Comment on
(Un)pleasant ... by Bond et al (2020)

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1 Introduction

It is well-known by practitioners that revenue data is frequently used to measure *output*, and not quantity data, when estimating production functions. This paper revisits the challenge of identifying a production function under unobserved output price variation, in addition to the standard unobserved productivity shock. A substantive body of work deals with the presence of output price variation in the estimation of production functions, by either adding additional structural assumptions on demand and conduct, or by constructing producer-level price data. The literature has also long recognized that the same challenge applies to the measurement of inputs: we observe input expenditures rather than input quantities, hereby introducing another potential bias —the input price bias. In contrast to the productivity literature, this paper is silent about this input price error, and this has implications for solutions to treat the problem at hand.

The authors start from this reminder, and draw conclusions for the production approach to markup estimation. This approach starts from rewriting the first order condition associated with cost minimization of a variable input (X) in production, to yield a simple markup (μ) formula:

$$\mu = \theta \frac{R}{P^X X}, \tag{1}$$

where R, $P^X X$ and θ, denote revenue, the variable input expenditure and the associated output elasticity, respectively. The authors correctly posit that if one relies on the revenue elasticity, instead of the output elasticity (θ), standard profit maximization (i.e., where the marginal revenue product of a (variable) input equals the associated input price) implies that this expression collapses to unity.[1]

To get around this well-known and documented issue, practitioners take care to rely on correct units of output. Following De Loecker and Warzynski (2012) page 2438, when applying this approach, the conversion to output takes the form of adding more data (prices and quantities) or adding more structure. In fact, throughout the literature, the presence of output price variation is featured prominently in the discussion of the actual implementation.[2]

[1]If we use incorrectly rely on the revenue elasticity, $\frac{\partial R}{\partial X}\frac{X}{R}$, the measured markup would be given by $\frac{\partial R}{\partial X}\frac{1}{P^X}$. Static optimal input choices imply that $\frac{\partial R}{\partial X} = P^X$.

[2]E.g. Collard-Wexler and De Loecker (2015), De Loecker et al. (2020), De Loecker

Production Approach to Markups Before I discuss these approaches in a bit more detail, it is very important to make, what may perhaps seem an obvious, but important point: the production approach to markup measurement does not hinge on a particular approach to estimate the production function. Rather it is an approach that delivers markups (and potentially marginal costs) for each individual producer (and time period), by exploiting standard cost minimization of a variable input in production. It does not require to specify a model of conduct or a particular demand system. The attraction of this approach is that it is flexible in considering multiple variable inputs, it can be extended to accommodate imperfect factor markets and it does not restrict the underlying production function (See e.g. Rubens (2020) for an extension to monopsony.) The authors briefly discuss the presence of adjustment costs. Again, the production approach allows for inputs facing adjustment costs, and it is precisely up to the researcher to select the inputs most plausibly being variable.[3] This is precisely why De Loecker et al. (2016) rely on intermediate inputs, and check the results using electricity, while not relying on labor given the inherent labor market rigidities documented in the case of India. De Loecker et al. (2020) document distinct patterns when relying on SG&A as an input in production, indicating the very likely adjustment costs related to inputs such as advertising, marketing, and overhead labor. The approach is complementary to the *demand* approach, where a specific model of conduct and consumer demand is specified to recover the same object.[4] When implementing the approach, however, the user has to confront a host of measurement issues (like in all applied work), one of them being the potential price variation captured by revenue data.

In this short comment, I start by reminding the reader of the existing literature on production function estimation in the presence of output price variation. It is important to distinguish between the ability to identify the output elasticity (required for the markup measurement) and the entire production function (including the productivity term, which is typically mostly of interest).[5]

et al. (2016), Mertens (2019), Morlacco (2017) and Rubens (2020).

[3]Under adjustment costs, the long run patterns of markups are identified, and one may be hesitant to compare markups in the cross section. Moreover, combining variable inputs with those subject to adjustment costs, is informative about the latter.

[4]See De Loecker (2011b) and De Loecker and Scott (2016) for a discussion of both approaches.

[5]If the residual contains the price, in addition to productivity, and are orthogonal to

First, I only consider the implications for the production function estimation, before connecting it to the production approach to markup measurement. This is important: the measurement of markups relies, in addition to revenue and expenditure on a plausibly variable input of production, on an *estimate* of an output elasticity (of that respective input). As such the method is not wedded to a particular approach to measuring this elasticity. The applied researcher has, in fact, a wide range of options, each with pros and cons. These options range from factor (or cost) shares, to control function and dynamic panel data approaches (see De Loecker et al. (2020) and De Loecker and Syverson (2021) for a discussion).

2 Comments

2.1 Literature

A survey by De Loecker and Goldberg (2014) takes stock of the literature that relies on production function estimation and summarizes the impact of the presence of price heterogeneity on the analysis of firm performance broadly defined (including markups, productivity and returns to scale). Relying on revenue data yields the so-called revenue-generating production function, as recognized in Olley and Pakes (1996), and the prior literature. The point is simple, even if productivity were data, running a regression of revenue on inputs on the data would fail to deliver an estimate of the output elasticity. We can broadly classify this literature into two approaches: adding more structure on the underlying demand system or adding price information (either at the industry, product, or product-firm level). Both approaches intend to eliminate the price variation, either by turning the price into an observable, or by making an assumption about what governs the price variation.

Adding a demand system Including a particular demand system, and thus additional demand-side information allows to identify the production function by essentially projecting revenue on inputs, and demand-side controls. The specific form of demand then allows to unpack the parameters of the reduced-form revenue generating production function into production and demand parameters.[6] This approach can thus be used whenever the

inputs, output elasticity are identified, while the productivity term cannot be recovered.

[6] See Klette and Griliches (1996), Levinsohn and Melitz (2002) and De Loecker (2011a).

researcher feels comfortable adding these additional structural assumptions, and whenever additional demand-side data can be brought to bear.

Adding price data In light of the constraints of adding a specific demand system, and requiring observing demand shifters, researchers have adopted a variety of practices to mitigate the presence of unobserved prices in the production function.[7] These practices share the same ambition: convert the units of output recorded in monetary units (e.g. USD) into physical output data. Typically in applied work one of the following is adopted: 1) Deflate firm-level revenues by the industry price index (the norm in the literature if nothing else), 2) Use product-level price data to create firm-level prices (using product-level weights), 3) Use product-firm price and quantity data (unit values). The first approach will eliminate common price trends from revenue data, and in the specific case of homogeneous products without any other sources of price heterogeneity (be it a spatial or regulatory dimension) this will convert revenue into effectively quantity data. This allows for the classic model of Cournot competition under a homogeneous product. The second and third approach introduce a product dimension to the production analysis, and effectively generate firm-specific prices. The latter is the least restrictive approach, and as long as units of output can be compared, this turns the revenue data into quantity data.[8] However, constructing a price index relies on a set of underlying assumptions regarding the nature of product space (see below).

Output and input price heterogeneity Under the more likely setting that both output and input prices vary across producers, De Loecker et al.

[7]The focus has been primarily on the presence of output price variation, for at least two reasons. First, there has been an unwritten rule that the presence of input price variation is somehow less prevalent once we consider producers in a single industry, and control for the variation in geographical location. Second, output prices have started to make their way into the observable column of production datasets, hereby suggesting (perhaps incorrectly) that input price variation is not a first-order concern. See De Loecker and Syverson (2021) for more discussion.

[8]A sample of applications using one of these approaches are Collard-Wexler and De Loecker (2015); Smeets and Warzynski (2013); Dhyne et al. (2020); Foster et al. (2008); Rubens (2020); Allcott et al. (2016); Morlacco (2017); Eslava and Haltiwanger (2020); Forlani et al. (2016); Valmari (2016); Orr (2019); Itoga (2019); Stiebale and Vencappa (2018); Atalay (2014); Backus (2020), De Loecker et al. (2020), De Loecker et al. (2016), Mertens (2019).

(2020) show how output elasticities can be recovered by adding controls for the joint output and input price term. This follows the spirit of the first approach (i.e. adding structure), but instead of adding the complete demand system, it only requires taking a stand on which factors arguably control the pass-through of input price to output price variation.

2.2 Production Approach to Markup Estimation

The authors then ask how the omitted price bias, when estimating the production function, impacts the markup measurement using the production approach. Again, in applications researchers have used a wide range of approaches to obtain reliable and robust measures of the output elasticity to plug into the first order condition (equation (1)). In particular recent applications of the production approach rely on estimated output elasticities that come from estimating production functions where revenues are converted to quantities using either industry-wide deflators, product-level prices, product-firm level prices, adding demand systems, or explicitly acknowledging the presence of input prices generating an output-input price wedge and adding shifters that govern this wedge. Alternatively, producer or industry-specific cost shares are used to measure output elasticities. Of course, in the absence of *any* price correction, the point made in this paper stands. However, in most applications great care is given to obtain reliable output elasticities, dealing not only with the omitted price bias, but also with the traditional simultaneity and selection bias.

This is not to say that the solutions used in applications are perfect or cover all cases, and in that sense if one needs a reminder, this paper does a good job, but it risks leaving the applied researcher with only a partial view of the set of trade-offs.

Finally, the production approach to markups can be informative about markups (across producers, products or time) even without taking a stand on the output elasticity, and therefore it can refrain from worrying about any of the challenges that come with estimating a production function. The only constraint for this type of analysis is that one cannot analyze markup variation within the dimension that is held fixed in the output elasticity. For example, if a producer's output elasticity does not change year-to-year, the change in the ratio of revenue to the variable input's expenditure is a direct estimate of the change in the markup. Or if we want to assume that in a given year a set of producers rely on the same output elasticity, markup differences across producers are again directly identified simply by inspecting the variation of this ratio.

2.3 Adding an alternative approach

The second half of the paper starts from the observation made in Ackerberg et al. (2015), that if one is willing to assume an AR(1) for productivity (hereby ignoring selection induced by endogenous exit, and potentially endogenous non-linear productivity processes, like R&D), the inversion step (of optimal input demand used) in the control function approach can be avoided all together.[9] To put it simply we can get straight to the moment condition on the joint error term capturing the productivity shock and the (quasi) differences measurement error term. That again is well known, and it is here that I see a promising path forward in offering an alternative approach to obtain output elasticities in the presence of imperfect competition. Under this setup, one does not have to add the explicit input demand shifters in the analysis, but it comes at the cost of adding more restrictions on the properties of the productivity process, and the time-series profile of output and inputs. The latter implicitly brings back the discussion on how inputs are chosen, without observing relevant shifters to even test the plausibility of the assumed structure. [10] This surely means that applied work should consider these alternatives and check robustness of the output elasticities, and perhaps of the markups if that is the end goal of the analysis.

Note that this is completely orthogonal to the issue of unobserved output prices. In fact, the dynamic panel data approach, introduced by Arellano and Bond (1991) and Blundell and Bond (1998) lives in the tradition of quantity generating production functions. The presence of imperfect competition, however, provides ground for restoring the identification of the variable input coefficient by appealing to unobserved demand or input price shocks.

[9] Or as mentioned in Ackerberg et al. (2015), if there is no measurement error in output, one can immediately go the final step of the ACF approach.

[10] The dynamic panel approach can in addition not distinguish measured markups from markups stripped from measurement in output (regardless of the price error), an illustration of the many trade-offs that the applied researcher faces between the various approaches.

3 Concluding remarks

A deeper issue, which is not discussed, is that even when quantities are observed, the mere presence of product differentiation makes it hard to compare quantities across products and producers. This suggests that merely running a regression of output quantity on inputs will not solve the problem. In fact, under strict assumptions the use of revenue allows to compare differentiated products and thus estimate a production function, provided that one of the solutions discussed above are adopted. A recent development in the literature explicitly introduces quality differences in the production function. De Loecker et al (2016) consider the case where output is recoded in quantities, while inputs are not. They introduce a framework to correct for the inherent quality variation, and obtain reliable estimates of the output elasticity exploiting the relationship between output-, input prices and quality in a general class of models.

Finally, what do the authors actually propose that an empirical researcher should do? There is not much guidance in the paper. But one can arguably conclude that it is useful to consider a wide(r) range of alternatives to measure output elasticities and inspect the robustness of the main results of interest. If anything the recent literature shows that there is a great need and demand for more evidence-based discussion around market power. This requires measures of markups, among others, to avoid uniquely paying attention to measures of industry concentration (see e.g. Berry et al. (2019) and Syverson (2019)). The rising markup trend in the US, documented in the literature, is robust to a wide range of output elasticities (those that do and do not rely on production function estimation). The bottom line from that line of research is that the ratio of revenue to a variable input's expenditure is what fundamentally changes over time and across firms. There are clearly empirical challenges, but that is inherent to empirical work, so one may not want to call this *unpleasant* but rather *it comes with the job.*

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