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Using the production approach to recover firm performance measures: empirical applications in the food and beverage supply chain

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Vienna, 18 October 2019 Simon Pröll

DECLARATION OF AUTHORSHIP

I hereby declare that I am the sole author of this work; no assistance other than that permitted has been used and all quotes and concepts taken from unpublished sources, published literature or the internet in wording or in basic content have been identified by footnotes or with precise source citations.

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ABSTRACT

In this thesis, it is discussed how firm performance measures can be recovered from production function estimations to answer research questions in the food and beverage supply chain. Any firm performance measure based on a production function estimate requires the identification of unbiased coefficients. To achieve this, the econometrician faces several challenges including (i) endogeneity and (ii) unobserved firm specific prices. In regard to (i), we apply traditional estimators and more novel semiparametric estimation techniques resolving problems of traditional methods. In regard to (ii), we follow Klette and Griliches (1996) in estimating a reduced form model capturing production and demand side to account for price dispersion. We utilize these methods in order to answer three different research questions. Our first application provides a method to separate a product differentiation markup from other sources of market power. Results for breweries in Germany reveal that a significant part of the markup is due to product differentiation. The second application investigates the role of advertising in beer pricing. Using production data, it is shown that firm- and time-specific markups, profit ratios and prices are positively related to advertising expenditures. The final application elaborates on total factor productivity growth of Austrian crop farms between 2003 and 2017. The results reveal substantial productivity growth accompanied by large fluctuations over time and that productivity growth can be mainly attributed to growth within farms as opposed to reallocation between firms.

KURZFASSUNG

Diese Dissertation diskutiert, wie aus ökonometrisch geschätzten Produktionsfunktionen verschiedene Unternehmensmaßzahlen, wie etwa die Gesamtfaktorproduktiviät oder der Preisaufschlag einer Firma, abgeleitet werden können. Wir nützen diesen Umstand, um Forschungsfragen in der Nahrungs- und Genussmittelindustrie zu beantworten. Voraussetzung für die richtige Messung der Unternehmensmaßzahlen ist die Schätzung unverzerrter Produktionsfunktionsparameter. Dies stellt den/die Ökonometriker/in vor zahlreiche Herausforderungen wie etwa (i) Endogenität und (ii) unbeobachtete firmenspezifische Preise. Mit Bezug auf (i) kommen in dieser Arbeit traditionelle Schätzer aber auch semiparametrische Schätzmethoden, welche Probleme ersterer zumindest teilweise lösen, zur Anwendung. In Bezug auf (ii) verwenden wir ein Modell von Klette und Griliches (1996), welches die Produktionsseite und die Nachfrageseite abbildet und so für Preisdispersion kontrolliert. Wir verwenden diese Methoden um drei Forschungsfragen zu beantworten. In der ersten Anwendung wird eine Methode entwickelt, die es erlaubt jenen Teil des Preisaufschlags, der durch Produktdifferenzierung bedingt ist, zu identifizieren. Die Ergebnisse zeigen, dass der größte Anteil des Preisaufschlags deutscher Brauereien auf Produktdifferenzierung zurückzuführen ist. In der zweiten Anwendung wird die Rolle der Werbungsausgaben bei der Preissetzung von Bier analysiert. Die Untersuchung von Produktionsdaten zeigt, dass firmen- und zeitspezifische Preisaufschläge, Stückgewinne und Preise von Brauereien positiv mit deren Werbungsausgaben korreliert sind. Die letzte Anwendung beschäftigt sich mit dem Produktivitätswachstum österreichischer Getreidebaubetriebe zwischen 2003 und 2017. Die Resultate zeigen erhebliches Wachstum begleitet von starken Schwankungen. Außerdem deuten die Ergebnisse daraufhin, dass der größte Teil des Produktivitätswachstums innerhalb der Firmen stattfindet und nicht durch Strukturveränderungen im Sektor.

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1 INTRODUCTION

1.1 Production functions – a brief historical overview

Although the production process can be described in a more general way, production functions have evolved to economists' most frequently used concept to model input factors (i.e. raw materials) being transformed into outputs. Implicitly stated production functions can be traced back before 1800 to Turgot who already articulated the law of diminishing returns in production. English classical economists Malthus and Ricardo provided their concepts using arithmetic and geometric series instead of explicitly formulating production functions (see Lloyd (1969)). In that, they already used the idea of diminishing marginal returns (i.e. diminishing marginal product of labor). While Malthus suggested a logarithmic production function, Ricardo used a quadratic form to describe the relation between input and output. However, both assumed inputs being used in fixed proportions violating the substitutability assumption of the neoclassical production function used in contemporary empirical work. Johann Heinrich von Thünen was not only the first one to allow for substitutability between inputs, but also the first one to algebraically formulate an economic production function already nesting the widely used Cobb-Douglas form. As a further step, Marshall first used the concept of an aggregate production function in the 19th century. More than 20 years before Cobb and Douglas published their influential article, Wicksell provided the first exact formulation of the Cobb-Douglas production function.[1,2] However, Cobb and Douglas (1928) presented an econometric production function that is still applied in contemporary economic research and showed that their functional form provides a good description of their aggregate

[1] Description of the evolution of production before Cobb and Douglas borrows liberally from Humphrey (1997).

[2] It should be noted that this short historical development of production functions is by no means a complete treatment and above all neglects the history of limitational production functions.

data. Since the work of Cobb and Douglas, contributions to the production function literature moved in several directions however not isolated from other findings.

Although the Cobb Douglas form exhibits the desirable mathematical properties of a neoclassical production function, subsequent contributions to the literature aimed to generalize the functional form. Introducing their constant elasticity of substitution (CES) function, Arrow, Chenery, Minhas, and Solow, (1961) show an important generalization allowing for input substitution ratios other than one as in the Cobb-Douglas case or zero as in the Leontief case. As a drawback, the substitution elasticity is still assumed constant over input combinations and scale. More importantly, Uzawa (1962) and McFadden (1962, 1963) prove infeasibility of a constant elasticity functional form with more than two input factors. Diewert (1971) addresses the shortcomings in introducing a generalized Leontief production function that allows for an arbitrary set of partial elasticities of substitution between input factors. Introducing the translog function, Christensen, Jorgenson and Lau (1973) suggest an even more flexible functional form that provides two important generalizations of preceding work. In the first line, it allows the substitution elasticity to change with output and/or the level of input use and secondly it allows the scale elasticity to change with output and/or factor proportions (Heathfield and Wibe, 1987). The flexible functional form may however come at the cost of multicollinearity when estimating production function parameters.[3,4]

Using Shephard's (1953) proof of the duality property between cost functions and production functions, the "duality literature" has emerged as an alternative approach to gain insights in production technology. In contrast to the "conventional approach", modelling the

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[3] The literature provides several other suggested functional forms to capture the production technology of economic entities. A more comprehensive treatment can be found in Mishra (2007)

[4] The interested reader refers to Mishra (2007) for a more comprehensive treatment of the evolvement of functional forms of production functions.

production process as a set of physical technological possibilities, insights are gained through directly using observed economic data such as supplies, demands, prices, costs and profits (Fuss and McFadden, 1978). Using the insight that a production function satisfying certain properties, has a dual representation such as a price function or a cost function one can estimate substitution elasticities between more inputs, shed light on the character of differences in technology and the role of economies of scale (Jorgenson, 1986).

Over time, production functions have also been applied to a wider range of settings and data. Initially, the success of the Cobb Douglas production function was based on the notion that it represented well the technology in a macro environment and provided empirical evidence for the marginalist theory of production, i.e. estimated labor and capital coefficients were close to their distributive shares in national income. Yet, several authors criticized the meaningfulness of the Cobb Douglas function in representing an aggregate production technology (e.g. Fisher, 1971). Griliches and Mairesse (1998) point out that due to the lack of plausibility, applications of production functions to macro data, especially in agriculture, accordingly shifted to micro data and provide the work of Tintner (1944), Mundlak (1961) and Heady and Dillon (1961) as examples. Production functions have also proven useful in estimating technological change. In his contribution, Solow (1957) shows to recover technical change as part of output growth not explained by growth in inputs, known as the Solow residual.[5] His work can be regarded as the origin of total factor productivity, a concept that has been used in various fields of economics such as macroeconomics, industrial organization, labor or trade.[6] Production functions also pose an integral part of the stochastic

[5] In the initial work of Solow (1957), total factor productivity is recovered without the use of econometric estimation procedures, but using a method suggested by Klein (1953) which is based on the assumption of profit maximization and allows to use factor shares as estimates of production function parameters.

[6] see Syverson (2011) for a review on total factor productivity estimation.

frontier analysis literature which is based on the findings of Aigner, Lovell, and Schmidt (1977), Meeusen and van Den Broeck (1977) and Jondrow, Knox Lovell, Materov, and Schmidt (1982). Using the production function representing the maximum output possibility frontier allows to measure technical efficiency of economic entities.

1.2 Estimation of production functions and emerging problems

To capture the production technology of a firm i in period t, a commonly used representation is

$$y_{it} = f(\boldsymbol{x}_{it}; \boldsymbol{\beta}) + \omega_{it} + \varepsilon_{it}, \tag{1}$$

where small letters denote variables in logs. Hereby, the observed measure of output, y_{it}, can be described as a function of inputs, collected in $\boldsymbol{x}_{it}$. The input vector $\boldsymbol{x}_{it}$ captures both variable input factors $\boldsymbol{x}_{it}^{V}$ and fixed input factors $\boldsymbol{x}_{it}^{F}$. Unobserved productivity differences varying across firms and time periods are denoted by ω_{it}. We assume ω_{it} being scalar valued and Hicks-neutral. Unobserved i.i.d. shocks to production are captured by ε_{it}. The coefficients to be estimated including an intercept are collected in vector $\boldsymbol{\beta}$.

In aiming to identify the production parameters in $\boldsymbol{\beta}$, the researcher is to be confronted with several challenges in the fashion of those raised by Griliches and Mairesse (1998). Which level of aggregation is most suitable to analyze production technology (e.g. national level, industry level, firm level, plant level)? Is the sample representative of the population of interest? Does the assumed functional form capture the production technology of the economic entities? Are inputs and outputs measured correctly? Are inputs truly independent or are they determined by factors outside of the production function?

The level of aggregation is usually determined by the nature of the dataset available. In case the researcher is refraining to investigate the data on a more aggregate level, she is relatively limited to the dataset of choice.

While the question of external validity is certainly determined by the data collection process in the first place, the researcher has the possibility to account for shortcomings by econometric techniques. In a dataset of firms, some observations may not be missing at random but due to some firm characteristics leading to biased production function coefficients. The procedure by Olley and Pakes (1996) is a good example of controlling for firm selection in production function estimation.[7]

Choosing a functional form, the researcher makes important a priori assumptions on the production technology of economic entities. The functional form most importantly determines if, and to which degree, inputs are allowed to be substituted for each other, whether non-constant returns to scale are allowed and whether production technologies may differ between economic entities (e.g. firms).

Considering the third question of correct measurement from an econometric point of view, incorrectly measured inputs or outputs can be described as a measurement error of an independent or a dependent variable respectively. While a dependent variable measurement error only causes biased coefficients if the measurement error (i.e. the deviation of the proxy variable from the unobserved variable of interest) is systematically related to one or more of the explanatory variables, the effects of a measurement error in the explanatory variable depends on the correlation between proxy variable and measurement error. In case of a measurement error that is uncorrelated with the observed proxy variable, the model can be estimated consistently using ordinary least squares (OLS) under the usual assumptions. If the measurement error is however correlated with the proxy variable, all of the coefficients suffer from bias when estimated using OLS (Wooldridge, 2010). In estimating production functions, the measurement error problem arises from the unavailability of appropriate measures for

[7] See Gronau (1973) or Heckman (1974) for early models to correct for selection.

inputs and outputs. The researcher aims to measure the relation between the inputs and outputs in physical quantities. Due to their unavailability, physical inputs and outputs are often proxied by monetary values (e.g. sales, wage bill or material cost) deflated by an industry-level price index. Whether using these proxies produces biased production function coefficients depends in the first line on whether firms face uniform input prices and a uniform output price, corresponding to price-taking firms in the input factor market and perfect competition in the market for the produced good respectively. In starting to illustrate the problem of measurement error in output variables, known as omitted price bias, we first assume that inputs are correctly measured and consider first the case where physical output q_{it} is used as the output measure, such that $y_{it} = q_{it}$. Thereafter (1) can be written as

$$q_{it} = f(\boldsymbol{x}_{it}; \boldsymbol{\beta}) + \omega_{it} + \varepsilon_{it}. \quad (2)$$

If the researcher however uses sales deflated by an industry price index instead of physical output q_{it}, the output measure y_{it} becomes

$$y_{it} = p_{it} + q_{it} - p_t^L, \quad (3)$$

where p_{it} denotes the price of firm i's product in period t and p_t^L denotes the average industry price (e.g. the industry price index).[8] Using (2) to substitute for q_{it} in (3) yields

$$y_{it} = f(\boldsymbol{x}_{it}; \boldsymbol{\beta}) + (p_{it} - p_t^L) + \omega_{it} + \varepsilon_{it}. \quad (4)$$

Equation (4) shows that when there is no output price dispersion, such that $p_{it} = p_t^L, \forall i$ corresponding to a perfectly competitive market, the use of the output proxy in (3) does not generate any bias. Even though price dispersion might be prevalent in the market, the production function parameters can be estimated unbiasedly if $E[\boldsymbol{x}_{it}(p_{it} - p_t^L)] = \boldsymbol{0}$ holds. Only in the case of correlation between input use levels and firm price deviations, a bias may

[8] Note that small letters indicate variables in logs.

be introduced in the input coefficients.[9] Klette and Griliches (1996) suggest a reduced form model allowing to control for omitted price bias by explicitly accounting for output price dispersion.[10] Omitted input price bias follows a similar pattern. If input quantities in $\boldsymbol{x}_{it}$ are proxied by their monetary values deflated by industry level prices, we rewrite equation (4) as

$$y_{it} = f(\widetilde{\boldsymbol{x}}_{it}; \boldsymbol{\beta}) + (p_{it} - p_t^L) + \omega_{it} + \varepsilon_{it}, \tag{5}$$

where $\widetilde{\boldsymbol{x}}_{it} = \boldsymbol{p}_{it}^{IN} + \boldsymbol{x}_{it} - \boldsymbol{p}_t^{IN}$. The vector $\boldsymbol{p}_{it}^{IN}$ captures all input prices firm i faces in period t and $\boldsymbol{p}_t^{IN}$ contains industry-level price indices of all input factors. In the case of $\boldsymbol{p}_{it}^{IN} = \boldsymbol{p}_t^{IN}$, such that there is no price variation in any of the inputs, industry-price deflated monetary input values are suitable proxies. If, however, input price dispersion is prevalent and $E[\boldsymbol{x}_{it}(\boldsymbol{p}_{it}^{IN} - \boldsymbol{p}_t^{IN})] \neq \boldsymbol{0}$, bias is introduced to the coefficient vector $\boldsymbol{\beta}$. Although there are several studies exploiting information on input prices and quantities to resolve omitted price bias, van Beveren (2012) points out that a formal solution to the input price induced bias in the absence of firm-level price data has not yet been introduced.

Of all questions above, the simultaneity problem has been discussed most extensively in the literature. Several remedies, such as econometric techniques, have been proposed to tackle the problem and therefore the simultaneity problem is also treated in somewhat more detail here. 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.[11] The most prominent of the “traditional” solutions to the

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[9] De Loecker (2007b) provides a short discussion on the direction of omitted price variable bias.

[10] De Loecker (2011a) provides an extension in allowing for multiproduct firms.

[11] We refer to Ackerberg, Benkard, Berry, and Pakes (2007) for a more comprehensive treatment of the endogeneity problem in estimating production functions.

problem include fixed effects estimation (Mundlak, 1961; Hoch, 1962) and instrumental variable estimation (Griliches and Mairesse, 1998).

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, 1998, 2000) and proxy methods (henceforth PM) (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009; Ackerberg, Caves, and Frazer, 2015). 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).[12] In the subsequent applications to the German beer industry and the Austrian crop farmers, we face highly variable input factors such as barley, hop or electricity in the brewing industry and pesticides, fertilizer or seeds in crop farming. The assumption of costly factor adjustment, which is at the heart of DP's identification strategy, is therefore implausible in both applications. We therefore draw our attention to PM in the rest of this section and the empirical applications.

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

Olley and Pakes (1996) (henceforth OP) made the first contribution to the PM literature. 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.[13] 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.

Ackerberg, Caves and Frazer (2015) (henceforth 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).[14] ACF propose an alternative procedure to avoid the functional dependence problems. Using Monte Carlo simulations, they show that their procedure, unlike OP and LP,

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

[14] 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.

consistently identifies the production function coefficients in several alternative data-generating processes.

1.3 Research questions and outline of the thesis

The aim of this thesis is to show how production functions can be applied to analyze distinct phenomena in the food and beverage supply chain. An integral part of the thesis is to provide empirical evidence on the production technology of firms. In order to reliably estimate production function parameters, we therefore implement econometric methods aiming to unbiasedly estimate production functions to data on German breweries and Austrian crop farms. Hereby, making use of the information production functions exhibit on the economic environment, the thesis addresses the following research questions:

- Do German brewers price above marginal cost and, if so, to which extent are those markups determined by product differentiation?
- Are markups positively related to advertising expenses in the German brewing sector?
- Has the productivity of Austrian crop farmers been increasing over the past years? How do total factor productivity growth measures vary due to econometric techniques?

This thesis is organized as follows. Section 2 describes difficulties estimating production functions and econometric techniques aiming to resolve these problems. Section 3 discusses how price-cost-markups can be recovered from production function estimates. In section 4, the reader finds two applications in the German brewing sector. Hereby the first application is tightly related to Karagiannis, Kellermann, Pröll and Salhofer (2017) and shows recovery of general markups, picking up any forms of market imperfection, and markups capturing price-cost wedges due to product differentiation. The second application investigates the link between brewers' advertising efforts and the size of markup and other firm performance measures and borrows liberally from a work by Pröll, Salhofer and Karagiannis (2019), available as discussion paper of the Institute for Sustainable Economic Development of the University of Natural Resources and Life Sciences, Vienna. In section 5, total factor productivity growth of Austrian crop farms is analyzed using the parametric approach of production function estimation and using distinct econometric techniques. Section 6 summarizes findings and concludes this study.

2 ECONOMETRIC APPROACHES TO THE ESTIMATION OF PRODUCTION FUNCTIONS

2.1 Specification of the production function

Prior to the discussion of estimation procedures, the functional form in $f(\boldsymbol{x}_{it};\boldsymbol{\beta})$ must be specified. In assuming a transcendental logarithmic functional form Christensen et al., (1973), firm's output elasticities of input factors are allowed to vary across firms and time, an important characteristic for calculations of firm performance measures. Furthermore, a gross output production function is considered, relaxing the assumption of a fixed material-output proportion in the production process.

The resulting production function taken to the data can then be stated as:

$$y_{it} = \beta_0 + \boldsymbol{r}_{it}\boldsymbol{\beta} + \omega_{it} + \varepsilon_{it} \tag{6}$$

where $\boldsymbol{r}_{it}$ captures variables resulting from the second order polynomial of all inputs in $\boldsymbol{x}_{it}$ and the corresponding parameters are collected in $\boldsymbol{\beta}$.

2.2 Traditional solutions for the simultaneity problem

As traditional solutions to the simultaneity problem, authors typically refer to panel data estimators and the instrumental variable (IV) approach. Making use of the longitudinal nature of the data and the assumption of fixed productivity differences across producers, such that

$\omega_{it} = \omega_i, \ \forall i$, allow to apply the random effects (RE) and fixed effects (FE) panel data estimators. The choice of the appropriate estimator hereby depends crucially on the assumptions about the structure of ω_{it} the researcher is willing to make.

Applying the RE estimator requires unobserved productivity being uncorrelated to the level of input use, such that $E[\omega_i|\boldsymbol{x}_{it}] = E[\omega_i] = 0, \forall i, t$. In addition, application of the RE model requires strict exogeneity of i.i.d. production shocks ε_{it} from inputs and unobserved productivity, such that $E[\varepsilon_{it}|\boldsymbol{x}_{it}, \omega_i] = 0, \ \forall i, t$, ruling out any effects from past productivity shocks to contemporary input use.

The FE estimator, in contrast to RE, allows consistent estimation of production function coefficients when the level of input usage is correlated to unobserved productivity by equally assuming time invariant unobserved productivity. In order to relax the assumption of a constant error variance without losing in terms of efficiency, the feasible fixed effects generalized least squares (FEGLS) estimator can be used to estimate production function parameters (Wooldridge, 2010).

A natural approach to allow for time varying unobserved firm heterogeneity is to instrument endogenous input factors with variables that are uncorrelated with both ω_{it} and ε_{it} but correlated to the respective level of input use. Economic theory suggests the use of input prices as they directly influence input factor demand (Ackerberg et al., 2015).

While both FE and RE rely on the assumption that unobserved productivity is time invariant, the IV approach can be limited due to the availability of appropriate instruments. 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, Navarro, and Rivers (2017) conclude that standard econometric solutions are "theoretically problematic and unsatisfactory". Thereafter, at the core of the empirical part of this thesis, there is the estimation of production functions using two techniques that are part of the proxy methods literature, the WDG framework and the ACF procedure. These methods overcome several drawbacks of the traditional approaches and allow to identify unbiased production function coefficients introducing assumptions on the production process. Besides the benefits mentioned in the previous section, both procedures allow for estimation of a more flexible functional form in $f(\boldsymbol{x}_{it};\boldsymbol{\beta})$ than other methods from the proxy methods literature such as the OP and LP procedures, which is crucial for deriving firm-specific output elasticities and other firm-specific performance measures.

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

The starting point for the WDG framework is a LP setup. Therefore, it is assumed that a firm's demand for intermediate inputs m_{it} is determined by the vector of fixed input variables $\boldsymbol{x}_{it}^F$ and ω_{it}, resulting in

$$m_{it} = \kappa_t(\boldsymbol{x}_{it}^F, \omega_{it}).\text{[15]} \tag{7}$$

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

$$\omega_{it} = \kappa_t^{-1}(\boldsymbol{x}_{it}^F, m_{it}). \tag{8}$$

Substituting for ω_{it} in (6), one can specify the first equation to identify $\boldsymbol{\beta}$.

$$y_{it} = \beta_0 + \boldsymbol{r}_{it}\boldsymbol{\beta} + \kappa_t^{-1}(\boldsymbol{x}_{it}^F, m_{it}) + \varepsilon_{it} \tag{9}$$

[15] 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 (9) and (11) respectively, magnifying the risk of multicollinearity.

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

$$\omega_{it} = E(\omega_{it}|\omega_{it-1}) + \xi_{it} = h(\omega_{it-1}) + \xi_{it}, \tag{10}$$

where ξ_{it} is an i.i.d. error that can be interpreted as the technical progress. Productivity is captured using (8) and (10). Substituting for ω_{it} in (6) one can form the second identifying equation

$$y_{it} = \beta_0 + \boldsymbol{r}_{it}\boldsymbol{\beta} + h[\kappa_t^{-1}(\boldsymbol{x}_{it-1}^F, m_{it-1})] + \xi_{it} + \varepsilon_{it}. \tag{11}$$

Identifying the parameters by jointly estimating (9) and (11) requires to deal with the unknown functions in κ_t^{-1} and h.[16.] 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

$$\kappa_t^{-1}(\boldsymbol{x}_{it}^F, m_{it}) = \lambda_0 + \boldsymbol{c}_{it}(\boldsymbol{x}_{it}^F, m_{it})\boldsymbol{\lambda}. \tag{12}$$

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:

$$h(\omega_{it-1}) = \rho_0 + \rho_1\omega_{it-1} + \dots + \rho_G\omega_{it-1}^G. \tag{13}$$

Substituting for $\kappa_t^{-1}(\boldsymbol{x}_{it}^F, m_{it})$ and $h(\omega_{it-1})$ in (9) and (11) yields

$$y_{it} = \delta_0 + \boldsymbol{r}_{it}\boldsymbol{\beta} + \boldsymbol{c}_{it}(\boldsymbol{x}_{it}^F, m_{it})\boldsymbol{\lambda} + \varepsilon_{it} \tag{14}$$

and

$$y_{it} = \zeta_0 + \boldsymbol{r}_{it}\boldsymbol{\beta} + \rho_1\{\boldsymbol{c}_{it}(\boldsymbol{x}_{it-1}^F, m_{it-1})\boldsymbol{\lambda}\} + \dots + \rho_G\{\boldsymbol{c}_{it}(\boldsymbol{x}_{it-1}^F, m_{it-1})\boldsymbol{\lambda}\}^G + \nu_{it} \tag{15}$$

[16] In the original procedure, LP identify the production function parameters estimating equations (9) and (11) 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.

where $\delta_0 = \beta_0 + \lambda_0$, $\zeta_0 = \beta_0 + \lambda_0 + \rho_0$ and $\nu_{it} = \xi_{it} + \varepsilon_{it}$. Due to the translog-specification of $f(\boldsymbol{x}_{it}, \boldsymbol{\beta})$, determining instruments in a general setting is not straightforward. Therefore, instruments are chosen according to the prevailing application and according to the moment conditions required for GMM estimation:

$$E\left[\boldsymbol{Z}'_{it}\begin{pmatrix}\varepsilon_{it}(\delta_0, \boldsymbol{\beta}, \boldsymbol{\lambda},)\\ \nu_{it}(\zeta_0, \boldsymbol{\beta}, \boldsymbol{\lambda}, \boldsymbol{\rho})\end{pmatrix}\right] = 0. \tag{16}$$

where $\boldsymbol{Z}_{it}$ is a matrix of instruments for every firm i in every period t. The row vectors $\boldsymbol{z}_{it1}$ and $\boldsymbol{z}_{it2}$ collect all instrumental variables for (14) and (15) respectively.

$$\boldsymbol{Z}_{it} = \begin{pmatrix}\boldsymbol{z}_{it1} & \boldsymbol{0}\\ \boldsymbol{0} & \boldsymbol{z}_{it2}\end{pmatrix}. \tag{17}$$

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

In accordance with the ACF approach, material demand is assumed to be a function of l_{it} in addition to fixed inputs $\boldsymbol{x}_{it}^F$ and ω_{it}. However, as a gross output specification is used, we have to depart from the value-added ACF procedure and include additional material demand shifters that are collected in $\boldsymbol{u}_{it}$ (i.e., variables that lead to differences in input demand across firms in κ_t).[17] Therefore, material input demand is given by

$$m_{it} = \kappa_t(\boldsymbol{x}_{it}^F, l_{it}, \omega_{it}, \boldsymbol{u}_{it}). \tag{18}$$

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

$$\omega_{it} = \kappa_t^{-1}(\boldsymbol{x}_{it}^F, l_{it}, m_{it}, \boldsymbol{u}_{it}). \tag{19}$$

We give up on identifying any production function parameters in the first stage and therefore rewrite (6) replacing ω_{it} by (19); that is:

[17] 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 $m_{it} = \kappa_t(\boldsymbol{x}_{it}^F, l_{it}, \omega_{it})$.

$$y_{it} = \varphi_{it}(\boldsymbol{x}_{it}^F, l_{it}, m_{it}, \boldsymbol{u}_{it}) + \varepsilon_{it}, \tag{20}$$

where $\varphi_{it}(\boldsymbol{x}_{it}^F, l_{it}, m_{it}, \boldsymbol{u}_{it}) = \beta_0 + \boldsymbol{r}_{it}\boldsymbol{\beta} + \kappa_t^{-1}(\boldsymbol{x}_{it}^F, l_{it}, m_{it}, \boldsymbol{u}_{it})$. 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

$$\omega_{it} = \hat{\varphi}_{it} - \beta_0 - \boldsymbol{r}_{it}\boldsymbol{\beta}^*, \tag{21}$$

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 (10) and approximate h by a third-order polynomial in ω_{it-1}. We form independent moment conditions on ξ_{it} making use of (10) and (21) as

$$E[\boldsymbol{z}_{it}\xi_{it}(\boldsymbol{\beta})] = 0, \tag{22}$$

where the vector $\boldsymbol{z}_{it}$ captures all instruments. The parameter vector $\boldsymbol{\beta}$ can then be identified by using standard GMM techniques and exploiting the moment conditions in (22). Standard errors can be obtained making use of the bootstrap.

3 ESTIMATION OF MARKUPS FROM PRODUCTION FUNCTIONS

In the industrial organization literature, markups have been typically estimated using the demand approach. Hereby, the researcher estimates demand parameters in order to calculate markups from a fully specified model of consumer choice (De Loecker and Scott, 2016). The approach relies on rather disaggregated data including product prices and product attributes. Both, the requirement of a priori specifying a model of conduct and high data requirements limit the applicability of the demand approach. As an alternative, markups can be estimated using production data. The approach exhibits comparably low data requirements and facilitate the estimation of markups in industries where disaggregated consumer data is not available. The production approach has gained more attention and has been applied in various fields as international trade (De Loecker, Goldberg, Khandelwal, and Pavcnik, 2016; De Loecker and Warzynski, 2012) or mergers and acquisitions (e.g. Stiebale and Vencappa, 2018).

3.1 A framework to recover general markups

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.

As a point of departure we follow De Loecker and Warzynski (2012), in assuming that firm i's production technology in period t can be represented by

$$Q_{it} = F_{it}(\boldsymbol{X}_{it}\,, \omega_{it}), \tag{23}$$

where Q_{it} represents output, $\boldsymbol{X}_{it}$ captures all variable inputs $\boldsymbol{X}_{it}^{V}$ and all quasi-fixed inputs $\boldsymbol{X}_{it}^{F}$. Unobserved log productivity, which adds to the level of output, is denoted by ω_{it}. We assume firms minimizing their costs by choosing their optimal levels of variable inputs, resulting in the following optimization problem.

$$\min_{\boldsymbol{X}_{it}^{V}} \mathcal{L}_{it} = \boldsymbol{W}_{it}\boldsymbol{X}_{it} - \lambda_{it}(F_{it}(\boldsymbol{X}_{it}, \omega_{it}) - \bar{Q}_{it}) \tag{24}$$

The vector $\boldsymbol{W}_{it}$ captures input prices and captures prices for variable inputs $\boldsymbol{W}_{it}^{V}$ and quasi-fixed inputs $\boldsymbol{W}_{it}^{F}$. From the first-order condition for variable input v, we derive

$$\frac{\partial F_{it}(\boldsymbol{X}_{it}, K_{it}, \omega_{it})}{\partial X_{it}^{v}} \frac{X_{it}^{v}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{W_{it}^{v} X_{it}^{v}}{Q_{it}}, \tag{25}$$

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

$$\mu_{it}^{v} = \frac{\theta_{it}^{v}}{\alpha_{it}^{v}}, \tag{26}$$

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 in 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 additionally able to recover the profit ratio defined as $\psi_{it} \equiv \frac{P_{it}}{AC_{it}}$. Following Crépon, Desplatz, Mairesse, and Desplatz (2005), we calculate ψ_{it} as

$$\psi_{it} = \frac{\mu_{it}^{v}}{\delta_{it}}, \tag{27}$$

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

3.2 Recovering markups resulting from product differentiation

The approach to recover markups resulting from product differentiation is based on the estimation of a reduced form model introduced by Klette and Griliches (1996) as a remedy to omitted price bias. In an ideal setting, the researcher observes firms' physical output. Hence, a firm's production process may be described by

$$q_{it} = f(\boldsymbol{x}_{it}; \boldsymbol{\beta}) + \omega_{it} + \varepsilon_{it}, \tag{28}$$

where all production factors in $\boldsymbol{x}_{it}$ and physical output q_{it} are in logs.[18] A major challenge in estimating the production function in (28) 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. To correct for such bias, Klette and Griliches (1996) suggest to model price dispersion with a demand system and to estimate 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, 1976; Dixit and Stiglitz, 1977)

$$Q_{it} = \left(\frac{P_{it}}{P_t^L}\right)^{\eta} Q_t^L \exp(\upsilon_{it}), \tag{29}$$

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.[19] Any other unobserved demand shocks, such as changes in consumer tastes or advertising effects, are captured in the residual term υ_{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

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[18] Note that the model departs from (1) as y_{it} is solely a measure of output. Furthermure, ε_{it} may contain additional measurement error in output in (1).

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

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 (29), 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 υ_{it}.

$$p_{it} - p_t^L = \eta^{-1}(q_{it} - q_t^L - \upsilon_{it}), \tag{30}$$

where $p_{it} - p_t^L = \log\left(\frac{P_{it}}{P_t^L}\right)$ and $q_{it} - q_t^L = \log\left(\frac{Q_{it}}{Q_t^L}\right)$. Substituting this expression into the production function (28) results in

$$y_{it}^L = \left(\frac{\eta+1}{\eta}\right) f(\boldsymbol{x}_{it}; \boldsymbol{\beta}) + \left(\frac{\eta+1}{\eta}\right)\omega_{it} + \left(\frac{\eta+1}{\eta}\right)\varepsilon_{it} - q_t^L\eta^{-1} + \upsilon_{it}\eta^{-1}, \tag{31}$$

where y_{it}^L are a firm's log-revenues deflated by an industry-level price index, i.e. $y_{it}^L = q_{it} + p_{it} - p_t^L$. Hence, (31) is a reduced form model allowing us to recover production function parameters $\boldsymbol{\beta}$ 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 recover price-cost wedges resulting from product differentiation . 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)

$$\mu_\eta = \frac{\eta}{\eta+1}\,. \tag{32}$$

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.

4 EMPIRICAL APPLICATIONS IN THE GERMAN BREWING SECTOR

4.1 Industry Background

Beer is deeply rooted in German culture. With 93,013 million hectoliters (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).

4.2 Markup and product differentiation in the German brewing sector

4.2.1 Introduction and research question

The German brewing industry is a good example of a differentiated product market (J. Hausman, Leonard, and Zona, 1994; Slade, 2004; Rojas and 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, and Meulenberg, 2003; Profeta, Enneking, and Balling, 2008; Hasselbach and 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, 2017a).[20]

The aim of this empirical application 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. To recover general markups, that can be due to all kinds of market imperfection, we employ the method proposed by (Hall, 1988, 1990) and De Loecker and Warzynski (2012). 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 and 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

[20] 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, 2017b). 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).

other sources. Our approach is closely related to (Crépon et al., 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.

4.2.2 Empirical model

To estimate the general markup and the markup related to product differentiation we need to specify an estimable form of equation (31). We allow for non-neutral technical change in the empirical specification and therefore t also appears in the function transforming inputs to outputs in (31), that is $f(\boldsymbol{x}_{it}, t; \boldsymbol{\beta})$. Hereby the input vector $\boldsymbol{x}_{it} = [l_{it}, k_{it}, m_{it}]$ captures labor, capital and material input use respectively. Specifying the functional form in $f(\boldsymbol{x}_{it}, t; \boldsymbol{\beta})$, as translog and assuming unobserved productivity differences being time invariant, e.g. $\omega_{it} = \omega_i, \forall i$, we have

$$y_{it}^{L} = \tilde{\beta}_0 + \boldsymbol{r}_{it}\widetilde{\boldsymbol{\beta}} + t\boldsymbol{x}_{it}\widetilde{\boldsymbol{\beta}}^{t} + \tilde{\beta}_t t + \tilde{\beta}_{tt} t^2 - \eta^{-1} q_t^{L} + \widetilde{\omega}_i + \gamma_{it}, \tag{33}$$

where $\boldsymbol{r}_{it}$ is the vector of inputs resulting from the translog-specification of $f(\boldsymbol{x}_{it}; \boldsymbol{\beta})$ and $\widetilde{\boldsymbol{\beta}}$ captures the corresponding reduced form parameters that combine production and demand parameters, i.e. $\widetilde{\boldsymbol{\beta}} = \left(\frac{\eta+1}{\eta}\right)\boldsymbol{\beta}$. While $\widetilde{\boldsymbol{\beta}}^{t} = [\tilde{\beta}_{lt} \quad \tilde{\beta}_{kt} \quad \tilde{\beta}_{m}]'$ captures reduced-form-coefficients corresponding to interactions between inputs and the time trend, the error term γ_{it} contains unobserved production and demand shocks, so $\gamma_{it} = \left(\frac{\eta+1}{\eta}\right)\varepsilon_{it} + \upsilon_{it}\eta^{-1}$.[21]

[21] Please note that since (33) 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.

From the estimated parameters in (33) we can directly obtain η and the markup related to product differentiation (equation (32)). 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 do not 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 et al. (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 θ_{it}^{M} is given by

$$\theta_{it}^{M} = \beta_m + \beta_{mm} m_{it} + \beta_{lm} l_{it} + \beta_{km} k_{it} + \beta_{mt} t. \tag{34}$$

Based on (34), we derive firm- and time-specific output elasticities.

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

$$\alpha_{it}^{M} = \frac{W_{it}^{M} X_{it}^{M}}{P_{it} Q_{it} \exp(-\hat{\gamma}_{it})} \tag{35}$$

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 (26) enables the calculation of any individual firm's markup in any year.

4.2.3 Data

We employ an unbalanced panel of German breweries participating in a voluntary benchmarking program conducted on behalf of the German Brewers Association[22] (GBA)

[22] 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

over a period of 13 years from 1996 to 2008.[23] 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.

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

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.).

[23] 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.

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.

Table 2: Descriptive statistics – German beer market

Variable	Mean	Median	Min	Max	Std
Output[1] Y_{it}^{L}	10,946	5,538	407	239,000	20,396
Labor L_{it}	2,335	1,337	100	36,664	3,518
Capital K_{it}	4,705	2,271	84	82,897	8,256
Material M_{it}	3,328	1,789	138	75,368	6,870

[1] Output refers to revenues deflated by an industry price index. $Y_{it}^{L} = \frac{P_{it}Q_{it}}{P_{it}^{L}}$

All variables are measured in 1,000€.

Number of observations: 1,324.

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

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.[24] 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

[24] 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.

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 (Statistisches Bundesamt, 2002, 2006, 2008).

4.2.4 Estimation and results

We estimate the reduced form equation (33) by means of different panel data estimation methods. First, we the RE estimator and the FE estimator (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 $\widetilde{\omega}_i$ 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 used the Breusch and 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.

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

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 5, 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 (De Loecker, 2007a; van Beveren, 2012). 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.

Table 4: Estimated parameters of equation (33) – 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

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 $\delta_{it} = \theta_{it}^{L} + \theta_{it}^{K} + \theta_{it}^{M}$ of $\bar{\delta} = 1.290$.

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

We obtain a mean general markup of $\overline{\mu}$ = 1.650. We test the null hypothesis that the average markup is not statistically different than 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 and 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 (27) we calculate the average profit ratio $\bar{\psi}$ to 1.155. Although 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.

Table 6: Hypothesis testing

Null hypothesis	Critial values Lower5%	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

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.

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

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.

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

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.

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.

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.

Table 10: Estimated parameters of equation (33) 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.

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.

4.2.5 Conclusion and limitations

The increasing market concentration, and the existence of market power and imperfect competition in food and beverage supply chains are issues of increasing concern to competition authorities worldwide (OECD, 2014). According to 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.

4.3 Advertising and markups: the case of the German brewing industry

4.3.1 Introduction and research question

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 beverage 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.[25] 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

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

the Stigler (1961) model, 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 empirical application 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. Firm- and time-specific markups are calculated following Hall (1988, 1990) and De Loecker and Warzynski (2012). Any firm's profit ratios (price over average cots) is derived based on the markup and a firm's returns to scale (Crépon et al., 2005). To recover unbiased output elasticities and returns to scale, we estimate the production function using the framework developed by WDG and LP and the method proposed by Ackerberg et al. (2015). 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, Kang, and Chilek (2015) 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.

4.3.2 Empirical model

Based on (26) and (27), 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 depicted in (1) with common technology parameters across a set of producers.[26] In the empirical application in 4.2 we assume time-invariant unobserved heterogeneity in production to econometrically correct for transmission bias by a FEGLS estimator. We choose a distinct strategy in this application to infer production function parameters and thereafter use the WDG and LP framework and the ACF procedure allowing to relax the time-constant productivity assumption and to allow for dynamic implications in the production process.

As a basis for the application of the WDG and ACF estimators, we assume the production technology of a firm being represented by gross output and translog-specified production function in (6). We refrain from assuming a Cobb-Douglas form as it restricts output elasticities being constant across firms and over time, which may lead to ascribing technological variation to variation in markups or other firm performance measures calculated from production function coefficients. As we specify $\boldsymbol{x}_{it} = [l_{it} \quad k_{it} \quad m_{it}]$, $\boldsymbol{r}_{it}\boldsymbol{\beta}$ is the second order polynomial in the elements of $\boldsymbol{x}_{it}$.

To estimate the production function parameters using the WDG framework, we closely follow the procedure outlined in section 2.3 specifying $\boldsymbol{x}_{it}^F = k_{it}$. In order to make feasible the joint estimation of the functions in (9) and (11), we approximate $\kappa_t^{-1}(\boldsymbol{x}_{it}^F, m_{it})$ by a third-order polynomial in k_{it} and m_{it}. Furthermore, we assume that productivity follows a random walk with drift, which restricts $G = 1$ and $\rho_1 = 1$ in (13).[27] Substitution for κ_t^{-1} and h in (9) and (11) yields

$$y_{it} = \delta_0 + \boldsymbol{r}_{it}\boldsymbol{\beta} + \boldsymbol{c}_{it}\boldsymbol{\lambda} + \varepsilon_{it} \tag{36}$$

and

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

[27] 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.

$$y_{it} = \zeta_0 + \boldsymbol{r}_{it}\boldsymbol{\beta} + \boldsymbol{c}_{it-1}\boldsymbol{\lambda} + \nu_{it}. \tag{37}$$

Instruments for the first equation are

$$\boldsymbol{z}_{it1} = [1 \quad \boldsymbol{r}_{it} \quad \boldsymbol{c}_{it} \quad \boldsymbol{c}_{it-1} \quad \boldsymbol{w}_{it-1}], \tag{38}$$

where $\boldsymbol{w}_{it-1} = [l_{it-1} \quad l_{it-1}^2 \quad l_{it-1}m_{it-1} \quad l_{it-1}k_{it} \quad k_{it}m_{it-1}]$.[28] Instruments for the second equation are

$$\boldsymbol{z}_{it2} = [1 \quad \boldsymbol{r}_{it}^0 \quad \boldsymbol{c}_{it-1}], \tag{39}$$

where $\boldsymbol{r}_{it}^0$ captures the terms corresponding to a second-order polynomial of $l_{it-1},\ m_{it-1}$ and k_{it}. Specifying the instrument matrix using $\boldsymbol{z}_{it1}$ and $\boldsymbol{z}_{it2}$, we can form moment conditions according to

$$E\left[\boldsymbol{Z}_{it}'\begin{pmatrix}\varepsilon_{it}(\delta_0, \boldsymbol{\beta}, \boldsymbol{\lambda},)\\ \nu_{it}(\zeta_0, \boldsymbol{\beta}, \boldsymbol{\lambda})\end{pmatrix}\right] = 0.\text{[29]} \tag{40}$$

The moment conditions in (40) are estimated using the Gauss-Newton search algorithm of Stata's gmm command and allowing for cluster-robust standard errors.[30]

In order to apply the ACF procedure, we tailor the rather general representation of the method in section 2.3.3 to the peculiarities of the German beer market. To ensure identification of parameters in the gross output case, we need to specify the vector of material input demand shifters $\boldsymbol{u}_{it}$. Hereby, we collect 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 material shifters in $\boldsymbol{u}_{it}$. Furthermore, we choose elements in $\boldsymbol{z}_{it}$, reflecting assumptions on input timing, according to the characteristics of the beer market. We consider capital to be a dynamic input that is chosen

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

[29] Note that the coefficient vector $\boldsymbol{\rho}$ in (16) is not part of the residual function in $\nu_{it}(.)$ in (40) due to the assumption of productivity following a random walk with drift.

[30] The initial weighting matrix is specified as unidentified and error terms are assumed to be independent.

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:

$$\boldsymbol{z}_{it} = [1, l_{it-1}, l_{it-1}^2, k_{it}, k_{it}^2, m_{it-1}, m_{it-1}^2, l_{it-1}k_{it}, l_{it-1}m_{it-1}, k_{it}m_{it}]'.^{31} \tag{41}$$

Using the instruments defined in $\boldsymbol{z}_{it}$, the moments in (22) are estimated using standard GMM techniques to obtain $\widehat{\boldsymbol{\beta}}$, and standard errors are calculated by block bootstrapping.

4.3.3 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

$$\hat{\theta}_{it}^M = \hat{\beta}_m + 2\hat{\beta}_{mm}m_{it} + \hat{\beta}_{lm}l_{it} + \hat{\beta}_{km}k_{it}. \tag{42}$$

Similar to (35), we correct the share in revenue from material $\hat{\alpha}_{it}^M$ by the predicted production function error according to

$$\hat{\alpha}_{it}^M = \frac{W_{it}^M M_{it}}{P_{it}\frac{Y_{it}}{e^{\hat{\varepsilon}_{it}}}}. \tag{43}$$

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 (20) as $\hat{\varepsilon}_{it} = y_{it} - \hat{\varphi}_{it}$. The general markup μ_{it}^M is calculated according to (26). 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 (27).

[31] 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.

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

$$\ln \mu_{it}^{M} = \boldsymbol{x}_{it}\boldsymbol{\beta} + \sigma_i + \epsilon_{it}, \tag{44}$$

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 $\boldsymbol{\beta} = [\beta_0 \quad \beta_{ad} \quad \beta_2 \quad \cdots \quad \beta_L]'$, 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 (44) using $\ln \psi_{it}$ and $\ln P_{it}$ as dependent variables.

4.3.4 Data

The dataset used for the empirical application is, in essence, identical to the data described in 4.2.3. As a minor deviation, we had to drop three observations due to missing values in a variable used only in this application, which entails some minor deviations in the summary statistics of input factors. Table 11 presents output, inputs, prices and advertising expenses, for the according set of observations. We use a different variable to proxy for output as we do not intend to estimate a reduced form model as in (31). Thereafter, a firm's output is given as revenue deflated by a firm-specific price index with 2005 as base year.[32]

Table 11: Further descriptive statistics – German beer market

Variable	Mean	Median	Min	Max	Std
Output[1] Y_{it}	11,023	5,515	314	225,574	20,801
Labor L_{it}	2,337	1,338	100	36,664	3,518
Capital K_{it}	4,708	2,274	84	82,897	8,258
Material M_{it}	3,579	1,900	152	83,133	7,353
Physical output Q_{it}	128	64	4	2,516	232
Price P_{it}	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

[1] Output refers to revenues deflated by a firm specific price index.
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.
Number of observations: 1,321
Source: Authors' calculations from German Brewers Association (GBA) data.

We build this firm-specific 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

[32] 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.

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. Physical output is measured in thousands of hectoliters and includes beer, beer-mix drinks (shandy) and non-alcoholic beverages.

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 3 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.

4.3.5 Results

Table 12 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 13 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.

Table 12: 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 13: 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.

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.

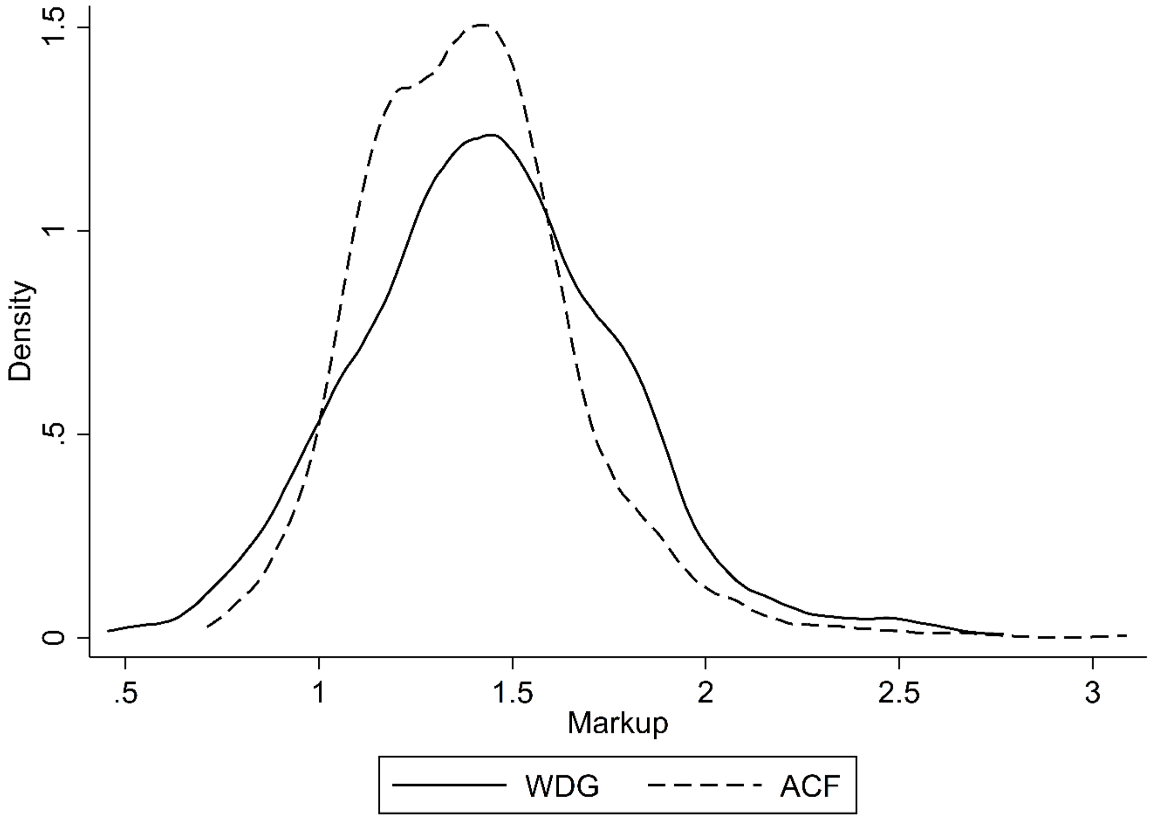

Figure 1: Distribution of markups based on different estimation procedures.

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.

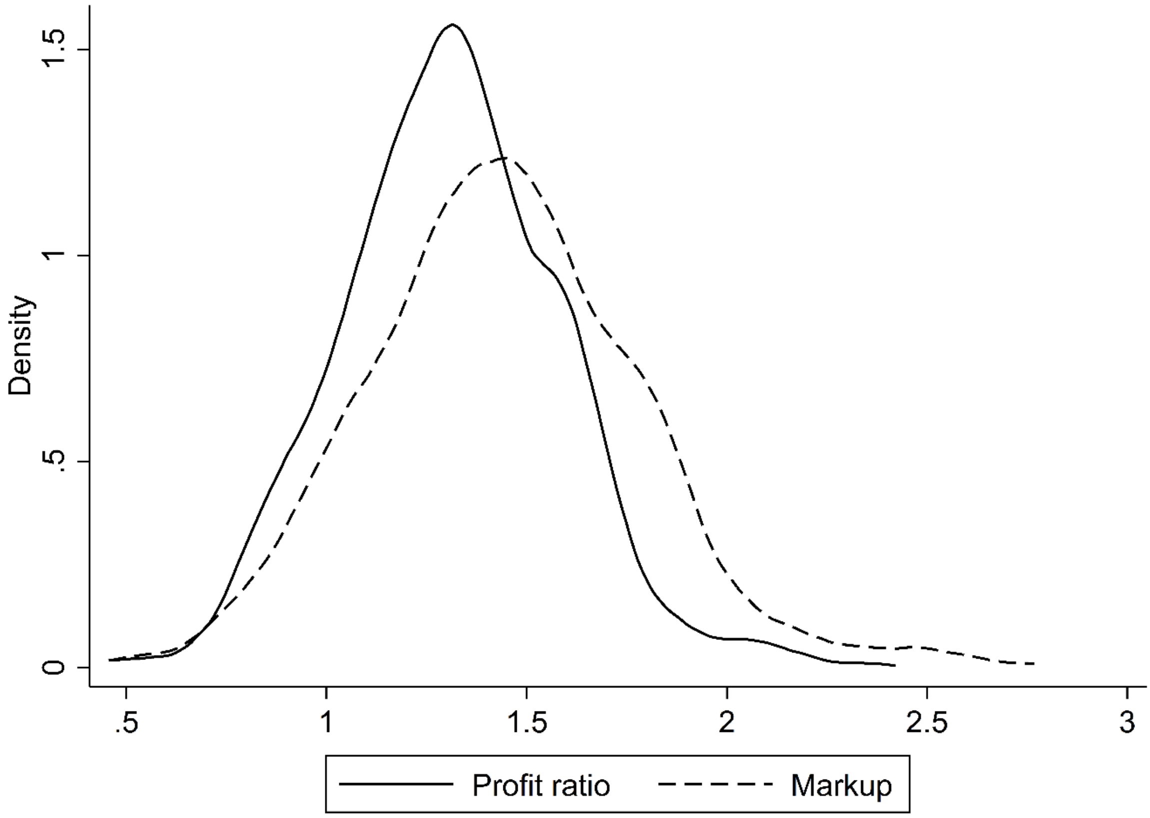

Figure 2: Distribution of profit ratios and markups

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 14 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.

Table 14: 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.

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.[33] In column 2, we add the breweries' revenue shares from beer sold under their own private brands. Breweries with

[33] Note that in section 4.2.4, we find the highest mean markup in the group of breweries producing the largest quantities. In contrast to the procedure applied in section 4.2.4, the calculation of mean markups for different size groups of breweries, we assume a linear relationship between markup and the firm size while controlling for other factors.

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 De Loecker and Warzynski (2012) 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 $\widetilde{\widetilde{\omega}}_{it}$ from (14) as $\boldsymbol{c}_{it}\hat{\boldsymbol{\lambda}}$.[34] In the ACF procedure, we recover productivity from (20) as $\widehat{\omega}_{it} = \hat{\varphi}_{it} - \hat{\beta}_0 - \boldsymbol{r}_{it}\widehat{\boldsymbol{\beta}}$. 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.

Table 15: 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.

[34] 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.

In addition, we want to evaluate whether firms can increase their profit ratios and prices through advertising efforts. Table 15 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.

4.3.6 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 (Guinard, Uotani, and Schlich, 2001; Galizzi and Garavaglia, 2012) 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 consumers exhibit brand loyalty for "local" beers. Karagiannis, Kellermann, Pröll and Salhofer (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, in turn, may 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 WDG and LP 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, Pinkse and Slade (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. (2018) 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.

5 EMPIRICAL APPLICATION TO AUSTRIAN CROP FARMS

5.1 Introduction

Measurement of total factor productivity (henceforth TFP) and TFP change is of large importance in agricultural economics. Mundlak (1992) highlights, among other reasons, interest in food supply, aspects in growth, the competitive position of agricultural input markets, off farm labor migration and farmers' income as a rationale for the study of agricultural TFP. In a more global perspective, agricultural TFP growth has been the main driver to prevent a Malthusian crisis (Fuglie, Wang and Ball, 2012). Insights in agricultural TFP growth can therefore constitute important support for policy in decision making.

In order to estimate TFP, several methods have emerged that can be categorized into nonparametric methods, including index numbers and data envelopment analysis (henceforth DEA) and parametric methods such as stochastic frontier analysis (henceforth SFA) and production function estimation. Van Biesebroeck (2007) shows that all methods have advantages and drawbacks.[35] Index methods, which are based on assumptions on market structure and firm behavior, are flexible in specification of technology. In addition, straightforward computation without estimation of parameters is an advantage of index methods. DEA makes use of linear programming to estimate each firm's productivity and hereby does not require any assumptions on the functional form or firm behavior. Due to their deterministic nature, nonparametric methods do not allow for unobservables. Moreover, both index numbers and DEA are problematic when inputs or output variables suffers from measurement error. Using simulation techniques, Van Biesebroeck (2007) shows that index numbers especially do not perform well under measurement error in inputs, while DEA is particularly vulnerable to incorrectly measured outputs. Parametric methods, such as SFA and

[35] The remaining paragrah borrows liberally from Van Biesebroeck (2007).

production function estimation, rely on the a priori specification of a production function and its econometric estimation to recover TFP. In contrast to production function estimation, SFA allows to measure technical efficiency (i.e. the output of a firm as a fraction of maximum possible and feasible output) in making assumptions on the distribution of unobserved productivity. Although the assumption of common technology (i.e. input substitution patterns) of firms may be problematic in heterogeneous samples of firms, parametric methods are likely to be less vulnerable to outliers and measurement errors. In simulated experiments, Van Biesebroeck (2007) shows that in particular PM (in his case OP) perform well under partly persistent idiosyncratic shocks to production as it exploits the firm's knowledge about these shocks. As discussed in Petrick and Kloss (2018), agricultural production is characterized by large unobserved shocks, where besides some highly variable shocks such as weather events or rainfall, the econometrician is also confronted with more persistent unobservables such as management abilities, human capital of labor force or the availability of a farm successor. While nonparametric methods and SFA are widely used in an agricultural context, the use of PM has been limited. To the best of our knowledge, the applications of Rizov, Pokrivcak and Ciaian (2013), Petrick and Kloss (2018), Frick and Sauer (2018) and Jang and Du (2019) are the only examples of the use of PM in agricultural economics.

The aim of this application is threefold. First, although, there are several studies investigating productivity in the grain farming sector in Europe (e.g. Mary (2013) and Dakpo, Desjeux, Jeanneaux, and Latruffe (2019) for France, Marzec and Pisulewski (2019) for Poland, Cechura, Kroupova, and Rudinskaya (2015) for the Czech Republic and Amadi, Piesse and Thirtle (2004) for South England), to the best of our knowledge, this is the first contribution with respect to Austria. Hereby, we want to add to the literature in estimating TFP in the context of agriculture in a sector that has not been investigated extensively so far. Secondly, we apply an estimation method that has been seldom used in agricultural economics and discuss differences to productivity estimates of the traditional FE estimator.

Thirdly, in contrast to existing literature in agricultural economics, we aim to apply the ACF procedure, providing several advantages over the preceding OP and LP methods, using a translogarithmic form.[36] This enables us to estimate firm- and time specific productivity measures and we can allow for a more flexible production process of farms.

5.2 Recovering total factor productivity from production functions

In order to estimate total factor productivity, we assume that farm i's production technology can be captured by (1). Following Solow (1957), we consider productivity as the residual resulting from the variation in output that cannot be explained by variation in input. Rearranging (1), we can express total factor productivity[37] as

$$TFP_{it} = \frac{\exp(y_{it})}{\exp(f(\boldsymbol{x}_{it};\boldsymbol{\beta}))}. \tag{45}$$

In aggregating productivity to the industry-level, we follow OP and weigh farms' productivity levels by their shares in total industry revenue s_{it} and aggregate farm level productivities

$$TFP_t = \sum_{i=1}^{N_t} s_{it} TFP_{it}, \tag{46}$$

where N_t is the number of firms in the market in period t. According to OP, industry level productivity can be decomposed into "within TFP", capturing TFP growth within farms, and "between TFP", as productivity originating from shifting production to more productive firms in the industry. Hence, (46) can be decomposed into

[36] see section 1.2 and 2.4 or the original work of ACF for advantages of the ACF procedure over the methods proposed by OP and LP.

[37] Discrepancies emerge, when it comes to authors' definition of TFP. Some authors consider ω_{it} as TFP (e.g. van Beveren (2012)) while others additionally include the i.i.d error ε_{it} (e.g. Frick and Sauer (2018)). We use the measure applied by Frick and Sauer as we want to capture all factors that might influence TFP growth.

$$TFP_t = \overline{TFP}_t + \sum_{i=1}^{N_t} \Delta s_{it}\, \Delta TFP_{it}, \tag{47}$$

where $\overline{TFP}_t = N_t^{-1} \sum_{i=1}^{N_t} TFP_{it}$ represents unweighted mean productivity in period t. Deviations from the unweighted mean of firms' shares in total revenue $\bar{s}_t$ and deviations from the unweighted mean productivity $\overline{TFP}_t$ are captured by $\Delta s_{it} = s_{it} - \bar{s}_t$ and $\Delta TFP_{it} = TFP_{it} - \overline{TFP}_t$ respectively.

Calculation of TFP_{it} according to (45) requires to obtain a predicted value of $f(\boldsymbol{x}_{it}; \boldsymbol{\beta})$. We therefore apply the FE estimator as a traditional and frequently used method as well as the ACF procedure as an estimator from the newer PM literature. The input vector $\boldsymbol{x}_{it}$ captures the log of all inputs and is specified as $\boldsymbol{x}_{it} = [l_{it} \quad k_{it} \quad m_{it} \quad ld_{it}]$, where in addition to labor, capital and material input, we introduce cultivated area of farm i in period t as ld_{it}. We consider a gross output production function and the functional form in $f(\boldsymbol{x}_{it}; \boldsymbol{\beta})$ is assumed being translogarithmic. Accordingly, the vector $\boldsymbol{r}_{it}$ in (6) captures all terms resulting from a second order polynomial approximation of $f(\boldsymbol{x}_{it}; \boldsymbol{\beta})$.

FE estimation, that is briefly discussed in 2.2, is applied allowing for Hicks-neutral technical change in including time dummies. Application of the ACF procedure described in 2.4 requires more modification. As opposed to the application of the ACF procedure in 4.3, the vector of quasi-fixed inputs $\boldsymbol{x}_{it}^F$, which is included in material demand, captures land in hectares in addition to the capital stock. In the empirical specification, we allow, similar to the FE estimation, for Hicks-neutral technical change in the first stage of the ACF procedure in including time dummies in (20). Productivity can then be recovered from the first stage as

$$TFP_{it} = \beta_0 + \widehat{\omega}_{it} + \boldsymbol{t^d}\widehat{\boldsymbol{\beta}}^d + \hat{\varepsilon}_{it}, \tag{48}$$[38]

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[38] In several applications, ω_{it} is considered as the measure of productivity. We refrain from using ω_{it} in order to remain consistent with the expression in (45).

where $\boldsymbol{t^d} = [t_{2003} \quad \cdots \quad t_{2017}]$ captures indicator variables for each year and $\boldsymbol{\beta}^d = [\beta_{2003} \quad \ldots \quad \beta_{2017}]'$ is the corresponding coefficient vector. As we are also interested in identifying production function coefficients, we have to choose instruments in $\boldsymbol{z}_{it}$ to form GMM moment conditions according to (22). As mentioned above, we consider capital and land as dynamic inputs as farmers apparently face adjustment costs when changing either the level of capital (e.g. building new facilities) or land.[39] Material is assumedly a flexible input that can be adjusted in period t as the level of intermediate inputs in agriculture (e.g. seeds, fertilizer or pesticides) is considered highly variable.[40] Although labor is frequently considered as flexible (e.g. OP and LP), in the case of crop farms, where the vast majority is family owned, this assumption is not plausible. We assume that labor has been chosen in period $t-1$, and allow for labor adjustment that is not perfectly flexible.[41]

We can now form moment conditions according to (22) and specify the instrument vector in $\boldsymbol{z}_{it}$ as

$$\boldsymbol{z}_{it} = [1, l_{it}, l_{it}^2, k_{it}, k_{it}^2, m_{it-1}, m_{it-1}^2, ld_{it}, ld_{it}^2, l_{it}k_{it}, l_{it}m_{it-1}, l_{it}ld_{it}, k_{it}m_{it-1}, k_{it}ld_{it}, m_{it-1}ld_{it}]'. \tag{49}$$

Production function parameters in $\boldsymbol{\beta}$ are estimated using standard GMM techniques and standard errors are calculated using block bootstrapping.[42]

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[39] Land sales markets are very tight, and in that, little land is offered. The rental market for land is more flexible but still especially for cropland we can assume that there is surplus demand.

[40] For a classification of production factors according to their variability and observability see Petrick and Kloss (2018).

[41] As labor is not in the information set in period t, the identification problem of gross output function functions pointed out by Gandhi, Navarro, and Rivers (2017) can be avoided.

[42] Estimation is executed in Stata using an own estimation routine which borrows from Rovigatti and Mollisi'´s (2018) "prodest" command and the code from De Loecker and Warzynski (2012).

5.3 Data

The dataset consists of Austrian bookkeeping farms and serves as a basis for Austrian farm data included in the European Farm Accountancy Data Network (FADN).[43] While the full dataset includes approximately 2,000 farms in each year, we restrict our sample to specialized crop farms, which we define as enterprises having revenues from crop income making up for 65% of total revenues at least. In addition, we require farms appearing in the sample for at least two consecutive years. This leaves us with an unbalanced panel of 261 crop farms, which we observe over a period of 15 years from 2003 to 2017 at a maximum. The median farm is in the panel for approximately 11 years. In total, the number of observations accounts to 2,604.

Table 16 shows summary statistics of input factors and output.

Table 16: Descriptive statistics – Austrian crop farms

	Mean	Median	p5	p95	Std.
Output (€)	85.524	69.923	16.869	198.376	66.865
Labor (AWU)	1.015	0.910	0.220	2.100	0.630
Capital (€)	165.888	135.076	22.306	400.444	125.198
Material (€)	60.528	46.654	14.652	142.099	52.324
Land (ha)	67.847	59.525	21.690	141.730	38.202

Output, capital and material are measured in 1,000 Euros. Labor captures annual working units (AWU) and land is measured in hectares.
Number of observations: 2604.

[43] The FADN is a dataset serving the European commission as a means to evaluate the income of agricultural holdings and the impacts of the Common Agricultural Policy. The data is collected in order to constitute a representative sample of farms from the European Union member states in terms of region, economic size and type of farming.

We proxy farm output by aggregate turnover net of all subsidies. [44] Labor (L_{it}) is measured in annual working units (AWU), defined as “Total hours worked divided by the average annual hours worked in full-time jobs in the country” (Eurostat, 2019). Labor includes family labor and hired labor. Capital (K_{it}) is measured as the sum of assets from buildings, livestock, machinery and permanent crops reported at the beginning of the year. Material (M_{it}) captures the sum of all expenses on intermediate inputs such as energy, heating, feed or fertilizer. Land (LD_{it}) includes the total area cultivated, i.e. own and rented land, and is measured in hectares. We deflate all variables in monetary terms by appropriate price indices from the Austrian statistical office (Statistik Austria).

5.4 Results

Table 17 shows production function coefficients estimated using FE and the ACF procedure. All first order effects are significantly different from zero at a 1% level. Except for the coefficient of land, all first order effects of FE are lower than their counterparts estimated using the ACF procedure.In particular, the magnitude of the FE capital coefficient is smaller than the capital coefficient estimated using the ACF procedure. Ackerberg, Benkard, Berry, and Pakes (2007) note that FE often produces unreasonably low estimates of capital coefficients, i.e. the capital coefficient is considerably below the capital’s cost share or/and returns to scale are extremely low.

[44] Aggregate turnover is the sum of turnover from crops, grain, oil, energy, rootcrop, proteincrop, industrycrop and foddercrop.

Table 17: FE and ACF estimation results

	FE	SE	ACF[2]	SE[1]
Labor	0.145	0.020	0.293	0.021
Capital	0.070	0.016	0.108	0.018
Material	0.349	0.021	0.589	0.036
Land	0.439	0.041	0.136	0.031
Labor*Labor	0.023	0.017	0.002	0.018
Capital*Capital	0.006	0.003	-0.003	0.011
Material*Material	0.057	0.014	0.151	0.088
Land*Land	0.194	0.047	0.146	0.072
Labor*Capital	0.047	0.016	0.127	0.022
Labor*Material	0.021	0.027	-0.094	0.049
Labor*Land	-0.041	0.043	0.056	0.050
Capital*Material	0.001	0.016	0.045	0.040
Capital*Land	-0.0945	0.030	-0.143	0.031
Material*Land	-0.212	0.047	-0.336	0.135
Observations	2604		2343	

Time indicators are included in the FE model and the first stage estimation of the ACF procedure.
[1] Block bootstrapping is used to calculate ACF standard errors (1,000 repetitions).
[2] Estimates are based on the assumption that the level of labor input is decided in period $t-1$.

Table 18: Mean output elasticities Austrian crop farms

	FE		ACF	
	Mean	SE[1]	Mean	SE[2]
Labor	0.121	0.018	0.264	0.020
Capital	0.070	0.015	0.094	0.014
Material	0.346	0.021	0.567	0.033
Land	0.471	0.040	0.212	0.032
Observations	2604		2343	

[1] Standard errors are calculated using the Delta method.
[2] Block bootstrapping is used to calculate standard errors (1,000 repetitions).

Derived mean output elasticities in Table 18 follow a similar pattern with relatively low FE-derived elasticities of labor, capital and material in comparison to mean elasticities derived using the ACF method. Returns to scale calculated using FE are nearly constant with a mean value of 1.008, while ACF gives increasing returns to scale of 1.137, a more plausible value considering the small structure of Austrian crop farmers.

Using (45), we recover any farm's TFP in any period. Weighting individual farms' TFP's by their share in total industry revenue, we calculate aggregate TFP according to (46). Figure 3 depicts the cumulative evolution of changes in industry productivity from 2003 to 2017. With mean annual growth rates of aggregate TFP of 1.8% for FE and 2.8% for ACF, the results indicate overall TFP growth over the observed time span. As Figure 3 however shows, Austrian crop farmers mainly faced growth in aggregate TFP during the period between 2003 and 2011. The subsequent period is characterized by an overall downward trend, however peaking in 2016. Figure 3 also reveals that during the observation period, TFP growth rates have been fluctuating substantially.

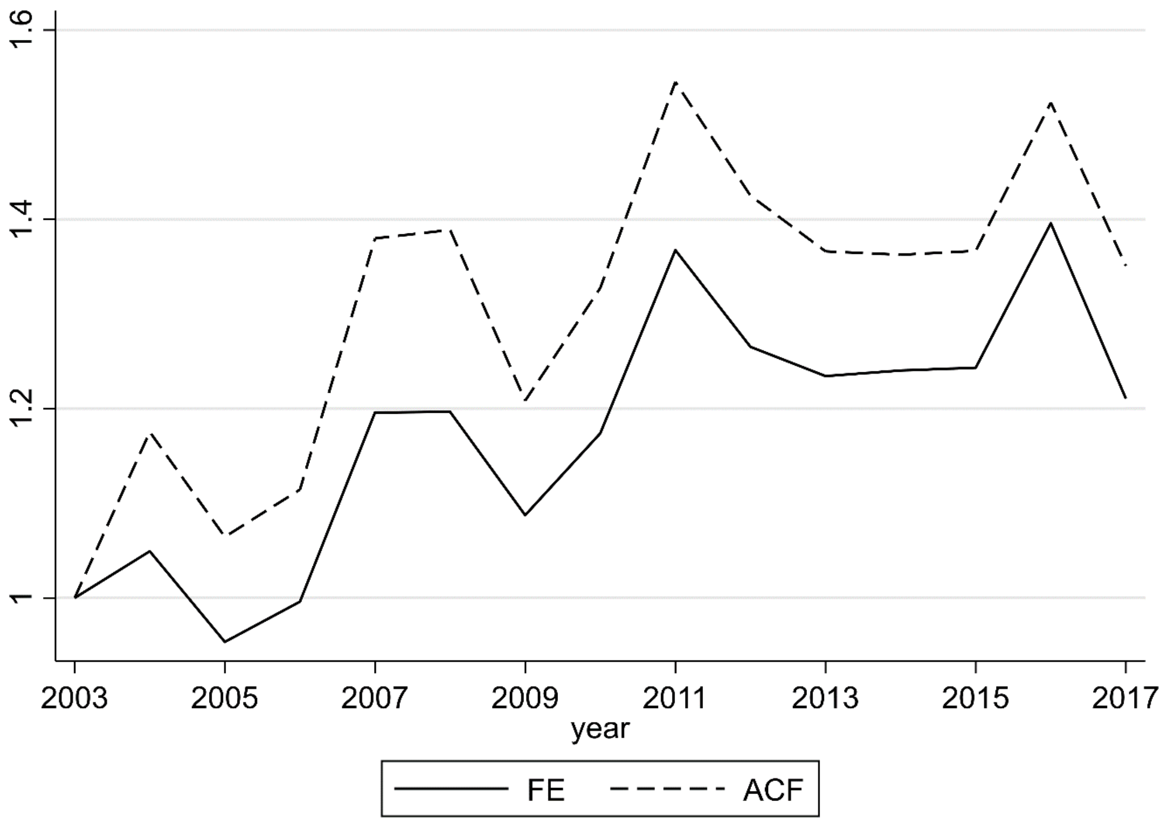

Figure 3: Evolution of aggregate TFP by estimation method over the period 2003 – 2017

In the periods between 2006 and 2007 and 2010 and 2011, we report the highest unweighted TFP growth rates with over 20% for both estimation techniques applied. This is in line with findings by Dakpo, Desjeux, Jeanneaux, and Latruffe (2019) reporting a maximum increase in TFP growth rates of 19.5% in France between 2009 and 2010. We can decompose TFP following OP according to (47) to gain further insight into the forces behind productivity growth changes. Table 19 shows aggregate TFP (first and second column) decomposed into "within" productivity (column three and four) and "between" productivity (column five and six) calculated using FE and ACF production function estimates. The results reveal that the major part of increase in aggregate productivity is due to productivity growth within farms. For TFP estimated using FE, we report between productivity accounting on average to 12% of aggregate TFP and for TFP estimated using ACF, between productivity on average makes up for 6% per year.

Table 19: OP decomposition

	TFP_t^{FE}	TFP_t^{ACF}	$\overline{TFP}_t^{FE}$	$\overline{TFP}_t^{ACF}$	$\sum_i \Delta s_{it} \Delta TFP_{it}^{FE}$	$\sum_i \Delta s_{it} \Delta TFP_{it}^{ACF}$
2003	1.000	1.000	0.854	0.978	0.146	0.022
2004	1.049	1.175	0.942	1.131	0.107	0.044
2005	0.954	1.065	0.827	0.998	0.127	0.066
2006	0.996	1.114	0.853	1.033	0.143	0.082
2007	1.196	1.380	1.057	1.297	0.139	0.083
2008	1.197	1.389	1.093	1.335	0.103	0.054
2009	1.087	1.208	0.938	1.103	0.150	0.106
2010	1.174	1.328	1.040	1.252	0.134	0.075
2011	1.368	1.545	1.261	1.515	0.107	0.030
2012	1.265	1.425	1.138	1.355	0.127	0.070
2013	1.234	1.366	1.074	1.270	0.160	0.096
2014	1.240	1.363	1.077	1.256	0.164	0.106
2015	1.243	1.367	1.085	1.275	0.159	0.092
2016	1.396	1.523	1.225	1.426	0.171	0.097
2017	1.211	1.351	1.066	1.256	0.145	0.095

We therefore face industry-productivity-growth rather due to farms getting more productive as opposed to shifting production away from less productive farms to highly productive farms. Comparing results from different estimators, we face remarkably large differences between FE and ACF. While productivity growth estimated using FE is approximately 21%, productivity growth estimated using ACF is nearly 35% from 2003 to 2017. We also face differences in the composition of aggregate productivity. Hereby the "between" part of TFP is considerably higher for FE-estimated productivity.

5.5 Discussion

Our results indicate that aggregate TFP of Austrian crop farmers has been, on average, increasing during 2003 and 2017. Taking a closer look, however, shows that TFP growth mainly occurred in between 2003 and 2011 while after that time period, it was mainly stagnating and even negative after 2016. We further observe that aggregate TFP growth is mainly due to within farm TFP growth but we also notify a non-negligible part of between TFP growth.

Comparing TFP estimates based on the production function coefficients of the FE estimator or the ACF method, we notify that the magnitude of TFP estimates is largely deviating. Hereby, we observe in each year a lower industry productivity estimated using FE than industry productivity estimated using ACF. The FE estimator only controls for time invariant unobserved farm heterogeneity, an assumption that might be problematic in a longer panel, even for our fourteen-year observation period. A time varying part of the error might remain and still correlate with input use levels. Consequently, production function coefficients and TFP suffer from bias. We do not expect that kind of bias from the ACF procedure as we explicitly control for the unobserved error and allow for dynamic implications.

A rationale for the deviating results of production function coefficients and TFP of the FE estimator and the ACF method is also provided by Griliches and Hausman (1986), who show that possible measurement errors in the input variables are magnified through within-transformation. In particular, if inputs are more time-persistent than their measurement error, their signal-to noise ratio is reduced and fixed effects coefficients are biased downwards. Although we use appropriate price indices to deflate monetary values, we cannot rule out measurement error in the input factors (e.g. farmers may over- or underreport several values). Petrick and Kloss (2018) point out that especially in agriculture, several inputs display little variation over time such as land, labor and fixed capital. We therefore expect that even small measurement errors can have a serious impact on production function coefficients and TFP estimates.

6 SUMMARY AND CONCLUSIONS

The origins of production functions can be traced back into the eighteenth century. Since then, researchers urged to model the production process and represent production technology in a parametric form. In their influential work, Cobb and Douglas (1928) introduce a framework to estimate the parameters of a production function econometrically and pave the way for a broad literature on the estimation of production functions. Economists are however not solely interested in learning about the production process of enterprises, industries or countries but also in additional information that can be unveiled by estimating a production function. This thesis shows how to exploit the information of a production function and recover firm performance measures that are not included in ordinary firm level datasets. We use the production approach in order to answer several research questions in the food and beverages sector. First, we investigate price setting behavior in the German brewing industry and examine to which degree price-cost margins are determined by product differentiation.

Second, we evaluate whether markups in the German brewing sector are positively related to advertising and thirdly, we measure productivity growth and its origins for Austrian crop farms and compare results of distinct estimators.

As a prerequisite for any firm performance measure based on production function estimates, the researcher must provide unbiased production function parameters. Omitted price bias, which is often due to the lack of an adequate output proxy, and simultaneity bias, resulting from firms optimally choosing their level of inputs as a function of their productivity, pose ubiquitous problems to the econometrician aiming to identify production function parameters. Especially simultaneity bias has been discussed frequently in economic literature. Traditional solutions to simultaneity include the fixed effects estimator and instrumental variable estimation. Identification using fixed effects stems from the assumption that unobserved productivity is time invariant, which is especially problematic in long panels. Instrumental variable estimation, although being a natural approach to allow for time varying unobserved productivity, requires the presence of exogenous input demand shifters as instruments that are often hard to find in praxis. In addition to dynamic panel data methods, relying on the assumption of costly input adjustment, another strand of literature in production function estimation, proxy methods, has emerged. Initiated by the work of Olley and Pakes (1996), proxy methods make use of assumptions on firm behavior and the evolution of productivity allowing to unbiasedly estimate production function parameters while overcoming the pitfalls of traditional methods.

The availability of unbiased production function estimates serves as foundation for recovering firm performance measures required for the applications to German brewers and Austrian crop farmers. Following Hall (1988, 1990) and De Loecker and Warzynski (2012), we can calculate general markups from the production side. As opposed to the frequently used demand approach relying on disaggregated product level data, recovering markups from the production side requires data on the firm level that is more prevalent. Using the assumption of firms minimizing cost and behaving as price takers, the markup measure captures any sort of imperfect competition without placing any assumption on market structure and competitive behavior of firms. In addition, we can recover a markup measure that captures price-cost wedges resulting from product differentiation. To correct for omitted price bias induced by price dispersion, Klette and Griliches (1996) suggest to model individual firms' demand by a CES demand function. The resulting reduced form model embedding both production and demand side allows to recover a "product-differentiation" markup from reduced form parameters.

The German brewing market is investigated in order to shed light on the first two research questions. Although Germany is one of the largest beer producing nations, production and consumption are following a downward trend whereas production declined by 23% from 1991 to 2017 and per capita consumption decreased by 50% between 1976 and 2017. Due to high transportation cost, the market is very much nationally oriented. Compared to other countries, market concentration is relatively low but there is still some evidence of collusive behavior and, in addition, breweries may exert market power through the possibility to integrate vertically. Another characteristic of the market is that its' product, beer, is much differentiated with different styles and brands. Consumers have been investigated being very aware on brands and having preferences towards locally brewed beer. Accordingly, relatively large price differences can be observed even within the same style of beer. To differentiate their beers, German brewers invest heavily in marketing. Advertising expenditures in the German beer market have been increasing over the last two decades. Hereby, brewers spend double the sum on advertising expenditures than the producers of all other alcoholic beverages and have the third highest marketing expenditures in the food and beverage sector (Zühlsdorf and Spiller, 2012; Statista, 2019).

In order to investigate the first research question, we estimate Klette and Griliches' (1996) reduced form model, allowing us to recover demand-driven markups from reduced form parameters, and general markups using the output elasticity of material. Specifying the functional form as translogarithmic allows inferring firm- and time specific output elasticities as well as general markups. Using a panel of 197 German breweries observed from 1996 to 2008, we identify the parameters of the reduced form model using the random effects, fixed effects and the fixed effects generalized least squares estimator whereas we prefer the latter for our estimations. We recover a mean general markup estimate of 1.650, which is statistically different from 1, the value corresponding to a perfectly competitive output market. The demand-driven markup accounts to 1.49 and therefore amounts for a large part of the general markup. Results also indicate that general markups have been rising over time which goes in line with a rise in market concentration. We also find that Bavaria, the state with the highest brewery density, has the lowest general markup but the highest demand-driven markup, indicating that Bavarians have high preferences towards a specific brand or specific style of beer. Although the existence of market power and imperfect competition are issues of concern, pricing above marginal cost does not necessarily imply illegal collusion. As our results show, markups may also reflect consumers' preferences towards certain products or brand loyalty. Estimated markups may however not translate completely into profits (P>AC) due to breweries not operating on an optimal level of scale. Correspondingly, we observe increasing returns to scale on average.

In aiming to answer the second research question we test whether, on average, a firm's markup, profit ratio and price are positively related to its marketing efforts. To recover firm- and time specific general markups and profit ratios, we estimate a translog production function using the Wooldridge (2009) and Levinsohn and Petrin (2003) procedure and the Ackerberg et al. (2015) method. Both procedures corresponding to the proxy methods literature allow for time-varying productivity and dynamic implications of productivity. We estimate a gross output production function necessary to identify the output elasticity of the most flexible production factor material and therefore tailor both estimation routines accordingly. This is important in order to calculate unbiased markups and profit ratios. As opposed to estimating a reduced form model as in 4.2 to control for output price bias, we deflate revenues by a firm-specific price index and use them as a proxy for output to avoid measurement error. Using production function coefficients from the Wooldridge (2009) and Levinsohn and Petrin (2003) procedure and Ackerberg et al. (2015) method, we recover median output elasticities that are all significantly different from zero except for labor calculated using the Ackerberg et al. (2015) procedure. We estimate median markups of approximately 1.4, confirming the results in 4.2, which point towards an imperfectly competitive market. Our findings also reveal that firms are very heterogeneous when it comes to the ability to set prices above marginal costs. In a regression model, we evaluate whether advertising intensity relates to markups, profit ratios or prices whilst controlling for several firm characteristics and find a positive relationship between advertising intensity and each one of them. The positive relationship of markups and advertising intensity indicates that overall, German brewers use advertising as a mean to raise their price cost wedges.

The objective of the last application is to measure productivity growth of Austrian crop farms. In contrast to the widely used index number methods, data envelopment analysis and stochastic frontier analysis, we make use of the production approach to estimate total factor productivity as Van Biesebroeck (2007) shows that especially proxy methods perform well under persistent idiosyncratic errors that are common in agricultural economics. In addition, the use of proxy methods in agricultural economics has been limited. Using an unbalanced panel of 261 specialized Austrian crop farms that are observed from 2003 to 2017, we therefore estimate productivity using the Ackerberg et al. (2015) procedure and the traditional fixed effects estimator. As estimation of total factor productivity requires an expected value of output, we identify the parameters of a production function, whereas the latter is specified as gross output and translogarithmic. Based on estimated coefficients, we can calculate total factor productivity and report annual mean growth rates of 1.8% for estimates based on fixed effects and 2.8% for estimates based on the Ackerberg et al. (2015) procedure. Over the total time-period, we find total factor productivity growth of over 21%. Taking a closer look reveals that productivity growth occurred mainly between 2003 and 2011, whereas in the remaining period a downward trend is observed. In addition, we find large fluctuations in productivity, which are in a comparable range with results from related literature. We follow Olley and Pakes (1996) and decompose aggregate TFP growth into a “within” part, capturing productivity growth within firms and a “between” part, as productivity originating from shifting production to more productive firms in the industry. The Olley and Pakes (1996) decomposition reveals that the largest share in aggregate productivity is due to within productivity. A non-negligible amount of between productivity can however also be found. We can therefore identify positive productivity changes within farms as the main driver of productivity growth of Austrian crop farms. Lastly, we find substantial differences between total factor productivity estimates based on coefficients estimated using fixed effects and the Ackerberg et al. (2015) procedure respectively. The fixed effects estimator does not account for idiosyncratic errors that might correlate to the level of input use. As a result, we might find biased fixed effects coefficients that translate into biased total factor productivity estimates. In addition, measurement errors in inputs are magnified through within transformation resulting in a total factor productivity bias through the same channel.

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