DEREGULATION AND PRODUCTIVITY – EMPIRICAL EVIDENCE ON DAIRY PRODUCTION

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Abstract

We investigate development of productivity and its relation to resource reallocation effects in the dairy sector in South-East Germany during the phase-out of the EU milk quota. We use a dataset containing dairy farm accounting data of 15 years. Farm-level productivity is estimated by applying a proxy approach recently discussed in the literature and compared to other estimation approaches and an index analysis. After aggregation we decompose sector productivity into unweighted mean productivity and a covariance term quantifying the allocation of production resources towards 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 are triggered by extreme prices possibly powered by market deregulation. We seek to find support for this hypothesis in a regression analysis linking the covariance term and price variability. However, we find only little support for our hypothesis in this analysis.

1. Introduction

In a well-functioning and free market, firms which cannot keep up with competitors are forced to reduce their market share or even cease their market participation, freeing the resources bound by their production activity and making 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 EU milk quota system. The milk quota was introduced by the European Community in 1984, in order to restrict production volumes and avert high production surpluses that could only be removed from the market with 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 impeded by the additional costs of quota acquisition and quota 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 usually was 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 from 2003 and confirmed in 2008. A phase-out was performed by a stepwise increase of the quota volumes. It can be expected that in the first years the distortionary effect imposed by the quota was strong considering the large additional costs an expanding producer faced due to high quota prices. Towards the end of the quota the market disturbing effect might have become less significant since quota prices on the exchanges decreased[1].

2. Background and Conceptual Framework

Production quotas might affect farm and industry productivity in several ways[2]. Central to our study is the supposed hindered resource flow from less to more productive firms. This should be reflected in decelerated structural change. Results of HUETTEL AND JONGENEEL (2011) show that this must not necessarily be the case. They apply a Markov chain model on aggregate data

[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 list besides hindered resource flow and scale restriction also the farmer's risk behaviour and impeded investment behaviour as possible reasons for lower technical efficiency under quota regimes.

of Dutch and German dairy farms and examine the structural change quantified by mobility indicators for different size classes before and after implementation of the quota system. They find that overall mobility of dairy farms increases rather than decreases with the milk quota and attribute this effect to the stronger interdependency between growing and shrinking farms due to the quota. However, they find exit mobility to be decreased under the quota regime, indicating that small and possibly less efficient farms are kept in the market.

Most studies that examine the effect on quotas on sector performance directly come to the conclusion that quotas have a negative effect on efficiency and productivity in the sector, however that the negative effect is reduced with increasing quota tradability.

This result is found e.g. in GILLESPIE ET AL. (2015). They apply a stochastic frontier framework and calculate 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 negative effect of the quota implementation and the counteracting effect of liberalized quota trade on sector productivity.

COLMAN (2000) shows that tradability of quota rights reduces sector inefficiency as quota can be transferred from less to more efficient farms. However, he shows that in the case of the UK (in 1996/97), the optimal allocation of quota was not achieved and hence some inefficiency remained in the market. He also argues that with high quota prices the quota cost amounts to a significant share of total production cost and thus poses a barrier for expanding farmers.

A similar conclusion is drawn in HENNESSY ET AL. (2009). They show that overall cost inefficiency of milk production in Ireland could be reduced by a national quota trading system compared to the existing regional trading system.

The effect of the termination of production quotas in the tobacco sector is examined by KIRWAN, UCHIDA AND WHITE (2012). After the sudden elimination of quotas they find considerable resource reallocation flows accompanying the restructuring process in the sector and show their positive effect on aggregate productivity.

Although the termination of the EU milk quota is of great concern among politicians and industry participants, we are not aware of studies which are directly concerned with the resource reallocation effect on sector productivity.

Estimation of TFP

The methodological difficulties of estimating production functions are known since MARSCHAK AND ANDREWS (1944) but have been of renewed interest in more recent years as new techniques became available to overcome the endogeneity problems[3]. The basic problem that econometricians face stems from the fact that firms choose production inputs endogenously and it must be assumed that their choice is correlated with factors unobserved by the econometrician. As we employ different estimation techniques in our study we give some indication of the problem of endogenous input choice, with the remark that more detailed information can be found elsewhere (e.g. VAN BEVEREN, 2012). Assuming a Cobb-Douglas technology a firm's production process can be described as

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + v_{it} \quad (1)$$

i.e. firm i's output y in year t explained by the production inputs capital k, labour l, and intermediates m, all in logarithmic values. Besides the stochastic error, v captures a firm's

[3] A comprehensive overview of techniques that have been proposed can be found in VAN BEVEREN (2012).

productivity and a tempting way of measuring productivity is to estimate (1) and calculate productivity as

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

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

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \epsilon_{it}. \quad (3)$$

ϵ represents a stochastic component due to measurement error or random shocks to production. Factors like managerial ability or expected weather events are included in ω. Both terms are not observed by the econometrician, however, ω may be known or predicted by the firm prior to choosing levels of variable inputs[4]. If this is the case, variable inputs and v are not independent and estimation of (1) using OLS yields biased results.

To encounter this issue, OLLEY AND PAKES (1996) develop 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 which are observed by the firm and correlated with variable inputs[5]. LEVINSOHN AND PETRIN (2003, 'LP' hereafter) point out that the approach of OLLEY AND PAKES (1996) can be problematic due to the fact that capital is an input costly to adjust in many cases leading to lumpy investment and datasets with a considerable share of zero investments. In this case the assumption that investment is strictly increasing in the unobserved productivity shocks does not hold and thus ω cannot be formulated as a function of capital and investment. Hence, they modify the approach and use intermediate inputs rather than investment as the proxy for unobserved productivity shocks.

The standard approaches of both OLLEY AND PAKES (1996) and LEVINSOHN AND PETRIN (2003) are challenged by remarks made by ACKERBERG, CAVES AND FRAZER (2006). They demur that without further assumptions, the labour coefficient is not identified in the first stage of the algorithms due to collinearity between labour input and the non-parametric function used to substitute for productivity shocks. WOOLDRIDGE (1996) shows how the two-step approaches of OLLEY AND PAKES (1996) and LEVINSOHN AND PETRIN (2003) can be reduced to an instrumental variable GMM setup. His proposed method has two advantages: it is robust to the criticism of ACKERBERG, CAVES AND FRAZER (2006) and standard errors are easily calculated.

While these relatively new approaches have received considerable attention in the general economics literature, applications in agricultural economics are rare. MARY (2013) estimate the TFP of French crop farms by using a GMM approach in a dynamic panel setting but does not adapt the principle of using a proxy to control for productivity shocks. In their study on the Kentucky tobacco sector KIRWAN, UCHIDA AND WHITE (2012) use the LP estimator to generate production function estimates necessary for the construction of aggregate industry productivity. PETRICK AND KLOSS (2013; KLOSS AND PETRICK; 2014) apply the LP approach on European crop farms comparing different estimators. They conclude that the LP estimator poses a viable approach to productivity measurement also with respect to agricultural applications. In a second paper, KLOSS AND PETRICK (2014) also find the WOOLDRIDGE (2009) LP modification to be a viable alternative. In both papers they note that the control function approach incorporating

[4] 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)

[5] For details on the methodology of OLLEY AND PAKES (1996) we refer to their original publication and also ACKERBERG, CAVES AND FRAZER (2006), VAN BEVEREN (2012), and ACKERBERG ET AL. (2007).

intermediates as proxy may be questionable in the agricultural context. Other than for example in the manufacturing sector, it is doubtful whether intermediates as a general input category lends itself to control for productivity shocks. Often in agriculture, a farmer's reaction to a positive productivity shock would be to use less intermediate inputs instead (e.g. favourable weather conditions requiring less intensive chemical plant protection).

Another approach of estimating productivity is the estimation of production frontiers. Productivity change can then be calculated indirectly with a Malmquist index considering technical efficiency change, technical change, and possibly a scale efficiency change effect. APURBA AND STEFANOU (2011) remark that the argument of endogenous input choice does not only apply to the estimation of average production functions but also to the estimation of production frontiers. Therefore, the 'standard' stochastic frontier approaches to productivity measurement can be suspected to yield similarly biased results like OLS estimation of production technologies.

In light of the recent developments in productivity estimation we apply several approaches to productivity measurement. 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.

3. Dataset

We make use of a dataset which is part of the European Farm Accountancy Data Network (FADN) and comprises Bavarian dairy farms. Bavaria is a federal state (NUTS 1 region) in the south-east of Germany and produces the largest share of milk in Germany. Agriculture in Bavaria is still characterised by a large share of small family farms. In 2013, all farms in Bavaria cultivated an average of 33.6 hectares of land; this number increased from 2005 to 2013 by a yearly rate of 3.4%, while the number of farms decreased by a yearly rate of 3.4% in the same period[6]. Dedicated aim of the Bavarian state government is to slow down the structural change for reasons of social acceptance of agricultural production. In the latest agricultural report, a decelerated yearly rate of farm closings of 1.5% (from 2010 to 2013) is seen as a welcome response to political efforts (StMELF, 2014).

The data we use contain financial records and additional socio-economic variables providing information on e.g. the use of family labour, education of the farm manager, or physical input quantities. The dataset comprises a time span of 15 years (2000 to 2014). Descriptive statistics of output and input variables and details on their construction are reported in the appendix. Although our dataset is restricted to Bavarian farms we argue that the results of the study are also relevant in the larger context of the EU since (i) Bavaria is the largest milk producing region of Germany and also accounts for a significant proportion of the milk production in the EU[7], and (ii) the dairy farm structure in Bavaria is characterised by a large share of small family farms and slow structural change and therefore representative for many other European regions[8].

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[6] These numbers are calculated using the Eurostat database (EUROSTAT, 2015) with data on total number of holdings and utilised agricultural area in NUTS 1 regions.

[7] In 2004, Bavaria produced approximately 27% and 5% respectively of the milk in Germany and the EU27 (EUROSTAT, 2015)

[8] Using the numbers from the Eurostat database (EUROSTAT, 2015) aggregated for NUTS 1 regions, it can be shown that from 2005 to 2013 the number of specialised dairy farms in the regions decreased at an average yearly rate of -4.8% (standard deviation 3.8%). The average yearly rate of -3.5% for Bavaria lies close to this value. Speaking of farm size levels (2005 through 2013, 4 years available), the regions show an average of 94.4 life stock units (LSUs) per farm while in Bavaria 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

4. Empirical modelling

Calculation of TFP

In order to verify the robustness of our estimation results and also to compare the performance of different methodologies we calculate productivity in various ways. We apply (i, ii) two specifications of the WOOLDRIDGE (2009) LP modification approach ('WLP', hereafter), (iii) a stochastic frontier approach ('SFA') where we calculate a Malmquist TFP index as a result of technical efficiency change, technical change and scale effects, (iv) an alternative SFA approach but using a reduced set of inputs and outputs in order to eliminate problems due to input aggregation, (v) an OLS approach based on fixed effects modelling ('FE') and (vi) a deterministic approach using a calculated Törnqvist TFP index. For the WLP approach the question of a suitable proxy to control for productivity shocks must also 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) costs for concentrated feed, and (2) costs of 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. 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 endogeneity problems and allows the estimation of TFP levels rather than growth rates.

Decomposition of TFP

Following BAILY, HULTEN AND CAMPBELL (1992) and OLLEY AND PAKES (1996) we 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 share of physical milk output of the sample in year t. Sector productivity is then 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 (4) is the unweighted mean productivity in year t. We call the second term on the right-hand side a covariance-like term as it resembles the calculation of the sample covariance, simply without division by the sample size.

PETRIN AND LEVINSOHN (2012) point out 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 effects. Nevertheless, we still deem the method used in our study for aggregation and decomposition of productivity as a valid index suitable for quantifying sector productivity and reallocation

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which represents 75% of all included regions. On average, from 2005 to 2013 LSUs per farm grew by 4.7% per year (standard deviation 3.0%) in the regions while in Bavaria specialised dairy farms grew at a similar rate of 3.3% per year.

effects. Furthermore, we do not experience problems with large and volatile reallocation terms as PETRIN AND LEVINSOHN (2012) do with their data on manufacturing firms.

5. Preliminary results

In Table 1 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% corresponding to an average yearly growth of approximately 1.1%. The third and fourth column suggest that by deregulation based reallocation of production resources the covariance term amounts to 4.8% in 2014. Notably, the covariance term lingers on a steady level in the first years and then shows a steeper increase starting from 2007. Several interpretations of this pattern might be possible: (i) the development of milk prices and (ii) quota prices, as well as (iii) the confirmation of the quota abolition in 2008 may have had implications on a farmer's (dis)investment decisions.

Table 1: Weighted industry productivity, mean productivity, covariance term of WLP specification I, and information on milk price, quota price, mean growth in farm-level quota stock, mean farm-level overproduction

Year	p_t	$\overline{p_t}$	cov	Milk price[1] (EUR/kg)	Milk quota price[2] (EUR/kg)	Mean absolute milk quota growth	Overproduction (index, 2000=1)
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

[1] Milk prices are yearly averages observed in our dataset.

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

As shown in Table 1 quota prices showed more of a steady decrease rather than experiencing sudden price shocks. We can therefore rule out that plumping quota prices posed an 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 decision, however, we also cannot confirm such an effect with our data. Looking at milk prices seems to offer more explanatory power. Milk prices were on 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 of 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 in increased trade of quotas between farms. We calculated the yearly means of the absolute values of farm level growth in quota stock as shown in the seventh column in Table 1. 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 which seems to have not affected the reallocation term. The last column in Table 1 shows that especially in the last years, farmers seem to accept overproduction (and a possible superlevy) instead of acquiring additional quota. Therefore, reallocation of resources might no longer be captured in the quota stock growth of farmers.

Explaining Productivity Dynamics

In this second part of our study we explore further the relationship between reallocation events and milk prices. We hypothesize that sharp decreases in milk prices force less productive farms out of the market, freeing resources that can be absorbed by more productive firms which can cope better with price plunges. On the other hand, increased price volatility in general might lead to greater perceived risk and encourage less productive farms to retreat from production. We examine these hypotheses in two regression models. In both models we use as the dependent variable the change in the farm-level covariance term, constructed as

$$\Delta cov_{it} = \left(\lambda_{it} - \bar{\lambda}_t\right)(p_{it} - \bar{p}_t) - (\lambda_{it-1} - \bar{\lambda}_{t-1})(p_{it-1} - \bar{p}_{t-1}) \tag{6}$$

with the same variables already used in (5). With this dependent variable we try to break down the increase in the aggregated covariance term into contributions by individual farms. A farm shows positive Δcov_{it}, if it is more productive than average and was able to increase its market share, or if it is less productive than average and decreased its market share. For a lack of a theoretical base of the functional relationship we look for evidence for our hypothesis in a simple linear regression model. As independent variables we choose (besides control variables) the log growth of the observed farm-level milk price and in the second model the standard deviation of a farm’s milk price in the last three years in present and lagged values.

Detailed results of this analysis cannot yet be given. However, first results show that in these regression models we only find weak support for our stated hypotheses. Coefficients are mostly insignificant with changing signs. We find the strongest support in the relationship between Δcov_{it} and milk price growth as negative but insignificant coefficients. The negative signs suggest that decreasing milk prices lead to stronger reallocation like we hypothesized.

6. Conclusions

We show that in a sample of specialized dairy farmers in southeast Germany reallocation of resources towards more productive farms increased gradually during the phase-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) during the period of study, one would expect a steady increase in resource reallocations. The SFA models and the index approach show a more monotonistic increase than the endogeneity-robust WLP specifications. Both types of models however show an accelerated resource reallocation effect starting from 2007 coinciding with volatile milk prices farmers received but also the confirmation of the abolition of the milk quota in late 2008. Whether market prices or quota restrictions has the stronger impact on resource reallocation in the dairy sector is not to say, keeping in mind that the abolition of the quota could have an indirect effect on the reallocation by influencing market prices. Nevertheless with our results we are tempted to conclude that extremes in milk market prices can function as an ignition of reallocation events which are now after the abolition of the quota no longer restricted in their extent. So far we failed to find explicit support for this hypothesis. In light of the recent low in milk prices in 2015 and 2016 evidence supporting this view could also be found in future studies.

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