Markups and Product Differentiation in the German Brewing Sector

ABSTRACT

In this paper we provide a method to separate the product differentiation markup from other sources of market power, i.e. collusive behavior or lack of market transparency, based on the estimation of a single reduced form equation. We apply this method to a sample of about 200 breweries in Germany, since beer is a differentiated product and at the same time the sector has repeatedly been suspected to show collusive behavior. Our empirical results show that a significant part of the estimated markup is due to product differentiation. This is especially true for beers produced in Bavaria. However, there are other important sources of imperfect competition. Markups are higher for large firms and increase over time. In addition, we observe increasing returns to scale and average costs above marginal costs. Hence, in the German brewing sector a high markup does not necessarily translate into a high profit margin. [EconLit citations: L13; L66].

1. INTRODUCTION

The modern global brewing industry is highly concentrated. In 2015 the four largest firms (Anheuser-Busch InBev, SABMiller, Heineken International, Carlsberg Group) accounted for almost 50% of the global beer production (Statista, 2017a).[1] As a global exception, the brewing industry in Germany is still characterized by a relatively low concentration. Only two of the global market leaders (AB-InBev as number two and Carlsberg as number nine) are listed among Germany's top ten breweries, and these two firms accounted for approximately 15% of the German beer production in 2012 (NGG, 2013). In fact, as illustrated in Figure 1, the number of breweries in Germany increased slightly over the last two decades, from 1,276 in 1996 to 1,388 in 2015 (Deutscher Brauerbund, 2017). However, these aggregated figures give a very incomplete picture of the German beer market dynamics. The number of "very small" breweries (producing up to 5,000 hectoliter (hl) per year) increased from 625 in 1994 to 964 in 2015 (DeStatis, 2010, 2016) while breweries in all other groups showed a steady decrease. These developments are closely related to changes in consumption patterns. Though Germany still ranks among the top five beer drinking countries in the world, annual per capita consumption has steadily decreased from more than 150 liters in the mid-70's to 106 liters in 2015 (Private Brauereien Bayern e.V., 2016).[2] Even though exports have increased, they did not fully compensate for a decrease in domestic consumption of about 1.3% per year, leading to a decrease in production by 18.2% during the last 21 years (Figure 2). Nevertheless, the beer market in Germany is still very much nationally oriented. Exports accounted on average for 12.3% of domestic production and imports accounted on average for 5.3% of consumption between 1995 and 2015.

Despite the low industrial concentration, there is some evidence of collusive behavior in the German brewing sector. In 2014, the German Federal Cartel Office (Bundeskartellamt) imposed fines amounting to € 338 million to 11 breweries for two illegal price fixing agreements in 2006 and 2008 (Bundeskartellamt, 2014). In another proceeding, which started in 2010, the Bundeskartellamt imposed fines of about € 94 million on different food retailers for vertical price fixing with AB-Inbev (Bundeskartellamt, 2016). Moreover, beer is also a good example of a differentiated product market (Hausman, Leonhard & Zona, 1994; Slade, 2004; Rojas & Peterson, 2008) with different styles (e.g. Lager, Pils, Wheat beer) and many different brands available. In fact, there exist considerable price differences across beers from different breweries, even those of the same style. This may be due to consumers' attachment to specific brands, preferences for products from a specific place-of-origin or preferences for local products (van Ittersum, Candel & Meulenberg, 2003; Profeta, Enneking & Balling, 2008; Hasselbach & Roosen, 2015). In investigating price differences between the top-ten ranked pilsener and the top-ten ranked wheat beer brands in Germany, Loy and Glauben (2015) use scanner data covering a two-year period from 2000 to 2001 and report average regular prices for these brands ranging from 1.24 (Oettinger) to 2.58 Deutsche mark (Warsteiner) per liter. Observing considerable price differences is in line with the results of a repeated survey on brand awareness in Germany between 2011 and 2016, according to which about 50% of consumers pay attention to the brand, and only about 30 % to price, when buying beer (Statista, 2017b).[3]

The aim of this paper is to investigate whether German breweries price above marginal costs and to what extent their markups are due to product differentiation or other sources of imperfect competition. In his seminal work, Hall (1988, 1990) developed a simple way to estimate constant (or average) industry markups using firm- or industry-level data on inputs usage and total value of sales. Based on these ideas, De Loecker and Warzynski (2012) developed a method to uncover firm- and time-specific markups based on firm level data. This measure relies on the insight that the output elasticity of a variable input is only equal to its expenditure share in total revenue when price equals marginal cost of production. This "general" markup serves as a measure of imperfect competition without placing any assumption on the market structure and the competitive behavior of the firms. Hence, observed markups may be due to market concentration, collusion, product differentiation or other sources such as the lack of market transparency. To derive this measure, one has to estimate a production function. Since firm-specific output quantities and/or prices are often not available, it is very common to use revenue deflated by an industry-level price index as a proxy for output. However, if output prices are dispersed, as it is presumable in the case of beer, estimated markups will be downward biased (De Loecker & Warzynski, 2012). To account for this problem, we adopt a procedure by Klette and Griliches (1996) who explicitly model price differences by means of a demand function and derive a reduced form equation of production and demand. In addition, assuming product differentiation and monopolistic competition, the Klette and Griliches (1996) approach provides another, "demand-driven" markup measure. Comparing this measure to the general markup gives some indication of the importance of product differentiation relative to other sources. Our approach is closely related to Crépon, Desplatz and Mairesse (2005). However, while these authors follow Hall (1988, 1990) and derive a constant general markup, we derive firm- and time-specific general markups based on De Loecker and Warzynski (2012). This provides the opportunity to compare the markup between different subgroups of an industry (e.g. size classes) and over time.

The rest of the paper is organized as follows: the next chapter discusses our theoretical framework. Section 3 describes our data and our empirical model while section 4 presents the econometric results. We finish by drawing some conclusions and discussing the limitations of our analysis in section 5.

2. A MODEL TO ASSESS MARKET POWER IN THE GERMAN BREWING SECTOR

We follow De Loecker and Warzynski (2012), and model a firm producing a single output Q utilizing a vector of inputs ($\boldsymbol{X}$), some of which can be freely adjusted ($\boldsymbol{X^V}$), and quasi-fixed inputs facing adjustment costs ($\boldsymbol{X^F}$). We assume that imperfect competition is restricted to the output market, i.e. firms are price takers on the input markets. We further assume that firms minimize cost, where

$$C(\boldsymbol{W}, Q) = \min\{\boldsymbol{W}'\boldsymbol{X}: F(\boldsymbol{X^V}, \boldsymbol{X^F}) = Q\}\,, \tag{1}$$

where $\boldsymbol{W}$ is a vector of input prices. The first order conditions result in the optimal amount of each variable input j according to:

$$\frac{\partial \mathcal{L}}{\partial X_j^V} = X_j^V - \lambda \frac{\partial F(\boldsymbol{X^V}, \boldsymbol{X^F})}{\partial X_j^V} = 0, \tag{2}$$

where X_j^V is the price of variable input j. The Lagrangian multiplier $\lambda = \frac{\partial \mathcal{L}}{\partial Q} = \frac{\partial C(\boldsymbol{W},Q)}{\partial Q}$ can be interpreted as the marginal costs (MC). Multiplying both sides of equation (2) by $\frac{X_j^V}{Y}$, where $Y = QP$ is firm revenue, and P is the output price, and rearranging we obtain:

$$\frac{P}{MC}\frac{W_j^V X_j^V}{Y} = \frac{\partial F(\boldsymbol{X^V},\boldsymbol{X^F})}{\partial X_j^V}\frac{X_j^V}{Q}. \tag{3}$$

In equation (3) $\frac{W_j^V X_j^V}{Y} = s_V^Y$ is the revenue share of the variable input j and $\frac{P}{MC} = \mu$ is the markup parameter. The output elasticity of a variable input j is defined as $\varepsilon_V = \frac{\partial F(\boldsymbol{X^V},\boldsymbol{X^F})}{\partial X_j^V}\frac{X_j^V}{Q}$. Hence, we can rewrite (3) as

$$\mu = \frac{\varepsilon_V}{s_V^Y}. \tag{4}$$

From equation (4) we can see that under perfect competition, when firms price at their marginal cost, $\frac{P}{MC} = 1$ and the revenue share of a variable input equals its output elasticity. Estimating the "general" markup measure μ requires data on revenue shares of the variable input, which can usually be calculated from firm-level data, and the estimation of a production function to obtain the output elasticity of the variable input. Using equation (4) we can derive a markup for each firm in each period, because s_V^Y varies across firms and time and ε_V may vary in the same dimensions, depending on the functional form (e.g. Cobb-Douglas versus Translog) of the estimated production function.

We specify a general empirical firm-specific production function as

$$q_{it} = f(\boldsymbol{x}_{it}, t) + \sigma_i + e_{it}, \tag{5}$$

where q_{it} is the logarithm of physical output quantity Q_{it}, $f(\boldsymbol{x}_{it}, t)$ is a function of a vector of the log inputs $\boldsymbol{x}_{it}$ and the time trend t, which is used as a proxy for technological change, and i denotes different firms. Time-invariant and unobserved firm-specific differences, including time-persistent productivity differences, are captured by σ_i, while e_{it} denotes an i.i.d. error capturing idiosyncratic productivity shocks and measurement errors.

A major challenge in estimating the production function (5) is that most firm-level data sets do not provide information on output quantities and/or prices, but only revenue. Therefore, output is commonly approximated by deflating revenues by an industry-level price index. However, this becomes a problem if significant output price dispersion exists within the industry, as in the case of the German brewing industry. Though the basic problem was already addressed by Marschak and Andrews (1944), Abbott (1991) showed that using an industry price deflator instead of actual firm-level prices to deflate revenues (or alternatively, output in physical terms) will lead to biased estimates of the production function parameters. In related work, Klette and Griliches (1996) discussed that for the same reason estimates of production elasticities and returns to scale will be biased downward under quite general demand and cost specifications. In the context of our model, this would result in biased estimates of the markup measure in equation (4) (De Loecker & Warzynski, 2012). The magnitude of this bias is certainly an empirical question and mainly depends on the extent of the price dispersion. While De Loecker and Warzynski (2012) argue that the downward bias in their markup estimates is expected to be small, the considerable price dispersion that can be observed in the German brewing industry may lead to a significant bias. Hence, to correct for such bias we follow Klette and Griliches' (1996) approach by modelling price dispersion with a demand system and estimating a reduced form model embedding both production and demand side. In particular, by assuming imperfect substitutability between the firms' products (i.e. horizontal product differentiation), the demand facing the individual firm can be modelled by a CES function in the tradition of the Spence-Dixit-Stiglitz model (Spence, 1976a; Dixit & Stiglitz, 1977):

$$Q_{it} = \left(\frac{P_{it}}{P_t^L}\right)^{\eta} Q_t^L \exp\left(w_{it}\right), \tag{6}$$

where the demand for product Q_{it} is determined by the firm´s price P_{it} relative to the average industry price P_t^L and the aggregated industry demand Q_t^L.[4] Any other unobserved demand shocks, such as changes in consumer tastes or advertising effects, are captured in the residual term w_{it}. Assuming a CES demand function, η is constant across firms and can be interpreted as the own price elasticity of demand for each firm's product. In a perfectly competitive environment with perfectly elastic demand only one price can exist. Hence, η shows to which extent firms face a downward sloping demand curve for their products that allows for some flexibility in their pricing decision.

Taking logs and rearranging the terms of equation (6), we can express a firm's deviation from the industry price level as a function of individual market shares and the demand shocks in the error term w_{it}.

$$p_{it} - p_t^L = \eta^{-1}\left(q_{it} - q_t^L - w_{it}\right), \tag{7}$$

where $p_{it} - p_t^L = \log\frac{P_{it}}{P_t^L}$ and $q_{it} - q_t^L = \log\frac{Q_{it}}{Q_t^L}$. Substituting this expression into the production function (5) results in

$$y_{it}^L = \left(\frac{\eta+1}{\eta}\right) f(\boldsymbol{x}_{it}, t) + \left(\frac{\eta+1}{\eta}\right)\sigma_i - \eta^{-1} q_t^L + \left(\frac{\eta+1}{\eta}\right) e_{it} - \eta^{-1} w_{it} \tag{8}$$

where y_{it}^L are a firm's log-revenue deflated by an industry-level price index, i.e. $y_{it}^L = q_{it} + p_{it} - p_t^L$. Hence, equation (8) is a reduced form model allowing us to recover the parameters of $f(\boldsymbol{x}_{it}, t)$ by correcting for $\left(\frac{\eta+1}{\eta}\right)$ and the own price elasticity of demand for each firm's product η.

Assuming a specific price setting model, we can derive another markup measure. In particular, under monopolistic competition with firms competing in a Bertrand product differentiation fashion, we can derive a constant demand-driven markup measure (De Loecker, 2011a)

$$\mu_\eta = \frac{\eta}{\eta+1}\,. \tag{9}$$

Without product differentiation, η goes to infinity and consequently the demand specific markup μ_η goes to one. However, this case does not rule out other forms of imperfect competition, for example collusive behavior or lack of market transparency, captured in the general markup μ. It is important to stress at this point, that this approach does not assume any specific strategic interaction between firms. This is different to for example Nevo (2001) and Rojas (2008) who test for different models of pricing conduct. However, while Nevo's approach necessitates rather disaggregated, brand-level sales data, and the estimation of a complete demand system, our approach can be operationalized using firm level data.

In a monopolistically competitive market with heterogeneous products, we commonly expect firms to operate at decreasing average costs, i.e. at increasing returns to scale and excess capacity (Chamberlin, 1950; Carlton & Perloff, 2015). Hence, average costs are above marginal costs. In addition, without entry barriers profits are driven to zero, or prices are equal to average costs (Spence, 1976b). Following Crépon, Desplatz and Mairesse (2005), we can calculate the ratio between prices and average costs (AC) as

$$\frac{P}{AC} = \frac{\mu_\eta}{\delta}, \tag{10}$$

where δ represent returns to scale, i.e. the sum of production elasticities, which can also be derived from estimated production function parameters. Hence, to the extent that markups are demand-driven we expect $\frac{P}{AC} < \mu_\eta$ and with free entry $\frac{P}{AC} = 1$.

3. DATA AND EMPIRICAL MODEL

We employ an unbalanced panel of German breweries participating in a voluntary benchmarking program conducted on behalf of the German Brewers Association[5] (GBA) over a period of 13 years from 1996 to 2008.[6] In this benchmarking program the breweries provided their regular profit and loss statements including all expenses and revenues and their balances of accounts, including information on assets and liabilities. In total, the sample includes 197 different firms and 1,324 observations. Each firm is in the panel for at least two years and on average 6.7 years.

As outlined in Table 1, the average number of breweries was 1,288 in Germany between 1996 and 2008. However, more than 2/3 or 870 breweries were very small with an output less than 10,000 hl per year. Our sample does not cover well this segment of very small breweries. However, it includes almost 1/3 of the middle sized firms with an output between 50,000 hl and 500,000 hl and about 23% of the breweries producing more than 10,000 hl. Most of our observations are located in three States: Bavaria (66.1%), Baden-Württemberg (16.1%) and North Rhine-Westphalia (13.1%).

Descriptive statistics of input and output variables are in Table 2. Firm output is calculated as firm revenue deflated by a brewing industry price index provided by the Federal Statistical Office of Germany. We aggregate inputs into three variables: material, labor, and capital. Material and labor are deduced from firms' profit and loss statements. Materials is an aggregate of all expenses for raw materials and intermediate products including malt, barley, hops, energy as well as purchased goods and services.[7] Before aggregation, all single components were deflated using specific price indices provided by the Federal Statistical Office of Germany. Labor is measured as the sum of all wages paid to employees including management and deflated by the labor cost index of trade and industry, from the Federal Statistical Office of Germany. We use the wage bill instead of the mere number of employees, because of missing information on the actual work hours, the educational status and tenure of the employees. Hence, we follow Fox and Smeets (2011) who show that the wage bill is a good approximation of quality adjusted labor input. Capital is measured as the end-of-year value of all machinery, equipment and buildings as stated in the firms' balances of accounts and deflated by the price index of machinery for food, beverages and tobacco manufacturing (Federal Statistical Office of Germany). Following De Loecker (2011b), the aggregated German beer demand Q_t^L is calculated as domestic production minus exports plus imports based on DeStatis (2002, 2006, 2008).

To estimate the general markup and the markup related to product differentiation we need to specify an estimable form of equation (8). Representing the production function $f(x,t)$ with a translog form (Jorgenson, Christensen & Lau, 1973) and including non-neutral technical change, we have

$$y_{it}^L = \tilde{\beta}_0 + \sum_{j=M,L,C} \tilde{\beta}_j x_{jit} + \frac{1}{2} \sum_{\substack{j= \\ M,L,C}} \sum_{\substack{k= \\ M,L,C}} \tilde{\beta}_{jk} x_{jit} x_{kit} + \sum_{j=M,L,C} \tilde{\beta}_{jt} t x_{jit} + \tilde{\beta}_t t + \tilde{\beta}_{tt} t^2 + \tilde{\sigma}_i - \eta^{-1} q_t^L + \omega_{it} \tag{11}$$

where M, L, C indicate materials, labor and capital, respectively. $\widetilde{\boldsymbol{\beta}} = \left(\frac{\eta+1}{\eta}\right)\boldsymbol{\beta}$ is a vector of reduced form parameters that combine production and demand parameters and $\boldsymbol{\beta}$ is a vector including all parameters of the production function $f(\boldsymbol{x}_{it}, t)$. The error term ω_{it} contains unobserved production and demand shocks, so $\omega_{it} = \left(\frac{\eta+1}{\eta}\right) e_{it} - \eta^{-1} w_{it}$.[8]

From the estimated parameters in equation (11) we can directly obtain η and the markup related to product differentiation (equation (9)). To obtain an estimate of the general markup term, we need the production elasticity and the revenue share of one variable input free of adjustment costs. Materials appears as a good candidate since we don't expect substantial adjustment costs. Capital is naturally considered as an input with costly adjustment. Whether we can expect adjustment costs for labor depends on the presence of hiring and firing costs. Klette (1999) and Crépon, Desplatz and Mairesse (2005) identify labor as variable input whereas De Loecker and Warzynski (2012) note the possibility of labor adjustment costs. Thus, we follow De Loecker and Warzynski (2012) and use materials to derive the general markup. The production elasticity of material ε_{it}^{M} is given by

$$\varepsilon_{it}^{M} = \beta_M + \beta_{MM} x_{Mit} + \beta_{ML} x_{Lit} + \beta_{MC} x_{Cit} + \beta_{Mt} t. \qquad (12)$$

Based on equation (12), we derive firm- and time-specific output elasticities.

In calculating the material revenue share s_M^Y, we follow De Loecker and Warzynski (2012) and correct observed revenues Y_{it} by the predicted error $\widehat{\omega}_{it}$ as the latter may be correlated with factors that are not among the inputs. Hence, revenue shares are:

$$s_M^Y = \frac{W^M X^M}{Y \exp(-\widehat{\omega}_{it})}. \qquad (13)$$

4. ESTIMATION AND RESULTS

We estimate the reduced form equation (11) by means of different panel data estimation methods. First, we use a random effects (RE) and a fixed effects (FE) estimators (Baltagi, 2013). A RE estimator produces consistent estimates if the covariates are independent on unobserved heterogeneity. Starting with Marschak and Andrews (1944), a number of researchers have questioned the independence of firm's input levels and unobserved productivity levels (van Beveren, 2012). Hence, we test for orthogonality between $\tilde{\sigma}_i$ and the regressors by the Hausman (1978) test and compare the efficient RE estimator with the consistent FE estimator. With $\chi^2_{15} = 127.77$ $(\chi^2_{crit(.001)} = 37.7)$, we reject the null hypothesis of no systematic differences between the results of the RE and FE estimators. Moreover, as shown by the values presented in Table 2, firms in our sample differ considerably in size as measured by output and input quantities. Therefore, homoscedasticity, i.e. the assumption of a constant variance in errors across firms, might not hold. We use the Breusch-Pagan (1979) test and we reject the null hypothesis of constant variance with $\chi^2_{15} = 149.62$ $(\chi^2_{crit(.001)} = 37.7)$. Hence, we use a feasible fixed effects generalized least squares (FEGLS) estimator. This allows us to relax the assumption of a constant error variance without losing in terms of efficiency (Wooldridge, 2010). Even though our results are based on the FEGLS estimates, pooled ordinary least squares (OLS) and FE regression results are provided for comparison purposes. Regarding model specification, we use a Wald test (Table 3) to examine the hypothesis of no second order effects (Cobb-Douglas functional form), no technical change and Hicks-neutral technical change and we reject all of them at any level of significance.

Table 4 reports the estimation results for FEGLS, FE and pooled OLS. As it can be seen from the values in Table 4, mean OLS first-order effects are considerably larger than their FE and FEGLS counterparts. This finding is not surprising as positive productivity shocks trigger higher input demand, resulting in upward biased material and labor coefficients (van Beveren, 2012, De Loecker, 2007). On the contrary, only minor differences are observed between FE and FEGLS coefficient estimates. Taking a closer look at the FEGLS results, all first-order effects have the expected sign and are significant at least at the 1% level. In addition, all other estimated coefficients are significant at the 1% level, except the interaction between time and capital.

The mean output elasticities are calculated at 0.571 for materials, 0.654 for labor and 0.064 for capital (see Table 5). On average, we observe returns to scale of $\delta = \varepsilon_{it}^{M} + \varepsilon_{it}^{L} + \varepsilon_{it}^{C} = 1.290$. We obtain a mean general markup of $\overline{\mu}$ = 1.650. We test the null hypothesis that the average markup is not statistically different from 1 (H_0: $\overline{\mu} - 1 = 0$) by using 90%, 95% and the 99% bias corrected percentile confidence intervals based on 1,000 bootstrap replications (Efron & Tibshirani, 1993). Since 0 lies outside the 99% confidence interval (lower limit of 0.031 and upper limit of 3.337), we can reject the null hypothesis at the 1% significance level (Table 6).

The estimated negative inverse demand elasticitiy $(-\eta^{-1})$ is also significant at the 1% level with a value of 0.329. This corresponds to a demand elasticity of -3.040, and a demand-driven markup parameter of $\mu_{\eta} = \frac{\eta}{\eta+1} = 1.49$. We test for the difference between the mean general markup and the demand-driven markup, and reject the null hypothesis of $\bar{\mu} - \mu_{\eta} = 0$ at the 10% level. Moreover, based on equation (10) we calculate the ratio between prices and average costs to be $\frac{P}{AC} = \frac{\mu_{\eta}}{\delta} = \frac{1.49}{1.29} = 1.155$. Though relatively close to one, we cannot reject the null hypothesis of zero profits from product differentiation *P/AC* – 1 = 0 at the 1% significance level.

Using a flexible translog specification for the production function with non-neutral technical change allows us to estimate firm- and time-specific production elasticities, scale elasticities and markups and enables us to compare those measures across years and firm-size groups. Mean and median values of markups along with standard deviations are reported for all the years in Table 7. Markups increase over time from 1.330 in 1996 to 1.757 in 2008. Table 8 presents markups by firm size. We split our sample in four different size classes: firms with output less than 25,000 hl; between 25,000 and 50,000 hl; between 50,000 and 100,000 hl; and more than 100,000 hl. We observe larger firms tending to have higher markups. The markup of breweries with more than 100,000 hl output is about 1/3 larger than that of small breweries with less than 25,000 hl. We can reject the null hypothesis of equal mean markups between breweries producing less than 50,000 hl (first two size classes) and breweries producing more than 50,000 hl at the 5 % significance level.

Table 9 provides information on differences in markups by region. With a mean value of 1.609, Bavaria exhibits the lowest markup in the sample. Smaller markups in Bavaria may be attributed to the smaller structured brewing sector and the larger number of breweries as compared to the rest of Germany. We can reject the hypothesis of no differences between the markup in Bavaria and that of other regions only at the 10% significance level.

Finally, in order to investigate dispersions in demand-driven markup and as a robustness check of our estimates, we split our sample in Bavarian breweries and the rest of Germany. The rationale for doing so is twofold. First, almost half of German breweries are located in Bavaria, hence, it is the State with the highest density of breweries. Second, since two thirds of the observations in our sample are from breweries located in Bavaria, the Bavarian subsample provides a better representation of the Bavarian brewing sector than the whole sample may do for the entire Nation's. Coefficients based on FEGLS estimates are reported in Table 10. Based on the estimated negative inverse demand elasticity $-\eta^{-1}$ we calculate demand-driven markups of 1.407 for Bavaria and 1.287 for the rest of Germany. These findings suggest price differentiation to be a more important determinant of the markup in

Bavaria compared to other German regions. However, we cannot reject the hypothesis of no difference between the two markups.

5. CONCLUSION AND LIMITATIONS

The increasing market concentration, and the existence of market power and imperfect competition in food and beverages supply chains are issues of increasing concern to competition authorities worldwide (OECD, 2014). According to the OECD (2013), more than 180 antitrust investigations along the food supply chain were initiated by national competition authorities of the European Union over the period 2004 – 2011. However, charging prices above marginal costs does not necessarily imply an abuse of market power or illegal collusion. In a market with differentiated products higher markups may also reflect consumer preferences for certain products, or brand loyalty. In this paper, we provide a method to derive two different markup measures. Following De Loecker and Warzynski (2012), we derive a general, firm-specific markup. This measure is not conditional on any assumption about the behavior of the firms. By assuming monopolistic competition with imperfect substitutability between the firms' products, we are able to obtain a sector-wide average markup which basically reflects horizontal product differentiation. We show how both measures can be derived by estimating a reduced form model embedding both the supply- and demand-side of the market.

Our results clearly point towards breweries in Germany operating under increasing returns to scale in an imperfectly competitive market. Increasing returns in the brewing industry are in line with findings by (for example) Nelson (2005), Tremblay, Iwasaki and Tremblay (2005) and Madsen and Wu (2014). Moreover, a considerable share of the measured markup is due to product differentiation, reflecting consumers' preferences for specific brands or beer from specific breweries, e.g. local breweries. This effect is stronger, though not statistically significant, for Bavaria, the State with the highest density of breweries and largest per capita consumption, than for the rest of Germany. Hence, consumers in Bavaria may have strong preferences and loyalty for local beer.

Even though, product differentiation can explain a considerable share of the observed general markup, it does not explain all of it. We find the general markup being significantly different from the demand-driven markup. Moreover, we measure larger markups for larger breweries. This may indicate large firms' cost advantages and/or possibilities for collusive behavior. The latter is in line with several cases of illegal price fixing, where large breweries were mainly involved (Bundeskartellamt, 2014, 2016). In addition, we also observe markups to increase over time. Though the total number of breweries increased in the last two decades, the market became more concentrated, because the majority of entrants were small-sized breweries (with annual output less than 5,000 hl), whereas all other size categories saw a decrease in the number of firms. In fact, during the investigated time period (1996 – 2008) the number of breweries with more than 5,000 hl output/year decreased by 27%, from 605 to 441. Hence, the increasing markups over time may be due to increasing market concentration.

The relatively high markups do not necessarily translate into high profits, since the firms are not scale efficient. This reflects the general structure of the German brewing industry. As most breweries are too small to be competitive on the international market, German breweries do not play a significant role on a global level. The largest German brewery (Radeberger Gruppe KG) is only at 23rd position and the three largest German breweries (Radeberger, Oettinger und Bitburger) account for 1.6 % of the world market (NGG, 2013).

Though our research gives some insights into the markups and pricing behavior of the German brewing sector, it also suffers from some shortcomings. First, given the aggregated nature of our data, we are not able to explicitly model the demand for specific brands and types of beer. Rather, we have to assume a CES demand function with constant own-price demand elasticity across firms and time periods. By using data at the product level, and estimating a demand system as in Nevo (2001) or Rojas (2008), one would be able to test for different strategic interactions between firms.

Second, our data set is not a random sample of German breweries and this may introduce bias in our results. Our sample is not representative of the large group of very small breweries with less than 5,000 hl. However, most of these very small firms are not breweries in the conventional sense, but rather brewpubs, which sell most or all of their beers directly to consumers in the pub, while also generating revenue through other activities (restaurant, gastronomy etc.). Hence, it is not clear if these very small firms show the same production technology as larger, conventional breweries. Moreover, as all firms in the sample have participated voluntarily in the benchmarking program of the German Brewing Association, used to collect the data, issues of self-selection may be present. If more efficient and productive firms were more likely to participate in the program, our results would be biased towards lower average returns to scale, higher average markups, and higher average price to average cost ratio. However, we have no information on what influenced the firms to participate in the benchmarking program, as, to our best knowledge this is the first study of the German brewing industry based on this kind of firm-level data.

TABLE 1: Average number of breweries in Germany and in the sample in different size classes between 1996 and 2008

Size class	No. of breweries in Germany	No. of breweries in sample	% of breweries in sample
< 5000 hl	773	2	0.3
5,0001 hl - 10,000 hl	97	4	4.0
10,001 hl - 50,000 hl	214	42	19.7
50,001 hl - 100,000 hl	76	25	32.4
100,001 hl - 200,000 hl	44	17	39.4
200,001 hl - 500,000 hl	34	8	23.0
500,001 hl - 1 mill. hl	20	3	12.8
> 1 mill. hl	29	1	4.7
Sum	1,288	102	7.9

Sources: Deutscher Brauerbund (2017) and author’s calculations from German Brewers Association (GBA) data

TABLE 2: Summary statistics of input and output variables in 1,000 €

Variable	Mean	Median	Max.	Min.	Std.
Output	10,946	5,538	239,000	407	20,396
Material	3,328	1,789	75,368	138	6,870
Labor	2,335	1,337	36,664	100	3,518
Capital	4,705	2,271	82,897	84	8,256

Source: Author's calculations from German Brewers Association (GBA) data

TABLE 3: Wald tests of model specifications

Null hypothesis	χ^2 value	χ^2_{crit}: $\alpha = 0.05$	p-value
No second order effects H_0: $\tilde{\beta}_{ML} = \tilde{\beta}_{MC} = \tilde{\beta}_{LC} = \tilde{\beta}_{MM} = \tilde{\beta}_{LL} = \tilde{\beta}_{CC} = 0$	1062.778	$\chi^2_6 = 12.592$	0.000
No technical change H_0: $\tilde{\beta}_t = \tilde{\beta}_{tt} = \tilde{\beta}_{tM} = \tilde{\beta}_{tL} = \tilde{\beta}_{tC} = 0$	120.230	$\chi^2_5 = 11.070$	0.000
Hicks-neutral technical change H_0: $\tilde{\beta}_{tM} = \tilde{\beta}_{tL} = \tilde{\beta}_{tC} = 0$	96.030	$\chi^2_3 = 7.815$	0.000

Source: Author's calculations from German Brewers Association (GBA) data

TABLE 4: Estimated parameters of equation (11) – full sample

	FEGLS	Std.err.	FE	Std.err.	OLS	Std.err.
Material	0.339***	(0.010)	0.333***	(0.040)	0.449***	(0.023)
Labor	0.478***	(0.014)	0.511***	(0.052)	0.451***	(0.032)
Capital	0.059***	(0.006)	0.065***	(0.020)	0.180***	(0.019)
Material*Labor	-0.181***	(0.011)	-0.182***	(0.041)	-0.180***	(0.024)
Material*Capital	0.028***	(0.008)	0.022	(0.021)	-0.024	(0.021)
Labor*Capital	-0.045***	(0.009)	-0.048*	(0.028)	-0.049*	(0.025)
Material^2	0.155***	(0.008)	0.156***	(0.039)	0.159***	(0.022)
Labor^2	0.228***	(0.020)	0.237***	(0.065)	0.243***	(0.043)
Capital^2	0.032***	(0.007)	0.034	(0.022)	0.101***	(0.019)
T	-0.002***	(0.002)	0.001	(0.004)	0.009	(0.008)
T^2	0.001***	(0.000)	0.001	(0.000)	0.000	(0.001)
Material*T	0.010***	(0.001)	0.010**	(0.004)	0.002	(0.003)
Labor*T	-0.010***	(0.001)	-0.010***	(0.004)	0.002	(0.004)
Capital*T	-0.000	(0.001)	-0.001	(0.002)	-0.005*	(0.003)
Industry demand	0.329***	(0.085)	0.397***	(0.139)	0.690	(0.493)
Intercept	0.000	(0.001)	-0.164***	(0.020)	-0.106**	(0.048)
Observations	1,324		1,324		1,324	
R^2 overall^2			0.978		0.981	
R^2 within			0.839			
R^2 between			0.983			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Through the transformation of variables, a reliable goodness of fit measure of FEGLS cannot be reported. A pseudo R^2 would not be bounded between 0 and 1.
Source: Author's calculations from German Brewers Association (GBA) data

TABLE 5: Estimated markups and input factor elasticities – full sample

Variable	Mean	Median	Min	Max	Std. err.
Elasticity material	0.571	0.569	0.251	1.187	0.181
Elasticity labor	0.654	0.660	-0.082	1.062	0.221
Elasticity capital	0.064	0.066	-0.051	0.220	0.028
Returns to scale	1.290	1.287	1.205	1.382	0.415
General markup	1.650	1.599	0.752	3.977	0.521

Standard errors reported are derived by bootstrapping using 1,000 replications.
Source: Author's calculations from German Brewers Association (GBA) data

[1] In October 2016 SABMiller was acquired by Anheuser-Busch InBev.

[2] According to Kirin Holding Company (2017) the country ranking of per-capita beer consumption in 2014 was led by Czech Republic (142.6 liter per-capita) followed by Seychelles (114.6 liter), Austria (104.8 liter), Germany (104.7 liter) and Namibia (104 liter).

[3] Markets under monopolistic competition are often characterized by high marketing expenditures. In the last decade, the German brewing sector spent annually approximately € 375 million, or 4.7% of the sector's total revenues on marketing (Statista, 2017c). After sweets and milk, the brewing industry exhibits the third highest marketing expenditures and accounts for 12% of all marketing expenditures in the food and beverages sector (Zühlsdorf and Spiller, 2012).

[4] De Loecker (2011a) uses a very similar approach and derives segment specific demand elasticities while allowing for multiproduct firms.

[5] The German Brewers Association (Deutscher Brauer-Bund) was founded in 1871 and is an umbrella organization comprised of the most important professional federations of the German brewing sector, e.g. the Bavarian Brewers Federation (Bayerischer Brauerbund

e.V.) and the Federation of Export Breweries of North-, West and Southwest Germany (Verband der Ausfuhrbrauereien Nord-, West- und Südwestdeutschlands e.V.).

[6] As firms participate voluntarily in the program, we neither have information about firms' motivation to participate nor why they enter or exit the sample. Hence, we have to assume that participation in the program is random and uncorrelated with firms' levels of inputs and outputs. If this is not the case, estimated production elasticities are biased. Olley and Pakes (1996) for example raise concerns of a possible correlation between the firms' decisions to enter and exit a sector and the size of their capital stock.

[7] According to a brewing industry expert, the set of components included in the variable material is a good representation of a brewery´s variable costs.

[8] Please note that since (11) is a reduced form equation of production and demand, t and t^2 may also capture shifts in demand, e.g. a general trend of decreasing beer consumption. If this is the case, we are no longer able to identify technological change separately. However, this is not the aim of this study.

TABLE 6: Hypothesis testing

Null hypothesis	Critial values						Result
	Lower 5%	Upper 5%	Lower 2.5%	Upper 2.5%	Lower 1%	Upper 1%	Result (sig. level)
General markup: $H_0: \bar{\mu} - 1 = 0$	0.199	1.960	0.132	2.630	0.031	3.337	Rejected (1%)
Difference between general and demand-driven markup: $H_0: \bar{\mu} - \mu_\eta = 0$	0.014	0.429	-0.018	0.501	-0.081	0.708	Rejected (10%)
No profits from product differentiation: $H_0: P/AC - 1 = 0$	0.090	0.240	0.075	0.259	0.050	0.289	Rejected (1%)
Difference between size classes $H_0: \bar{\mu}_{\bar{Q}_i > 50,000} - \bar{\mu}_{\bar{Q}_i \leq 50,000} = 0$	-0.579	-0.074	-0.642	-0.031	-1.017	0.057	Rejected (5%)
Difference in general markup between regions: $H_0: \bar{\mu}_{Bavaria} - \bar{\mu}_{Rest} = 0$	-0.292	-0.011	-0.326	0.016	-0.468	0.086	Rejected (10%)
Difference in demand-driven markup between regions: $H_0: \mu_{\eta_{Bavaria}} - \mu_{\eta_{Rest}} = 0$	-0.295	0.657	-0.295	0.853	-0.295	0.853	Not rejected

Source: Author's calculations from German Brewers Association (GBA) data

TABLE 7: Estimated markups by year

Year	No. obs.	Mean	Median	Std. err.
1996	99	1.330	1.252	0.449
1997	114	1.403	1.329	0.461
1998	126	1.502	1.415	0.492
1999	122	1.577	1.500	0.513
2000	121	1.636	1.593	0.524
2001	114	1.629	1.539	0.517
2002	110	1.689	1.596	0.533
2003	103	1.801	1.712	0.557
2004	97	1.761	1.689	0.544
2005	88	1.797	1.767	0.561
2006	83	1.918	1.842	0.603
2007	78	1.891	1.741	0.591
2008	69	1.757	1.599	0.549
Total	1324	1.650	1.599	0.521

Standard errors reported are derived by bootstrapping using 1,000 replications.
Source: Author's calculations from German Brewers Association (GBA) data

TABLE 8: Estimated markups by firm-size class (in hl)

Size Class	N	Mean(μ)	Std. err. (μ)
$\bar{Q}_i \leq$ 25,000	336	1.403	0.475
25,000 < $\bar{Q}_i \leq$ 50,000	288	1.588	0.505
50,000 < $\bar{Q}_i \leq$ 100,000	322	1.667	0.525
$\bar{Q}_i$ > 100,000	378	1.904	0.601
Total	1324	1.650	0.521

$\bar{Q}_i = T^{-1}\sum_{t=1}^{T} Q_{it}\,, where\ Q = Output\ and\ i = 1, \dots, N.$

Standard errors reported are derived by bootstrapping using 1,000 replications.
Source: Author's calculations from German Brewers Association (GBA) data

TABLE 9: Estimated markups by region

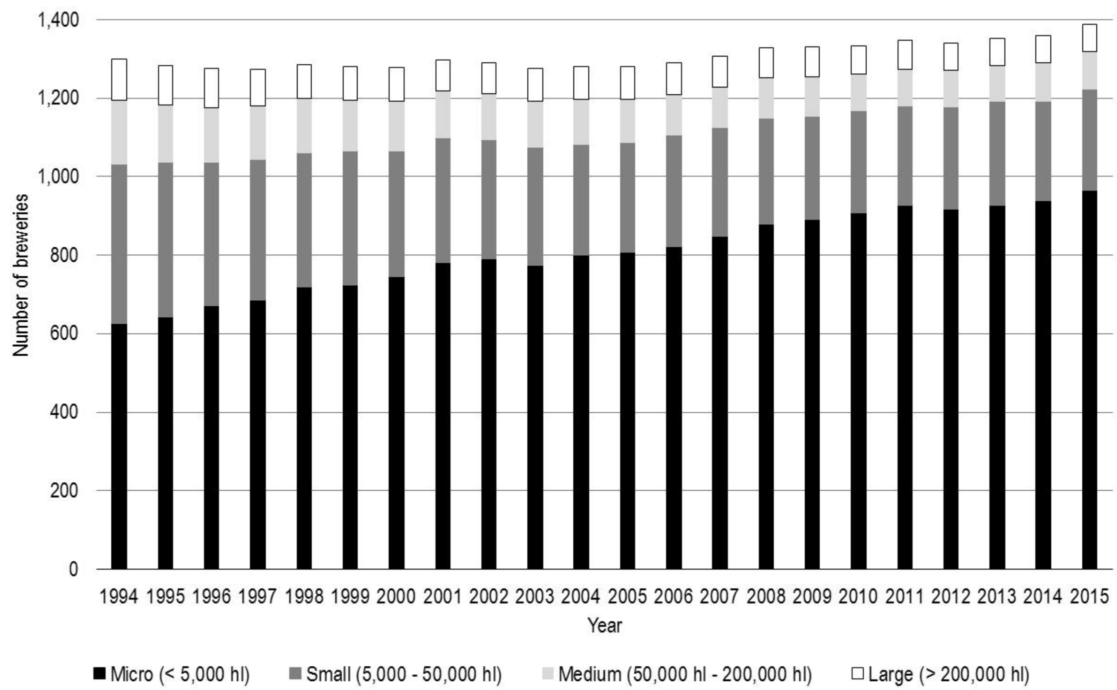
Region	No. obs.	Mean	Median	Std. err.
Baden-Württemberg	213	1.676	1.624	0.533
Bavaria	875	1.609	1.551	0.509
Northrhine Westfalia	174	1.738	1.668	0.555
Other	62	1.902	1.869	0.601
Total	1324	1.650	1.599	0.521

Standard errors reported are derived by bootstrapping using 1,000 replications.
Source: Author's calculations from German Brewers Association (GBA) data

TABLE 10: Estimated parameters of equation (11) utilizing FEGLS – Bavaria and rest of Germany

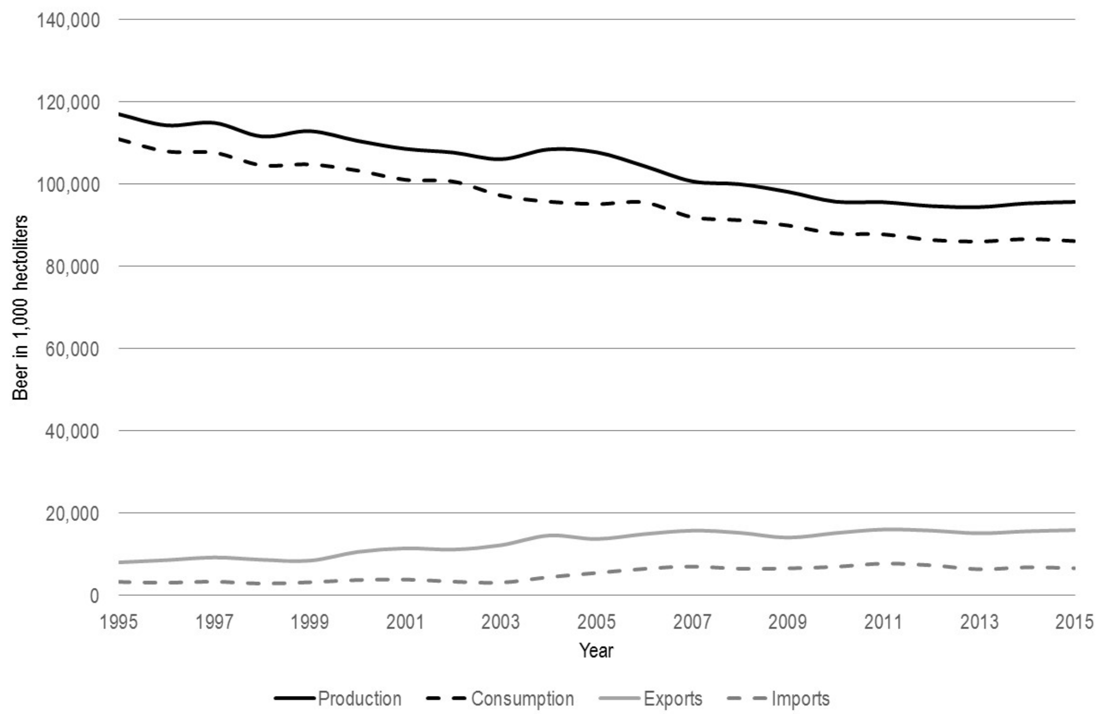
	Bavaria	Std.err.	Rest of Germany	Std.err.
Material	0.318***	(0.014)	0.368***	(0.022)
Labor	0.446***	(0.016)	0.571***	(0.026)
Capital	0.078***	(0.008)	0.029***	(0.011)
Material*Labor	-0.218***	(0.032)	-0.183***	(0.018)
Material*Capital	0.031**	(0.015)	0.025*	(0.013)
Labor*Capital	-0.040***	(0.013)	-0.044***	(0.016)
Material^2	0.173***	(0.035)	0.179***	(0.018)
Labor^2	0.273***	(0.038)	0.214***	(0.037)
Capital^2	0.038***	(0.010)	0.013	(0.013)
T	-0.002	(0.002)	-0.001	(0.002)
T^2	0.001***	(0.000)	0.001***	(0.000)
Material*T	0.008***	(0.001)	0.009***	(0.002)
Labor*T	-0.006***	(0.001)	-0.015***	(0.002)
Capital*T	-0.000	(0.001)	0.001	(0.001)
Industry Demand	0.289***	(0.104)	0.229*	(0.138)
Intercept	0.000	(0.001)	-0.000	(0.001)
Observations	875		449	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Author's calculations from German Brewers Association (GBA) data



Source: Authors' illustration based on Deutscher Brauerbund (2017)

Figure 1: Number of breweries in Germany by class-size: 1994- 2015



Source: Authors’ illustration based on Private Brauereien Bayern e.V. (2016)

Figure 2: Production, consumption, export, and import of beer in Germany in 1,000 hl: 2005- 2015.

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FOOTNOTES