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Abstract

We decompose aggregate industry labor productivity growth into seven distinct components: input deepening, technical change, technical efficiency, scale effect, between-firm reallocation, effects from exits and entry. The first four components measure the productivity growth within a firm. The latter three components capture industry dynamics. Applied to a sample of 118 small and medium sized breweries in Germany over 13 years, we found that within-firm effects, in particular technical change and the scale effect, clearly dominated the effects from industry restructuring.

Keywords: labor productivity, productivity growth, structural change, brewing industry, Germany

JEL Classification: D24, J24, L16, O12

Introduction

Today, the brewing industry worldwide is highly concentrated. In 2017, the top 2 (5) brewing groups (AB-InBev, Heineken (China Resources Snow Breweries, Carlsberg, Molson-Coors Brewing)) account for 46.2% (60%) of global beer production (Barth-Haas Group, 2018). As a global exception, the brewing industry in Germany is still dominated by relatively small firms. Only two of the five worldwide market leaders (AB-InBev as number two and Carlsberg as number ten) are listed among Germany's top ten breweries, and these firms account for less than 10% of the German beer production (Stern, 2018). Moreover, German's largest brewery, the Radeberger Group, with a market share of 0.6% is only listed at 20th position worldwide (Barth-Haas Group, 2018). Nevertheless, with an output of about 93 million hectoliters (hl) Germany is still the largest beer producer in Europe and number five (after China, United States, Brazil and Mexico) worldwide (Barth-Haas Group, 2018). However, the German brewing industry has also faced considerable structural changes in the last three decades. Beer consumption hit a record with 151 liters per capita in 1976, was still relatively high until the mid-1980s (146.6 liters per capita in 1986), but has constantly decreased since then to 101.2 liters per capita in 2017, corresponding to the decrease of -31% in total or 1.2% per year (Deutscher Brauer-Bund, 2018). In addition to a decrease in quantity, there was also a considerable change in consumer preferences away from consuming Pils and Lager on a more frequent basis in pubs to occasional consumption of specialty beers at home. Although net-exports increased by more than 4.1 million hl between 1995 and 2017, this was not enough to compensate for the decrease in domestic consumption (Deutscher Brauer-Bund, 2009; 2018). As a consequence, beer production decreased by 20.4% from 116.9 million hl in 1995 to 93 million hl in 2017 (Deutscher Brauer-Bund, 2018). During the same time, the number of brewery employees decreased by almost 44% from 48,216 in 1995 to 27,233 in 2017 (NGG, 2010; Deutscher Brauer-Bund, 2018).[1]

Interestingly, in the last two decades, the number of breweries has increased from 1,282 in 1995 to 1,492 in 2017 (Deutscher Brauer-Bund, 2018). However, these aggregated numbers give an incomplete picture of the developments. The numbers of firms increased only in the group of very small breweries. Therefore, the number of breweries producing up to 5,000 hl/year increased from 643 in 1994 to 1,065 in 2017 (Deutscher Brauer-Bund, 2009; Destatis, 2018).[2] While the number of very large breweries (more than 500,000 hl/year) was relatively stable between 54 in 1995 and 47 in 2017, we observe the largest decrease for breweries between 10,000 and 500,000 hl/year. Their numbers decreased from 459 to 277 or almost 40% during the same time period. These breweries are in a fierce competition for a decreasing demand.

The aim of this paper is to investigate the development of the labor productivity in this industry as a key factor for firms to increase their competitiveness. To do so, we combine two strands of the literature on (labor) productivity decomposition. One strand originates from empirical studies that use micro-data to describe the productivity growth dynamics of an industry. Several decomposition methods have been proposed to analyze the sources of aggregate productivity change via a within-firm effect and the reallocation effects between incumbent firms as well as entering and exiting firms (Baily et al., 1992; 1996; 2001; Griliches and Regev 1995; Foster et al. 2001; Melitz and Polanec 2012). The other strand combines index number theory with stochastic frontier analysis (Nishimizu and Page, 1982; Bauer, 1990; Lovell, 1996) and decomposes firm-specific productivity growth into several components including technical change, change in technical efficiency and the scale effect. Here, we show how to combine those two approaches to analyze the dynamics of aggregated industry labor productivity in great detail. In particular, we decompose industry labor productivity change into seven components: input deepening, technical change, technical efficiency, scale effect, between-firm reallocation and the effects from exits and entry. The first four of these components constitute the within-firm effect. Applying our method to a sample of 118 German breweries between 1996 and 2008 provides useful insights into the development of (labor) productivity and its driving forces.

Method

Labor productivity (LP) of a single firm i in time period t in its logarithmic form is defined as $LP_{it} = \ln\left(\frac{y_{it}}{l_{it}}\right)$, where y_{it} is the quantity of output produced and l_{it} is the utilized amount of labor. Moreover, we define labor productivity of the whole industry I consisting of N firms (or a sample of firms N within an industry) at time t as the share-weighted average labor productivity $LP_t^I = \sum_{i=1}^{N} s_{it} LP_{it}$, where s_{it} represents a firm's share within the industry. The change in labor productivity of a single firm and of the whole industry from period $t-1$ to t is given by $\Delta LP_{it} = LP_{it} - LP_{it-1}$ and $\Delta LP_t^I = LP_t^I - LP_{t-1}^I$, respectively.[3]

To decompose the change in industry labor productivity (ΔLP_t^I) into its components we proceed as follows. In a first step, we differentiate between effects within firms, effects between firms and effects from firms that enter and exit the sample and/or the industry. In a second step, we further decompose the within-firm component into the effect of technical change, the scale effect, the change in technical efficiency effect and an input deepening effect. Our decomposition of the change in industry labor productivity (ΔLP_t^I) in the first step is closely related to the one proposed by Griliches and Regev (1995). Given the nature of our data, we further decompose the net entry term to distinguish the effect associated with firms that enter/exit the industry (and therefore the sample) from that of firms that drop in and out of the sample for other unknown reasons.[4] Therefore, in each period, our sample is divided into continuing firms (C), new firms that enter the industry (N_E), existing firms that enter the sample (N_S), firms that shut down (or change ownership) (X_E) and firms that exit the sample for other reasons but continue to produce (X_S). Given this, the industry's labor productivity can be decomposed into

$$\Delta LP_t^I = \sum_{i\in C} \widetilde{s_{it}}\, \Delta LP_{it} + \sum_{i\in C}\left(\widetilde{LP_{it}} - \widetilde{LP_t^I}\right)\Delta s_{it} + \sum_{i\in N_E} s_{it}\left(LP_{it} - \widetilde{LP_t^I}\right)$$

$$(1) \qquad + \sum_{i\in N_S} s_{it}\left(LP_{it} - \widetilde{LP_t^I}\right) - \sum_{i\in X_E} s_{it-1}\left(LP_{it-1} - \widetilde{LP_t^I}\right) \qquad \forall\, t \neq 1$$

$$- \sum_{i\in X_S} s_{it-1}\left(LP_{it-1} - \widetilde{LP_t^I}\right)$$

where a tilde over a variable denotes its arithmetic mean for t and $t-1$ (i.e., $\widetilde{s_{it}} = \frac{1}{2}(s_{it} + s_{it-1})$), and a delta in front of a variable denotes its first-difference (i.e., $\Delta s_{it} = s_{it} - s_{it-1}$). The first term on the right hand side is the aggregated effect of the individual firms' weighted labor productivity change (within-firm component). Loosely, this is positive if firms improve their performance on average. The second term shows the effect of shifts in the shares between firms (between-firm component) weighted by the firm's deviation in its average productivity in t and $t-1$ from the industry's respective productivity. This is positive if the relative weight of high-productivity to low-productivity firms increases. The third (fifth) term is the effect of firms that enter (exit) the industry and therefore the sample. The effects on labor productivity of the whole industry are positive if better (worse) than average performing firms enter (exit) and negative otherwise. Finally, the fourth (sixth) term gives the aggregated effects of firms that enter or exit the sample but not the industry. The same reasoning applies for the direction of the effects on industry productivity.

Various methods have been used in the literature to decompose the change in labor productivity into these components. Baily et al. (1992) were the first to differentiate between a within-firm and a between-firm component and also distinguished between surviving, entering and exiting firms. The main difference between their method and the method we use based on Griliches and Regev (1995) is that the latter introduces the average aggregate industry productivity level between the two periods $\widetilde{LP_t^I}$ as a reference point (Melitz and Polanec, 2015). This has the interpretive advantage that the contribution of entering and exiting firms (terms three to six in equation (1)) on the industry productivity change can be positive or negative, whereas the contribution of entry (exit) is always positive (negative) in Baily et al. (1992). Another popular decomposition is Foster et al. (2001). Although it also adds an additional component, a cross-firm effect, the main difference compared to Griliches and Regev (1995) is that Foster et al. use the industries' initial productivity level LP_{t-1}^{I} rather than the time average $\widetilde{LP_t^I}$ as a reference point. Recently, Melitz and Polanec (2015) introduced another decomposition: a dynamic version of the well-known static Olley and Pakes (1996) decomposition. Hence, they decompose the change in industry labor productivity into a change in the unweighted mean of firm's productivities, the covariance change between market share and productivity, and the contributions of entrants and exiting firms. In contrast to Griliches and Regev (1995) and Foster et al. (2001), Melitz and Polanec (2015) use surviving firms at time t $(t-1)$ as a benchmark to value the contribution of entering (exiting) firms. Although it is clear that any choice of reference group will influence the contribution of entrants and exiting firms, it remains debatable which approach is superior. Balk (2003) and Diewert and Fox (2010) argue that the decomposition of Griliches and Regev (1995) (as compared to that of Foster et al. (2001)) has the advantage of treating time in a symmetric fashion, which makes the within term in this decomposition a Divisia index of the continuing firms' productivity change (Foster et al., 2008).

In a second step, we further decompose the within-firm component of productivity growth (first right-hand-side term in equation (1)) by using a parametric frontier approach following Nishimizu and Page (1982), Bauer (1990) and Lovell (1996). To do so, we describe a firm's production technology with a well-behaved production function but also account for the possibility of technical inefficiency:

(2) $$y_{it} = f(\boldsymbol{x}_{it}, t)TE_{it}(t)$$

where y_{it} is the output of firm i at time t, $f(\quad)$ describes a common production technology, $\boldsymbol{x}_{it} = (x_{1it}, x_{2it}, \dots, x_{Jit})$ is a vector of J inputs, $TE_{it}(t)$ is the output-oriented measure of technical efficiency defined over the range $(0,1]$ and t is a time trend that accounts for technological change in the production function. Hence, if $TE_{it}(t) = 1$, the production is at the technically efficient level, which is described by the production frontier $y_{it} = f(\boldsymbol{x}_{it}, t)$. Taking logarithms of both sides of equation (2) and totally differentiating them with respect to time results in:

$$(3) \qquad \Delta \ln y_{it} = \sum_{j=1}^{J} \varepsilon_{jit} \Delta \ln x_{jit} + \Delta T_{it} + \Delta \ln TE_{it}.$$

The delta in front of a variable denotes its difference over adjacent time periods, i.e., its rate of growth (e.g., $\Delta \ln x_{jit} = \ln x_{jit} - \ln x_{jit-1} \approx \frac{d}{dt}\ln(x_{ij})$), $\varepsilon_{jit} = \partial \ln f\,(\boldsymbol{x}_{it}, t)/\partial \ln x_{jit}$ is the partial output elasticity of the jth input, $\Delta T_{it} = \partial \ln f\,(\boldsymbol{x}_{it}, t)/\partial t$ is the primal rate of technical change and $\Delta \ln TE_{it} = \partial \ln TE_{it}\,(t)/\partial t$ is the rate of change in technical efficiency.

By subtracting the growth of labor input $\Delta \ln l_{it} = \frac{d}{dt} \ln(l_i)$ from both sides of (3) and by adding and subtracting aggregate input growth $\sum_{j=1}^{J} \frac{\varepsilon_{jit}}{\varepsilon_{it}} \Delta \ln x_{jit}$ [5], we rearrange equation (3) to

$$(4) \qquad \Delta LP_{it} = \Delta \ln y_{it} - \Delta \ln l_{it} = \sum_{j=1}^{J-1} \left(\frac{\varepsilon_{jit}}{\varepsilon_{it}}\right) \left(\Delta \ln x_{jit} - \Delta \ln l_{it}\right) + \Delta T_{it} + (\varepsilon_{it} - 1) \sum_{j=1}^{J} \left(\frac{\varepsilon_{jit}}{\varepsilon_{it}}\right) \Delta \ln x_{jit} + \Delta \ln TE_{it},$$

Where the input *labor* is defined to be the J-th input, i.e., $x_{Jit} = l_{it}$, and $\varepsilon_{it} = \sum_{j=1}^{J} \varepsilon_{jit}$ are returns to scale. Equation (4) decomposes firm level labor productivity growth into four components. The first term on the right-hand side is the input deepening effect, i.e., it accounts for changes in factor intensities. Input deepening relates to factor substitution and indicates that labor productivity can increase, if the other inputs grow faster than labor and eventually replace it in the production process. Technical change (second term) has a one-to-one contribution to labor productivity growth. The contribution of the scale effect (third term) is positive if the production technology exhibits increasing returns to scale ($\varepsilon_{it} > 1$) and the aggregate input usage expands or if $\varepsilon_{it} < 1$ and the input usage is reduced. In the case of constant returns to scale ($\varepsilon_{it} = 1$) or constant input quantities, the scale effect becomes zero. Finally, technical efficiency change (fourth term) indicates a catching up effect (Färe et al. 1994) that contributes positively to labor productivity growth as firms move closer to the production frontier. The last three terms correspond to Bauer's (1990) and Lovell's (1996) decompositions of total factor productivity growth (ΔTFP_{it}). Hence, one may rewrite equation (4) as $\Delta LP_{it} = \sum_{j=1}^{J-1}\left(\frac{\varepsilon_{jit}}{\varepsilon_{it}}\right)\left(\Delta \ln x_{jit} - \Delta \ln l_{it}\right) + \Delta TFP_{it}$, where $\Delta TFP_{it} = \Delta \ln y_{it} - \sum_{j=1}^{J}\left(\frac{\varepsilon_{jit}}{\varepsilon_{it}}\right)\Delta \ln x_{jit}$. This highlights the advantage of the present decomposition of labor productivity growth in equation (4). It preserves the intuitive concept of a partial productivity measure but still features the differences between the substitution effects and productivity growth due to technical progress, efficiency change and the scale effect.

Once the parameters of the production frontier $y_{it} = f_{it}(\boldsymbol{x}_{it}, t)TE_{it}(t)$ are econometrically estimated, we can calculate all four components without knowledge of the input prices and the assumption of constant returns to scale (Bauer, 1990). Several models for the econometric estimation of production (or cost) frontiers from panel data have been proposed and discussed in the literature (e.g., Greene, 2008). A stochastic frontier panel model can be formulated as

(5) $$\ln y_{it} = \ln \boldsymbol{x}_{it}{}'\boldsymbol{\beta} + \alpha_i + u_{it} + e_{it}$$

where $\boldsymbol{\beta}$ are parameters to be estimated, α_i are time-invariant firm-specific effects, u_{it} is a non-negative term that represents inefficiency and e_{it} is statistical noise.

The main distinguishing features of the various proposed models are the way inefficiency (u_{it}) is modeled, whether inefficiency is allowed to vary over time (u_{it} versus u_i)

and the way firm heterogeneity α_i is taken into account.[6] Greene (2005a, 2005b) addressed the issue of between-firm heterogeneity and proposed the "true" fixed-effects and "true" random-effects model, where α_i is a constant or an iid normal distributed random term, respectively. The "true" effects models present a great improvement in dealing with potential between-firm heterogeneity in the stochastic frontier framework. Nevertheless, the models have some complexities, and their implementation requires involved econometric estimation procedures.[7]

Here we follow Karagiannis and Kellerman (2017) by explicitly modeling firm heterogeneity in the spirit of Mundlak (1978). In particular, one of their formulations incorporates Mundlak (1978) treatment of firm heterogeneity in a MLE frontier model as the following:[8]

$$\ln y_{it} = \sum_{j=1}^{J} \beta_j \ln x_{jit} + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} \beta_{jk} \ln x_{jit} \ln x_{kit} + \beta_t t + \frac{1}{2}\beta_{tt} tt + \sum_{j=1}^{J} \beta_{tj}\, t \ln x_{jit} + \alpha_i - u_{it} + e_{it}$$

with

(6)

$$\alpha_i = \sum_{j=1}^{J} \gamma_j \left(\overline{\ln x_{jit}}\right) + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} \gamma_{jk} \left(\overline{\ln x_{jit}\ \ln x_{kit}}\right) + \sum_{j=1}^{J} \gamma_{tj} \left(\overline{t \ln x_{jit}}\right),$$

$$u_{it} = u_i \exp\left(-\eta(t-T)\right) \rightarrow u_i \sim N^{+}(0, \sigma_u^2),$$

$$e_{it} \sim iidN(0, \sigma_e^2)$$

where all the βs, γs and η are parameters to be estimated. A bar over a variable denotes its cross-section mean, i.e., $\bar{x}_{it} = \frac{1}{T_i}\sum_{t=1}^{T_i} x_{it}\ \ \forall\, i$ [9]. To avoid imposing unnecessary a priori restrictions on the production technology, we use the flexible translog form with symmetry imposed as $\beta_{jk} = \beta_{kj}\ \forall\ j, k$. The firm-specific effect α_i is explicitly modelled based on the following reasoning: heterogeneity may be unobservable to only the econometrician but not the decision making unit. Thus, we can expect that the firms have adjusted their inputs according to their given production conditions. Hence, unobserved heterogeneity is assumed to be correlated with the observed levels of input usage. If this assumption holds, we can model α_i by adding the individual group means of inputs as auxiliary variables. In this way, we can account for the unobserved heterogeneity that is correlated with the firm's level of input usage.

A second but no less relevant virtue of this approach is that it mitigates the heterogeneity bias in the slope parameters. Mundlak (1978) showed that including the group means of the explanatory variables in a GLS random effects model yields the unbiased within estimator for the slope parameters. This result cannot be strictly applied to stochastic frontier models with an asymmetric composed error term. However, we can expect the heterogeneity bias to be minimal to the extent that the auxiliary variables capture the correlation between the unobserved effect and input quantities (Farsi et al. 2005).

To allow for temporal variation in the one-sided inefficiency component u, we use the time-varying formulation of Battese and Coelli (1992). Finally, we have a symmetric noise component e_{it}.

After the econometric estimation of (6) we can calculate the four components of firm-level labor productivity growth. To calculate the input deepening effect $\left(ID_{it} = \sum_{j=1}^{J-1}\left(\frac{\varepsilon_{jit}}{\varepsilon_{it}}\right)(\Delta \ln x_{jit} - \Delta \ln l_{it})\right)$ and the scale effect $\left(SC_{it} = (\varepsilon_{it} - 1)\sum_{j=1}^{J}\left(\frac{\varepsilon_{jit}}{\varepsilon_{it}}\right)\Delta \ln x_{jit}\right)$ of firm i in time t, we need percentage changes in inputs ($\Delta \ln x_{jit}$) and the scale elasticity calculated as

$$\varepsilon_{it} = \sum_{j=1}^{J} \varepsilon_{jit} = \sum_{j=1}^{J} \frac{\partial \ln f\,(\boldsymbol{x}, t)}{\partial \ln x_{jit}} = \sum_{j=1}^{J}\left(\hat{\beta}_j + \sum_{k=1}^{J} \hat{\beta}_{jk} \ln x_{kit} + \hat{\beta}_{tj} t\right) \tag{7}$$

where a hat over a parameter indicates that it is an estimated value. The technology exhibits constant returns to scale ($\varepsilon_{it} = 1$) for $\sum_{j=1}^{J} \hat{\beta}_j = 1;\ \hat{\beta}_{jk} = 0\ \forall\ j,k$ and $\hat{\beta}_{tj} = 0\ \forall\ j$. Output elasticities ε_{jit} and associated scale elasticities vary across producers and time unless $\hat{\beta}_{jk} = 0\ \forall\ j,k$ and $\hat{\beta}_{tj} = 0\ \forall\ j$, respectively.

The primal rate of technical change for firm i in time t is calculated as

$$\text{(8)} \qquad \Delta T_{it} = \frac{\partial \ln f\,(\boldsymbol{x}, t)}{\partial t} = \hat{\beta}_t + \hat{\beta}_{tt} t + \sum_{j=1}^{J} \hat{\beta}_{tj} \ln x_{jit}$$

Technical change varies across producers unless it is Hicks-neutral with respect to inputs ($\hat{\beta}_{tj} = 0\ \forall\ j$) and across periods except $\hat{\beta}_{tt} = \hat{\beta}_{tj} = 0\ \forall\ j$.

The technical efficiency change of firm i in time t can be derived from

$$\text{(9)} \qquad \Delta TE_{it} = \frac{\partial \ln \widehat{TE_{it}}(t)}{\partial t} = -\frac{\partial \hat{u}_{it}}{\partial t} = \hat{u}_i \hat{\eta}\, exp\big(-\hat{\eta}(t - T)\big)$$

This expression also varies across producers unless $\hat{u}_i = u\ \forall\ i$ and across periods with the same trend for all i unless $\hat{\eta} = 0$, but the latter case would imply a time-invariant technical efficiency.

Finally, the within-firm component as measured by the first right-hand-side term in equation (1) is calculated as

$$\text{(10)} \qquad \textstyle\sum_{i \in C} \widetilde{s_{it}}\, \Delta LP_{it} = \sum_{i \in C} \widetilde{s_{it}}\, (ID_{it} + SC_{it} + TC_{it} + TE_{it})$$

where s_{it} is a firm's share in total wage expenditures[10].

Data and Empirical Implementation

We use an unbalanced panel of German breweries that were participating in a voluntary benchmarking program conducted on behalf of the German Brewers Association over a period of 13 years from 1996 to 2008. We exclude microbreweries that produce less than

5,000 hl/year and large breweries that produce more than 300,000 hl/year from the sample, since it can be expected that these breweries use different production technologies. This leaves us with 118 breweries and 826 observations. On average, each brewery was observed for approximately 7 years. Comparing our sample to official statistics in table 1 reveals that our sample has a fairly good representation of the segment of the industry with an output between 10,000 hl/year and 300,000 hl/year.[11] For example, our sample includes on average, over all years 27.9% of all firms and 28.1% of the output in the size class from 100,000 to 200,000 hl/year.[12] Hence, the breweries in the sample are small and midsized businesses with an average of 48 employees and revenues of 7.8 million €. Nevertheless, they represent the core of the German brewing industry. Most of the observed breweries are located in Bavaria (57%) and Baden-Württemberg (19%) in southern Germany.

Table 2 summarizes the descriptive statistics for the input and output variables. We aggregate the inputs into three categories: *materials* including expenses for malt and barley, hops, water, energy and purchased goods and services; *labor* measured by the total wages paid[13]; and *capital* given by the end of year value of all machinery, equipment and buildings. Using appropriate price indices from the German Federal Statistical Office (Destatis), all the monetary values were deflated to base year 2005 values.

Output is measured by total revenues deflated by a firm-specific price index. This allows us to take any price dispersion between the breweries and price changes over time into account and create a quantity-type measure of output and productivity. Compared to the use of a common industry-based price index as a deflator, this approach is beneficial in two ways. First, we avoid an omitted variable bias in the econometric estimation of the production technology. Klette and Griliches (1996) note that, in most cases, omitted price dispersion will be negatively correlated with input quantities and introduces a downward bias in the estimated scale elasticities. Second, we ensure that we measure physical productivity growth that is free of demand-side price effects[14]. Abbott (1990) showed that revenue-based productivity growth equals physical productivity plus a price change component. In addition, Foster et al. (2008) show how firms' output prices are positively correlated with firm-specific demand factors and negatively correlated with physical total factor productivity. Eslava et al. (2004), Mairesse and Jaumandreu (2005) and Ornaghi (2006) also use firm-specific prices to deflate revenues to generate a quantity-type measure of output.

Our dataset contains information on the physical production and the respective revenues from various categories of beverages. These categories include beer, beer-mix beverages, and non-alcoholic beverages, which are all distinguished by whether they are packaged in bottles or kegs and by beer produced in license brewing. From the reported revenues and the physical output, we calculate category-specific prices that are then aggregated to a firm-specific price index using the categories revenue shares as weights. The firm specific price index is constructed as:

$$P_{it}^{*} = \sum_{r}^{R} \left(\frac{\Pi_{rit}}{q_{rit}}\right)\left(\frac{\Pi_{rit}}{\sum_{r}^{R} \Pi_{rit}}\right) \tag{11}$$

where Π_{rit} denotes the revenues that the single firm i in time t generates from the product category r and q_{rit} denotes the respective quantity. This index is also normalized using the year 2005 as the base, i.e., the average price index across all firms in the year 2005 is equal to 100. That way we create a convenient output aggregate of the different products, such as beer in kegs and bottles as well as mixed beer beverages.

As summarized in table 3, we perform several specification tests on our empirical model in equation (6). The hypotheses that the Cobb-Douglas production function, which is a special case of the translog functional form, is a sufficient specification of the production technology is rejected at the 1% level. We also reject the hypotheses that all breweries are technically efficient and that they operate on the production frontier. This result favors the stochastic frontier model over the conventional average production function approach. The hypothesis of zero and Hicks neutral technical change is rejected at the 1% level. Hence, the technical change component has a significant effect on output growth. We reject the hypotheses of constant returns to scale and time-invariant technical efficiency at the 1% and the 5% level, respectively. These results indicate that all three components of the within TFP growth contribute to growth in labor productivity and should be included in equation (2). Based on a Hausman test[15], we can reject the null hypothesis that the individual effects α_i are not correlated with the explanatory variables at the 1% level. Moreover, the null hypothesis that all auxiliary group-mean variables of the Mundlak adjustment are jointly equal to zero is rejected at the 1% level. We take the results of the last two tests as an indication that the input variables are correlated with individual effects i.e., unobserved firm heterogeneity. All the tests together confirm our model specification in equation (6).

Results

The estimated parameters for the production frontier and the composed error term are reported in table 4. The coefficients of the first-order parameters are positive and significantly different from zero. The coefficients of the trend variables are positive but not significantly different from zero. However, the significant positive and negative coefficient of the variables *material* and *labor* interacted with the time trend, indicate material-using and labor-saving technical change, respectively. We check whether the theoretical requirements for a well-behaved production function implied by economic theory, namely the monotonicity and quasi-concavity, are met at all the data points. Flexible functional forms such as the translog functional form, in contrast to the Cobb-Douglas, do not meet these requirements globally (Lau, 1978; Diewert and Wales, 1987). Hence, the function's properties must be imposed or checked posteriori to avoid serious implications for the interpretation of the obtained parameters and efficiency scores. In a production function, monotonicity requires positive marginal products for all inputs. Because both y and $\boldsymbol{x}$ contain only strictly positive numbers, it is sufficient to check the sign of the output elasticities (ε_{jit}) at all data points. We find no violations of monotonicity. To check for quasi-concavity, we find that the condition of a negative semi-definite bordered Hessian matrix of the first- and second-order derivatives is met in more than 98% of the data points. Hence, we conclude that the estimated translog production frontier is well-behaved and satisfies the regularity conditions of monotonicity and quasi-concavity very well.

Based on the input data and the estimated coefficients of the production frontier, we calculate firm specific output elasticities and returns to scale according to equation 7. In table 5 we report the elasticities at the sample mean. The results indicate that the inputs material and labor contribute most to the production of beer on average and that the impact of additional capital on production is rather low. We observe decreasing returns to scale at the sample mean.

In table 6, we present the decomposition of labor productivity growth per year as averages for three periods (1996 – 2000, 2001 – 2004, 2005 – 2008) and for the whole period (1996 – 2008), respectively. We take averages to avoid year-to-year fluctuations. Between 1996 and 2008, we measure an aggregated industry-wide labor productivity change of 1.46% per year. However, a significant part of this productivity change is related to sampling issues. In particular, firms which drop from the sample have a productivity below average and new firms included in the sample have a productive above average. Both effects increase our productivity measure by 0.27% and 0.32%, respectively. Abstracting from this issue, the aggregated annual labor productivity change is 0.88%. The biggest share of this change is due to productivity increases within the firm. In fact, the within-firm effect (0.96%) is more than twice as strong as the effects from industry dynamics (0.45%). Moreover, within the firm mainly technical change (0.98%) and to a lower extent the scale effect (0.27%) and material deepening (0.23%) are important. Deepening of capital (0.01%) plays no role and the firms' average technical efficiency is significantly decreasing (-0.53%). In regard to industry dynamics, we distinguish between two effects: a shift of shares from less to more productive firms (0.22%) and industry exits of firms that are less productive than the average firm (0.23%).

If we compare the different time periods, we observe that the within-firm effect and the between-firm are relatively stable, but the decomposition within these two effects vary considerable over time. Technical change is the most important single factor of productivity growth in all periods, though increasing over time. Technical efficiency is significantly decreasing in all periods. However, the scale effect is more important in the first and third period, while the material deepening effect is only positive and important in the first two periods. In regard to industry dynamics, the between-firm effect is largest in the second period, while the effect from exiting firms is larger in the first and third period.

To exam the robustness of our findings Table 7 provides average annual growth rates for three different size classes: small (< 50,000 hl), medium (50.000 hl – 100,000 hl) and large (>100.000 hl) firms. While the overall tendency is similar in all size classes, there are also differences. Within-firm effects are similar for medium sized and large firms, but smaller for small firms. Since all three classes have approximately the same total factor productivity change, the difference is due to the deepening effect. Small firms tend to be resource saving (-0.13) while medium (0.42) and large (0.34) firms are resource using. There is a negative correlation between firm size and technical change. However, the negative effect in regard to technical efficiency also increases with decreasing firm size. Industry dynamics are strongest for the large firms (0.41), but the strongest effect of less productive firms leaving the industry is for the class of small firms (0.32). Overall, the highest productivity growth, after accounting for sample exits and entries, is measured for the medium sized breweries (0.92).

Discussion and Conclusions

According to many recent sectoral reports and comments by industry experts the German beer industry faces a sever and lasting crises (Maack et al. 2011; Fazel et al. 2013; Verstl, 2014;

Filtz, 2014; Stracke and Homann, 2017). Sparked by significant demographic changes, in particular, a decrease in the beer-drinking population in the 18-34 age group, a decline in the frequency of beer consumption, and other changes in consumption habits, domestic demand has constantly decreased over the last 30 years (Fazel et al. 2013, Filtz, 2014). Though net-exports increased to some extent this could not compensate for domestic consumption declines. While the number of very small microbreweries (less than 1000 hl/year) often producing high-priced "craft beers" has steadily increased and the number of very large firms (more than 500,000 hl/year) has remained fairly stable, the number of mainly traditional small and medium sized breweries has sharply decreased. This is the segment where most of the structural adjustment takes place.

In this paper we examine how labor and total factor productivity in this segment of the industry (5,000 – 300,000 hl/year) developed based on a sample of 118 breweries between 1996 and 2008. We provide a method to decompose industry labor productivity into seven components: input deepening, technical change, technical efficiency, scale effect, reallocation effect and the effects from exits and entry. Looking at the development and importance of these components helps us to understand what is going on in this industry.

Our empirical results very much confirm the picture of a shrinking and struggling industry. Despite the decreasing numbers of breweries, some experts number existing overcapacities as 10% to 30% (Maack et al. 2011). This is clearly reflected in our result of decreasing economies of scale. Moreover, a positive scale effect in all size classes and over the whole period of time implies that breweries are trying to improve their productivity by reducing their input usage, in particular labor, and adjusting the scale of their operations. This picture is also confirmed by our finding of decreasing technical efficiency. Although the production frontier as formed by the best firms is shifted upwards, as indicated by a strong technical change effect, not all firms are able to follow this development. Hence, the performance of the firms in the industry diverges. This seems typical for shrinking industry with some firms following an active strategy and investing in new technology and others staying passive and producing as long as possible with the existing technology. This effect even became stronger over time and is largest for the smallest firms. According to our results technological change is mainly labor-saving. Given that the elasticity of substitution between material (mainly malt and hops) with other input factors can be expected to be low, rationalization is the main strategy for cost reduction. Though less important than the between-firm effect, there is also a steadily restructuring process. It is mainly driven by a shift of production in the segment of larger firms and exits of smaller, less productive firms.

Unlike the rest of the world and despite all these structural adjustments the German beer market is still highly fragmented. As one explanation, it has been argued that preferences for "local" beer are strong in Germany (Scherer et al. 1975, Adams, 2006). However, low concentration also implies strong competition and low profits. According to Verstl (2014) profits per hectoliter in Germany are $ 10 compared to a global average of $ 18. This may explain to some extent that the share of the global big players (AB-INbev, Heiniken, Carlsberg) is still relatively low. Maybe the German beer market is just not attractive enough (Verstl, 2014).

All these findings together fit well into an industry that is dominated by mid-sized, family owned businesses with a long tradition. On average, these firms stay rather passive and either try to defend their market shares by becoming more productive through investments in technology or continue producing with the old technology as long as possible. Hence, structural change and thinning out of the middle will continue.

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Footnotes

1 The number of employees is only available for firms with at least 20 employees.

2 In fact, it is the breweries with less than 1,000 hl/year which increased in numbers. However, data for this group of "nano" breweries is only available from 2005 onwards. It reveals that between 2005 and 2017 the number of breweries with less than 1,000 hl/year increased by 316 while the number of breweries between 1,000 and 5,000 hl/year actually decreased by 59 (Destatis, 2011; 2018).

3 Because labor productivity is in logarithms, ΔLP_{it} (ΔLP_t^I) is the percentage change or a discrete rate of change in a firm's (industry's) labor productivity.

4 Baily et al. (1992) noted the possibility that a firm that exits their sample may still operate. However, they note that they do not regard this as a problem of magnitude for their sample (Baily et al. 1992, fn. 11). The firms in our dataset participate on a voluntary basis. Hence, we cannot neglect the issue of exits/entries to the sample that do not reflect the true behavior of the firm.

5 Aggregate input growth is denoted by $\sum_{j=1}^{J} c_j \, \Delta \ln x_{jit}$, where $c_j = \left(w_j x_j\right)/C$ is the cost share of the jth input, w_j is the respective input price and C are the total costs. Chan and Mountain (1983) show that under the assumption of profit maximization, $c_j = \frac{\varepsilon_j}{\varepsilon}$, where $\varepsilon = \sum_{j=1}^{J} \varepsilon_j$ is the scale elasticity.

6 Pitt and Lee (1981) and Schmidt and Sickles (1984) made early contributions to panel data models and assume time-invariant technical efficiency. Battese and Coelli (1992) and Cornwell et al. (1990) extend the models of Pitt and Lee (1981) and Schmidt and Sickles (1984) to allow for time-varying inefficiency. These earlier models did not specifically account for firm heterogeneity (α_i) within the model. Hence, the contamination of the

measure of inefficiency with unobserved firm-specific heterogeneity is an issue discussed in the more recent literature (e.g., Greene 2005a, Farsi et al. 2005).

7 See Greene (2005a, 2005b, 2008) and Wang and Ho (2010) for further details.

8 Other formulations in Karagiannis and Kellermann (2017) include various specifications in the spirit of Mundlak, applied in GLS random effects and Greene's "True" random effects stochastic frontier models.

9 Note that we use a bar to indicate a cross-section mean, while a tilde, e.g. in equation (1), indicates the mean between two time periods.

10 In general, the weights used to aggregate the productivity of individual firms should mirror the importance of each firm in the industry (Bartelsman and Doms, 2000). Van Biesebroeck (2008) and Fox (2012) discuss the effects of aggregation weights and the resulting effects on the monotonicity and interpretation of aggregated productivity measures. They strongly encourage the use of input shares as weights, which in our case of labor productivity is the firm's share in total wage expenditures. This is also reflected in Färe and Karagiannis (2017) denominator rule where consistent aggregation of ratio type performance indicators requires weights to be in terms of the denominator variable of the ratio. Then aggregate and firm-level performance indicators have exactly the same intuitive interpretation.

11 Note that official statistics do not report the number of firms between 200,000 - 300,000 hl/year, but rather between 200,000 - 500,000 hl/year. Hence, the 42% in table 1 are based on the assumption that breweries in the class 200,000 - 500,000 hl/year are uniformly distributed and therefore might overestimate the representativeness of our sample in the class 200,000 - 300,000 hl/year to some extent.

12 Note that official statistics in regard to beer output in size classes are only available for the years 2005 to 2008. Therefore, numbers in the last column of table 1 represent averages for this period.

[13] We use data on the wages instead of the mere number of employees because we are missing information on the actual work hours, the educational status and tenure of employees in the firms. Hence, we follow Fox and Smeets (2011), who show that the wage bill is a good approximation of quality adjusted labor input among others in the Danish food and beverages industry.

[14] We do not observe firm-specific prices on the input side of production. Hence, our measure of "physical" productivity may still contain price effects on the input side, i.e., firms that face higher factor prices will appear to utilize a relatively higher level of inputs and thus to be less productive. As Foster et al. (2008) note, using quantity output, productivity reflects firms' "idiosyncratic cost components, both technological fundamentals and factor prices." See also Ornahghi (2006) for a discussion on the effects of input price differences.

[15] The test statistic is based on the comparison of the estimates of conventional fixed and random effects models.

Table 1: Representativeness of the sample for different size classes

Class	Number of breweries			Output	
	Germany		Sample	Representativeness (%)	
	1996	2008	average	average	average
5,000 - 10,000	119	93	2	2.0	1.0
10,000 - 50,000	246	176	25	11.8	15.0
50,000 - 100,000	93	66	20	25.8	25.3
100,000 - 200,000	46	38	12	27.9	28.1
200,000 - 300,000	16	11	5	42.0	41.1

Table 2: Summery statistics of input and output variables

	Mean	Max.	Min.	Std. Dev.
Material (1000 €)	2223.9	10296.2	197.8	1763.0
Labor (1000 €)	1833.8	6530.7	99.8	1376.8
Capital (1000 €)	3577.5	26523.3	210.4	3523.8
Output (1000 €)	7849.2	57703.5	584.0	6359.9

Number of observations: 827

Table 3: Model specification tests

Hypotheses	**LR-statistic**	**Critical value** (α = 0.05 / 0.01)
Cobb-Douglas ($H_0: \beta_{jk} = \gamma_{jk} = 0, \forall\, j, k$)	56.25	$\chi^2{}_{12}$ = 21.03 / 26.22
Technical efficiency ($H_0: \sigma_u = 0$)	1014.72	$\chi^2{}_{1}$ = 2.71 / 5.41 [a]
Zero technical change $H_0: \beta_t = \beta_{tt} = \beta_{tj} = \gamma_{tj} = 0, \forall\, j$	55.19	$\chi^2{}_{8}$ = 15.51 / 20.09
Hicks neutral technical change $H_0: \beta_{tj} = \gamma_{tj} = 0, \forall\, j$	32.31	$\chi^2{}_{6}$ = 12.59 / 16.81
Constant returns to scale ($H_0: \sum \beta_j = 1;\ \sum \beta_{1j} = \sum \beta_{2j} = \sum \beta_{3j} = \sum \beta_{tj} = 0\ \forall\, j$)	15.71	$\chi^2{}_{5}$ = 11.07 / 15.09
Time-invariant technical efficiency ($H_0: \eta = 0$)	5.78	$\chi^2{}_{1}$ = 3.84 / 6.63
Individual effects ($H_0: \alpha_i \perp x_{kit}$)	32,32	$\chi^2{}_{14}$ = 23.69 / 29.68
Individual effects $H_0: \gamma_j = \gamma_{kj} = \gamma_{tj} = 0\ \ \forall\, k, j$	118,94	$\chi^2{}_{9}$ = 16.91 / 21.67

[a] Kodde and Palm (1986)

Table 4: Parameter estimates of the production frontier

Parameter	Coefficient	S.E.	
β_0	0.2354	0.0342	a
β_1 $(Material)$	0.3262	0.0283	a
β_2 $(Labor)$	0.5233	0.0320	a
β_3 $(Capital)$	0.0477	0.0131	a
β_{11}	0.0777	0.0587	
β_{22}	0.1162	0.0913	
β_{33}	0.0180	0.0172	
β_{12}	-0.1068	0.0668	
β_{13}	-0.0089	0.0323	
β_{23}	-0.0134	0.0283	
β_t $(Trend)$	0.0076	0.0047	
β_{tt} $(Trend^2)$	0.0005	0.0005	
β_{t1} $(t * Material)$	0.0076	0.0033	b
β_{t2} $(t * Labor)$	-0.0111	0.0035	a
β_{t3} $(t * Capital)$	0.0003	0.0016	
γ_1	0.9392	0.1932	a
γ_2	-1.0591	0.1757	a
γ_3	0.1190	0.1190	
γ_{11}	0.3268	0.2852	
γ_{22}	1.0329	0.4099	b
γ_{33}	0.2557	0.1362	c
γ_{12}	-0.4502	0.3404	
γ_{13}	0.0750	0.1898	
γ_{23}	-0.4650	0.1461	a
γ_{t1}	-0.1134	0.0251	a
γ_{t2}	0.1132	0.0234	a
γ_{t3}	0.0143	0.0162	
$\lambda = \sigma_u/\sigma_v$	5.4288	0.0219	a
σ_u	0.4164	0.0089	a
η	-0.0174	0.0048	a
$Log\ LF$	726.53		

[a,b,c] statistical significance on 1%, 5 %, 10% level

Number of observations: 827

Table 5: Average output elasticities and returns to scale

Average output elasticities		
Material	0.385	(0.022)[a]
Labor	0.460	(0.025)[a]
Capital	0.050	(0.009)[a]
Returns to scale	0.894	(0.022)[a]

[a]Standard errors computed using Krinsky and Robb (1986). Number of observations: 827

Table 6: Decomposition of aggregate labor productivity growth for three periods and overall

Component	96/00	00/04	04/08	96/08
Within firms	1.03	0.85	0.99	0.96
Deepening	0.43	0.35	-0.06	0.24
Material	0.40	0.41	-0.12	0.23
Capital	0.03	-0.06	0.06	0.01
TFPC	0.60	0.51	1.05	0.72
Technical change	0.69	0.98	1.27	0.98
Tech. eff. change	-0.46	-0.53	-0.59	-0.53
Scale effect	0.37	0.07	0.37	0.27
Industry dynamics	0.46	0.43	0.45	0.45
Between firm	0.12	0.38	0.18	0.22
Exit (industry)	0.35	0.06	0.27	0.23
Exit (sample)	-0.21	0.71	0.31	0.27
Entry (sample)	1.02	0.05	-0.13	0.32
Residual[a]	-1.22	0.08	-0.46	-0.53
Overall aggregate	1.08	2.13	1.18	1.46
Overall aggregate without sample exits and entries	0.27	1.37	0.99	0.88

[a] The residual category is necessary because of differences between the directly calculated within-firm effect in equation (1) (first right-hand side term) and the one measured from the estimated production frontier (equation (10)).

Table 7: Decomposition of aggregate labor productivity growth 3 different size classes (< 50,000 hl, 50.000 hl – 100,000 hl. >100.000 hl)

Component	small	medium	large	all
Within firms	0.60	1.11	1.05	0.96
Deepening	-0.13	0.42	0.34	0.24
Material	-0.11	0.42	0.29	0.23
Capital	-0.02	-0.01	0.04	0.01
TFPC	0.73	0.70	0.71	0.72
Technical change	1.23	0.96	0.88	0.98
Tech. eff. change	-0.72	-0.50	-0.47	-0.53
Scale effect	0.22	0.24	0.30	0.27
Industry dynamics	0.17	0.11	0.41	0.45
Between firms	-0.14	0.11	0.25	0.22
Exit (industry)	0.32	0.00	0.16	0.23
Exit (sample)	1.23	0.00	-0.18	0.27
Entry (sample)	-0.01	0.00	0.01	0.32
Residual[a]	-0.10	-0.30	-0.85	-0.53
Overall aggregate	1.90	0.92	0.45	1.46
Overall aggregate without sample exits and entries	0.68	0.92	0.62	0.88

The residual category is necessary because of differences between the directly calculated within-firm effect in equation (1) (first right-hand side term) and the one measured from the estimated production frontier (equation (10)).

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