Estimating Market Power of Agricultural and Food Industries:  
An Issue of Data Aggregation

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Introduction

As agricultural and food industries become increasingly integrated and concentrated, there have been numerous studies estimating market power of these industries. New empirical industrial organization (NEIO) models first derive conceptual models from profit-maximizing-theory of a single “representative” firm, and then market power parameters are estimated using market- or industry-level data due to the lack of firm-level data. However, it is well known in empirical ecomometrics that when relations are derived from microeconomic theory, but are estimated by means of aggregated data, the aggregation can lead to biased parameter estimates.

Take the estimation of market power in the U.S. beef processing industry as an example. A conceptual model for this analysis may start from the theory of profit maximization and derive an individual processor’s price equation with a market conduct parameter typically represented by a conjectural coefficient or elasticity of the processor. However, the empirical estimation of the model is usually based on aggregate time-series data at either market or industry level, which does not consider the heterogeneity of individual processor’s firm behavior. The applied econometrics literature indicates that ignoring heterogeneity in estimates of individual firm behavior (represented by conjectural coefficient or elasticity) may result in biased estimation of overall market power of U.S. beef processors. Therefore, the issue of aggregation bias raises concerns regarding the validity of market power estimated from aggregate data and highlights the need for research designed to enhance our understanding of aggregation bias in estimating market power of agricultural and food industries.

Objectives

- This paper derives aggregation bias analytically from the previous NEIO approach. A statistical procedure is developed to quantify the degree of bias and conditions under which aggregation bias is likely to occur.
- New procedure is introduced to demonstrate how the aggregation bias can be reduced or eliminated by combining aggregated market-level data with published firm-level data.

Methodology

1. Traditional NEIO model

Let’s suppose that cost function is a trans-log cost function form as

\[
\log c = \beta_0 + \sum_{i=1}^n \beta_i \log w_i + \beta_y \log y + \sum_{i=1}^n \beta_{ai} \log w_i + \sum_{i=1}^n \beta_{yi} \log y + \beta_{ay} (\log y)^2 + v_i
\]

where \(\beta_{ai}\) and \(\beta_{yi}\) are input price, \(a = K, L, M, K, L, M\) is capital input, \(L\) is labor input, \(M\) is intermediate input and \(y\) is output.

The input demand function can be derived by Shephard’s Lemma when cost is minimized under profit maximization equation:

\[
s_i = a_i + \sum_{i=1}^n \beta_i \log w_i + \beta_y \log y \quad (2)
\]

where \(a_i = \frac{x_i}{c}\), \(a = K, L, M\) and \(s_i\) is the industrial cost-share equation.

The equation (5) can be generated from the first order condition of profit maximization equation:

\[
p = \left(\frac{1}{n} + \frac{2}{n} \sum_{i=1}^n \beta_i \log w_i + \beta_y \log y + \beta_{ai} \log w_i + \beta_{yi} \log y + \beta_{ay} (\log y)^2\right) \left(1 - \frac{2}{n}\right)
\]

where \(n\) is demand elasticity, \(c\) is total cost.

The equation (6) is output demand function and can be written as

\[
\ln y = \alpha + \ln (p/S) + \ln (q/S)
\]

where \(q\) is demand elasticity, \(p\) is price income elasticity, \(q\) is GNP, \(S\) is GNP deflator.

2. Aggregation Bias

- Aggregation Bias from Cost Share Equation

Let’s assume that \(n\) firms exist, then sum each firm’s cost share equation and divide by \(n\), then the equation is expressed as

\[
p = \frac{1}{n} \sum_{i=1}^n \beta_i \log w_i + \frac{1}{n} \sum_{i=1}^n \beta_i \log y_i
\]

Adding and subtracting \(\frac{1}{n} \sum_{i=1}^n \beta_i \log w_i\) and \(\frac{1}{n} \sum_{i=1}^n \beta_i \log y_i\), the equation is

\[
p = \frac{1}{n} \sum_{i=1}^n \beta_i \log w_i + \frac{1}{n} \sum_{i=1}^n \beta_i \log y_i + \frac{1}{n} \sum_{i=1}^n \sum_{i=1}^n \frac{1}{n} \text{cov}(\beta_{ai}, \beta_{yi}) + \gamma (\log y_i)^2
\]

• Aggregation Bias from Price Equation

The equation (3) can be solved as equation (8):

\[
p = \frac{1}{2} \left(\frac{1}{n} \sum_{i=1}^n \beta_i \log w_i \right) \left(1 - \frac{2}{n}\right)
\]

where \(n\) is the mean of \(\frac{1}{n} \sum_{i=1}^n \beta_i \log w_i\) and \(\gamma\) is the harmonic mean of \(\frac{1}{n} \sum_{i=1}^n \beta_i \log y_i\).

Further Studies

- A new procedure that combines aggregate data and publically available firm-level data will be developed to reduce aggregation bias.
- Empirical analysis will be conducted to demonstrate the aggregation bias and how the aggregation bias can be reduced by combining aggregate data and publically available firm-level data in the newly developed procedure.

References