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Technological Change in Dairy Farming with Increased Price Volatility

Fabian Frick and Johannes Sauer

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Abstract

Accompanied by steps towards market liberalisation, dairy farmers in the European Union have been confronted with increased price risk in recent years, which might affect their innovation behaviour. We examine technological change and technical efficiency of specialised dairy farms in West Germany before and during a phase of volatile milk prices. Additionally, we compare the results with mixed dairy farms, which might have an advantage by diffusing price risk through diversification. Our results indicate a slowdown in technological change in specialised as well as in mixed dairy farming coinciding with the start of a volatile market phase.

Keywords: *Dairy farms*; *European dairy sector*; *milk price*; *price risk*; *technical change*; *technological change*.

JEL classifications: *Q12, Q18, O30*.

1. Introduction

Dairy farmers in the European Union have faced several changes in the production environment in recent decades. The implementation of labour-saving technologies has allowed herd sizes to grow continuously while the overall number of dairy farms has declined, resulting in considerable structural changes. Under the quota regime, total milk production has remained fairly stable, but from 2000 to 2013, the number of dairy farms in the three largest milk-producing countries declined by approximately 36%, 39% and 53% in Germany, France and the United Kingdom, respectively. Accordingly, average herd sizes increased in these countries by approximately 64%, 46% and 58% (Eurostat, 2018). This development was accompanied by efforts of the European Commission to lead the dairy sector towards deregulation by lowering intervention price levels, eliminating export subsidies, liberalising milk quota transfers, gradually increasing quota volumes and, finally, abolishing the milk quota in 2015. Even before this date, dairy farmers in Europe were confronted with increased volatility of milk prices. While for a long period milk price levels had been dominated

[1]Department of Economics, Law and Policy, Technical University of Munich, Germany. E-mail: fabian.frick@tum.de for correspondence. We thank DG AGRI for providing the EU FADN data, and anonymous reviewers and the editor David Harvey for their constructive comments on an earlier draft. Open access funding enabled and organized by Projekt DEAL.

by seasonal variation, a disruptive pattern began in 2007 (Figure 1). Strong domestic and worldwide demand led to a price high in 2007 that was followed by a sharp decrease due to lower demand and a rebound in supply, which resulted in the dairy sector crisis in 2009 (USDA, 2007, 2008).

Farm family income and a farm's financial resources for maintaining and expanding business activities are directly dependent on output prices. Increased price volatility therefore translates into increased risk for the financial well-being of farms. Although it is debatable to what degree the volatility of agricultural commodity prices has indeed increased when viewed in a historic context (Huchet-Bourdon, 2011), the financial distress of dairy farmers due to recent price movements is well documented by financial aids granted by the European Commission in 2009 (European Commission, 2009).

Technological change as well as the average level of technical efficiency within an industry depend on producers' willingness and ability to invest in new equipment and production techniques (Sauer and Latacz-Lohmann, 2015). If farmers are risk-averse in their investment decisions and abstain from or postpone investments because of the fear of not being able to meet future credit obligations, increased output price volatility can have negative implications for innovation adoption in the dairy sector. Although a link between price risk and innovation behaviour has been established by other authors (e.g., Sauer and Zilberman, 2012), we are not aware of any empirical studies directly examining technological change in view of the recent price turbulences in the European dairy sector.

We examine how technological change in the sector has been affected by increased price uncertainty. Studying the causal relationship between the two variables using microdata covering a limited time span is impeded by the fact that the period of volatile agricultural commodity prices coincided with profound changes in the regulatory environment and because milk price volatility varies over time but shows little variance across farms. Although our approach does not establish explicit causal links, it offers valuable insights into technological change during recent uncertain market

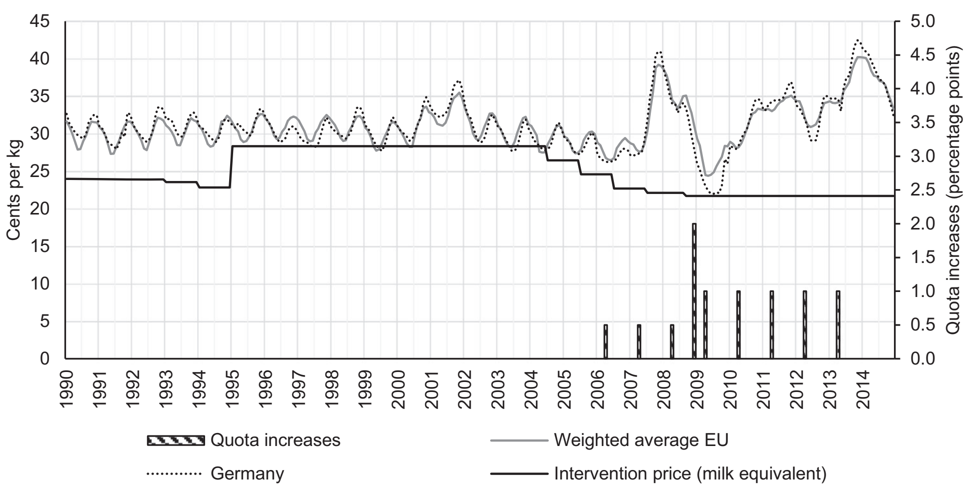

Figure 1. Development of milk prices and intervention price levels in the EU and Germany.
Sourceof data: EU Milk Market Observatory (2019)

phases. To this end, we examine the rate of technological change and technical efficiency change in West German dairy farming before and during a period of volatile milk prices. Additionally, we compare the results for specialised farms with the results for dairy production on mixed farms. As long as output prices are not perfectly correlated, diversification in output activities is a means of countering output price risk. Therefore, mixed dairy farms might behave differently from their more specialised peers.

In the next section, we review some of the related literature. We then examine average levels of net investment as an indicator for innovation activity in the sector during our study period. In the following two sections, we turn to the methodological framework and dataset used, before presenting the results separately by farm type and concluding in the last section.

2. Related Literature

Although the discussion of technology adoption was originally built on profitability as a determinant of the rate of technology diffusion (Griliches, 1957), it became apparent that education, learning, scale effects, credit constraints, and risk also play important roles (Foster and Rosenzweig, 2010). Risk is expected to influence the investment decisions of farmers. If farmers are risk-averse they would be expected to react cautiously to the risk inherent in new and unfamiliar technology by postponing adoption and gathering further information (Jensen, 1982; Just and Zilberman, 1983). Similar consequences are predicted by the real options framework, where increasing uncertainty generally increases the value of waiting and delays investment decisions even for risk-neutral decision-makers (Floridi *et al.*, 2013).

Dairy farmers face price risk not only on the demand side but also on the supply side. The largest portion of production cost in European dairy farming is purchased feedstuff (European Commission, 2018), making dairy farmers' profitability susceptible to feed price changes (Wolf, 2010). Like milk prices, crop and feed prices have been characterised by increased volatility after 2006 (Merener and Steglich, 2018). However, positive correlation between feed and milk prices could be observed in recent years (Schulte *et al.*, 2018; Merener and Steglich, 2018). This correlation can mitigate risk by partly offsetting revenue variability caused by fluctuating milk prices. On the other hand, Wolf (2010) remarks that for US dairy farms the milk-to-feed price ratio has been a weak proxy for farm profitability during volatile market phases, indicating that the relationship between the two might have lost its risk-mitigating effect during latest disruptive market phases.

Reflecting its dominant effect on overall farm profitability, existing studies mainly focus on the effect of output price volatility on the investment behaviour of dairy farms. For dairy farmers, low milk prices can critically diminish the liquidity of the farm, leading to constrained access to credit markets. If a farm has sufficient funds of its own or might be able to provide the necessary assets as collateral (e.g., by owned land), it might still refrain from investment if a combination of additional loan payments and increased price volatility puts the future liquidity of the farm at risk. Schulte *et al.* (2018) showed that increased milk price volatility can considerably affect the profitability of investment decisions if farmers are risk-averse. A negative effect of milk price volatility on the investment propensity of dairy farms was confirmed by Zimmermann and Heckelei (2012) for a dataset on European farms. For Pennsylvanian dairy farms, Stokes (2006) found that as output price volatility increased, the number of farm exits increased, the number of farm entries decreased, and farm size growth rates decreased. Especially relevant to our study is Sauer and Zilberman (2012), who investigated, among other factors, the role of profit risk in the decision to adopt automated milking systems amongst Danish dairy farms. They showed that both decreasing mean profit and increasing profit variability were negatively associated with the probability of adoption.

Alternatively, investing in more advanced technology could be a strategy to counter output price risk by increasing overall farm productivity. For example, Kim and Chavas (2003) found indications that technological change decreases risk exposure in corn production. For Louisianan dairy farming Rahelizatovo and Gillespie (2004) found a positive effect of risk aversion on the probability of adoption of several best management practices.

Along with risk, frequently discussed determinants for technology adoption include financial constraints such as access to credit and the level of liquidity, since the adoption of new technologies or inputs depends on a farmer's ability to provide the necessary funds, either from their own assets or by borrowing (Foster and Rosenzweig, 2010). Although there is no indication that the average European farmer faces capital market constraints (Petrick and Kloss, 2012), individual farmer behaviour can be expected to be significantly influenced by credit constraints. Hüttel *et al.* (2010) identified capital market frictions and irreversibility of investments as determinants of the investment behaviour of German farmers. Läpple *et al.* (2015) found a positive effect of credit access on the degree of innovation for a sample of Irish farms. El-Osta and Morehart (1999) found that credit reserves are positively related to technology adoption decisions in US dairy farms.

On the other hand, the period of volatile milk prices started in 2007 and coincided with the financial crisis beginning in 2008. Although the farming sector was less affected than other sectors, the crisis marked the beginning of a period of low interest rates that has lasted until today. The effect of interest rates on investment can be twofold. On the one hand, decreasing interest rates decrease the cost of technology adoption and thereby increase the probability of adoption. On the other hand, in a dynamic setting, interest rates discount future risk, which leads to a negative effect of decreasing interest rates on the probability of adoption (Tsur *et al.*, 1990).

In summary, we identify three macroeconomic factors potentially influencing recent investment behaviour in the dairy sector: milk price volatility, plunging interest rates, and a significant decline in government intervention. At the same time, reduced government intervention is a possible cause of milk price volatility, since decreases in intervention price levels lowered the price floor that acts as a safety net to farmers. Additionally, increases in the quota volumes opened room for supply growth, leading to downward price pressure due to stagnating demand (Bouamra-Mechemache *et al.*, 2008). Our main conjecture is that increased output price risk had significant implications for the innovation behaviour of European dairy farmers, affecting the rate of technological change as well as the level of technical efficiency in the sector. Comparison of specialised and mixed dairy farms is motivated by the proposition that specialised skill and scale effects (Foster and Rosenzweig, 2010) may advantage more specialised dairy farms. However, more diversified dairy farms are less vulnerable to milk price changes, which could prove dairy production in mixed farms advantageous during volatile market phases.

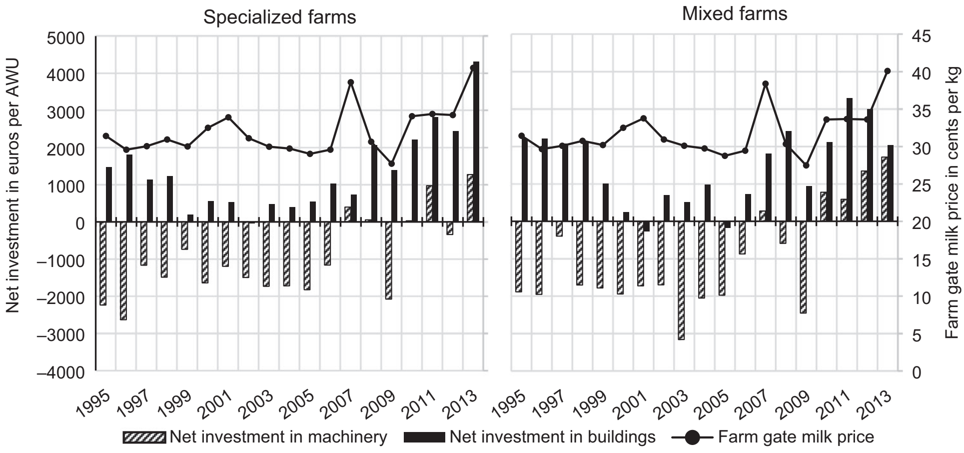

Figure 2. Development of net investment in machinery and buildings (per annual work unit, AWU, real values) and average farm gate milk price by farm type. *Source:*Authors' calculations based on FADN data.

3. Exploratory Indicators

In this section, we focus on net investment as an indicator for innovation activity during recent market events. We calculate net investment as gross investment less depreciation in machinery and equipment as well as in buildings.[1] Figure 2 presents mean net investment per worker (annual work unit, AWU) by farm type and in comparison to the average farm-gate milk price. It is evident that both specialised and mixed dairy farms adjusted net investment according to the level of milk prices. The milk price high in 2007 was accompanied by spikes in net investment in machinery in both farm types. Net investment with respect to both machinery and buildings dropped in 2009 when milk prices plunged to a low.

The strong positive relationship between average net investments and milk prices is confirmed by strong and positive correlation between these two variables (see Table 1). Table 1 additionally incorporates the rolling standard deviation of the mean milk price over $t-2$, $t-1$, and t as a measure of price volatility. Positive correlation of volatility with average net investment for specialised dairy farms reflect the high levels of net investment after 2007 already observed in Figure 2.

Farmers evidently adjusted investment activity according to milk prices and, contrary to our initial expectations, high levels of net investment could be observed especially in the period of high price volatility after 2007, for both specialised and mixed dairy farms. However, while farmers may well have followed a strategy of new investment to counter increased output price risk, there were also the confounding factors (lower support prices, quota elimination, and low interest rates) over this period.

Nevertheless, it is not guaranteed that the relatively high levels of net investment resulted in positive technological change or an increase in technical efficiency. It could be that the investments were used for expansion of farm activities or for replacing

[1]Because depreciation can be influenced to some extent by accounting practices and might be adjusted according to farm profits in single years, we compared gross to net investment but found small differences between their yearly changes.

Table 1
Spearman correlation coefficients of yearly averages of net investment (NI), milk price level, and standard deviation (SD) of past average milk prices

	Specialised farms				Mixed farms			
	NI machinery	NI buildings	Milk price	SD	NI machinery	NI buildings	Milk price	SD
NI machinery	1.00				1.00			
NI buildings	0.40*	1.00			0.54**	1.00		
Milk price	0.70***	0.41*	1.00		0.67***	0.24	1.00	
SD	0.33	0.20	0.25	1.00	0.12	−0.05	0.24	1.00
Observations	*19*				*19*			

Note: SD is the rolling standard deviation of the average milk prices in the sample over $t{-}2$, $t{-}1$, and t over the period 1995–2013. Significance levels are ***0.01, **0.05, and *0.10.

equipment and not necessarily investment in innovative technology. In the following section, we therefore turn to the analysis of the production technology in a distance function framework to measure technical progress and technical inefficiency.

4. Methodology

4.1. Distance function framework

To account for multiple outputs and multiple inputs in both specialised and mixed dairy farms, we adopt a distance function framework. The output distance function is defined by the maximum possible amount by which a farmer can increase outputs with given production inputs while still remaining in the production possibility set (Färe and Primont, 1995).[2] Formally, $D^O(X,Y,T,Z) = \min\{\Theta : (Y/\Theta)\varepsilon P(X,T,Z)\}$, where X and Y are input and output vectors, respectively, T represents technological change as one external shift factor, and Z denotes changes in environmental conditions. The distance function can be implemented in translog form. Imposition of linear homogeneity with respect to outputs and defining $\ln D^O = -u$ results in the estimable equation:

$$\begin{aligned}-\ln y_{1it} &= \alpha_0 + \sum_{m=2}^{M}\alpha_m \ln y^*_{mit} + \frac{1}{2}\sum_{m=2}^{M}\sum_{n=2}^{M}\alpha_{mn}\ln y^*_{mit}\ln y^*_{nit} + \sum_{k=1}^{K}\beta_k \ln x_{kit}\\ &+\frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ln x_{kit}\ln x_{lit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{m=2}^{M}\gamma_{km}\ln x_{kit}\ln y^*_{mit} + \ln T \\ &+u_{it} + \sum_{p=1}^{2}\eta_p z_{pit} + \mu_i + v_{it}.\end{aligned} \tag{1}$$

[2]Although milk production was restricted by quotas at the national level, farmers were still able to adjust output by purchasing or renting additional quota rights. Therefore, the output orientation is adequate, especially considering that inputs like land and labour are likewise not fully flexible (Newman and Matthews, 2007; Emvalomatis *et al.,* 2011). If returns to scale approach unity, as is the case in our study, efficiency estimates will not differ between the input and output orientation (Orea *et al.,* 2004).

v_{it} is a normally distributed random error and with Z_{pit} we introduce additional variables accounting for environmental conditions. Firm-specific inefficiency is quantified by u_{it}. μ_i denotes time-invariant firm effects that act as frontier shifters and are not considered part of technical inefficiency (e.g., soil quality). ln T denotes the technological change component and will be discussed below. We impose linear homogeneity in outputs by dividing other outputs by the farm's milk output, that is, $y^*_{mit} = y_{mit}/y_{1it}$. The symmetry conditions are imposed by $\alpha_{mn} = \alpha_{nm}(m,n=2,\ldots,M)$ and $\beta_{kl} = \beta_{lk}(k,l=1,\ldots,K)$.[3]

Useful measures can be derived from the distance function in the form of derivatives. Distance elasticities with respect to inputs $(\partial \ln D^0/\partial \ln x_k = \partial(-\ln y_1)/\partial \ln x_k = -\varepsilon_{y_1 x_k})$ represent the percentage change in y_1 by a 1% change in x_k while holding the output ratios y^*_m constant, that is, a change in total output, and are therefore equivalent to output elasticities with respect to inputs in a production function framework. In contrast, derivatives with respect to the normalised outputs $(\partial \ln D^0/\partial \ln y^*_m = \partial(-\ln y_1)/\partial \ln y^*_m)$ are output m's share in total production and indicate its relative importance in production (Morrison Paul and Nehring, 2005).

4.2. Formulation of technological change

We aim to evaluate the rate of technological change for milk production by specialised and mixed dairy farms. For specialised farms, which only realise a minor share of their output in the form of non-milk products, we rely on the standard time trend approach to measure technological change. That is, in equation (1) we let:

$$\ln T = \delta_t t + \frac{1}{2}\delta_{tt} t^2 + \sum_{m=2}^{M} \alpha_{mt} t \ln y^*_{mit} + \sum_{k=1}^{5} \beta_{kt} t \ln x_{kit}. \tag{2}$$

where the first two terms account for neutral technological change and the last two terms for output and input biases in technological change. The rate of technological change can then be evaluated as:[4]

$$\dot{T}_t \equiv -\frac{\partial(-\ln y_1)}{\partial t} = -\frac{\partial \ln T}{\partial t} = -\left(\delta_t + \delta_{tt} t + \sum_{m=2}^{M} \alpha_{mt} \ln y^*_{mit} + \sum_{k=1}^{5} \beta_{kt} \ln x_{kit}\right). \tag{3}$$

Since equation (2) includes a term quadratic in t, $\dot{T}_t$ depends on t and is sufficiently flexible to detect a possible slowdown (or speedup) in (neutral) technological change.

To allow for a more erratic pattern of technological change we additionally compare this specification to a time dummy variable specification; that is, we let $\ln T = \sum_{t=1996}^{2013} \lambda_t D_t$ in equation (1). This specification allows a more flexible inspection of technological change (Sauer and Park, 2009) and corresponds to the general

[3]A concern that has been raised with regard to the estimation of distance functions is the possible endogeneity of transformed outputs appearing on the right-hand side of the estimation equation. Until now, there is no consensus on how to treat this issue. Some attempts have been made to treat this possible source of endogeneity (e.g. Plastina and Lence, 2018). Others have argued that due to the ratio form of the output terms, no severe endogeneity problem arises (Brümmer *et al.*, 2002).

[4]Because $\partial \ln T/\partial t$ is negated in our definition, positive values of $\dot{T}_t$ are interpreted as technological progress.

technological change index formulation by Baltagi and Griffin (1988) with the assumption of Hicks-neutral technological change.[5]

For mixed farms, which generate a considerable share of their output from non-milk outputs, an evaluation of technological change in this manner would yield an imprecise measure (in the context of our study) since this technological change measure shows frontier shifts in the aggregate output mix of the farm. Moreover, we want to evaluate product-specific technological change. One possibility to achieve this would be to estimate separate, product-specific production functions by allocating production inputs across production outputs according to, for example, observed revenue shares (Foster *et al.*, 2008) or by using estimates from single-product firms (Loecker *et al.*, 2016). Examples for product-specific analyses of productivity and technological change with observed input allocations include Cherchye *et al.* (2013) and Walheer (2019). Because revenue shares fluctuate with output prices and we do not observe input allocations, we instead rely on measures that can be derived from an enhanced formulation of technological change based on the distance function. More specifically, we focus on measures of technological change biases. In general, technological change biases with respect to an input contain information about whether technological change is relatively input-saving or input-using, meaning that new technology allows to use less or requires more of one specific input in relation to the other inputs in order to produce the same amount of output. Transferring this idea to outputs, a bias towards one output implies that with the same amount of inputs, a relatively greater amount of this output can be produced. This, in turn, can be interpreted as relatively stronger technological advances realised in the production of this output.

In our formulation of technological change, we follow Stevenson (1980), who introduces additional third-order interaction terms (a truncated third-order Taylor-series expansion) into a cost function. While Stevenson (1980) uses terms of time multiplied with interactions across the other regressors (i.e. $t \times \sum_j \sum_k X_j X_k$), we use terms of quadratic time interacted with linear terms of inputs and outputs (i.e. $t^2 \times \sum_j X_j$); that is, we specify:

$$\ln T = \delta_t t + \frac{1}{2}\delta_{tt} t^2 + \sum_{m=2}^{M} \alpha_{mt} t \ln y^*_{mit} + \sum_{k=1}^{5} \beta_{kt} t \ln x_{kit} + \frac{1}{2}\sum_{m=2}^{M} \alpha_{mtt} t^2 \ln y^*_{mit} + \frac{1}{2}\sum_{k=1}^{5} \beta_{ktt} t^2 \ln x_{kit}. \tag{4}$$

The rate of technological change is then:

$$\dot{T}_t \equiv -\frac{\partial \ln T}{\partial t} = -\left(\delta_t + \delta_{tt} t + \sum_{m=2}^{M} \alpha_{mt} \ln y^*_{mit} + \sum_{k=1}^{5} \beta_{kt} \ln x_{kit} + \sum_{m=2}^{M} \alpha_{mtt} t \ln y^*_{mit} + \sum_{k=1}^{5} \beta_{ktt} t \ln x_{kit}\right). \tag{5}$$

In contrast to equation (3), the technological change biases are now measured with two additional terms that are dependent on t. That is, whereas the usual formulation only allows for technological change biases in constant rates, we allow for changing rates in technological change biases. The relative importance of an output in the production process is then given by:

[5]We restrict technological change in this specification to be Hicks-neutral since the full specification by Baltagi and Griffin (1988) interrelates the neutral and biased technological change components, which is unsuitable for our analysis of mixed farms.

$$\frac{\partial(-\ln y_{1it})}{\partial \ln y^*_{mit}} = \alpha_m + \alpha_{mm}\ln y^*_{mit} + \frac{1}{2}\alpha_{mn}\ln y^*_{nit} + \sum_{k=1}^{5}\gamma_{km}\ln x_{kit} + \alpha_{mt}t + \frac{1}{2}\alpha_{mtt}t^2. \tag{6}$$

and this measure's change over time by:

$$\frac{\partial}{\partial t}\left[\frac{\partial(-\ln y_{1it})}{\partial \ln y^*_{mit}}\right] = \alpha_{mt} + \alpha_{mtt}t, \tag{7}$$

where $\alpha_{mt}>0(<0)$ indicates increasing (decreasing) significance of output m in the production process, that is, output-m-favouring (discriminating) technological change, at an increasing ($\alpha_{mtt}>0$) or decreasing ($\alpha_{mtt}<0$) rate. In this way, we can evaluate whether technological change in milk production by mixed farms decelerated or accelerated relative to other outputs during volatile market phases. A deceleration of technological change in milk production would correspondingly indicate a shift in innovation efforts towards other outputs.

4.3. Generalised Malmquist index

After the estimation of technological change, we explore possible reasons for the observed pattern of technological change. Because farmers' primary interest lies in profitability (that is, productivity with given input and output prices), this entails examination of the components of productivity other than technological change and technical efficiency. An approach that lends itself to this purpose is proposed by Orea (2002). From discrete changes in the output distance function from one period to the next, a Malmquist productivity index can be calculated that separates total factor productivity into technical efficiency change (TEC), scale efficiency change (SEC), and technological change (TC). Starting from an output distance function as defined by equation (1), the index can be defined as:

$$\begin{aligned}
\ln G^O_{it} \equiv & \frac{1}{2}\sum_{m=1}^{M}\left(\frac{\partial \ln D^O_{it}}{\partial \ln y_{imt}} + \frac{\partial \ln D^O_{is}}{\partial \ln y_{ims}}\right)(\ln y_{mit} - \ln y_{mis}) \\
& -\frac{1}{2}\sum_{k=1}^{K}\left(\frac{\partial \ln D^O_{it}/\partial \ln x_{kit}}{\sum_{k=1}^{K}\partial \ln D^O_{it}/\partial \ln x_{kit}} + \frac{\partial \ln D^O_{is}/\partial \ln x_{kis}}{\sum_{k=1}^{K}\partial \ln D^O_{is}/\partial \ln x_{kis}}\right)(\ln x_{kit} - \ln x_{kis}) \\
& = \frac{1}{2}\sum_{k=1}^{K}\left[\left(-\sum_{k=1}^{K}\frac{\partial \ln D^O_{it}}{\partial \ln x_{kit}} - 1\right)\frac{\partial \ln D^O_{it}/\partial \ln x_{kit}}{\sum_{k=1}^{K}\partial \ln D^O_{it}/\partial \ln x_{kit}}\right. \\
& \left. + \left(-\sum_{k=1}^{K}\frac{\partial \ln D^O_{is}}{\partial \ln x_{kis}} - 1\right)\frac{\partial \ln D^O_{is}/\partial \ln x_{kis}}{\sum_{k=1}^{K}\partial \ln D^O_{is}/\partial \ln x_{kis}}\right](\ln x_{kit} - \ln x_{kis}) \\
& + (\ln T_s - \ln T_t) + (u_s - u_t) \\
& + \frac{1}{2}\sum_{p=1}^{2}\left(\frac{\partial \ln D^O_{it}}{\partial z_{ipt}} + \frac{\partial \ln D^O_{is}}{\partial z_{ips}}\right)(z_{ips} - z_{ipt}) + (v_s - v_t) \\
& = SEC + TC + TEC + ZC + VC.
\end{aligned} \tag{8}$$

The terms to the right of the identity sign represent a total factor productivity (TFP) index with normalised output elasticities as weights for the aggregation of input changes. This corresponds to the generalised Malmquist index by Orea (2002) with the difference that we formulate technological change in a general form (where technical progress is observed when $\ln T_t < \ln T_s$), and we add changes in environmental variables (ZC) and idiosyncratic errors (VC).

As an extension and for the purpose of exploring changes in inputs and outputs underlying technological change, we restate the index equation as:

$$TC = \left[\frac{1}{2}\sum_{m=1}^{M}\left(\frac{\partial \ln D_{it}^{O}}{\partial \ln y_{imt}} + \frac{\partial \ln D_{is}^{O}}{\partial \ln y_{ims}}\right)(\ln y_{mit} - \ln y_{mis}) - \frac{1}{2}\sum\nolimits_{k=1}^{K}\left(\frac{\partial \ln D_{it}^{O}/\partial \ln x_{kit}}{\sum_{k=1}^{K}\partial \ln D_{it}^{O}/\partial \ln x_{kit}} + \frac{\partial \ln D_{is}^{O}/\partial \ln x_{kis}}{\sum_{k=1}^{K}\partial \ln D_{is}^{O}/\partial \ln x_{kis}}\right)(\ln x_{kit} - \ln x_{kis})\right] - SEC - TEC - ZC - VC. \tag{9}$$

In a way similar to a growth accounting approach, technological change can be 'decomposed' into separate (weighted) growth rates of inputs and outputs, while still considering scale and technical efficiency effects. This allows us to track movements in outputs and inputs that are intermediately responsible for the observed technological change patterns. That is, although we do not observe changes in production techniques originally responsible for technological change, comparing growth rates of inputs and outputs allows us to gain some further insight into the symptoms of technological change.

4.4. Data and estimation

We use unbalanced panel data from the EU's Farm Accountancy Data Network (FADN) on West German farms for the period 1995–2013. We exclude East German farms from the analysis because of structural differences in the form of the presence of very large mixed farms in the East German dataset, which would impair the comparison between specialised and mixed farms. We distinguish between specialised and mixed dairy farms according to the FADN 'TF8' classification, which is based on shares of standard output. The pooled sample of specialised and mixed dairy farms contains information from 7,612 farms, with an average of 5.4 observations per farm. For specialised dairy farms, we distinguish two farm outputs: 'milk' and 'other output' (i.e., M = 2 in equation (1)) and five production inputs 'dairy cows', 'intermediates', 'labour', 'land', and 'other capital'. Milk output (y_1) is defined as the physical quantity of milk produced on-farm.[6] By using the physical quantity, we use an output measure free of any price biases possibly not fully accounted for by deflating revenues with a national price index. 'Other output' consists of all other goods produced on the farm, aggregated by summing up the deflated value of production (less the value of products consumed on-farm) in various categories. To account for animals that are reared but not sold during the same accounting period, we add the deflated value of animal stock changes to farm output. For mixed farms, we disaggregate this output category into two outputs ($M = 3$): 'plant production' and 'other animal production'. Inputs are defined in the same way for specialised and mixed farms. Input 'cows' (x_1)

[6]The value of milk consumed on-farm is not subtracted from this variable because of missing values in one year. As the share of milk used on-farm (e.g., for feeding calves) is only a minor share in the total value of milk output (2.5% on average), we do not expect this to introduce any bias into the output variable.

Table 2
Descriptive statistics

Variable	Unit	Specialised dairy farms		Mixed farms	
		Mean	Std. Dev.	Mean	Std. Dev.
Inputs					
Cows	Number	50.3	36.4	28.5	19.6
Labour	Annual work units	1.8	0.8	1.8	0.9
Intermediates	Euros	50,794	45,970	72,801	74,007
Land	Hectares	60.2	39.9	70.7	54.1
Capital (depreciation)	Euros	19,304	13,889	19,250	13,621
Outputs					
Milk	kg	349,993	317,019	188,504	165,591
Other output	Euros	33,831	33,629		
Other animal output	Euros			63,891	89,473
Plant output	Euros			28,628	43,300
Output value shares					
Milk	%	74.9	12.4	41.2	18.0
Other animal production	%	20.4	11.0	36.4	25.0
hereof: cattle sales	%	93.8	16.4	58.7	37.8
hereof: pig sales	%	4.3	14.6	37.5	38.0
Plant production	%	4.7	7.8	22.4	17.7
Number of observations		30,818		10,458	

Note: Output value shares are based on the value of total production (less farm use) and shown for descriptive purposes only and not used for estimation. Monetary values are in constant 1995 prices. Annual work units are full-time equivalents.

is measured by the average number of dairy cows, and 'intermediates' (x_2) are defined by expenditures for feed, animal purchases, other livestock specific inputs, energy, and crop specific inputs, each deflated by suitable price indices from Eurostat's online database. Input 'labour' (x_3) is the farm's annual work units (AWU), 'land' (x_4) is the amount of land used in production, and 'capital' (x_5) is measured by deflated depreciation for farm buildings and machinery. For both samples, we removed observations where the farm did not produce milk anymore or has not yet produced any milk.

We further control for environmental conditions by including weather data from 22 weather stations, where each observation is assigned the data of the likely nearest weather station.[7] That heat stress indicators are important control variables in dairy farming is shown, for example, by Finger *et al.* (2018). We include two proxies for weather shocks: the number of days per year with a maximum air temperature above 30°C to account for heat stress of dairy cows (z_1), and the log of the cumulative rainfall per year to account for growing conditions (z_2).

Descriptive statistics of the two samples are given in Table 2. Specialised and mixed farms are on average of similar size in terms of labour and capital endowments.

Inspecting output value shares reveals that the output of specialised farms mainly consists of milk and cattle sales, while mixed farms source, on average, significant

[7]The data are publicly available from the German meteorological service DWD (www.dwd.de).

shares of their output from milk, other animal production, as well as plant production.

The number of observations per year is reported in Table S1 in the Online Appendix, which shows gradual changes in the compositions of the two samples. The sample of mixed farms shows a rather steady and slow decline in the number of observations. For specialised farms, the number of observations increases distinctively after 2008, which might have implications for our results if farm entry and exit are systematic. However, we reran the frontier estimation for specialised farms excluding the farms entering the sample after 2008 and obtained almost identical results.

As additional regressors we include 27 region dummy variables (government regions at the NUTS 2 level). For estimation of the distance functions, we rely on the stochastic frontier estimation routine suggested by Kumbhakar *et al.* (2014). The model has the general advantage of separating random noise, firm heterogeneity, time-invariant and time-varying inefficiency. The model can be estimated in a stepwise procedure.[8] The first step consists of the consistent estimation of the frontier coefficients in a random or fixed effects panel data regression. We opted for a fixed effects approach, which is robust to endogeneity by correlation of unobserved time-invariant farm heterogeneity (e.g., soil quality or climatic conditions) with the frontier regressors. In the following steps, total inefficiency.

u_{it} can be calculated as the sum of time-invariant and time-varying inefficiency, which are obtained from two separate frontier estimations that regress the predicted firm effects and predicted residuals on a constant. We assume that both time-invariant and time-varying inefficiency follow an exponential distribution, which yielded the highest log-likelihood value in the frontier estimations. All calculations were performed in Stata 15.

5. Results and Discussion

After the fixed effects estimations, both the predicted fixed effect and the time-varying error showed statistically significant positive skew, justifying our stochastic frontier formulation. The full model estimation results are given in the Online Appendix in Table S2. Overall, the model fit of the distance functions for both the specialised and the mixed farm sample was satisfactory with 43% (specialised farms) and 42% (mixed farms) of the coefficients showing statistical significance at the 10% level or lower. This rather high share of insignificant parameters is commonly observed in distance function estimations due to the large number of parameters and resulting multicollinearity (Brümmer *et al.*, 2002; Morrison Paul and Nehring 2005; Pieralli *et al.*, 2017). A Wald test on the coefficients related to technological change showed high joint significance in both models. As shown in the following sections, first derivatives with respect to all inputs at the sample mean show the expected signs, fulfilling the monotonicity criterion of theoretical consistency (Sauer *et al.*, 2006). Additionally, we checked monotonicity and curvature for each observation in our dataset. The results are listed in Table S4 in the Online Appendix. The extent to which the regularity conditions should be fulfilled or imposed *ex ante* in empirical studies is still an open question. While some studies emphasise that unreliable efficiency estimates can arise when the theoretical properties are not fulfilled (O'Donnell and Coelli, 2005; Feng and

[8]For all details we refer to 'model 6' in Kumbhakar *et al.* (2014).

Table 3
Average estimated marginal effects in specialised farming

	Average marginal effect	S.E.
Other output	0.135***	0.009
Cows	−0.623***	0.013
Intermediates	−0.269***	0.008
Labour	−0.025***	0.006
Land	−0.083***	0.010
Capital	−0.020***	0.003
Returns to scale	−1.021	0.013
Time	−0.010***	0.000

Note: Standard errors are calculated using the delta method. Stars indicate a statistically significant difference from zero (from one for returns to scale).

Serletis, 2010), others find very similar results with respect to efficiency estimates (Balcombe *et al*., 2006) or predictive power (Parmeter *et al*., 2014) when estimation techniques with and without imposed regularity conditions are compared. Other authors abstain from curvature checks given the limited chance of fulfilling the conditions with a large number of inputs and outputs (Zhu and Lansink, 2010). In our estimations, for specialised farms the conditions are fulfilled for most observations except for convexity of the distance function in outputs. We consider this to be less of a problem for our results since the main application of the curvature conditions is the proof of duality (Feng and Serletis, 2010; Färe and Grosskopf, 1994). Some more violations occur for mixed farms. Therefore, these results must be interpreted with greater caution, but still serve well as a comparison to the results obtained for specialised farms.

5.1. *Specialised farms*

Average estimated distance elasticities for the sample of specialised farms are given in Table 3. Because of the distance function formulation with negative output as the dependent variable, elasticities with respect to outputs are expected to have a positive sign and elasticities with respect to inputs a negative sign. As expected from output value shares, the distance elasticity with respect to other output amounts to 13.5%, signifying that specialised milk farms generate most of their output from milk production. All elasticities with respect to inputs show the expected negative sign with milk cows being the most important production input. The sum of the elasticities with respect to inputs suggests that specialised farms on average operate at slightly increasing but close to (not significantly different from) constant returns to scale.

Our main interest lies in the estimates of technological change. On average for the whole sample period, specialised farms realised technical progress at a rate of 1.0% per year (Table 3), which is in line with the results of other studies (Emvalomatis, 2012; Cechura *et al*., 2017; Kellermann and Salhofer, 2014). However, when examining the estimated rate of technological change per year, we see a slowdown in technological change. The second column of Table 4 gives average predicted rates of technological change by year. Technological change decelerated over time with growth rates of 1.3% at the beginning and 0.9% at the end of the study period. We

Table 4
Average rates of technological change and predicted inefficiency by year for specialised farms

	$\dot{T}_t$				
Year	Baseline model: common TC trend for all years		Allowing for break in neutral TC in 2009		Inefficiency (u)
1995	0.013***	(0.001)	0.008***	(0.001)	0.187
1996	0.012***	(0.001)	0.009***	(0.001)	0.182
1997	0.012***	(0.001)	0.009***	(0.001)	0.183
1998	0.012***	(0.001)	0.009***	(0.001)	0.177
1999	0.012***	(0.001)	0.010***	(0.001)	0.171
2000	0.011***	(0.001)	0.010***	(0.001)	0.164
2001	0.011***	(0.000)	0.011***	(0.000)	0.174
2002	0.011***	(0.000)	0.011***	(0.000)	0.181
2003	0.011***	(0.000)	0.012***	(0.000)	0.177
2004	0.010***	(0.000)	0.011***	(0.000)	0.178
2005	0.010***	(0.000)	0.012***	(0.001)	0.178
2006	0.010***	(0.000)	0.012***	(0.001)	0.175
2007	0.009***	(0.000)	0.012***	(0.001)	0.180
2008	0.009***	(0.000)	0.013***	(0.001)	0.171
2009	0.009***	(0.000)	0.003***	(0.001)	0.172
2010	0.009***	(0.001)	0.002***	(0.001)	0.169
2011	0.009***	(0.001)	0.001	(0.001)	0.172
2012	0.008***	(0.001)	0.000	(0.001)	0.167
2013	0.009***	(0.001)	0.000	(0.001)	0.167
Total	0.010***	(0.000)	0.011***	(0.000)	0.175

Note: The numbers in the second and third columns show predicted marginal effects averaged by year and across all years ('total'). Estimates in the second column are based on a common TC trend for all years; in the third column the estimation allows for a structural break in 2009 by incorporating dummy variable interactions with neutral technological change. Standard errors in parentheses and significance levels were calculated using the delta method.

illustrate this in Figure 3, which plots the results of the distance function estimation with year dummies in place of the continuous year variable.

The graph plots the year dummy coefficients λ_t alongside the predicted frontier from the baseline model (equations (1) and (2), with inputs and outputs held constant at the sample mean and normalised to 1995 = 0). Although both specifications capture the same long-term trend, the dummy variable specification shows a plateau in the technology level after 2008. This pattern is further confirmed by allowing for differing rates of neutral technological change starting from 2009. We incorporate this by interacting the neutral technological change terms with a dummy variable, assuming the value of 1 for the years 2009 to 2013, that is, we add $\delta_{Dt}D_{t\geq 2009}t+\delta_{Dtt}D_{t\geq 2009}t^2$ in equation (2). The two additional coefficients are both statistically significant. The predicted technological change rates are given in the third column of Table 4 and suggest that yearly technical progress remained at a stable level of around 1.1% per year until 2008, whereas the rates were close to zero for the period after 2008.

The estimates for technical inefficiency (last column of Table 4, calculated on the basis of a common TC trend for the two periods) reveal that the level of inefficiency

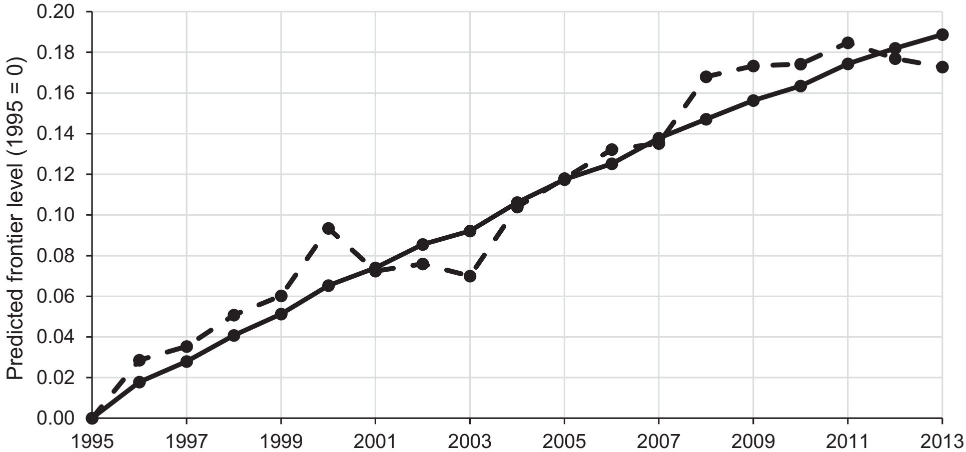

Figure 3. Predicted frontier levels per year estimated by models with a time trend (solid line) and a time dummy formulation (dashed line).

averaged 17.5% for the whole sample period. This level of inefficiency seems relatively high compared to other studies on similar data (Brümmer *et al*., 2002; Cechura *et al*., 2017). However, relatively high inefficiency estimates from this type of frontier model can be expected when compared to more conventional frontier models (Kumbhakar *et al*., 2014). In our case, the inefficiency estimates were driven by a relatively large proportion of the time-invariant component of inefficiency, with a mean of approximately 13% across all observations. While time-varying technical inefficiency was fairly stable, the average time-invariant inefficiency decreased by 2.4 percentage points on average, being the main driver of the decrease in total technical efficiency of 2.0 percentage points from 1995 to 2013 as indicated by the last column of Table 4. The likely explanation for this is that farms that did not achieve a reduction in their high level of time-invariant inefficiency were more likely to exit the sector.

The largest decrease in inefficiency occurred in 2008, when mean inefficiency is estimated to be reduced by 0.9 percentage points. The frontier shift visible in the time dummy specification and the drop in inefficiency in the time trend formulation in 2008 were preceded by a spike in milk prices in 2007 (see Figure 2). Recalling the spike in farm machinery and equipment observed in Figure 2, this suggests that farmers used additional revenue to update their equipment, which translated into productivity growth either ascribed to increased technological change (in the time dummy specification) or reduced inefficiency (in the time trend specification). However, the continuing stagnation in technological change and technical inefficiency after 2008 is not in line with increasing levels of net investment observed after 2009. In general, one would expect farmers to need some time to adjust to newly implemented techniques. For example, the construction of new farm buildings requires additional attention from the farmer, and herd management must be adjusted to the new conditions. Therefore, some latency until major investments manifest themselves in increased productivity is plausible. Yet the peculiarity of our observation lies in the endurance of the technological change stagnation. That is, the high levels of net investment from 2009 onward did not result in technical progress during the following 4 years. This contrasts with results from earlier studies that established shorter time lags between investment

Table 5
Results for the Malmquist index decomposition

		Output and input changes											
Period	TC	Milk	Other output	Cows	Mate-rials	Labour	Land	Capital	TFP	SEC	TEC	ZC	VC
1996–2008	0.013	0.016	0.000	0.005	−0.001	0.000	0.001	−0.001	0.011	0.000	−0.001	−0.001	0.000
2009–2013	0.001	0.017	0.001	0.009	0.007	0.000	0.001	0.000	0.001	0.000	−0.002	0.001	0.000

Note: Positive numbers (in all columns apart from input growth rates) contribute positively to TFP. Growth rates of outputs and inputs are weighted by corresponding elasticities.

Table 6
Average estimated marginal effects in mixed farming

	Average marginal effect	S.E.
Animal output	0.261***	0.009
Plant output	0.079***	0.005
Cows	−0.592***	0.017
Intermediates	−0.377***	0.016
Labour	−0.022*	0.012
Land	−0.070***	0.021
Capital	−0.016**	0.007
Returns to scale	−1.078***	0.026
Time	−0.006***	0.001

Note: Standard errors calculated with the delta method. Stars indicate a statistically significant difference from zero (from one for returns to scale).

activity and productivity effects (Sauer and Latacz-Lohmann, 2015). To gain additional insights, we explore possible reasons for the observed pattern in the next subsection.

5.1.1. Exploring the technological change stagnation

Several explanations for the pattern of technological change we observe come to mind. First, during uncertain market phases, farmers might shift their focus towards implementing already established techniques by imitating peers but neglect new (unknown and therefore riskier) techniques that are able to push the frontier outward. This behaviour would explain technological change stagnation and would be observable in increased technical efficiency. Second, especially towards the end of the milk quota system, farmers might have tried to position themselves for a prospective increase in market share by shifting to growth strategies and using scale effects, for which a consequence would be increased scale efficiency. Third, high feed prices that were observed starting in 2007 might have dampened cow productivity. Lastly, one might wonder whether specialised dairy farms showed no technical progress *although* or *because* they showed high levels of net investment after 2008 – that is, positive output growth could have been outweighed by extraordinarily high capital input growth.

To explore the plausibility of these explanations, we show in Table 5 results for the Malmquist index decomposition as described by equation (9) and based on the time dummy specification. While we report the average changes for each year in Table S5 in the Online Appendix, we show in Table 5 averages for the two periods before and starting from 2009. Overall, the numbers indicate technological change to be the most important driver of productivity, leading to synchronous progressions of technological change and total factor productivity change. For calculation of the Malmquist index, only changes in time-varying technical efficiency are relevant. Time-varying technical efficiency change is estimated as close to zero, suggesting that the average dairy farmer did not move closer to the frontier after 2009, which was already indicated by the stable levels of time-varying technical inefficiency as described above for the time trend formulation. This contradicts the presumption that farmers shifted their attention to the adoption of established technologies.

Table 7
Average rates of technological change and predicted inefficiency by year for mixed farms

	$\dot{T}_t$				
Year	Common TC trend for all years		Allowing for break in neutral TC in 2009		Inefficiency (u)
1995	0.003	(0.002)	0.001	(0.002)	0.179
1996	0.003*	(0.002)	0.002	(0.002)	0.171
1997	0.004**	(0.002)	0.003	(0.002)	0.170
1998	0.004***	(0.001)	0.004***	(0.001)	0.174
1999	0.005***	(0.001)	0.005***	(0.001)	0.171
2000	0.006***	(0.001)	0.006***	(0.001)	0.165
2001	0.006***	(0.001)	0.006***	(0.001)	0.172
2002	0.006***	(0.001)	0.006***	(0.001)	0.172
2003	0.006***	(0.001)	0.007***	(0.001)	0.170
2004	0.006***	(0.001)	0.007***	(0.001)	0.165
2005	0.006***	(0.001)	0.007***	(0.001)	0.166
2006	0.006***	(0.001)	0.007***	(0.001)	0.167
2007	0.007***	(0.001)	0.008***	(0.002)	0.173
2008	0.007***	(0.001)	0.008***	(0.002)	0.160
2009	0.007***	(0.001)	0.002	(0.002)	0.166
2010	0.007***	(0.001)	0.002	(0.002)	0.170
2011	0.007***	(0.001)	0.001	(0.002)	0.153
2012	0.008***	(0.001)	0.001	(0.003)	0.175
2013	0.008***	(0.002)	0.000	(0.003)	0.170
Total	0.006***	(0.001)	0.004***	(0.001)	0.170

Note: The numbers in the second and third columns show predicted marginal effects averaged by year and across all years ('total'). Estimations in the second column are based on a common TC trend for all years; in the third column the estimation allows for a structural break in 2009 by incorporating dummy variable interactions with neutral technological change. Standard errors in parentheses and significance levels were calculated by the delta method.

In addition, the influences of weather effects (ZC) and unobserved factors (VC) seem to be of minor importance. Similarly, scale efficiency gains are close to zero. The likely explanation is given by the estimates of returns to scale, which indicated constant returns to scale on average (Table 3); 36% of the observations show returns to scale statistically significantly (at the 5% level) below – 1 (i.e. increasing returns to scale). However, 90% of the observations lie in the range of – 1.07 to – 1.01. This leaves little room for productivity improvement by a growth strategy. Nevertheless, positive growth rates of milk output show that farms consistently grew in size throughout the two periods. Especially after 2009, this was likely facilitated by the increases in quota volumes. Additionally, after 2009, farm milk output grew faster than average herd size, which means that average cow productivity still increased during the period of technological change stagnation (if at slightly smaller rates). This contradicts a potential negative effect of high feed prices or a possible stagnation in improvements in cow genetics on technological change. Looking at growth rates of capital input reveals that capital is accredited only a minor share in production (as can be seen by low average distance elasticities in Table 3), and hence the observed

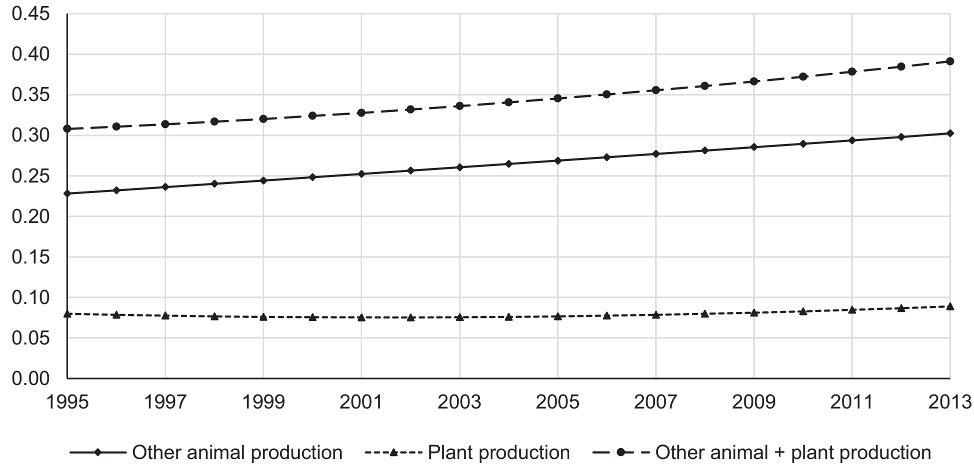

Figure 4. Predicted shares of other animal production and plant production over time for mixed farming.

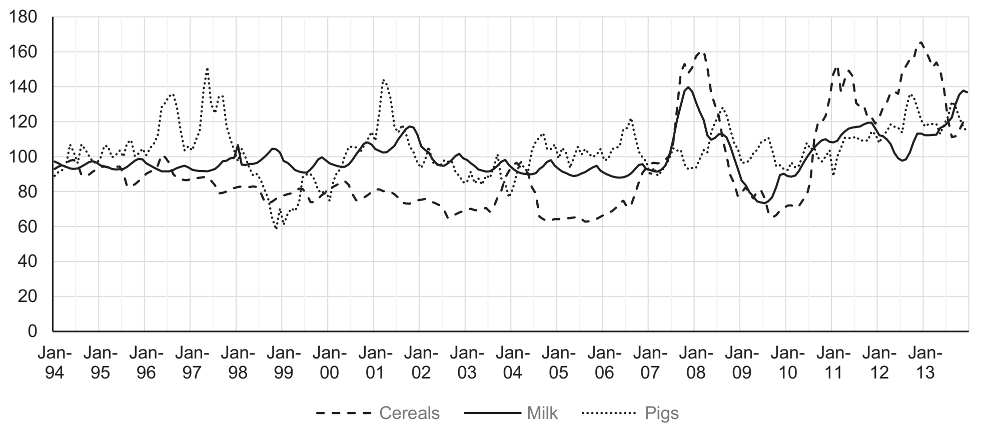

Figure 5. Indices of output prices for cereals, milk and pigs in Germany. *Sourceof data*: German National Statistical Office (Destatis, 2019).

high levels of investment (in capital goods other than cows) can be ruled out as a cause of the low technological change rates.

Apparently, the technological change stagnation after 2008 was associated with high growth rates in cow and material inputs. Dairy farms still achieved output growth rates at least similar in magnitude to those before 2009, but this output growth was consumed almost completely by growth in cow and material inputs. In general, growth in milk output and materials input seems more interrelated after 2008: growth in milk output was accompanied by synchronous growth in materials input (see Table S5 in the Online Appendix). From the yearly growth rates in cow input, it can also be seen that, coinciding with a milk price spike, average herd size growth was especially high in 2007, close to zero at the price low in 2009, and higher with recovering milk prices starting in 2010.

These results suggest that dairy farmers reacted to changing output prices and increased price volatility and entered an adjustment phase starting in 2007, which was characterised by an overall increasing scale of operations. The stagnation in technical progress during this phase indicates that many of the net investments were aimed at an expansion of operations and not necessarily at improving production techniques. Additionally, the potential for improvements in productivity by increases in scale efficiency were limited by returns to scale close to unity.

5.2. *Mixed farms*

Average estimated distance elasticities for mixed farms are given in Table 6. As for specialised farms, all elasticities show the expected sign. Animal and plant output are estimated to represent approximately 34% of total production, which is slightly less than their calculated revenue shares (Table 2). Over the whole sample period, mixed farms showed technical progress of 0.6% per year, which is less than the 1.0% estimated for specialised farms.

We explore the shape of technological change in the same way as for specialised farms in Table 7. The numbers show that in general, technology progressed more slowly over the whole study period for these farms as compared to specialised farms, supporting the assumption that specialised farms have a greater ability to acquire state-of-the-art technology. Allowing for a structural break in technological change in 2009 shows that, contrary to our expectation, we observe the same pattern of stagnating technological change after 2008: While growth rates hover between 0.3% and 0.8% in most years before 2009, no significant technical progress is realised during the years 2009–2013.

Compared to specialised farms, mixed farms show a similar level of average technical inefficiency of 17.0%. As in specialised farms, mean inefficiency decreased in 2008; however, this change is not too different in magnitude from the changes observed in other years. The more fluctuating nature of technical inefficiency might be due to the greater influence of weather conditions on plant production not controlled for by the weather proxies in our model.

To further explore the technical progress realised in specific outputs, we evaluate the coefficients of the technological change bias terms with respect to the outputs (α_{mt} and α_{mtt}). The individual coefficients are estimated to be close to zero and not statistically significantly different from zero for both animal and plant production (see Table S2 in the Online Appendix). However, they show joint statistical significance. With $\alpha_{2t}>0$, the average share of animal output shows a linear increase by approximately 7 percentage points over time. This is illustrated in Figure 4. With a constant share of plant output, this suggests that mixed farms achieved faster technological change in animal production at the expense of technological advances in milk production. This is in line with average dairy herd size growth rates that can be observed in our dataset (not shown for brevity). While specialised farms grew in herd size in almost all years, mixed dairy farms consistently showed shrinking herd sizes, on average. Hence, it is plausible that mixed farms invested a greater amount of resources into the growing farming activities. However, no change in the pace of this development can be observed ($\alpha_{2tt}\approx 0$). Therefore, there is no indication that mixed farmers shifted their innovation efforts as a reaction to the price developments in the last years of our study period. The low growth rates in overall technological change observed in mixed farms after 2008, however, suggest that like specialised farms, mixed farms did not realise substantial technological progress overall. An explanation for this might possibly be found by scrutinising output prices of the different agricultural outputs in recent years.

As can be seen in Figure 5, not only did milk show increased volatility since 2007 but the prices for cash crops did so as well. Moreover, the prices moved in a more concerted pattern.[9] With increased positive correlation between prices of different outputs, diversified farms lose their risk-spreading advantage over specialised farms (Merener and Steglich, 2018).

Inspecting further the series for pig prices in Figure 5 raises the question of whether farms with pig production had an advantage over farms without pig production, since pig prices seemed more stable after 2007. For brevity, we do not report separate estimation results, but note that further analyses showed that this was not the case. The distance function for mixed farms active in pig production also showed no shifts significantly different from zero when estimated for the period after 2008. This shows that also farms with a high degree of diversification showed no different innovation behaviour.

6. Conclusions

When estimating distance functions for dairy farms, we observe a slowdown in technological change during a phase of volatile milk prices. Our analysis also shows that mixed dairy farms did not exhibit different innovation behaviour from specialised dairy farms. We suspect that the reason for this can be found in the correlation between prices of different agricultural commodities during recent years by which diversification partly lost its risk-spreading advantage.

While the recent changes in the regulatory environment are a likely determinant of milk price volatility – for example, by lowering intervention price levels – they might have also had a direct effect on dairy farmers' investment behaviour by influencing their confidence in future business opportunities following quota expansion and elimination. Because of the simultaneity of the regulatory changes and milk price volatility, and since variation in prices happens across time rather than across farms, the two effects are hard to separate. Hence, asserting a causal effect of price volatility on technological change is difficult. Further analyses in our study and the attempt of incorporating output price risk in the frontier estimation with the help of milk price standard deviations generated ambiguous results and no conclusive findings. However, milk price volatility was one – if not the most – important determinant of dairy farmers' financial well-being in recent years and several empirical studies have confirmed that price volatility affects famer's investment decisions. Therefore, it is plausible to assume that price volatility played at least a partial role in the technological stagnation we observe.

Further, our results indicate that the stagnation in technological change happened despite comparatively high average levels of net investment, which questions our original expectation of a direct negative effect of price volatility on technological change. More likely, a combined effect of price volatility and phasing-out of the quota led

[9]This can be illustrated by looking at correlation of the price series: For the monthly prices shown in Figure 5, correlation coefficients before/after January 2007 amounted to 0.10/0.71, 0.02/0.30, and 0.19/0.40 for milk and cereals, milk and pigs, and cereals and pigs, respectively.

farmers into a turbulent adjustment period, where – as indicated by the high growth in average herd size and milk output – dairy farmers positioned themselves for a market free of quota limitations and an alignment to world market prices. Considering the rather steep increase in the technology level in 2008 following a year of high milk prices, it remains unclear whether the slowdown we observe is enduring or just a temporary rest – a question that should be addressed in future analyses. If the stagnation we observe turns out to be an adjustment period, improvements in technological change as a consequence of the previous high levels of net investment are likely for the following years.

Another conclusion is that if we do not observe the effect of a lack of willingness to invest, we might observe a lack of technological opportunities that were able to push the state of technology in the sector. Implemented technologies might put greater emphasis on progress we do not observe in the data, for example, on advances in product quality, such as in animal welfare. Further research should also focus in more detail on this missing link between farm net investments and technological change.

Supporting Information

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

Table S1 Number of observations per year.
Table S2 Estimation results.
Table S3 Estimation results (Continued).
Table S4 Evaluation of fulfilment of regularity conditions.
Table S5 Detailed results for yearly TFP components of specialized dairy farms.

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