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Diskussionspapier
DP-73-2019
Institut für Nachhaltige Wirtschaftsentwicklung

Juli 2019

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Abstract

The beer market in Germany may be described as a monopolistic competition with many breweries supplying a very large variety of different beer styles and brands. Advertising is one means of differentiating a product and increasing prices over marginal costs. Based on production data obtained from a sample of 197 German breweries and thirteen years of observation, we derive firm-specific markups, profit ratios and prices in each year and relate those to their advertising expenditures and firm size. We are able to show that advertising expenditures are positively correlated to a brewery's markup, profit ratio and price while firm size is negatively correlated.

Keywords: advertising, markup, imperfect competition, brewing

JEL: D22, L11, L66

Declarations of interest: none.

1 Introduction

German breweries invest heavily in promoting their beer. While domestic consumption has steadily decreased from a peak of 114.4 million hectoliters (hl) in 1992 to 83.6 million hl in 2017, advertising expenditures have been relatively stable over the last two decades, fluctuating around a mean of 375 million euro and peaking at 416 million euros in 2017 (Deutscher Brauerbund E.V. 2018; Statista 2019). Given an output of approximately 93 million hl and revenues of 7.843 billion euros, German breweries invested, on average, more than 4 euros per hl, or more than 5% of their revenues on advertising in 2017 (Deutscher Brauerbund E.V. 2018). Moreover, the German beer industry spends more on marketing campaigns than double the sum spent by all producers of other alcoholic beverages (Statista, 2019). After sweets and milk, the brewing industry has the third-highest marketing expenditures, and accounts for 12% of all marketing expenditures in the food and beverages sector (Zühlsdorf and Spiller, 2012).

The theoretical literature addressing the economics of advertising is dominated by two conflicting views. Advertising is seen as either being informative or persuasive.[1] Early contributions on this topic go back to Marshall (1919) and Chamberlin (1933); both assert that advertising can convey important information to the consumer and can increase demand but can also be a way to redistribute market shares towards the advertising firm. The second observation is the basis for the persuasive view, which is rooted in Chamberlin's (1933) theory of monopolistic competition and product differentiation. Advertising alters consumer preferences and leads to perceived product differentiation and brand loyalty. Brand loyalty may also create barriers of entry and higher market concentration (Bain, 1949). Through advertising, demand for a firm's product becomes more inelastic and its price increases. Hence, the persuasive view suggests that advertising can have important anti-competitive effects (Bagwell, 2007).

The informative view is largely associated with the Chicago school of economics. The basic contention of this view is that advertising directly or indirectly provides consumers with useful information about the existence, prices and characteristics of products. For example, in the Stigler model (1961), price dispersion is the result of high costs to consumers of obtaining information in regard to the existence, location and prices of products. Advertising directly conveys such information to consumers, thereby lowering search costs and price dispersion. Nelson (1970, 1974) develop a theoretical framework in which the indirect information contained in advertising is important, especially in the case of experience goods. By its willingness to spend on advertising, a firm signals efficiency (low cost) or high quality of their products to consumers. Hence, the informative view suggests advertising helps to overcome market imperfections through information and leads to a more elastic demand. This suggests that advertising can have important pro-competitive effects (Bagwell, 2007).

In this light, the aim of this paper is to evaluate whether advertising adds to a firm's markup, profit ratio and price in the German brewing industry. More specifically, we test whether, on average, a firm's markup, profit ratio and price are correlated to its advertising intensity, which is captured by the ratio of a brewery's marketing expenses to output. While a firm specific price index can be directly derived from our dataset, we recover firms' markups and profit ratios using production data. This approach enables the collection of firm performance measures without needing detailed demand data. Relying on firms' cost minimization behavior and the insight that factor output elasticities equal factor expenditures, we then estimate firm level markups (price over marginal costs) using an approach developed by De Loecker and Warzynski (2012) (henceforth DLW), who extended previous work by Hall (1988). Any firm's profit ratio (price over average costs) is derived based on the markup and a firm's returns to scale (Crépon et al., 2005). To recover output elasticities and returns to scale, we estimate the production function using the framework developed by Wooldridge (2009), and Levinsohn and Petrin (2003) (henceforth WDG), and the method proposed by

Ackerberg et al. (2015) (henceforth ACF). These semiparametric procedures respond to the endogeneity problem between unobserved firm productivity and input levels by imposing a structure on the production process that allows using the lag values of input factors as instruments. In contrast to the widely used value-added specification, we rely on a gross output production function to enable us to recover the output elasticity of the most flexible input factor material. This is important for recovering unbiased markups and profit ratios. Additionally, we use a translog functional form to model the production process of firms in a flexible manner, thus diverging from the majority of applications using the standard Cobb-Douglas form. The WDG framework in particular has not been used to the best of our knowledge to estimate a translog production function specified as gross output. Subsequently, we regress calculated markups, profit ratios and prices on advertising intensity, while controlling for other important firm characteristics.

Most of the literature studies the impact of advertising on the beer market (and other alcoholic beverages) on an aggregated level. In particular, these studies examine the influence of advertising on aggregated beer demand. Most of these studies find little evidence that advertising boosts beer consumption. This is confirmed by authors such as Lee and Tremblay (1992), Nelson and Moran (1995), Nelson (1999), Wilcox and Gangadharbatla (2006) and Wilcox et al. for the U.S. beer (alcoholic beverages) market. Calfee and Scheraga (1994) find similar results in their literature review and study for several European countries. Nelson and Moran's (1995) statements are representative of this literature when they conclude "that advertising does not affect total consumption", therefore "alcohol beverage advertising serves to reallocate brand sales". However, "there may be welfare effects of advertising associated with market power and industry structure". Using more disaggregated brand-level data, Heimonen and Uusitalo (2009) find a low overall impact of advertising expenses on the market shares of beer brands, while controlling for prices in the Finnish beer market. We add to this literature by directly relating a firm's advertising efforts to its markups, profit ratios and prices. Instead of the widely used demand-side approach, we estimate markups using production data.

The remainder of this article is organized as follows. Section 2 provides a short overview of the German brewing industry. Section 3 presents the framework for determining to recover markups and profit ratios, and Section 4 provides the empirical model. Our dataset is described in Section 5, and the results are presented in Section 6. We discuss our findings in the concluding section.

2 Industry background

Beer is deeply rooted in German culture. With 93,013 million hl in annual production, Germany is the fifth-largest beer-producing nation in the world, topped only by China, the USA, Brazil and Mexico. At the same time, with approximately 100 liters of per capita consumption, Germans are third in beer consumption after the Czechs and Austrians (Kirin Holdings Company, 2018). Nevertheless, beer production declined by 23%, from approximately 120 million hl in 1991 to 93 million hl in 2017. Just as in other beer-drinking countries such as Belgium, the UK or the USA, per capita beer consumption also decreased substantially in Germany over the last 30 years. Between 1976 (when per capita beer consumption reached a peak of 150 liters per year) and 2017, the average German's beer consumption dropped by almost 50% (Deutscher Brauerbund E.V., 2012, 2018). Due to the high transportation costs for bulky beer bottles and kegs, exports and imports are typically only a small fraction of production (Adams, 2006). This also applies to the German beer market, where beer consumption closely followed production volumes between 1990 and 2015. Although net exports increased by approximately 4.1 million hl between 1995 and 2017, this was not enough to compensate for the decrease in domestic demand.

Unlike most other countries, Germany's beer market is still characterized by a relatively low market concentration. While the top five brewing groups (AB-InBev, Heineken, China

Resources Snow Breweries, Carlsberg, Molson-Coors Brewing) account for 60% of global beer production (Barth-Haas Group, 2018), only two of the five worldwide market leaders rank among Germany's top ten breweries (AB-InBev is second and Carlsberg is tenth), accounting for less than 10% of German beer production (Stern, 2018). In fact, in the last two decades, the number of breweries has slightly increased from 1,282 in 1995 to 1,408 in 2016, although the number of firms increased only within the group of very small breweries (less than 5,000 hl in annual production) (Deutscher Brauerbund E.V., 2017). Although the number of breweries is still high, there has been some evidence of collusive behavior. The German federal cartel office (Bundeskartellamt) imposed fines for price-fixing agreements between 11 breweries that occurred in 2006 and 2008, and for vertical price-fixing agreements between food retailers and AB-Inbev in 2006 and 2009 (Bundeskartellamt, 2014, 2016). Moreover, German breweries are permitted to integrate vertically, allowing them to tie pubs, restaurants and cafés to their products by providing them with equipment or financial credit (Brouwer, 2013).

It has been argued that Germans greatly prefer "local" beer (Scherer et al. 1975; Adams, 2006). Different beer styles corresponding to certain German regions have emerged over time. Accordingly, German consumers are highly loyal towards regional beer brands (Empen et al., 2012). In addition to preferences concerning style and origin, consumers have a high degree of brand awareness, which is reflected in the large price differences in beers from different breweries (Loy and Glauben, 2015). This is particularly true in the large and relatively homogeneous pilsner beer segment, where producers may signal quality by their prices. Advertising efforts allow producers to underscore perceived quality differences and transfer regionalism to their customers. This outcome is in line with Madsen and Wu (2016), who argue that even if there are few real product differences in the lager segment, there a large differences in consumers' perceptions of quality. Furthermore, Karagiannis et al. (2017) have found that German brewers, on average, price their beers above marginal cost and that a significant part of that price-cost wedge is due to product differentiation.

3 A framework to recover markups and profit ratios

Following DLW, firm i's production technology in period t is represented by the production function

$$Q_{it} = F_{it}(\boldsymbol{X}_{it}, K_{it}, \omega_{it}), \tag{1}$$

where Q_{it} represents output, $\boldsymbol{X}_{it}$ captures all freely adjustable inputs and capital K_{it} is assumed to be fixed in period t. Unobserved productivity, which adds to the level of output, is denoted by ω_{it}. We assume firms minimize their costs by choosing their optimal levels of variable inputs, resulting in the following optimization problem.

$$\min_{\boldsymbol{X}_{it}} \mathcal{L}_{it} = \boldsymbol{W}_{it}\boldsymbol{X}_{it} + r_{it}K_{it} - \lambda_{it}(F_{it}(\boldsymbol{X}_{it}, K_{it}, \omega_{it}) - \bar{Q}_{it}) \tag{2}$$

The vector $\boldsymbol{W}_{it}$ captures prices of variable inputs and r_{it} is the price of capital. From the first-order condition for variable input v, we derive

$$\frac{\partial F_{it}(\boldsymbol{X}_{it}, K_{it}, \omega_{it})}{\partial X_{it}^{v}} \frac{X_{it}^{v}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{W_{it}^{v} X_{it}^{v}}{Q_{it}}, \tag{3}$$

where the Lagrangian multiplier λ_{it} can be interpreted as marginal cost at output level $\bar{Q}_{it}$ and, hence, markup μ_{it} is defined as firm i's output price in period t, denoted by P_{it}, over marginal costs: $\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}}$. Denoting the share in revenues of variable input v as $\alpha_{it}^{v} = \frac{W_{it}^{v} X_{it}^{v}}{P_{it} Q_{it}}$, we can derive a markup measure by rearranging the first-order conditions as

$$\mu_{it}^{v} = \frac{\theta_{it}^{v}}{\alpha_{it}^{v}}, \tag{4}$$

i.e., as the ratio of the output elasticity $\theta_{it}^{v} = \frac{\partial F_{it}(\boldsymbol{X}_{it}, K_{it}, \omega_{it})}{\partial X_{it}^{v}} \frac{X_{it}^{v}}{Q_{it}}$ to the share of revenues of variable input v. Under perfect competition, a firm's output elasticity is equal to its revenue share and $\mu_{it}^{v} = 1$. Under any form of imperfect competition, the relevant markup drives a wedge between the input's revenue share and its output elasticity resulting in $\mu_{it}^{v} > 1$. Using our markup measure, we are able to recover the profit ratio defined as $\psi_{it} \equiv \frac{P_{it}}{AC_{it}}$. Following Crépon et al. (2005), we calculate ψ_{it} as

$$\psi_{it} = \frac{\mu_{it}^{v}}{\delta_{it}}, \tag{5}$$

where $\delta_{it} = \sum_{v} \theta_{it}^{v}$ captures returns to scale.

4 Empirical model

Based on (**Fehler! Verweisquelle konnte nicht gefunden werden.**) and (5), we can calculate every firm i's respective markup and profit ratio for any period t. Data on individual firms' revenues and input costs are available in most firm-level datasets and enable us to calculate α_{it}^{v}. Moreover, θ_{it}^{v} is obtained through the estimation of a production function with common technology parameters across a set of producers:[2]

$$y_{it} = f(\boldsymbol{x}_{it}, k_{it}; \boldsymbol{\beta}) + \omega_{it} + \varepsilon_{it}. \tag{6}$$

Small letters denote variables in logs and y_{it} is a proxy for q_{it} including a measurement error ε_{it}. The coefficients to be estimated including an intercept are collected in vector $\boldsymbol{\beta}$. While ε_{it} captures unobserved i.i.d. shocks to production, ω_{it} represents productivity differences across firms and time. In practice, the latter are unobserved by the econometrician and include managerial ability. We assume Hicks-neutral technical change; i.e., the productivity term ω_{it} does not change the balance of input usage and is therefore captured by a scalar. This framework embeds various functional representations of production technologies including the transcendental logarithmic form (Christensen et al., 1973) and its special case, the Cobb-Douglas form (Cobb and Douglas, 1928).

4.1 Previous literature on production function estimation

As already discussed by Marschak and Andrews (1944), there is a potential correlation between input levels $\boldsymbol{x}_{it}$ and the unobserved firm-specific productivity ω_{it}; i.e., firms that have a large positive productivity shock may respond by using more inputs. Hence, OLS will produce biased parameter estimates.[3] The most prominent of the "traditional" solutions to the problem include fixed effects estimation (Mundlak, 1961; Hoch, 1962) and instrumental variable estimation (Griliches and Mairesse, 1998). While the former approach relies on the assumption that unobserved productivity is time invariant (such that $\omega_{it} = \omega_i,\ i = 1 \dots N$), identification using the latter requires appropriate instruments for the production factors that are often not available in practice. According to Griliches and Mairesse (1998), the time invariant error assumption may cause unreasonably low estimates of the capital coefficient. Based on the findings of the latter, Gandhi et al. (2017) conclude that both standard techniques are "theoretically problematic and unsatisfactory".

More recent contributions aimed at solving the endogeneity problem in production function estimation explicitly model firm behavior and can be categorized in two strands: dynamic panel data estimators (henceforth DP) (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 2000, 1998) and proxy methods (henceforth PM) (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009; ACF). Both, DP and PM rely on placing stringent assumptions on the production process, and allow for the use of lagged inputs as instruments for current inputs. A priori beliefs about the timing of a firm's input use (i.e., costs of adjusting inputs) are an integral part of these assumptions and constitute a major distinction between DP and PM. While identification relies on the assumption of costly input adjustment in the DP literature, PM requires at least one flexible input (Bond and Söderbom, 2005; Petrick and Kloss, 2018). Moreover, input adjustment is allowed to take multiple periods in the DP but is restricted to one period in PM. In addition, assumptions differ with regard to productivity evolution in that DP imposes a linear structure, whereas it may evolve arbitrarily in PM (Petrick and Kloss, 2018).[4] In our application, it is hard to justify material use that is chosen by means of a dynamic optimization problem, possibly over several periods, and we therefore focus on PM in the rest of this section.

The first contribution to the PM literature was made by Olley and Pakes (1996) (henceforth OP). They provide a semiparametric estimator that is consistent under the presence of simultaneity and selection problems, and allows the relaxation of the assumption of time invariant unobserved productivity without relying on external instruments.[5] To identify unbiased production function parameters, OP exploit the firms' investment decisions, allowing the use of investment spending as proxy for unobserved productivity.

Levinsohn and Petrin (2003) (henceforth LP) point out that the application of the OP framework is only valid for firms with positive investment spending. It is therefore problematic to utilize the OP algorithm using a dataset that contains a significant number of companies with zero investment. LP suggest using intermediate inputs (where zero values are unlikely) as a proxy for productivity.

Wooldridge (2009) (henceforth WDG) introduced a framework with a single step for estimating the two-stage OP and LP procedures. Unlike the two-step estimation in the original OP and LP work, the WDG estimator accounts for correlation between errors of the equations resulting in efficiency gains. Furthermore, standard errors robust to heteroscedasticity and serial correlation are easily obtained without the need for bootstrapping.

ACF argue that labor input is functionally dependent on the intermediate input in LP (investments in OP) and capital in the first stage of the LP (OP) estimation algorithm, and therefore labor is not identified in the first stage of LP (OP).[6] ACF propose an alternative procedure to avoid the functional dependence problems. Using Monte Carlo simulations, they show that their procedure, unlike OP and LP, consistently identifies the production function coefficients in several alternative data-generating processes.

To take advantage of the benefits of the WDG and the ACF procedures over the previous methods described in this section, we apply both to determine output elasticities. In addition, WDG and ACF allow for estimation of a more flexible functional form in $f(\boldsymbol{x}_{it}, k_{it}; \boldsymbol{\beta})$ than the OP and LP procedures, which is crucial for deriving firm-specific output elasticities. The use of a Cobb-Douglas function, assuming constant output elasticities across firms and over time, may lead to ascribing technological variation to variation in markups.

4.2 Specification of the production function

To obtain a reliable measure of markup as described in (**Fehler! Verweisquelle konnte nicht gefunden werden.**), it is vital that the input v, used for markup calculation, is free of adjustment costs. Markups calculated using capital output elasticities may suffer from upward bias since the wedge between a firm's output elasticity of an input and its cost share in revenues will also capture adjustment costs. We can assume markup estimates from labor are similarly flawed, as Germany continues to experience substantial hiring and firing costs (Yaman, 2011; Deloitte, 2018). Therefore, we utilize a gross output production function instead of the widely used value-added specification. This allows us to relax the assumption of a fixed material-output proportion in the production process and to base our markup estimations on material, the most flexible input.

To recover firm and time-specific markups, we specify a gross output production function of a translog functional form:

$$y_{it} = \beta_0 + \boldsymbol{r}_{it}\boldsymbol{\beta} + \omega_{it} + \varepsilon_{it} \tag{7}$$

with $\boldsymbol{r}_{it} = [l_{it} \quad k_{it} \quad m_{it} \quad l_{it}k_{it} \quad l_{it}m_{it} \quad k_{it}m_{it} \quad l_{it}^2 \quad k_{it}^2 \quad m_{it}^2]$ and $\boldsymbol{\beta} = [\beta_l \quad \beta_k \quad \beta_m \quad \beta_{lk} \quad \beta_{lm} \quad \beta_{km} \quad \beta_{ll} \quad \beta_{kk} \quad \beta_{mm}]'$.

4.3 Estimation using the Wooldridge (2009) and Levinsohn and Petrin (2003) framework

Our starting point for the WDG framework is an LP setup. Therefore, it is assumed that a firm's demand for intermediate inputs m_{it} is determined by k_{it} and ω_{it}, resulting in

$$m_{it} = \kappa_t(k_{it}, \omega_{it}).^{7} \tag{8}$$

Given that κ_t is strictly increasing in ω_{it}, unobserved productivity can be expressed as a function of capital and the intermediate input:

$$\omega_{it} = \kappa_t^{-1}(k_{it}, m_{it}). \tag{9}$$

Substituting for ω_{it} in (7), we can specify the first equation to identify $\boldsymbol{\beta}$.

$$y_{it} = \beta_0 + \boldsymbol{r}_{it}\boldsymbol{\beta} + \kappa_t^{-1}(k_{it}, m_{it}) + \varepsilon_{it} \tag{10}$$

We assume that productivity follows a first-order Markov exogenous process, that is,

$$\omega_{it} = E(\omega_{it}|\omega_{it-1}) + \xi_{it} = h(\omega_{it-1}) + \xi_{it}, \tag{11}$$

where ξ_{it} is an i.i.d. error that can be interpreted as the technical progress. We capture productivity using (9) and (11) and substitute for ω_{it} in (7) to form the second identifying equation

$$y_{it} = \beta_0 + \boldsymbol{r}_{it}\boldsymbol{\beta} + h[\kappa_t^{-1}(k_{it-1}, m_{it-1})] + \xi_{it} + \varepsilon_{it}. \tag{12}$$

Identifying the parameters by jointly estimating (10) and (12) requires to deal with the unknown functions κ_t^{-1} and h. [8]. The WDG framework allows for a polynomial approximation up to an arbitrarily high degree for both functions, such that κ_t^{-1} can be expressed as

$$\kappa_t^{-1}(k_{it}, m_{it}) = \lambda_0 + \boldsymbol{c}_{it}(k_{it}, m_{it})\boldsymbol{\lambda}. \tag{13}$$

Hereby, all K terms resulting from the polynomial approximation are collected in the $1 \times K$ vector $\boldsymbol{c}_{it}$ and the corresponding coefficients in the $K \times 1$ vector $\boldsymbol{\lambda}$. The function h can be approximated by a polynomial in ω_{it-1} up to order G:

$$h(\omega_{it-1}) = \rho_0 + \rho_1\omega_{it-1} + \cdots + \rho_G\omega_{it-1}^{G}. \tag{14}$$

We approximate $\kappa_t^{-1}(k_{it}, m_{it})$ by a third-order polynomial and assume that productivity follows a random walk with drift, which restricts $G = 1$ and $\rho_1 = 1$.[9] Substitution of κ_t^{-1} and h in (10) and (12) yields

$$y_{it} = \delta_0 + \boldsymbol{r}_{it}\boldsymbol{\beta} + \boldsymbol{c}_{it}\boldsymbol{\lambda} + \varepsilon_{it} \tag{15}$$

and

$$y_{it} = \zeta_0 + \boldsymbol{r}_{it}\boldsymbol{\beta} + \boldsymbol{c}_{it-1}\boldsymbol{\lambda} + \nu_{it} \tag{16}$$

where $\delta_0 = \beta_0 + \lambda_0$, $\zeta_0 = \beta_0 + \lambda_0 + \rho_0$ and $\nu_{it} = \xi_{it} + \varepsilon_{it}$. Instruments for the first equation are

$$\boldsymbol{z}_{it1} = [1 \quad \boldsymbol{r}_{it} \quad \boldsymbol{c}_{it} \quad \boldsymbol{c}_{it-1} \quad \boldsymbol{w}_{it-1}], \tag{17}$$

where $\boldsymbol{w}_{it-1} = [l_{it-1} \quad l_{it-1}^2 \quad l_{it-1}m_{it-1} \quad l_{it-1}k_{it} \quad k_{it}m_{it-1}]$.[10] Instruments for the second equation are

$$\boldsymbol{z}_{it2} = [1 \quad \boldsymbol{r}_{it}^0 \quad \boldsymbol{c}_{it-1}], \tag{18}$$

where $\boldsymbol{r}_{it}^0$ is the second-order polynomial of l_{it-1}, m_{it-1} and k_{it}. We choose a matrix of instruments for every firm i in every period t:

$$\boldsymbol{Z}_{it} = \begin{pmatrix} \boldsymbol{z}_{it1} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{z}_{it2} \end{pmatrix}. \tag{19}$$

Finally, we state the moment conditions required for GMM estimation as

$$E\left[\boldsymbol{Z}_{it}' \begin{pmatrix} \varepsilon_{it}(\delta_0, \boldsymbol{\beta}, \boldsymbol{\lambda}) \\ \nu_{it}(\zeta_0, \boldsymbol{\beta}, \boldsymbol{\lambda}) \end{pmatrix}\right] = 0. \tag{20}$$ [11]

4.4 Estimation using the Ackerberg, Caves and Frazer (2015) procedure

In accordance with the ACF approach, we assume material demand to be a function of l_{it} in addition to k_{it} and ω_{it}. However, as we use a gross output specification, we have to depart from the value-added ACF procedure and include additional material demand shifters (i.e., variables that lead to differences in input demand across firms in κ_t. [12] We use the firms' average wage rate (per annum), since it is an argument in the conditional input demand function of a cost-minimizing firm, and the share of beer firm i produced under its own brand as shifters in m_{it}, and collect them all in vector $\boldsymbol{u}_{it}$. Therefore, material input demand is given by

$$m_{it} = \kappa_t(k_{it}, l_{it}, \omega_{it}, \boldsymbol{u}_{it}). \tag{21}$$

Assuming strict monotonicity of ω_{it} in m_{it}, we can invert κ_t to obtain

$$\omega_{it} = \kappa_t^{-1}(k_{it}, l_{it}, m_{it}, \boldsymbol{u}_{it}). \tag{22}$$

We give up on identifying any production function parameters in the first stage and therefore rewrite (7) replacing ω_{it} by (22); that is:

$$y_{it} = \varphi_{it}(k_{it}, l_{it}, m_{it}, \boldsymbol{u}_{it}) + \varepsilon_{it}, \tag{23}$$

where $\varphi_{it}(k_{it}, l_{it}, m_{it}, \boldsymbol{u}_{it}) = \beta_0 + \boldsymbol{r}_{it}\boldsymbol{\beta} + \kappa_t^{-1}(k_{it}, l_{it}, m_{it}, \boldsymbol{u}_{it})$. We use a third-order polynomial to approximate φ_{it}. The predicted value of the latter, $\hat{\varphi}_{it}$, represents produced output that is unaffected by the i.i.d. production shock ε_{it}.

The coefficients in $\boldsymbol{\beta}$ are identified in the second stage forming appropriate moment conditions and exploiting the law of motion in productivity. For any values in $\boldsymbol{\beta}$, productivity ω_{it} can be written as

$$\omega_{it} = \hat{\varphi}_{it} - \beta_0 - \boldsymbol{r}_{it}\boldsymbol{\beta}^*, \tag{24}$$

where $\boldsymbol{\beta}^*$ is a vector of candidate values for $\boldsymbol{\beta}$. Similar to the WDG framework, we assume that productivity follows the first-order Markov exogenous process in (11) and approximate h by a third-order polynomial in ω_{it-1}. We form independent moment conditions on ξ_{it} making use of (11) and (24) as

$$E[\boldsymbol{z}_{it}\xi_{it}(\boldsymbol{\beta})] = 0, \tag{25}$$

where the vector $\boldsymbol{z}_{it}$ captures all instruments. The choice of elements in $\boldsymbol{z}_{it}$ reflects the assumptions on input timing. We consider capital to be a dynamic input that is chosen in period $t-1$, and material to be a flexible input chosen in period t. While LP consider both labor and material as flexible inputs chosen in period t, the ACF procedure allows making several assumptions about the timing of labor. The latter may be assumed to be dynamic and chosen in period $t-1$, flexible and chosen in period t, or chosen at $t-b$ (with $0 < b < 1$), which is a point of time in between. We assume that labor is chosen after $t-1$ and form moment conditions according to it:

$$z_{it} = \tag{26}$$

$$[1 \quad k_{it} \quad k_{it}^2 \quad l_{it-1} \quad l_{it-1}^2 \quad m_{it-1} \quad m_{it-1}^2 \quad k_{it}l_{it-1} \quad k_{it}m_{it-1} \quad l_{it-1}m_{it-1}]'.$$[13]

Using the instruments defined in $\boldsymbol{z}_{it}$, the moments in (25) are estimated using standard GMM techniques to obtain $\widehat{\boldsymbol{\beta}}$, and standard errors are calculated by block bootstrapping.

4.5 Relating markups, profit ratios and prices to advertising expenditures

To recover markups, we first derive output elasticities of the most flexible input factor M_{it}, denoted as $\hat{\theta}_{it}^{M}$ using estimated coefficients $\widehat{\boldsymbol{\beta}}$ as

$$\hat{\theta}_{it}^{M} = \hat{\beta}_{m} + 2\hat{\beta}_{mm}m_{it} + \hat{\beta}_{lm}l_{it} + \hat{\beta}_{km}k_{it}. \tag{27}$$[14]

To calculate the revenue share of material, we correct the output measure using the predicted error: $ln\mathrm{Q}_{it} = lnY_{it} - \hat{\varepsilon}_{it}$. The error ε_{it} might be correlated to factors that are not among the inputs or productivity, but still influence the level of output (e.g., input prices, technology parameters and market characteristics). Using the WDG framework, $\hat{\varepsilon}_{it}$ is obtained from the two-equation estimation. In the ACF procedure, the predicted error is obtained from the first stage (22) as $\hat{\varepsilon}_{it} = y_{it} - \hat{\varphi}_{it}$. The revenue share of material $\hat{\alpha}_{it}^{M}$ is determined by

$$\hat{\alpha}_{it}^{M} = \frac{W_{it}^{M}M_{it}}{P_{it}\frac{Y_{it}}{e^{\hat{\varepsilon}_{it}}}} \tag{28}$$

Substituting for α_{it}^{v} and θ_{it}^{v}, where $v = M$, by their respective predicted values $\hat{\alpha}_{it}^{M}$ and $\hat{\theta}_{it}^{M}$ in (**Fehler! Verweisquelle konnte nicht gefunden werden.**) enables the calculation of individual firms' markups for each year.

We recover profit ratios by substituting calculated markups and returns to scale, computed as $\hat{\delta}_{it} = \hat{\theta}_{it}^{L} + \hat{\theta}_{it}^{K} + \hat{\theta}_{it}^{M}$, in (5).

Lastly, to draw some inferences from a firm's markup and its advertising expenditure, we utilize the simple regression model

$$\ln \mu_{it}^{M} = \boldsymbol{x}_{it}\boldsymbol{\eta} + \sigma_{i} + \epsilon_{it}, \tag{29}$$

where the vector $\boldsymbol{x}_{it} = [1 \quad \ln ad_{it} \quad x_{it2} \quad \cdots \quad x_{itL}]$ captures the log of advertising intensity and other control variables. The corresponding coefficients are captured in $\boldsymbol{\eta} = [\eta_0 \quad \eta_{ad} \quad \eta_2 \quad \cdots \quad \eta_L]'$, where η_{ad} is our parameter of interest as it provides us with information on the relationship between the firms' advertising expenditures and markup size. Time-invariant firm characteristics are captured by σ_i and ϵ_{it} is an i.i.d. error term. We suspect advertising expenditures to be correlated with time-invariant firm characteristics such as differences in management or location. To get unbiased estimates under the presence of σ_i, we estimate the model using fixed-effects transformation. To get insight into the relationship between profit ratios and advertising intensity, and between prices and advertising intensity, we estimate (29) using $\ln \psi_{it}$ and $\ln P_{it}$ as dependent variables.

5 Data description

We employ an unbalanced panel of 197 German breweries that were participating in a voluntary benchmarking program conducted on behalf of the German Brewers Association over a 13-year period from 1996 to 2008, resulting in a total of 1,321 observations. Each firm is in the panel for at least two years and the median observation time is six years. Table 1**Fehler! Verweisquelle konnte nicht gefunden werden.** presents descriptive statistics of output, inputs, prices and advertising expenses. Physical output is measured in thousands of hectoliters and includes beer, beer-mix drinks (shandy) and non-alcoholic beverages. Our sample includes breweries producing between 4,000 and 2.5 million hl per year, with an average of 128,000 hl. It does not cover the very small brewery segment well (less than 10,000 hl). However, it includes almost one-third of all mid-size breweries in Germany (annual output between 50,000-500,000 hl), and approximately 23% of all breweries producing more than 10,000 hl. Most of our observations (82.2%) are located in Southern Germany (Bavaria, Baden-Württemberg).

A firm's output is given as revenue deflated by a firm-specific price index with 2005 as base year.[15] We build this firmspecific price index using detailed information in our dataset about revenues and quantities for different products, including beer with the firm's own brand, other beer, beer-mix drinks, and non-alcoholic beverages in kegs or bottles. Our price index is the weighted average of prices in these different categories, where we use their output shares as weights. By doing so, we are able to take into account any price dispersion between breweries and price changes over time, and create a quantity-type measure of output. As discussed by Klette and Griliches (1996) and Mairesse and Jaumandreu (2005), this avoids an omitted variable bias in the econometric estimation of the production technology, and provides more reliable estimates of output elasticities. Given that there is a considerable price dispersion ranging between €36.26 and €122.68, and an average of €78.24 per hl, this seems important.

We aggregate inputs into three variables: material including expenses for malt, barley, hops, water, and energy but also purchased goods and services, and labor measured by the total sum of all wages and capital including the year-end value of all machinery, equipment and buildings. Advertising expenditures consist of advertising costs, sponsorship costs and expenses for public relations work. Using appropriate price indices from the German Federal Statistical Office (Destatis), all the monetary values were deflated to base year 2005 values. The average (median) firm spent €4.96 (3.56) per hl in marketing activity. This fits quite well with the industry average of €4 per hl, as reported in the introduction. However, Table 1 also reveals that firms are quite heterogeneous in their advertising efforts, and expenses range from €0.18 to €27.41 per hl, with the 75% interval between €1.65 and €9.04.

6 Results

Table 2 depicts production function parameters based on the WDG and ACF estimation procedures. Although the underlying assumptions of these methods differ, their estimated labor, capital and material coefficients are very similar in magnitude. All standard errors of coefficients using the more efficient WDG framework are lower than those of the ACF procedure. With the exception of the ACF labor coefficient, all first-order effects are significantly different from zero, at least on a 5% level.

Utilizing the estimated production function coefficients, we calculate markups and several other firm-specific measures. Table 3 reports median values of output elasticities, returns to scale, markups and profit ratio. Calculated values do not differ considerably between methods. We report median output elasticities of approximately 0.5 for labor, 0.1 for capital and 0.5 for material. All median elasticities are significantly different from zero on a 5% level, except for labor calculated using ACF. Both estimation procedures suggest that the median firm’s technology is characterized by slightly increasing economies of scale of 1.096. Median markups account for 1.434 and 1.375 based on WDG and ACF estimation respectively and thus exceed one (1), the value corresponding to a perfectly competitive market. Although median values are relatively close, Figure 1 shows that the WDG framework produces markups with a larger tailed distribution than the ACF-based markups. This is also reflected in a larger interquartile range of 0.436 compared to 0.348 for the ACF-based markups. The density plot also shows that only a very small proportion of breweries is pricing below marginal cost, as the 5% percentile of the WDG-based markup is still above one (1). The 99% percentile on the other hand shows that some firms are able to drive a considerable wedge between price and marginal cost, as they are able to price at more than double the marginal cost. Subsequently, we calculate the firms’ profit ratios and report median values of approximately 1.306 and 1.261, based on output elasticities estimated using the WDG framework and the ACF method, respectively. Figure 2 shows that the distribution of markups is centered around a higher value than the distribution of the profit ratios, indicating a higher average markup than the average profit ratio. This suggests that the price-marginal cost wedges of firms are partly due to imperfect competition and partly due to firms not operating at their optimal level of scale.

Based on our markup estimates, we are able to make some inferences about the relationship between markup values and advertising expenditures. We must emphasize that we are not interpreting the estimated coefficient as a causal parameter, rather we try to test whether, on average, firms with higher advertising expenditures have different markups. Column 1 in Table **Fehler! Verweisquelle konnte nicht gefunden werden.** presents the results of our base specification, a fixed-effects model including advertising intensity (advertising expenditures per hl produced), physical output as a proxy for company size, and a time trend as right-hand side variables. The markup, advertising expenditures per hl, and firm size are all expressed in logarithms. We estimate a positive and statistically significant relationship between advertising and markups. On average, one percent more in advertising expenditures per hl is associated with a 0.045 percent higher markup. The coefficient on firm size is negative, which might be due to the more elastic residual demand curves of large-scale breweries. In column 2, we add the breweries' revenue shares from beer sold under their own private brands. Breweries with higher shares are producing less quantities of non-alcoholic beverages, and/or are brewing less beer as contract brewers (e.g., for other breweries or for retailers under their store brand). Therefore, a higher share may indicate a stronger private brand. Thus, we are able to reveal this variable's positive correlation with the markup. In another variation of our base specification, we follow DLW in controlling for total factor productivity to pick up variations in marginal costs across firms. Using the WDG framework, we predict a measure of productivity $\widehat{\widetilde{\omega}}_{it}$ from (14) as $\boldsymbol{c}_{it}\widehat{\boldsymbol{\lambda}}$.[16] In the ACF procedure, we recover productivity from (22) as $\widehat{\omega}_{it} = \widehat{\varphi}_{it} - \widehat{\beta}_0 - \boldsymbol{r}_{it}\widehat{\boldsymbol{\beta}}$. Adding the control variables described before only results in minor changes in advertising coefficients. Similar results (not presented) are obtained using the ACF procedure, with advertising coefficients ranging from 0.042 to 0.044. Therefore, they seem to be robust to the estimation procedure upon which the markup is based. In addition, we want to evaluate whether firms can increase their profit ratios and prices through advertising efforts. Table 5 shows a positive and significant relationship between profit ratio (price) and advertising intensity while controlling for firm size and quality. The estimated magnitudes are very similar to the one for the markup.

7 Discussion

Compared to most other countries in the world, the German beer industry has a relatively low concentration ratio. More than 1,400 independent breweries exist today. In many areas of Germany, but especially in the South (where most of the breweries in our sample are located), there is competition between multiple local breweries complemented by supply from national brands (e.g., Beck's, Krombacher and Warsteiner). On one hand, beer is a relatively homogeneous product, especially within one style of beer (Pils, Wheat, Lager, etc.). On the other hand, there is some evidence that consumers have preferences for specific brands (Galizzi and Garavaglia, 2012; Guinard et al., 2001) and/or for beer from their home region (Profeta et al., 2008). As for Germany, Empen and Hamilton (2013, 2015) and Loy and Glauben (2015) show that German consumers exhibit brand loyalty for "local" beers. Karagiannis et al. (2017) discuss that German breweries can exert market power through product differentiation. To foster brand loyalty and expand perceived quality gaps between products, German brewers invest heavily in marketing and may, in turn, increase their prices, markups and even profits. However, theoretical literature on advertising is ambiguous regarding the relationship between a company's marketing expenses and market power. Proponents of the informative view contend that advertising expenditures raise market transparency and, in turn, lower industry demand elasticity. Consequently, the average firms' price decreases, as do its markup and profit ratio. In the persuasive advertising literature, a firm uses advertising solely as a means to shift its demand curve outwards. The effect of advertising on prices, markups and profit ratios of a firm therefore depends on whether advertising is cooperative (resulting in an outward shift in industry demand) or predatory (shifting market share within the industry) (Rojas and Peterson, 2008). We rely on a method proposed by De Loecker and Warzynski (2012) to recover firm- and time-specific markups using production data. The method relies on firms' cost minimization behavior and exploits deviations in the output elasticity to revenue share ratio of a flexible input. To provide reliable estimates of output elasticity, we estimate a production function using the Wooldridge (2009) and Levinsohn and Petrin (2003) framework, along with the procedure suggested by Ackerberg, et al. (2015). Similar to our study, De Loecker and Scott (2016) estimate mean markups in the U.S. brewing sector that range from 1.5 to 1.9, while Grieco et al. (2018) estimate mean markups of large U.S. and Canadian brewers that range from 1.16 to 1.19. We find that our estimates fall in between those of Grieco et al. (2017) and De Loecker and Scott (2016), and although conditional on differing datasets and estimation methods, are in a comparable range.

We can confirm a significant positive relationship between advertising intensity and firm-level markups, profit ratio and price while controlling for firm size, quality, productivity, and time-invariant unobserved firm characteristics. We can interpret our positive coefficients as a sign that the German brewing market is characterized by persuasive advertising rather than informative advertising. Intuitively, this makes sense, as ingredients are very similar in German beers due to the German purity law. Moreover, the German beer market is not characterized by a large number of entries and exits, so most customers are aware of the brands that exist. We observe a significant negative effect of firm size on markups. One explanation might be that small local breweries or small breweries with specialty beers are able to create higher markups.

References

Ackerberg, D., Benkard, L., Berry, S., Pakes, A., 2007. Econometric tools for analyzing market outcomes, in: Heckman, J., Leamer, E. (Eds.), Handbook of Econometrics. North Holland, Amsterdam, pp. 4171–4276.

Ackerberg, D., Caves, K., Frazer, G., 2015. Identification properties of recent production function estimators. Econometrica 83, 2411–2451. https://doi.org/10.3982/ECTA13408

Adams, W.J., 2006. Markets: Beer in Germany and the United States. The Journal of Economic Perspectives 20, 189–205. https://doi.org/10.1257/089533006776526120

Arellano, M., Bond, S., 1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. The Review of Economic Studies 58, 277–297. https://doi.org/10.2307/2297968

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. Journal of Econometrics 68, 29–51. https://doi.org/10.1016/0304-4076(94)01642-D

Bagwell, K., 2007. The Economic Analysis of Advertising, in: Armstrong, M., Porter, R. (Eds.), Handbook of Industrial Organisation. Elsevier Ltd, Oxford, pp. 1701–1802.

Bain, J.S., 1949. A Note on Pricing in Monopoly and Oligopoly. The American Economic Review 39, 448–464.

Barth-Haas Group (2018), The Barth-Report. Barth & Sohn: Nuremberg. [WWW Document]. URL. https://www.barthhaasgroup.com/images/mediacenter/downloads/pdfs/412/barth-bericht20172018en.pdf

Belleflamme, P., Peitz, M., 2010. Industrial Organisation: Markets and Strategies. Cambridge University Press, Cambridge.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87, 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Blundell, R., Bond, S., 2000. GMM Estimation with Persistent Panel Data: An Application to Production Functions. Econometric Reviews 19, 321–340. https://doi.org/10.1080/07474930008800475

Bond, S., Söderbom, M., 2005. Adjustment costs and the identification of Cobb Douglas production functions (Working Paper No. 05/04). IFS Working Papers, Institute for Fiscal Studies (IFS). https://doi.org/10.1920/wp.ifs.2005.0504

Brouwer, M.T., 2013. The European Beer Industry: Concentration and Competition, in: de Jong, H.W. (Ed.), The Structure of European Industry. Springer Science & Business Media.

Bundeskartellamt, 2014. Kartellverfahren gegen Bierbrauer mit weiteren Geldbußen abgeschlossen [WWW Document]. URL https://www.bundeskartellamt.de/SharedDocs/Meldung/DE/Pressemitteilungen/2014/02_04_2014_FernsehbiereII.html (accessed 2.11.19).

Bundeskartellamt, 2016. Aktualisierter Fallbericht vom 14.12.2016: Bußgelder wegen vertikaler Preisabsprachen beim Vertrieb von Bier [WWW Document]. Bundeskartellamt. URL https://www.bundeskartellamt.de/SharedDocs/Entscheidung/DE/Fallberichte/Kartellverbot/2016/B10-20-15.html?nn=3591568 (accessed 2.11.19).

Calfee, J.E., Scheraga, C., 1994. The Influence of Advertising on Alcohol Consumption: A Literature Review and An Econometric Analysis of Four European Nations. International Journal of Advertising, 13, 287-310. http://dx.doi.org/10.1080/02650487.1994.11104586

Christensen, L.R., Jorgenson, D.W., Lau, L.J., 1973. Transcendental Logarithmic Production Frontiers. The Review of Economics and Statistics 55, 28–45. https://doi.org/10.2307/1927992

Cobb, C.W., Douglas, P.H., 1928. A Theory of Production. The American Economic Review 18, 139–165. https://www.jstor.org/stable/1811556

Crépon, B., Desplatz, R., Mairesse, J., Desplatz, R., 2005. Price-Cost Margins and Rent Sharing: Evidence from a Panel of French Manufacturing Firms. Annales d'Économie et de Statistique 583–610. https://doi.org/10.2307/20777589

De Loecker, J., Scott, P., 2016. Estimating market power: Evidence from the US brewing industry. Unpublished.

De Loecker, J., Warzynski, F., 2012. Markups and Firm-Level Export Status. The American Economic Review 102, 2437–2471. https://doi.org/10.1257/aer.102.6.2437

Deloitte, 2018. The International Dismissal Survey 2018 [WWW Document]. URL https://www2.deloitte.com/be/en/pages/tax/articles/Tax-Studies-and-Surveys-Deloitte-Tax/The-International-Dismissal-Survey.html (accessed 1.9.19).

Deutscher Brauerbund E.V., 2012. Bierverbrauch in Deutschland 1950 - 2011 [WWW Document]. URL https://www.brauer-bund.de/download/Archiv/PDF/statistiken/120319%20Bierverbrauch%20in%20Deutschland%20bis%20einschliesslich%202011%20-%20Homepage.pdf (accessed 7.05.19).

Deutscher Brauerbund E.V., 2017. Braustätten [WWW Document]. URL https://www.brauer-bund.de/download/Archiv/PDF/statistiken/2016_Braust%C3%A4tten.pdf (accessed 7.05.19).

Deutscher Brauerbund E.V., 2018. Deutsche Brauwirtschaft in Zahlen [WWW Document]. URL https://www.brauer-bund.de/download/Archiv/PDF/statistiken/STATIST%202017.pdf (accessed 2.11.19).

Empen, J., Glauben, T., Loy, J.P., (2012). Spatial Pricing Strategies for Beer in Germany. Unpublished

Empen, J., Hamilton, S., 2013. How Do Supermarkets Respond to Brand-Level Demand Shocks? Evidence from the German Beer Market. American Journal of Agricultural Economics 95, 1223–1229.

Empen, J., Hamilton, S., 2015. How Do Retailers Price Beer During Periods of Peak Demand? Evidence from Game Weeks of the German Bundesliga. Southern Economic Journal 81, 679–696.

Lee, B., Tremblay, V.J., 1992. Advertising and the US Market Demand for Beer. Applied Economics 24, 69-76.

Galizzi, M.M., Garavaglia, C., 2012. Probably not the best lager in the world: effect of brands on consumers' preferences in a beer tasting experiment. Unpublished.

Gandhi, A., Navarro, S., Rivers, D., 2017. On the Identification of Gross Output Production Functions. Unpublished.

Chamberlin, E. (1933). The Theory of Monopolistic Competition. Harvard University Press, Cambridge.

Grieco, P., Pinkse, J., Slade, M., 2018. Brewed in North America: Mergers, marginal costs, and efficiency. International Journal of Industrial Organization 59, 24–65. https://doi.org/10.1016/j.ijindorg.2017.08.003

Griliches, Z., Mairesse, J., 1998. Production Functions: The Search for Identification, in: Econometrics and Economic Theory in the Twentieth Century: The Ragnar Frisch Centennial Symposium. Cambridge University Press, New York, pp. 169–203.

Guinard, J.-X., Uotani, B., Schlich, P., 2001. Internal and external mapping of preferences for commercial lager beers: comparison of hedonic ratings by consumers blind versus with knowledge of brand and price. Food Quality and Preference 12, 243–255. https://doi.org/10.1016/S0950-3293(01)00011-8

Hall, R.E., 1988. The Relation between Price and Marginal Cost in U.S. Industry. Journal of Political Economy 96, 921-47. https://doi.org/10.1086/261570

Heimonen, K., Uusitalo, O., 2009. The Beer Market and Advertising Expenditure, Marketing Intelligence & Planning 27, 945-975. http://dx.doi.org/10.1108/02634500911000243

Hoch, I., 1962. Estimation of Production Function Parameters Combining Time-Series and Cross-Section Data. Econometrica 30, 34–53. https://doi.org/10.2307/1911286

Karagiannis, G., Kellermann, M., Pröll, S., Salhofer, K., 2017. Markups and Product Differentiation in the German Brewing Sector. Agribusiness 34, 61–76. https://doi.org/10.1002/agr.21528

Kirin Holdings Company, 2018. Kirin Beer University Report: Global Beer Production by Country in 2017 [WWW Document]. URL https://www.kirinholdings.co.jp/english/news/2018/0809_01.html (accessed 2.11.19).

Klette, T.J., Griliches, Z., 1996. The Inconsistency of Common Scale Estimators When Output Prices are Unobserved and Endogenous. Journal of Applied Econometrics 11, 343–361. https://doi.org/10.2307/2284929

Levinsohn, J., Petrin, A., 2003. Estimating Production Functions Using Inputs to Control for Unobservables. Review of Economic Studies 70, 317–341.

Loy, J.P., Glauben, T., 2015. Spatial and temporal retail pricing on the German beer market, in: McCorriston, S. (Ed.), Food Price Dynamics & Price Adjustment in the EU. Oxford University Press, Oxford, pp. 102–122.

Madsen, E., Wu, Y., 2016. Marketing and Globalization of the Brewing Industry., in: Cabras, I., Higgins, D., Preece, D. (Eds.), Brewing, Beer and Pubs: A Global Perspective. Springer, pp. 34–53.

Mairesse, J., Jaumandreu, J., 2005. Panel-data Estimates of the Production Function and the Revenue Function: What Difference Does It Make? Scandinavian Journal of Economics 107, 651–672. https://doi.org/10.1111/j.1467-9442.2005.00431.x

Marschak, J., Andrews, W.H., 1944. Random Simultaneous Equations and the Theory of Production. Econometrica 12, 143–205. https://doi.org/10.2307/1907137

Marshall, A., (1919). Industry and Trade: A Study of Industrial Technique and Business Organization; and of Their Influences on the Conditions of Various Classes and Nations. MacMillan and Co., London.

Milgrom, P., Roberts, J., 1986. Price and Advertising Signals of Product Quality. Journal of Political Economy 94, 796–821. https://doi.org/10.1086/261408

Mundlak, Y., 1961. Empirical Production Function Free of Management Bias. Journal of Farm Economics 43, 44–56. https://www.jstor.org/stable/1235460

Nelson, J.P., 1970. Information and Consumer Behavior. Journal of Political Economy 78, 311–329. https://doi.org/10.1086/259630

Nelson, J.P., 1974. Advertising as Information. Journal of Political Economy 82, 729–754. https://doi.org/10.1086/260231

Nelson, J.P., Moran, J.R., 1995. Advertising and US Alcoholic Beverage Demand: System Wide Estimates. Applied Economics, 27:12, 1225-1236, https://doi.org/ 10.1080/00036849500000105

Nelson, J.P., 1999. Broadcast Advertising and U. S. Demand for Alcoholic Beverages. Southern Economic Journal 65, 774-790. https://www.jstor.org/stable/1061275

Olley, G.S., Pakes, A., 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry. Econometrica 64, 1263–1297. https://doi.org/10.2307/2171831

Ornaghi, C., van Beveren, I., 2012. Using Proxy Variables to Control for Unobservables When Estimating Productivity: A Sensitivity Analysis. Unpublished.

Petrick, M., Kloss, M., 2018. Identifying Agricultural Factor Productivity from Micro-data: A Review of Approaches with an Application to EU Countries. German Journal of Agricultural Economics 67, 67–79.

Profeta, A., Enneking, U., Balling, R., 2008. Interactions between Brands and CO Labels: The Case of “Bavarian Beer” and “Munich Beer” – Application of a Conditional Logit

Model. Journal of International Food & Agribusiness Marketing 20, 73–89. https://doi.org/10.1080/08974430802157655

Rojas, C., Peterson, E.B., 2008. Demand for differentiated products: Price and advertising evidence from the U.S. beer market. International Journal of Industrial Organization 26, 288–307. https://doi.org/10.1016/j.ijindorg.2006.12.003

Rovigatti, G., Mollisi, V., 2018. Theory and Practice of Total-Factor Productivity Estimation: The Control Function Approach using Stata. The Stata Journal 18, 618–662. https://doi.org/10.1177/1536867X1801800307

Scherer, F.M., Beckenstein, A., Kaufer, E., Murphy, R.D., 1975. The Economics of Multi-Plant Operation: An International Comparisons Study. Harvard University Press. Cambridge.

Statista, 2019. Bier - Werbeausgaben in Deutschland 2017 | Statistik [WWW Document]. Statista. URL https://de.statista.com/statistik/daten/studie/151374/umfrage/werbeausgaben-fuer-bier-in-deutschland-seit-2000/ (accessed 4.10.19).

Stern, 2018. Das sind die 10 größten Brauereien in Deutschland. [WWW Document]. URL. https://www.stern.de/wirtschaft/news/das-sind-die-zehn-groessten-brauereien-deutschlands-7917262.html (accessed 29.03.18).

Stigler, G.J., 1961. The Economics of Information. Journal of Political Economy 69, 213–225. https://doi.org/10.1086/258464

Wilcox, G.B., Gangadharbatla, H., 2006. What's Changed? Does Beer Advertising Affect Consumption in the United States?. International Journal of Advertising 25, 35-50. http://dx.doi.org/10.1080/02650487.2006.11072950

Wilcox, G.B., Kang E.Y., Chilek, L.A., 2015. Beer, Wine, or Spirits? Advertising's Impact on Four Decades of Category Sales. International Journal of Advertising 34, 641-657. https://doi.org/10.1080/02650487.2015.1019961

Wooldridge, J.M., 2009. On estimating firm-level production functions using proxy variables to control for unobservables. Economics Letters 104, 112–114. https://doi.org/10.1016/j.econlet.2009.04.026

Yaman, F., 2011. The costs of adjusting labor: Evidence from temporally disaggregated data. Unpublished.

Zühlsdorf, A., Spiller, A. (2012). Trends in der Lebensmittelvermarktung. [WWW Document]. URL. https://www.lebensmittelklarheit.de/sites/default/files/downloads/Marktstudie%2520-%2520Trends%2520in%2520der%2520Lebensmittelvermarktung_Studientext_final.pdf, (accessed 15.04.2019).

Tables

Table 1: Descriptive statistics

Variable	Mean	Median	Min	Max	Std.
Output	11,023	5,515	314	225,574	20,801
Labor	2,337	1,338	100	36,664	3,518
Material	3,579	1,900	152	83,133	7,353
Capital	4,708	2,274	84	82,897	8,258
Physical output	128	64	4	2,516	232
Price	78.24	78.68	36.26	122.68	12.06
Advertising expenses	1,108	247	3	63,529	3,798
Advertising intensity	4.96	3.56	0.18	27.41	4.16

Output, labor, material, capital and advertising expenditures are measured in 1,000 €. Physical output is measured in 1,000 hl and price in €/hl. Advertising intensity is measured in €/hl.
Source: Authors' calculations from German Brewers Association (GBA) data.

Table 2: WDG and ACF estimation results

	WDG	SE[1]	ACF	SE[2]
Labor	0.499	0.036	0.446	0.337
Capital	0.116	0.021	0.145	0.058
Material	0.453	0.042	0.477	0.130
Labor*Labor	0.083	0.042	0.073	0.110
Capital*Capital	0.001	0.016	0.027	0.027
Material*Material	0.027	0.032	0.064	0.089
Labor*Capital	0.015	0.051	-0.043	0.070
Labor*Material	-0.152	0.054	-0.160	0.133
Capital*Material	0.007	0.002	0.014	0.085
Observations		1125		1121

The number of observations differs due to missing values in additional variables in the control function of the ACF procedure.

[1] We report cluster-robust GMM standard errors and relax the assumption of independence of firm-specific errors.

[2] Block bootstrapping is used to calculate standard errors (1,000 repetitions).

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

Table 3: Statistics derived from WDG and ACF estimation

	WDG		ACF	
	Median	SE[1]	Median[2]	SE[1]
Elasticity labor	0.504	0.044	0.502	0.321
Elasticity capital	0.102	0.025	0.124	0.057
Elasticity material	0.497	0.060	0.466	0.149
Returns to scale	1.096	0.051	1.096	0.271
Markup	1.434	0.177	1.375	0.436
Profit ratio	1.307	0.125	1.261	0.680

[1] Block bootstrapping is used to calculate standard errors (1000 repetitions).
[2] We rely on the median as a measure of central tendency as it is more robust to the exceptionally high values of our derived variables
Source: Authors' calculations from German Brewers Association (GBA) data.

Table 4: Fixed effects regression - Dependent variable: ln(Markup) (derived using WDG framework)

	(1)	(2)	(3)
ln(Adv Exp/hl)	0.045***	0.038***	0.038***
	(0.007)	(0.007)	(0.007)
ln(Firm size)	-0.231***	-0.196***	-0.195***
	(0.017)	(0.017)	(0.018)
ln(Share of beer/Rev)		0.204***	0.204***
		(0.031)	(0.031)
TFP (WDG)			-0.077
			(0.223)
Observations	1321	1321	1321
R^2	0.357	0.381	0.381

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Time trend and intercept are included in all models
Source: Authors' calculations from German Brewers Association (GBA) data.

Table 5: Fixed-effects regression – different dependent variables

	ln(Profit ratio)[1]	ln(Price)
ln(Adv Exp/hl)	0.037***	0.030***
	(0.006)	(0.004)
ln(Firm size)	-0.160***	-0.086***
	(0.016)	(0.011)
ln(Share of beer/Rev)	0.188***	0.108***
	(0.028)	(0.020)
Observations	1321	1321
R^2	0.411	0.365

[1] Derived using the WDG framework
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Time trend and intercept are included in all models
Source: Authors' calculations from German Brewers Association (GBA) data.

Figures

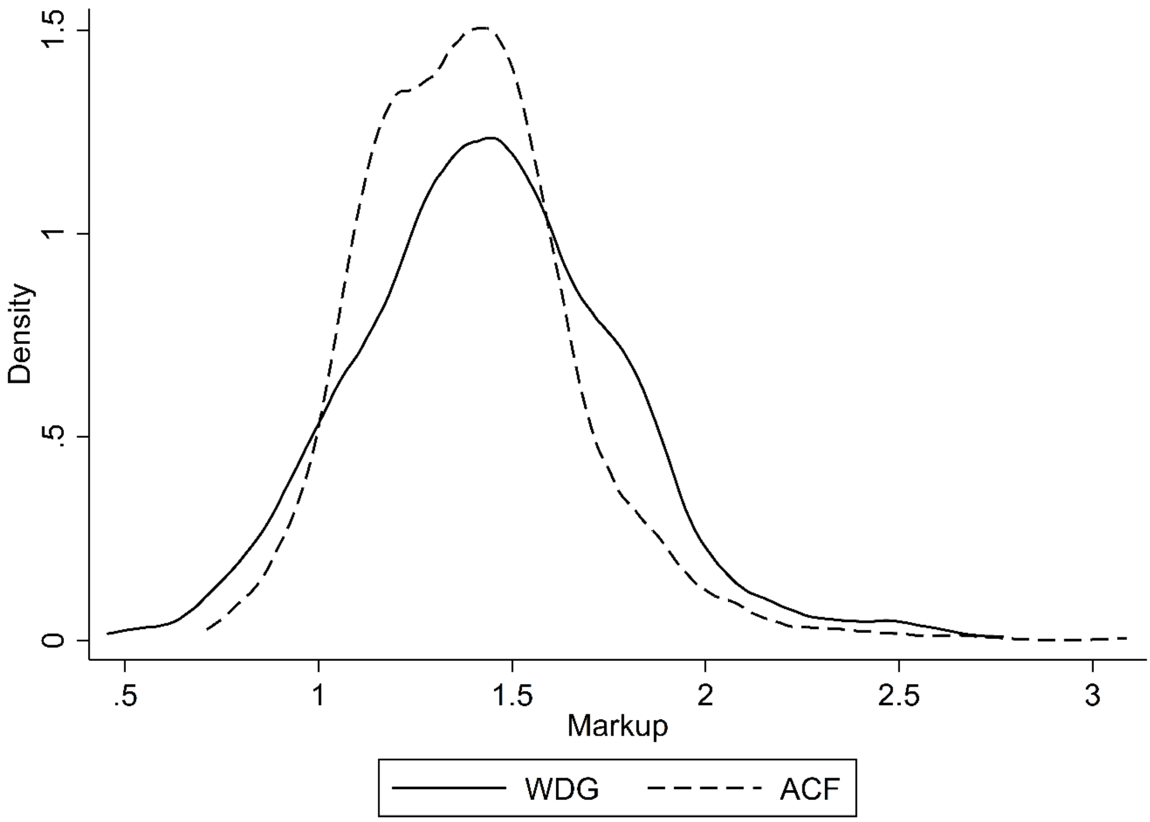

Figure 1: Distribution of markups based on different estimation procedures.

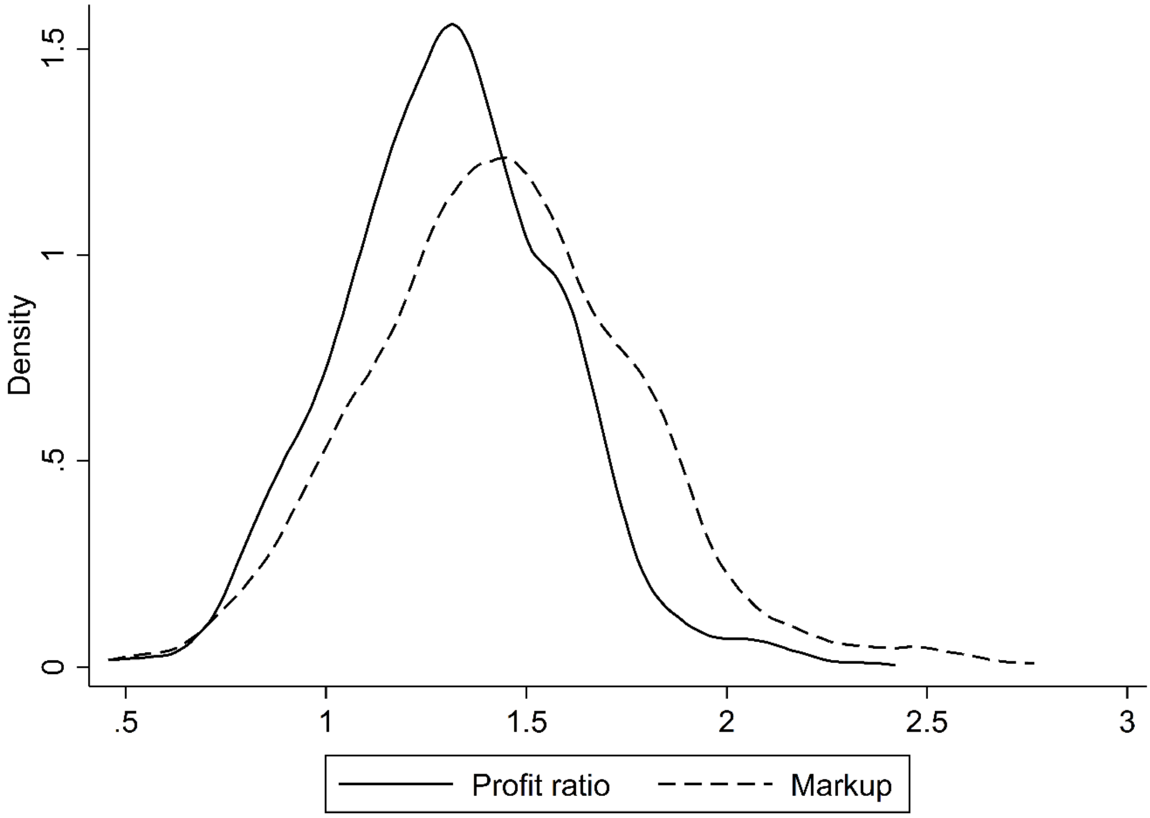

Figure 2: Distribution of profit ratios and markups.

[1] We neglect the much less-discussed complementary view and refer to Bagwell (2007, p. 1,720) for further discussion.

[2] Note that this does not imply that output elasticities are constant across firms.

[3] We refer to Ackerberg et al. (2007) for a more comprehensive treatment of the endogeneity problem in estimating production functions.

[4] ACF provide a more detailed discussion of the relationship between both strands of literature.

[5] According to ACF, using PM to relax these assumptions comes at the cost of introducing new assumptions.

[6] ACF discuss in detail the data-generating processes under which labor is identified in the OP/LP estimation framework. They find that this is the case only under very special circumstances.

[7] Including l_{it} in κ_t would correspond to the ACF critique. Hereby, l_{it-2} is the first potential lag to be used as an instrument for l_{it}. However, as an instrument, l_{it-2} may lack relevance and its use entails the loss of one additional period of observations. Ornaghi and van Beveren (2012) report unreasonably high or low labor coefficients in their ACF-WDG estimation, which they attribute to highly correlated variables in that specification. In our application, l_{it} and l_{it-1} would also show up in the control functions in (10) and (12) respectively, magnifying the risk of multicollinearity.

[8] In the original procedure, LP identify the production function parameters estimating equations (10) and (12) in two steps. They already determine some coefficients in the first stage, utilizing the predictions to substitute for their values in the second stage equation. This has the advantage of a computationally less intensive search over the parameters in the GMM estimation.

[9] This is a common assumption (e.g. Ornaghi and van Beveren (2012) and Rovigatti and Mollisi (2018)), since otherwise the search algorithm can face convergence problems.

[10] We do not need to include additional nonlinear functions of $\boldsymbol{c}_{it-1}$ in $\boldsymbol{z}_{it1}$ as we assumed $G = 1$ and $\rho_1 = 1$.

[11] The GMM criterion function is minimized using the Gauss Newton method. The initial weighting matrix is specified as unidentified and error terms are assumed to be independent.

[12] Gandhi et al. (2017) show that gross output production functions are not identified if the intermediate input m_{it} is perfectly flexible, and therefore additional variation is required in the material demand function $m_{it} = \kappa_t(k_{it}, l_{it}, \omega_{it})$.

[13] l_{it} may be chosen prior to m_{it} or both input levels may be chosen simultaneously. Only the dynamic implications of l_{it} are ruled out.

[14] All estimations are done using Stata, adapting parts of the code developed by Rovigatti and Mollisi (2018) and DLW.

[15] We prefer revenues deflated by a firm-specific price index to hectolitres. The latter raises the question of how to weight beer against beer-mix drinks and non-alcoholic beverages. The same issue arises with beer in kegs versus beer in bottles.

[16] Note that this measure excludes the intercept $\hat{\lambda}_0$, which we cannot recover. As $\hat{\lambda}_0$ does not add any variation to productivity, we can substitute $\widehat{\omega}_{it}$ by $\widetilde{\widetilde{\omega}}_{it}$ in our regression framework.

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The Discussion Papers are edited by the Institute for Sustainable Economic Development of the University of Natural Resources and Life Sciences Vienna. Discussion papers are not reviewed, so the responsibility for the content lies solely with the author(s). Comments and critique are welcome.

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