP changes in specific time-periods. TFPC estimates from Model 2a suggest that size class no. 8 (large) scores the highest TFP growth (0.83 percent) during the period of analysis, followed by size class no. 6 (medium). Interestingly, for size class no. 8, SEC is the second most important component driving the TFPC. Estimates from Model 1a suggest that size class no. 6 (medium) had the highest TFP growth (0.81 percent) followed by size class no. 8 (large) with a TFPC of 0.79 percent. Not only the medium and large farms have enjoyed scale effects, they have also improved their TE in order to pull up TFP. At the other extreme, size class no. 3 (small) registers an overall fall in TE and mean SEC is also the lowest amongst these groups.

4 Discussion

This study attempts to contribute to the existing literature by incorporating climatic conditions or weather as environmental inputs in dairy production frontier estimation to conduct subsequent TFP change analysis. We demonstrate how ‘average’ dairy farms of various herd size groups experienced different TFP change over last three decades in the NY state, net of climatic influence. We utilize the parameter estimates from stochastic frontier models to decompose TFP growth into technical change, technical efficiency change, and scale efficiency change using an index number approach. The TFP in NY dairy farming has grown at an average of around 0.75 percent over the study period, largely owing to technological progress. Our analysis leads to two major findings. First, climatic conditions do have strong influence on TFP change in the

Figure 3. TFP change for four size classes (3,6,8,10) from Model 1a

case of NY dairy farm sector. When temperature effects are included in the frontier model, they tend to absorb some fluctuations in TFP change numbers which arise from a frontier model without temperature variables. Second, average temperature in summer has a positive impact on dairy production while average temperature in winter has no significant impact. This finding may seem unexpected or even contradictory to existing literature, but can't be overruled completely. Although there are recent instances of heat stress related milk yield loss in NY, the average summer temperatures in the study period remain way below the critical temperature that initiates heat stress in cows. So, on an average rising summer, temperature may have played a positive role so far.

There are some caveats in this study and one should keep this restriction in mind while comparing our findings with others results. First of all, due to data access issues, we have to work with a highly unbalanced panel on constructed ‘average’ dairy farms. The small number of observations and the unbalanced nature of the data set limit our model choice and analysis to a large extent. Several extensions of this paper can be carried out as future research because we see this work as a modest pilot study to investigate the implications of changing climatic conditions on TFP growth in dairy farming. A logical extension would be to generate a balanced panel of individual dairies over a long time-period and employ more sophisticated stochastic frontier models to study the impacts of popular climatic index (e.g. THI) on TFP growth.

Conflict of interest: Authors declare no conflict of interest.

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