Deregulation and Productivity:

Empirical Evidence on Dairy Production

Fabian Frick and Johannes Sauer, Technical University of Munich

fabian.frick@tum.de

jo.sauer@tum.de

Selected Paper prepared for presentation at the 2016 Agricultural & Applied Economics Association Annual Meeting, Boston, Massachusetts, July 31-August 2

“Deregulation and Productivity: Empirical Evidence on Dairy Production” by Fabian Frick and Johannes Sauer was published in the American Journal of Agricultural Economics in 2018, Volume 100, Issue 1, 1 January 2018, Pages 354–378.

Abstract

We investigate productivity development and its relation to resource reallocation effects in the dairy sector in southeast Germany during the phasing-out of the European Union milk quota. We use a farm level dataset containing financial accounting data for a period of 15 years. Farm-level productivity is estimated by applying a proxy approach recently introduced in the literature. We compare this approach to other estimation approaches as well as an index based analysis. After aggregation we decompose sector productivity into unweighted mean productivity and a covariance term measuring the allocation of resources toward more productive farms. We observe an increase in the covariance term coinciding with a period of rather volatile milk prices. Therefore, we hypothesize that reallocation of production resources due to market deregulation is triggered or even enforced by extreme price levels. We seek to find support for this hypothesis by a regression analysis linking the measure for the potential covariance between resource reallocation and productivity on the one hand and price variability on the other. In this analysis we find some empirical evidence for this hypothesis.

Introduction

In a well-functioning and free market, firms that cannot keep up with competitors are forced to reduce their market share or even cease their market participation. Thereby these firms release the resources bound by their production activity and make them available for production by more productive firms. This process contributes to a more efficient production at the sector level (i.e. aggregate productivity). Market regulation, however, is suspected to hinder this resource flow by keeping firms with low productivity in the market. This suspicion can also be applied to the case of the European Union (EU) milk quota system. The milk quota was introduced by the European Community in 1984 to restrict production volumes and avert high production surpluses that could only be removed from the market by high intervention costs. Originally introduced as only a temporary instrument for five years, the use of the quota was prolonged several times. With the quota regime in place, the expansion of a dairy operation was, in general, hindered by the additional costs of quota acquisition and ownership that can be seen as a source of additional rents for less productive farms. European dairy farmers were restricted to a certain output level by imposition of the "superlevy", a farmer was usually obliged to pay for production volumes exceeding the farm's quota. The final date of the abolition of the quota was introduced in the CAP reform of 2003 and confirmed in 2008. A phasing-out was performed by a stepwise increase of the quota volumes (soft landing approach). It can be expected that in the first years the distortionary effect imposed by the quota was strong considering the large additional costs expanding producers faced due to high quota prices. Toward the end of the quota system, the market disturbing effect might have become less significant since quota prices significantly decreased[1].

Deregulation cannot be regarded as the sole driver for resource reallocation among farms. An important exogenous factor for a farmer's investment decision is the output price. The 2015/16 "milk crisis" in Europe and other parts of the world shows how susceptible farmers are to output price risk. Insisting calls for financial aid illustrate the serious effect on the farm structure and indicate that price plunges are possibly followed by a significant resource reallocation in the sector. Our analysis considers both deregulation and output prices as potential drivers for resource reallocation in the dairy sector.

Background

Restuccia (2016) described the underlying idea behind resource misallocation within an industry sector. The optimal reallocation of input resources among farms is given, when resources flow from farms with the smaller to farms with the greater marginal product. Any policy that dissuades an industry sector from reaching an optimal point of resource allocation will compromise aggregate output and productivity. In the following we review part of the vast literature concerned with the effects of policy influence on the performance of firms or industry sectors. We remark that this review is by no means exhaustive but is meant to merely illustrate that policy distortions predominantly tend to be found negatively related to firm or sector performance. This is not just the case for the agricultural economics literature but also in studies examining other industry sectors.

Eslava et al. (2004) examined the influence of resource reallocation on aggregate productivity of Colombian manufacturing firms in the context of labor market, trade, financial, and social security reforms. They found that after the reforms in the early 1990s, reallocation largely accounted to aggregate productivity growth.

Restuccia and Rogerson (2008) applied a growth model calibrated with US data. They examined the effect of policy induced reallocations of resources among producers with heterogeneous productivity. They concluded that these distortions can largely affect industry productivity especially in the case when distortions are correlated with the productivity of firms.

Hsieh and Klenow (2009) examined the dispersion of revenue productivity in the manufacturing sector of China, India, and the US. They found that in all countries, but especially in India and China, industry productivity could be increased by an optimal resource reallocation that equalizes revenue productivities across firms within industry sectors. In addition, they observed an improvement of allocation efficiency for China during a period of market reforms. For India, however, they found ambiguous results with declining allocation efficiency despite reforms.

In a growth model, Guner, Ventura, and Xu (2008) examined the effect of policies that restrict production of large firms or encourage production of small firms, thereby inducing a decrease of mean firm size. For taxes on capital use they found a reduction in aggregate output as well as a decrease in labor productivity. If size restrictions were implied by taxes on labor use they found a comparable decrease in labor productivity, however, aggregate output remained nearly unchanged. Finally, by subsidies for small firms, aggregate output was also unchanged and contrary to the other cases, labor productivity tended to increase. These results indicate that different policies that have the same effect on mean firm size might affect productivity measures in different ways.

As the agricultural sector is influenced by various policy measures in many countries, the effect of (de-)regulation on sector performance is also of wide interest in the agricultural economics literature. An example of intensive policy control is the European

Common Agricultural Policy and the implied subsidies and production quotas. With the abolition of the milk quota system the EU takes another step toward a more liberalized agricultural market already in place in other industrialized regions. Gray, Oss-Emer, and Sheng (2014), for example, examined productivity dynamics in the Australian broadacre agriculture in the context of policy reforms. They concluded that facilitated by comprehensive policy reforms, reallocation significantly influenced sectoral productivity gains and helped offset farm-level total factor productivity (TFP) decline.

Production quotas might affect farm and industry productivity in several ways[2]. Central to our study is the hypothesis of a hindered resource flow from less to more productive firms. This should be reflected in decelerated structural change. The results of Huettel and Jongeneel (2011) showed that this is not necessarily be the case. They applied a Markov chain model on aggregate data for Dutch and German dairy farms and examined the structural change quantified by mobility indicators for different size classes before and after implementation of the quota system. They found that the overall mobility of dairy farms increased rather than decreased with the milk quota and attributed this effect to the stronger interdependency between growing and shrinking farms. However, they found exit mobility to be decreased under the quota regime, indicating that small and possibly less efficient farms stayed in the market despite a low and further declining efficiency of production.

Nevertheless, the majority of studies that examine the effect of quotas on sector performance, most often come to the conclusion that production quotas negatively impact efficiency and productivity in the sector, however, the negative effect is reduced with increasing quota tradability.

This result is e.g. confirmed in the study by Gillespie et al. (2015). They applied a stochastic frontier framework and a Malmquist productivity index for a panel of Irish dairy farmers reaching back to the pre-quota period. High productivity growth rates before the quota implementation, low growth rates in the first years of the quota regime, and increasing growth rates following policy reforms reflect the hypothesized effect of the quota implementation and a liberalized quota trade on sector productivity.

Colman (2000) showed that tradability of quota rights reduces sector inefficiency as quota can be transferred from less to more efficient farms. However, he demonstrated that in the case of the UK (in 1996/97), the optimal allocation of quota was not achieved, therefore, some inefficiency remained in the market. Furthermore, he also argued that with high quota prices, the quota cost amounts to a significant share of total production cost, thereby posing a barrier for expanding farmers.

A similar conclusion is drawn by Hennessy et al. (2009), who concluded that overall cost inefficiency of milk production in Ireland could be reduced by a national quota trading system compared with the existing regional trading system.

Kirwan, Uchida, and White (2012) examined the effect of the termination of production quotas in the tobacco sector in Kentucky. After the sudden elimination of quotas they found considerable resource reallocation flows accompanying the restructuring process in the sector and showed their positive effect on aggregate productivity.

Before closing this section, a remark is in order about what is measured by the effect of resource misallocation on sector productivity. With productivity we examine the predominantly technical aspects of production and neglect other aspects that are of importance for agricultural production. In the context of resource reallocation this might be most prominently farm structure. If returns to scale are increasing, then efficient resource allocation impacts farm structure. In Bavaria, structural change in the agricultural sector is primarily considered as an unwanted development by many policy makers and sector representatives as small family businesses are regarded as an essential characteristic for the region highly valued by consumers.

Conceptual Framework

The methodological difficulties of estimating production functions are known since Marschak and Andrews, Jr. (1944) but have received renewed interest in more recent years as new techniques became available to overcome the problem of endogenous input choice. A comprehensive overview of techniques that have been proposed is provided by van Beveren (2012). Firms choose production inputs according to factors potentially unobservable by the econometrician. Assuming a Cobb-Douglas technology a firm's production process can be formalized as

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + v_{it}, \tag{1}$$

that is, firm i's output y in year t is described by the production inputs capital k, labor l, and intermediates m, all in logarithmic values. Besides the stochastic error, v captures a firm's productivity and a simple way of measuring productivity seems to consist of estimating (1) by OLS and calculate productivity as

$$\hat{p}_{it} = \hat{\beta}_0 + \hat{v}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it}. \tag{2}$$

However, it must be assumed that v is not only determined by random effects but rather has two components which can be shown by rewriting (1),

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \epsilon_{it}, \tag{3}$$

where ϵ represents a stochastic component due to measurement error or random shocks experienced by the production process. Factors such as managerial ability, expected weather events or livestock related characteristics are included in ω. Both terms are not observed by the econometrician, however, ω may be known or predicted by the farmer prior to choosing levels of variable inputs[3]. If this is the case, then variable inputs and v are not independent and estimation of (1) using OLS yields biased results.

To counter this, Olley and Pakes (1996) developed a two-stage procedure where in a first stage a reduced production function is estimated with investment used as a proxy for the productivity shocks observed by the firm and correlated with variable inputs (for details see Olley and Pakes 1996; Ackerberg, Caves, and Frazer 2006; van Beveren 2012; Ackerberg et al. 2007). Petrin and Levinsohn (2012, "LP") pointed out that the approach suggested by Olley and Pakes (1996) can be problematic due to the fact that capital is an input costly to adjust, probably leading to lumpy investment and datasets with a considerable share of zero investments. In this case, the assumption that investment is strictly increasing in unobservable productivity shocks does not hold, thus, ω cannot be formulated as a function of capital and investment. Hence, LP modified the approach and suggested intermediate inputs rather than investment as the proxy for unobserved productivity shocks.

The approaches by both Olley and Pakes (1996) and LP are challenged by Ackerberg, Caves, and Frazer (2006). They pointed out that without additional assumptions, the labor coefficient cannot be identified in the first stage of the algorithms due to collinearity between labor input and the non-parametric function used to substitute for productivity shocks. Wooldridge (2009) showed how the two-step approaches by Olley and Pakes (1996) and Levinsohn and Petrin (2003) can be reduced to an instrumental variable procedure. This approach has two main advantages: it is robust to the criticism of Ackerberg, Caves, and Frazer (2006) and standard errors can be easily obtained.

Several applications of these approaches exist in agricultural economics. Kazukauskas, Newman, and Thorne (2010) applied a modified approach of Olley and Pakes (1996) on a sample of Irish dairy farms. Kazukauskas et al. (2013) did not estimate productivity but included in their estimation model a control function based on LP. Rizov, Pokrivcak, and Ciaian (2013) extended the approach of Olley and Pakes (1996) to estimate the effect of subsidies on farm-level productivity in the EU-15. In their study on the Kentucky tobacco sector, Kirwan, Uchida, and White (2012) used the LP estimator to generate production function estimates used then to construct aggregated industry productivity. Petrick and Kloss (2013) applied the LP approach on European crop farms comparing different estimators. They concluded that the LP estimator offers a viable approach to productivity measurement also with respect to agricultural applications. In a second article, Kloss and Petrick (2014) also found the Wooldridge (2009) LP modification to be a viable alternative. However, they noted that the control function approach incorporating intermediates as a proxy to control for productivity shocks may be questionable in the agricultural context, as a farmer's reaction to a positive productivity shock might be to use fewer instead of more intermediate inputs (e.g. favorable weather or livestock conditions requiring less intensive chemical plant protection or veterinary input).

Another widely applied approach to measure productivity at farm/firm level consists of estimating stochastic production frontiers. Productivity change can then be calculated indirectly applying a Malmquist index comprising technical efficiency change, technical change, and possibly a scale efficiency change effect. The error term is divided into a random noise component and a stochastic inefficiency component. Endogenous regressors can be correlated with either of these two components (see e.g. Mutter et al. 2013). Therefore, standard stochastic frontier approaches to productivity measurement are expected to yield similarly biased results as obtained by OLS based estimation approaches. However, there are numerous studies concerned with endogeneity-robust estimation of production frontiers (Kutlu 2010; Shee and Stefanou 2015; Tran and Tsionas 2013; Kazukauskas, Newman, and Thorne 2010).

Given these recent developments in endogeneity corrected productivity estimation, we apply several approaches in this study. Using the estimations of farm-level productivity, we examine the effect of the milk quota on the dynamics of dairy sector productivity in southeast Germany to quantify possible distortionary effects.

Dataset

We employ a dataset on Bavarian dairy farms that is part of the European Farm Accountancy Data Network (FADN). Bavaria is a German federal state (NUTS 1 region) located in the southeast of Germany. Its raw milk production accounts for the largest share of milk produced in the country. Agriculture in Bavaria is still characterized by relatively small family farms. In 2013, the average farm in Bavaria cultivated about 33.6 hectares of land. However, the average land per farm increased by 3.4% p.a. in the period 2005 to 2013, whereas the number of farms decreased by about 3.4% p.a. in the same period[4]. A major goal of the Bavarian state government is to slow down the pace of structural change for reasons of social and regional policy as well acceptance of modern agricultural production in society (a relatively low yearly rate of 1.5% of all farms closing in the period

2010 to 2013 is regarded as mid-term goal for regional agricultural policy, see (StMELF 2014).

The data we use contain financial records and additional socio-economic information on the use of family labor, education of the farm manager, or physical input quantities. The dataset covers a period of 15 years (2000-2014). Descriptive statistics of output and input variables and details on their construction are discussed in the Appendix. Although our dataset is based on a regional sample of farms, the results of the study are highly relevant in a larger European context: (i) Bavaria is the largest milk producing region in Germany and accounts for a significant proportion of the milk production in the EU[5], and (ii) dairy farming in Bavaria is characterized by a large share of small family farms and slow structural change and, therefore, is representative for many other European regions[6].

Empirical modelling

To verify the robustness of our estimation results and to compare the performance and robustness of different methodologies we measure productivity in various ways. We apply (i, ii) two specifications of the Wooldridge (2009) LP modification approach ("WLP"), (iii) a conventional stochastic frontier approach ("SFA"), where we calculate a Malmquist TFP index as a result of technical efficiency change, technical change, and scale effects, (iv) a second SFA approach using a reduced set of inputs and outputs to address problems due to input aggregation, (v) an OLS approach based on fixed effects modelling ("FE") and (vi) a deterministic approach using a Törnqvist TFP index.

For the WLP approach the question of a suitable proxy to control for productivity shocks must be considered. As mentioned before, not every category of intermediate inputs might be correlated with productivity shocks at farm level. We apply two different proxies: (1) deflated costs for concentrated feed only, and (2) deflated costs for all intermediates by following the “standard” LP approach. We argue that the first model is based on a more realistic approach since in dairy farming additional milk output caused by productivity shocks must be balanced out with additional energy equivalents in feed rations (in simple words: if a cow produces more milk, it needs to have greater feed intake to balance energy output and input, see e.g. House 2011). We imagine a situation where a farmer achieves a greater milk output relative to another or the same farmer in the previous year through greater managerial effort; then, the more productive herd needs to have the greater feed intake. Hence, assuming equal capital and labor endowments of the two farms, feed consumption should be correlated with TFP. This might not be the case for other intermediate inputs—take as an example veterinary costs, which might even be negatively correlated with productivity (assuming that good managerial ability leads to greater milk output and better health status of the herd). We also find a counter-argument for the feed proxy. Consider two farms with the same feed inputs, and one farmer with greater managerial ability; then, there is no connection between productivity and feed input if the farmer with inferior managerial ability does not adapt his feeding strategy (or if lower feed intake of the herd is not reflected in the accounting data, e.g., because of storage of concentrates). As the choice of proxy is not straightforward, we employ two different proxies: the feed proxy and the total intermediates proxy based on the “standard” LP approach, which enables us to compare the outcomes of both specifications.

Table 1 compares the approaches applied in this study. Details for all estimated models and calculations are given in the Appendix. The first WLP specification is our preferred model since it is robust to potential endogeneity and allows the estimation of TFP levels rather than growth rates.

Following Baily, Hulten, and Campbell (1992) and Olley and Pakes (1996), we first aggregate individual productivity levels to sector productivity as the output share weighted mean

$$p_t = \sum_{i=1}^{N} \lambda_{it} p_{it}, \tag{4}$$

where p_t denotes aggregate sector productivity and p_{it} is individual productivity. λ_{it} represents farm i's sample share of physical milk output in year t. Sector productivity is then further decomposed according to

$$p_t = \bar{p}_t + \sum_{i=1}^{N} (\lambda_{it} - \bar{\lambda}_t)(p_{it} - \bar{p}_t), \tag{5}$$

where bars over variables denote unweighted means. The first term on the right-hand side of equation (4) is the unweighted mean productivity in year t. We denote the second term on the right-hand side as covariance-type term as it resembles the calculation of the sample covariance without division by sample size[7].

Petrin and Levinsohn (2012) indicate that such a definition of aggregate industry productivity might be problematic. They argue that the definition of industry productivity and reallocation effects used by Baily, Hulten, and Campbell (1992) and Olley and Pakes (1996) might not correspond exactly to the true aggregate productivity and reallocation dynamics. We cannot reject that our results might be flawed by this discrepancy between the calculated aggregate productivity and the true aggregate productivity. Nevertheless, we still consider the method used in our study to be a valid index suitable for quantifying sector productivity and reallocation effects. Finally, we do not experience problems with large and volatile reallocation terms as Petrin and Levinsohn (2012) do with respect to their data on manufacturing firms.

Results and Discussion

All estimated models show a satisfactory statistical significance at parameter and overall model level. Detailed estimates and model results can be obtained from the authors upon request. Estimated partial elasticities for the various model specifications are given in table 2. Returns to scale (rts) per model vary from about 0.95 (decreasing rts) to about 1.15 (increasing rts). For the Törnqvist index approach calculated cost shares are reported in table 2. The WLP specifications show low elasticities for “other capital” which could be explained by multicollinearity with respect to the lagged value used in the control function.

Productivity Growth Rates

Unweighted mean productivity growth rates are given in table 3. Growth rates for the WLP models start from 2003 since lags of up to order two are used to estimate productivity levels. Relatively high values are obtained for the SFA2 model specification. For all models, growth rates are positive apart from the last year in the time period considered, further the levels of the estimated growth rates are similar across all models. Although the productivity growth rates obtained by the first SFA specification and the FE model sum up to the lowest total productivity levels, we fail to identify explicit differences between the models not corrected for potential endogeneity (SFA and FE) and the ones that are corrected (the WLP and the index approach).

Table 4 reports the values for the respective correlation coefficients of the estimated farm-level productivity growth rates between the different models. Strong correlations are observed between the WLP and FE models as well as the index approach. Rather weak correlations are observed between the second SFA specification and all other models, questioning the results obtained by this specification based on a reduced set of inputs and outputs.

Productivity Levels and Covariance

In table 5 we report sector and mean productivity levels and covariance terms for the preferred model specification (WLP1). The second column shows that sector productivity increased by approximately 14% over the total period, corresponding to an average annual growth of approximately 1.1%. This is well in line with annual growth rates of productivity in dairy production found by other studies (e.g. Kazukauskas, Newman, and Thorne 2010). The third and fourth columns suggest that given deregulation-based reallocation of production resources, the covariance term amounts to 4.8% in 2014. Contributions of farm-level productivity growth and resource reallocation to sector productivity growth are illustrated in figure 2. Notably, the covariance term lingers on a steady level in the first years and then shows a significant increase starting from 2007. Several interpretations of this pattern might be possible: (i) the development of milk prices, (ii) quota prices, and (iii) the confirmation of the quota abolition in 2008 may have had implications on farmers' (dis)investment decisions. As shown in table 5, quota prices showed more of a steady decrease rather than experiencing sudden price shocks. We can, therefore, rule out that plumping quota prices posed a sudden investment incentive to farmers. We cannot rule out, that the confirmation of the abolition of the milk quota in 2008 had an impact on farmers' investment decisions. However, the level and development of milk prices seem to offer more explanatory power. Milk prices were at a steady low level until 2007, then showed a peak in 2008 and decreased again sharply to a low in 2010. The increase of the covariance term, therefore, coincides with no clear price trend but with a period of volatile prices. One could assume that the long period of low prices led to disinvestment decisions by less productive farms, before high milk prices in 2008 posed an investment incentive for more competitive farms with farmers willing to expand their production.

The reallocation of production resources should also be mirrored by an increased trade of quotas between farms. We calculated the yearly means of the absolute (non-negative) values of farm-level growth in quota stock as shown in the seventh column in table 5. It can be seen that the increase of the covariance term was accompanied by a peak in the mean of absolute growth rates of the quota stock in 2009. However, we cannot explain the high mean quota growth rate in 2006 (see figure 2), which seems to have not affected the reallocation term. The last column in table 5 shows that especially in the last years, farmers seem to accept overproduction (and a possible superlevy) instead of acquiring additional quota (see also figure 2). Therefore, the reallocation of resources may no longer be captured in the quota stock growth of farmers. Sector and mean productivity as well as the covariance term based on the alternative models are given in table 8 in the Appendix. The magnitude of the reallocation effect differs between models, but, in general, we find the same pattern of an increasing reallocation effect from 2007 onwards.

Increasing reallocation effects in the context of market deregulation are also found by Gray, Oss-Emer, and Sheng (2014). They examined the extent of reallocation effects in three different periods for the Australian broadacre agriculture. They found that following elimination of the wool price support scheme and sector restructuring, resource reallocation effects played a significant role for sector TFP and partly offset average farm-level TFP decreases.

Kimura and Sauer (2015) examined TFP development in dairy farms in the Netherlands, Estonia, and the UK for a similar time period as we do in our study. For the Netherlands, they found that sector input and output both increase from 2008 on, possibly as a reaction to the confirmation of the phasing-out of the milk quota by the European Commission. The starting point of this increase coincides with the increase of the covariance term in our study. However, the reallocation effects found in their study show a different pattern than our results. For the Netherlands, they found a stagnating reallocation effect over the whole time period, whereas for the UK the reallocation effect was declining due to a decreasing TFP gap between farms. Only for Estonia, the reallocation effect was on a high level and increasing from 2003 to 2009, however, it declined again thereafter.

Explaining Productivity Dynamics

In this second part of our study, we further explore the determinants of reallocation events. Two factors are of special interest in this context: (1) the influence of the milk quota's regulatory power, quantified by the price at which farmers are able to trade quota rights on quota exchanges. The lower the price for quota rights, the lower the investment barrier for more productive farmers willing to expand their production. Hence, the market share of more productive farms should increase, and lower quota prices should be associated with a higher farm-specific covariance term. This would also correspond to the hypothesis stated by Huettel and Jongeneel (2011). If the quota regime keeps the production volumes of farms tied together, decreasing quota prices would only further accelerate resource reallocation toward more productive farms.

(2) The volatility of milk prices. We hypothesize that volatile milk prices force less productive farms to exit the market, freeing resources that can be absorbed by more productive farms with a more solid financial basis to cope with price volatility. On the other hand, volatile milk prices might discourage more productive farms from expanding their production: More productive farmers are more likely to expand their production, and stable milk prices are required with respect to securing a stable financial basis for necessary investment steps.

We examine these hypothesized links in a fixed effects panel estimation set-up. As dependent variable we use the farm-level covariance term, given as

$$cov_{it} = (\lambda_{it} - \bar{\lambda}_t)(p_{it} - \bar{p}_t), \tag{6}$$

with variables defined as before. Herewith, we focus on the individual farm level with respect to the covariance term. A farm shows a positive cov_{it}, if it is more productive than average and holds an above-average market share, or if it is less productive than average and has a below average market share. As hypothesized, we expect quota exchange prices to have a negative impact on the covariance term and farm-level milk price volatility to have a positive impact on the covariance cov_{it}. We measure price volatility as the standard deviation of the milk price the farmer received in the current and the preceding years. The question is how many lags of the farm-level milk price are to be considered with respect to the volatility measure, i.e. whether only the last year's milk price change or also volatility in earlier years has an influence on the farmer's present behavior. We calculated several standard deviations with differing time horizons from two years up to the last five years.

To avoid collinearity in the model (as standard deviations show high correlation coefficients) we decided to include only one volatility measure. The same applies to the quota exchange price that shows a high correlation with its lagged values. We include only last year's quota price to account for the possibly delayed effect of the quota price on investments. We control for farm-specific effects by the following variables: The availability of a farm successor (a dummy variable indicating that there is at least one child with agricultural education in the farmer's household); the share of grassland cultivated; the age of the farmer; a dummy variable indicating that farm income is only secondary income for the farmer's household; and a dummy variable for organic farming. "Availability of a farm successor", "age of farmer", and "farming as secondary income" are incorporated to control for the willingness of farm investments. "Share of grassland" and "organic farming" are incorporated to control for available production alternatives. Results of the model are summarized in table 6.

Despite the relatively modest model fit which we attribute to measurement error rather than the omittance of important variables, the regression results provide support for our hypotheses[8]. As expected, the coefficients for milk price volatility show a positive sign, indicating that disinvestment decisions of less productive farmers (as a result of volatile milk prices) possibly outweigh the effect of volatile milk prices discouraging more productive farms from extending their production. Also, the estimates for quota prices carry the expected signs supporting the hypothesis that declining regulatory power is associated with an increasing significance of resource reallocation for sector productivity. The result of an increasing sector productivity with an increasing tradability of the quotas is finally in line with the conclusions drawn by Gillespie et al. (2015), Colman (2000), and Hennessy et al. (2009).

Conclusions

Using a sample of specialized dairy farms in southeast Germany, we find empirical evidence that the reallocation of resources toward more productive farms increased gradually during the phasing-out of the EU milk quota. However, we interpret our results with caution. In light of steadily decreasing milk quota prices (and, therefore, steadily decreasing distortionary power by quota regulations) during the period of study, one would expect a steady increase in resource reallocations between individual farms. The SFA models and the index approach show a more monotonic increase than the endogeneity-robust WLP specifications. Both types of models, however, show an accelerated resource reallocation effect from 2007 on that coincides with volatile milk prices but also the confirmation of the abolition of the milk quota system in late 2008. Whether market prices or quota restrictions show the stronger impact on resource reallocation in the dairy sector is difficult to conclude, considering that the abolition of the quota could have an indirect effect on reallocation by influencing market prices. Nevertheless, we hypothesize that extremes in milk market prices can function as an ignition for major reallocation events that are no longer restricted in their extent. Using a fixed effects model, we find some evidence that volatile milk prices work in favor of resource reallocation toward more productive farms. In light of the recent “milk crisis” in 2015 and 2016, evidence supporting our view might be found in future studies. Methodologically, our study shows how the recently emerged endogeneity-robust WLP approach to productivity estimation can also be applied in an agricultural context. The results of the WLP model are insensitive to the choice of the specific proxy variable and are validated by a comparison with other estimation techniques. Given the relatively straightforward implementation based on existing software packages its importance for productivity measurement in agricultural economics should increase in the future.

Footnotes

1. The EU average quota price fell from approx. 60 cents per kg in 2005 to approx. 18 cents per kg in 2012 (European Comission 2012).
2. See Gillespie et al. (2015) who listed besides hindered resource flow and scale restriction, the farmer's risk behavior and impeded investment behavior as possible reasons for lower technical efficiency under quota regimes.
3. Inputs are divided into variable inputs (which can be chosen at the time of production) and fixed inputs (which are chosen before the time of production).
4. These numbers are calculated using the Eurostat database (European Comission 2015) with data on total number of holdings and utilized agricultural area in NUTS 1 regions.
5. In 2004, Bavaria produced approximately 27 and 5% respectively of the milk in Germany and the EU-27 (European Comission 2015).
6. Using numbers from the Eurostat database (European Comission 2015) aggregated for NUTS 1 regions, it can be shown that from 2005 to 2013 the number of specialized dairy farms in the European regions decreased at an average yearly rate of -4.8%. The average yearly rate of 3.5% for Bavaria lies close to this value. Speaking of farm sizes (2005-2013, 4 years available), the regions show an average of 94.4 livestock units (LSUs) per farm, whereas in Bavaria the farms are smaller with an average of 52.4 LSUs per farm. Still, it lies close to the average of 58.1 LSUs per farm of the group of regions with an average farm size up to 120 LSU per farm which represents 75% of all regions in the database. On average, from 2005 to 2013 LSUs per farm grew by 4.7% per year in all regions while in Bavaria specialized dairy farms grew at a similar rate of 3.3% per year.

7. Omitting division by sample size makes the covariance measure sensitive to changes in the sample size. Our sample indeed experiences growth in size to a level of 119% in 2006 compared with 2000. However, we do not assume this to be a problem for the results of our study since the sample size decreases after 2006 and the fluctuation in the number of observations does not coincide with variation in the covariance term.
8. For other model specifications with different combinations of varying time horizons for the standard deviation and varying lags of the quota price we find in general the same results. The coefficients for milk price standard deviation and milk quota are at least significant at the 5% level.

Tables

Table 1. Comparison of Approaches to Productivity Measurement

Approach	Parametric/ Nonparametric	TFP	Endogeneity-corrected?
Törnqvist TFP index approach	Nonparametric	TFP growth rate: growth of output index less growth of an input index	Deterministic approach, endogeneity not relevant
Fixed Effects panel estimation	Parametric	TFP level: predicted input elasticities and rearrangement of the production function, following equation (2)	If farm-level productivity is assumed to be time-invariant
Stochastic Frontier Analysis	Parametric	TFP growth rate: result of technical change, technical efficiency change and scale efficiency change	No
Wooldridge-Levinsohn-Petrin	Parametric	TFP level: predicted input elasticities and rearrangement of the production function following equation (2)	If farm-level productivity is assumed to be a function of proxy variable

Source: own compilation

Table 2. Partial Elasticities Per Model Specification

	WLP1	WLP2	FE	SFA1	SFA2	Törnqvist
Cows	0.544	0.495	0.564	0.567	0.749	0.036
Other capital	0.017	0.045	0.129	0.071	-	0.359
Labor	0.085	0.113	0.044	0.091	0.075	0.287
Intermediates	0.223	0.349	0.215	0.377	0.291	0.318
Concentrates	0.121					
Scale elasticity	0.990	1.003	0.953	1.106	1.115	1.000

Table 3. Unweighted Mean TFP Growth Rates

Year	WLP1	WLP2	FE	SFA1	SFA2	Törnqvist
2001	-	-	0.024	0.014	0.028	0.031
2002	-	-	0.019	0.013	0.010	0.007
2003	0.013	0.012	0.009	0.010	0.015	0.004
2004	0.008	0.007	0.010	0.012	0.016	0.014
2005	0.012	0.011	0.006	0.012	0.015	0.015
2006	0.006	0.007	0.005	0.009	0.011	0.001
2007	0.021	0.019	0.020	0.012	0.018	0.018
2008	0.010	0.009	0.002	0.007	0.006	0.007
2009	0.007	0.011	0.013	0.010	0.011	0.017
2010	0.013	0.011	0.011	0.012	0.009	0.019
2011	0.007	0.008	0.010	0.008	0.013	0.011
2012	0.033	0.031	0.032	0.008	0.010	0.016
2013	0.007	0.008	0.000	0.005	0.004	0.009
2014	-0.017	-0.017	-0.008	-0.001	0.002	-0.029

Table 4. Correlation Matrix for Productivity Growth Rates

	WLP1	WLP2	FE	SFA1	SFA2	Törnqvist
WLP1	1.00					
WLP2	0.98	1.00				
FE	0.94	0.96	1.00			
SFA1	0.73	0.75	0.75	1.00		
SFA2	0.42	0.44	0.47	0.50	1.00	
Törnqvist	0.86	0.90	0.89	0.71	0.45	1.00

Table 5. Weighted Industry Productivity, Mean Productivity and Covariance Term (WLP Specification I)

Year	p_t	$\overline{p_t}$	cov_t	Milk price[a] (EUR/kg)	Milk quota price[b] (EUR/kg)	Mean absolute milk quota growth	Over-production (index, 2000=1)[c]
2002	1.000	0.971	0.029	0.38	0.76	3.0%	1.0
2003	1.011	0.984	0.027	0.35	0.50	3.0%	0.9
2004	1.019	0.991	0.028	0.33	0.52	4.2%	1.2
2005	1.030	1.003	0.027	0.33	0.48	4.3%	1.1
2006	1.037	1.009	0.028	0.33	0.55	10.3%	1.0
2007	1.061	1.030	0.031	0.33	0.37	4.8%	1.2
2008	1.077	1.040	0.036	0.44	0.37	4.3%	1.0
2009	1.089	1.047	0.042	0.36	0.24	6.0%	1.0
2010	1.106	1.061	0.044	0.32	0.10	4.7%	0.8
2011	1.114	1.069	0.045	0.38	0.11	5.1%	1.2
2012	1.150	1.104	0.046	0.40	0.09	4.0%	1.9
2013	1.164	1.112	0.053	0.39	0.04	3.8%	1.8
2014	1.141	1.093	0.048	0.45	0.11	3.8%	2.6

[a] Milk prices are yearly averages of farm-level prices observed.

[b] Milk quota prices are provided by the Bavarian State Research Center for Agriculture (LfL 2015)

[c] The overproduction index is the yearly mean of farm-level production volumes that exceed quota volumes, relative to 2002.

Table 6. Fixed Effects Regression to Explain Farm-Level Covariance

cov_{it}	
SD3[a]	9.51×10^{-7} ***
	(3.44×10^{-7})
Quota exchange price$_{t-1}$	-27.3×10^{-6} ***
	(2.78×10^{-6})
Farm successor	-1.69×10^{-7}
	(25.5×10^{-7})
Share of grassland	-1.14×10^{-6}
	(14.9×10^{-6})
Age of farmer	8.26×10^{-8}
	(11.9×10^{-8})
Farming as secondary income	18.3×10^{-6} **
	(8.30×10^{-6})
Organic farming	3.85×10^{-6}
	(5.89×10^{-6})
Constant	3.96×10^{-5} ***
	(1.19×10^{-5})
N	11,776
Within R^2	0.015

[a] SD3 is the standard deviation of the farm-level milk price in the last three years.

Note: Standard errors are reported in parentheses. Significance levels are: ***1%, **5%, and *10%.

Figures

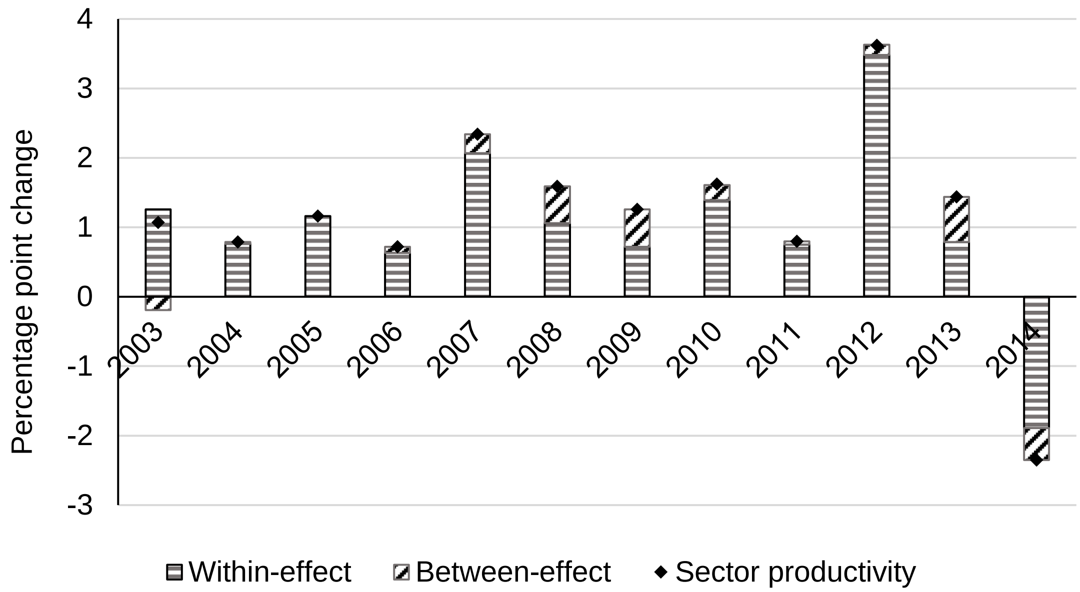

Figure 1. Contributions of farm-level productivity growth (within-effect) and resource reallocation (between-effect) to sector productivity growth

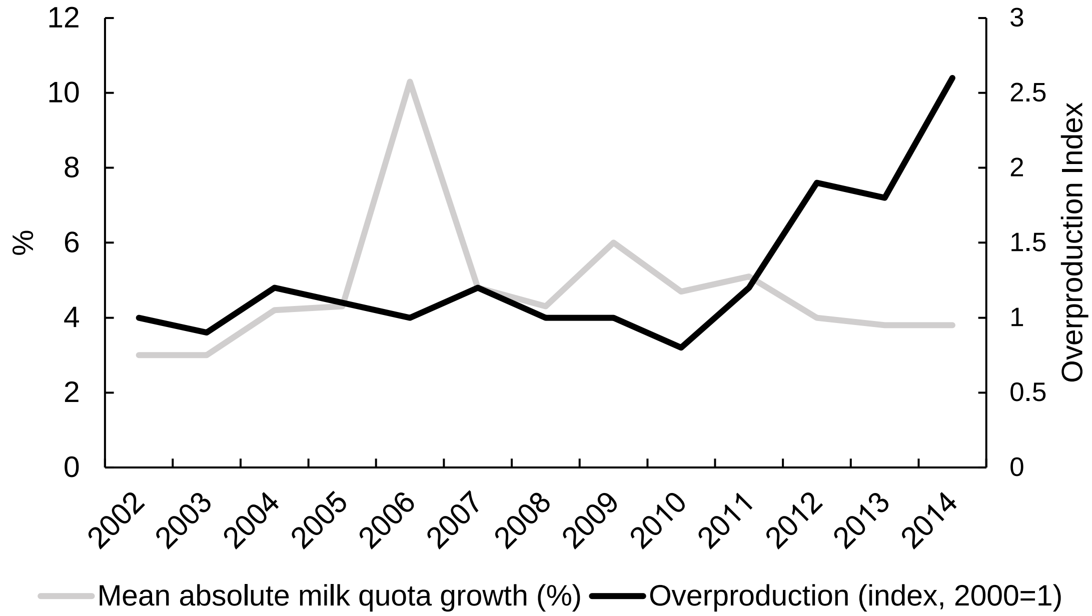

Figure 2. Development of farm-level quota stock and overproduction

References

Ackerberg, D., C. L. Benkard, S. Berry, and A. Pakes. 2007. Econometric Tools for Analyzing Market Outcomes. *Handbook of Econometrics* 6A: 4171–4276.

Ackerberg, D., K. Caves, and G. Frazer. 2006. Structural identification of production functions. Accessed March 27, 2015. https://mpra.ub.uni-muenchen.de/38349/.

Baily, M. N., C. R. Hulten, and D. Campbell. 1992. Productivity Dynamics in Manufacturing Plants. *Brookings Papers on Economic Activity: Microeconomics*.

Battese, G. E., and T. J. Coelli. 1995. A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics* 20: 325–32.

Colman, D. 2000. Inefficiencies in the UK milk quota system. *Food Policy* 25 (1): 1–16.

Destatis. 2015. GENESIS-Online Datenbank. Accessed November 08, 2015. https://www-genesis.destatis.de/genesis/online.

Eslava, M., J. Haltiwanger, A. Kugler, and M. Kugler. 2004. The effects of structural reforms on productivity and profitability enhancing reallocation: evidence from Colombia. *Journal of Development Economics* 75 (2): 333–71.

Gillespie, P. R., C. O'Donoghue, S. Hynes, F. Thorne, and T. Hennessy. 2015. Milk quota and the development of Irish dairy productivity: a Malmquist index using a stochastic frontier approach. Paper presented at the 29th International Conference of Agricultural Economists, Milan, Italy, August 8–14.

Gray, E. M., M. Oss-Emer, and Y. Sheng. 2014. Australian agricultural productivity growth: Past reforms and future opportunities. Canberra: ABARES.

Guner, N., G. Ventura, and Y. Xu. 2008. Macroeconomic implications of size-dependent policies. *Review of Economic Dynamics* 11 (4): 721–44.

Hennessy, T., S. Shrestha, L. Shalloo, and M. Wallace. 2009. The Inefficiencies of Regionalised Milk Quota Trade. *Journal of Agricultural Economics* 60 (2): 334–47.

House, J. 2011. A guide to dairy herd management: Meat & Livestock Australia Limited. Accessed June 15, 2016. http://www.livecorp.com.au/LC/files/3e/3ef9fb39-0c7f-4296-b389-2f55650cd2e9.pdf.

Hsieh, C.-T., and P. J. Klenow. 2009. Misallocation and Manufacturing TFP in China and India. *Quarterly Journal of Economics* 124 (4): 1403–48.

Huettel, S., and R. Jongeneel. 2011. How has the EU milk quota affected patterns of herd-size change? *European Review of Agricultural Economics* 38 (4): 497–527.

Kazukauskas, A., C. Newman, D. Clancy, and J. Sauer. 2013. Disinvestment, Farm Size, and Gradual Farm Exit: The Impact of Subsidy Decoupling in a European Context. *American Journal of Agricultural Economics* 95 (5): 1068–87.

Kazukauskas, A., C. Newman, and F. Thorne. 2010. Analysing the Effect of Decoupling on Agricultural Production: Evidence from Irish Dairy Farms using the Olley and Pakes Approach. *German Journal of Agricultural Economics* 59 (3): 144–57.

Kimura, S., and J. Sauer. 2015. Dynamics of dairy farm productivity growth: Cross-Country Comparison. OECD Food, Agriculture and Fisheries Papers, no. 87. Paris: OECD Publishing.

Kirwan, B. E., S. Uchida, and T. K. White. 2012. Aggregate and Farm-Level Productivity Growth in Tobacco: Before and After the Quota Buyout. *American Journal of Agricultural Economics* 94 (4): 838–53.

Kloss, M., and M. Petrick. 2014. The productivity of family and hired labour in EU arable farming. Paper presented at GEWISOLA annual meeting, Göttingen, Germany, 17–19 September.

Kutlu, L. 2010. Battese-coelli estimator with endogenous regressors. *Economics Letters* 109 (2): 79–81.

Levinsohn, J., and A. Petrin. 2003. Estimating Production Functions Using Inputs to Control for Unobservables. *The Review of Economic Studies* 70 (2): 317–41.

LfL. 2015. Milchquoten: Detailergebnisse früherer Übertragungsstellentermine. Accessed September 16, 2015. http://www.lfl.bayern.de/iem/milchquoten/033165/index.php.

Marschak, J., and W. H. Andrews, Jr. 1944. Random Simultaneous Equations and the Theory of Production. *Econometrica* 12 (3/4): 143–205.

Mutter, R. L., W. H. Greene, W. Spector, M. D. Rosko, and D. B. Mukamel. 2013. Investigating the impact of endogeneity on inefficiency estimates in the application of stochastic frontier analysis to nursing homes. *Journal of Productivity Analysis* 39 (2): 101–10.

Olley, S. G., and A. Pakes. 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica* 64 (6): 1263–97.

Petrick, M., and M. Kloss. 2013. Identifying Factor Productivity from Micro-data: The case of EU agriculture. *Factor Markets Working Paper* 34.

Petrin, A., and J. Levinsohn. 2012. Measuring aggregate productivity growth using plant-level data. *The RAND Journal of Economics* 43 (4): 705–25.

Restuccia, D. 2016. Resource Allocation and Productivity in Agriculture. Accessed March 01, 2016. https://www.economics.utoronto.ca/diegor/research/Restuccia_ResAlloc_Oxford.pdf.

Restuccia, D., and R. Rogerson. 2008. Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic Dynamics* 11 (4): 707–20.

Rizov, M., J. Pokrivcak, and P. Ciaian. 2013. CAP Subsidies and Productivity of the EU Farms. *Journal of Agricultural Economics* 64 (3): 537–57.

Shee, A., and S. E. Stefanou. 2015. Endogeneity Corrected Stochastic Production Frontier and Technical Efficiency. *American Journal of Agricultural Economics* 97 (3): 939–52.

StMELF. 2014. Bayerischer Agrarbericht 2014: Fakten und Schlussfolgerungen. Accessed February 09, 2016. http://www.agrarbericht-2014.bayern.de/politik-strategien/index.html.

Tran, K. C., and E. G. Tsionas. 2013. GMM estimation of stochastic frontier model with endogenous regressors. *Economics Letters* 118 (1): 233–36.

van Beveren, I. 2012. Total Factor Productivity Estimation: A Practical Review. *Journal of Economic Surveys* 26 (1): 98–128.

Wooldridge, J. M. 2009. On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters* 104 (3): 112–14.

Appendix

Data Preparation

To define our sample of specialized dairy farms, we include farms that generate at least two thirds of their output from milk sales. We use the farm's sales share averaged over the whole sample period, to avoid the exclusion of observations where the farm operates below this threshold in single years. As a single output we define total sales of the farm. Different output categories are aggregated by deflating total sales using a Törnqvist price index, calculated by weighting price changes in various output categories (e.g., milk, cereals, cattle, etc.) by the farm's individual sales shares. The price changes are calculated based on reported farm-individual prices and also based on price indices provided by the German statistics agency (Destatis 2015), if prices are not available. For the second stochastic frontier model we only use physical milk as output. Apart from the first WLP and the SFA specification, we distinguish four different input categories. Intermediates are calculated as total expenditures deflated with a Törnqvist price index, again consisting of price changes for intermediates categories weighted by expenditure shares. Since individual prices for inputs are not reliably reported, we use price indices reported by the German statistics agency. For the first WLP specification, we exclude costs for concentrated feed from intermediates and use concentrated feed as a separate input. The number of milk cows is included as a separate input. Other capital (buildings, machinery/equipment, and other animals) is aggregated to one input by cumulating deflated investments and treating the capital stock in the first year as initial investment. Land (owned and rented) is also incorporated here by multiplying the number of hectares of cultivated land with an initial per hectare value and adding the value to the capital variable. Labor is given by reported amounts of employed full-time equivalents.

Wooldridge-Levinson-Petrin Estimator

We estimate part of the Wooldridge-Levinson-Petrin GMM framework described in Wooldridge (2009). We use a Cobb-Douglas production function including a quadratic time trend as

$$y_{it} = x'_{1it}\beta + x'_{2it}\gamma + c'_{it-1}\lambda + \delta_t t + \delta_{tt} t^2 + u_{it}. \tag{7}$$

This corresponds to equation (2.11) in Wooldridge (2009). The exogenous regressors are represented by x'_{1it}. These are the state variable “other capital” and dummy variables for agro-ecological zones as well as organic production. Row vector x'_{2it} contains the endogenous regressors: the variable inputs “number of cows”, “labor”, and “intermediates” (only in the first specification) are instrumented by their one-period lags, the proxy variable “concentrated feed” (in the first specification) or “intermediates” (in the second specification) is instrumented by its two-period lag. c'_{it-1} consists of an intercept and a polynomial of order three of the one-period lags of the state variable and the proxy variable. u_{it} comprises random shocks not correlated with inputs, and the productivity innovation component that is possibly correlated with variable inputs (for further details see Wooldridge 2009). All production inputs are in logarithmic form. GMM estimation is performed in Stata 13 using the command *ivreg2*. Productivity levels are calculated as

$$\ln \hat{p}_{it}^{WLP} = y_{it} - x'_{1it}\hat{\beta} - x'_{2it}\hat{\gamma}. \tag{8}$$

Fixed Effects

In the fixed effects model, we assume that individual deviations from mean productivity are time-invariant. Then, a production function can be represented as

$$y_{it} = x'_{it}\beta + \delta_t t + \delta_{tt} t^2 + \omega_i + v_{it}. \tag{9}$$

We estimate (4) in translog form, with the row vector x'_{it} including linear, quadratic, and interactions of inputs as well as dummies for organic production and farm income as secondary income. The column vector β contains the parameters to be estimated. We include a quadratic time trend. v_{it} is an i.i.d. error term with $N(0, \sigma_v^2)$. We use the Stata command *xtreg* and the within regression estimator. Estimated productivity levels are then given by

$$\ln \hat{p}_{it}^{FE} = y_{it} - x'_{it}\hat{\beta}. \tag{10}$$

Stochastic Frontier Models

We estimate stochastic frontier models in translog form with the Stata command *sfpanel* following the model of Battese and Coelli (1995) as

$$y_{it} = x'_{it}\beta + v_{it} - u_{it} \tag{11}$$

with the logarithmic output y_{it}. The row vector x'_{it} contains logs of all linear, squared, and interaction terms for the defined inputs (with a reduced set in the second model) as well as the time trend, represented by a linear and squared term as well as interaction terms with the inputs. Also included are dummy variables accounting for organic production, farm income representing secondary income of the farmer, and agro-ecological zone. The column vector β contains an intercept and the other parameters to be estimated. v_{it} is an i.i.d. error component with $N(0, \sigma_v^2)$. Technical efficiency is quantified by $u_{it} \sim N^+(z'_{it}\delta, \sigma_u^2)$. We include in z'_{it} dummies for educational status and age of the farm manager, as well as dummies for farm income as secondary income, organic production, and a linear time trend. Productivity change is then calculated as

$$\ln \widehat{pc}_{it}^{SFA} = \ln \widehat{tec}_{it} + \ln \widehat{tc}_{it} + \ln \widehat{sec}_{it} \qquad (12)$$

with technical efficiency change $\ln \widehat{tec}_{it} = \ln\left(e^{-\hat{u}_{it}}/e^{-\hat{u}_{it-1}}\right)$, technical change $\ln \widehat{tc}_{it} = \frac{1}{2}\left(\frac{\partial \hat{y}_{it-1}}{\partial t} * \frac{\partial \hat{y}_{it}}{\partial t}\right)$, and scale efficiency change $\ln \widehat{sec}_{it} = \frac{1}{2}\sum_{k=1}^{K}\left[\left(\frac{\hat{\mathrm{E}}_{it}-1}{\hat{\mathrm{E}}_{it}} * \hat{\epsilon}_{ikt} + \frac{\hat{\mathrm{E}}_{it-1}-1}{\hat{\mathrm{E}}_{it-1}} * \hat{\epsilon}_{ikt-1}\right)(x_{ikt} - x_{ikt-1})\right]$, with K inputs and scale elasticity $\hat{\mathrm{E}}_{it} = \sum_{k=1}^{K}\hat{\epsilon}_{ikt}$ and partial elasticity of the kth input $\hat{\epsilon}_{ikt} = \frac{\partial \hat{y}_{it}}{\partial x_{ikt}}$. Productivity levels are calculated by setting $\ln p_{it=2000} = 0$ and cumulating growth rates: $\ln \hat{p}_{it}^{SFA} = \sum_{s=2}^{t}\ln \widehat{pc}_{it}^{SFA}$. Data gaps in single years are assigned the sample average growth rate. Farms entering the dataset at a later point in time start with the sample average productivity level.

Törnqvist Index

We calculate a Törnqvist TFP growth index in logarithmic form for farm i in year t as

$$\ln pc_{it}^{T} = (y_{it} - y_{it-1}) - \frac{1}{2}\sum_{k=1}^{4}(s_{kit} + s_{kit-1})(x_{kit} - x_{kit-1}) \qquad (13)$$

where y denotes output, x the four inputs, and s the cost share of the kth input. Again, the output and all inputs are in log form. As for the SFA approach, starting values are set and growth rates are cumulated to generate productivity levels as $\ln p_{it}^{T} = \sum_{s=2}^{t}\ln pc_{it}^{T}$. Data gaps and "latecomers" are treated in the same way as in the SFA approach. For easier comparison productivity levels (p_{it}) of all models are adjusted to normalize industry productivity to 1 in 2002.

Table 7. Descriptive Statistics

	2000				2014			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Output (EUR)	83,189	39,076	10,071	286,020	145,338	93,618	12,911	611,942
Cows (number)	33.3	13.6	4.6	135.0	47.6	25.5	2.0	182.2
Other capital (EUR)	865,438	422,448	152,443	6,052,293	1,328,346	701,914	199,943	5,850,496
Labor (FTE[a])	1.54	0.45	0.35	3.12	1.65	0.53	0.30	4.97
Intermediates (EUR)	25,608	15,248	2,096	134,459	43,006	32,038	3,137	297,997
Concentrated feed (EUR)	9,668	6,899	52	61,247	14,830	11,521	55	109,749
Number of observations	947				1,022			
Number of observations (all years)	15,833							
Number of farms (all years)	1,470							

[a]FTE = full-time equivalent

Table 8. Industry Productivity, Mean Productivity, and Covariance Term Per Model

Year	WLP2			FE			SFA1			SFA2			Törnqvist		
	p_t	$\overline{p_t}$	cov	p_t	$\overline{p_t}$	cov	p_t	$\overline{p_t}$	cov	p_t	$\overline{p_t}$	cov	p_t	$\overline{p_t}$	cov
2002	1.000	0.967	0.033	1.000	0.958	0.042	1.000	0.997	0.003	1.000	0.997	0.003	1.000	0.991	0.010
2003	1.010	0.978	0.032	1.007	0.967	0.040	1.012	1.007	0.004	1.017	1.012	0.005	1.005	0.995	0.010
2004	1.017	0.985	0.032	1.016	0.976	0.040	1.024	1.020	0.004	1.033	1.028	0.006	1.019	1.009	0.011
2005	1.029	0.996	0.033	1.020	0.982	0.039	1.037	1.032	0.005	1.048	1.042	0.006	1.033	1.024	0.011
2006	1.037	1.003	0.034	1.026	0.987	0.039	1.047	1.042	0.006	1.061	1.054	0.007	1.038	1.025	0.014
2007	1.059	1.022	0.037	1.047	1.007	0.040	1.061	1.054	0.006	1.080	1.074	0.007	1.060	1.043	0.016
2008	1.074	1.031	0.043	1.055	1.009	0.046	1.070	1.061	0.009	1.090	1.080	0.010	1.075	1.051	0.025
2009	1.089	1.043	0.047	1.070	1.022	0.048	1.083	1.072	0.012	1.105	1.091	0.013	1.096	1.069	0.028
2010	1.105	1.054	0.051	1.084	1.033	0.051	1.097	1.084	0.013	1.116	1.101	0.015	1.123	1.089	0.035
2011	1.116	1.063	0.053	1.095	1.044	0.051	1.108	1.093	0.014	1.132	1.115	0.016	1.142	1.100	0.041
2012	1.149	1.096	0.054	1.126	1.077	0.049	1.118	1.102	0.015	1.143	1.126	0.016	1.157	1.118	0.038
2013	1.165	1.105	0.060	1.131	1.077	0.054	1.126	1.108	0.018	1.149	1.130	0.018	1.173	1.128	0.046

2014	1.141	1.086	0.055	1.117	1.068	0.049	1.127	1.107	0.020	1.157	1.133	0.024	1.138	1.096	0.041

Note: The starting point of the reallocation term differs for the SFA models and the index approach since we are bound to calculate productivity levels from growth rates. Therefore both industry and mean productivity start with a common value in 2000 and the covariance effect is accordingly zero in the first year.