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LETTER

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Dynamics of industrial concentration and technical inefficiency in the Indonesian food and beverage industry

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1 | INTRODUCTION

The food and beverage industry contributed significantly to the Indonesian economy, accounting for about 7% of gross domestic product yearly since 2000 (Indonesian Central Bureau of Statistics [BPS], 2016). Nevertheless, previous research has shown that the Indonesian food and beverage industry is highly concentrated and has the potential to create distortions in the Indonesian economy (see Setiawan & Effendi, 2016). Setiawan and Oude Lansink (2018) also found that the technical inefficiency in the industry was attributed, among other reasons, to high industrial concentration.[1] Previous research has investigated the relationship between industrial concentration and technical inefficiency in the Indonesian food and beverage industry using the frameworks of the quiet-life and efficient-structure hypotheses (see Setiawan & Oude Lansink, 2018; Setiawan et al., 2012).[2] The research found a unidirectional relationship: only industrial concentration affected technical inefficiency (quiet-life hypothesis). The quiet-life hypothesis suggests that firms operating in highly concentrated industries tend to be inefficient because of a lack of pressure from competitors. Past studies have used a comparative static approach, assuming that the

Abbreviations: B, identifying restriction; BPS, Biro Pusat Statistik (Central Bureau of Statistics); DTI, dynamic technical inefficiency; HHI, Herfindahl–Hirschman Index; IC, industrial concentration; IDR, Indonesian Rupiah; IRF, impulse response function; *N*, total number of observations; PVAR, panel vector autoregression; TEI, logistic transformation of dynamic technical inefficiency; VAR, vector autoregression; WPI, wholesale price index.

[1]The relationship between technical inefficiency and industrial concentration can also be theoretically explained by Leibenstein's (1966) X-efficiency theory, which states that firms will have higher productive (technical) efficiency when competitive pressures (i.e., low industrial concentration) are high.
[2]Another study from Hirsch et al. (2014) suggests that high industrial concentration could cause higher profitability, which can be a sign of higher allocative inefficiency.

relationship between industrial concentration and technical inefficiency behaves as if it is in long-run equilibrium. The comparative static approach cannot distinguish the short- and long-term shock effects of industrial concentration on technical inefficiency and vice versa. Improperly accounting for short- and long-term deviations in the variables may result in an incorrect assessment of the relationship between technical inefficiency and industrial concentration, which may, in turn, lead to less adequate or even incorrect short-term policy recommendations.

To address this research gap, this paper examines the short- and long-term relationship between industrial concentration and technical inefficiency in the Indonesian food and beverage industry using a panel vector autoregression (PVAR) model. A second contribution is the estimation of technical inefficiency in a dynamic context, while accounting for unobserved adjustment costs of investments in quasi-fixed factors of production, such as learning costs or expansion planning fees. Kapelko et al. (2014), Setiawan (2019b), and Setiawan and Oude Lansink (2018) suggested that failure to account for adjustment costs in the technical inefficiency measurement may incorrectly attribute adjustment costs to inefficiency.

2 | INDUSTRIAL CONCENTRATION AND DYNAMIC TECHNICAL INEFFICIENCY (DTI)

The first step of this paper estimates DTI and industrial concentration. The second step applies a PVAR model to investigate the relationship between industrial concentration and DTI. The PVAR model is written as follows[3]:

$$\mathrm{TEI}_{it} = \gamma_i + \sum_{k=1}^{K} \alpha_k \mathrm{TEI}_{i,t-k} + \sum_{k=1}^{K} \beta_k \mathrm{IC}_{i,t-k} + v_{it}, \tag{1}$$

$$\mathrm{IC}_{it} = \eta_i + \sum_{k=1}^{K} \lambda_k \mathrm{TEI}_{i,t-k} + \sum_{k=1}^{K} \theta_k \mathrm{IC}_{i,t-k} + \varepsilon_{it}, \tag{2}$$

where $\mathrm{TEI}_{i,t}$ represents the logistic transformation of DTI of subsector i in period t; $\mathrm{IC}_{i,t}$ denotes the industrial concentration of subsector i in period t, again transformed using the inverse-logistic function.[4] The impact of a shock in each of the variables is estimated using the impulse responses implied by the coefficients in the PVAR model. The impulse response function is defined as

$$\frac{\partial y_{t+p}}{\partial \varepsilon_t} = \varphi^p B, \tag{3}$$

where Equation (3) represents the response of y_{t+p} for all p periods after a shock that occurs at time t. φ^p is the coefficient from the reduced-form VAR of each variable (DTI or industrial concentration) and B is the identifying restriction.

3 | VARIABLES AND DATA

We use the Herfindahl–Hirschman Index (HHI) as a measure of industrial concentration. Technical inefficiency for each subsector is an average of the DTI of the firms in the subsector. The dynamic directional input distance function is applied to estimate the dynamic technical inefficiency of each firm following Oude Lansink and Silva (2004) and Setiawan and

[3]The issue of endogeneity that remains to be handled in the PVAR model is the one that stems from the inclusion of lagged endogenous variables which may correlate with the error terms. To handle this issue, the Arellano–Bond estimator applied to PVAR model employs instrumental variables that represent lagged endogenous variables varying with t. The lag endogenous variables are assumed to be orthogonal to the error terms.

[4]Both technical efficiency and industrial concentration assume values on the unit interval. By having this logistic transformation, the range of error terms in the PVAR model does not need to be restricted.

TABLE 1 Descriptive statistics of the variables across subsectors, 1980–2014

Variable	Mean	Standard deviation	Coefficient of variation
Output (billion IDR)	234	456	1.949
Material (billion IDR)	0.275	0.597	2.167
Labor efficiency (person index)	276.812	571.139	2.063
Fixed assets (billion IDR)	0.640	7.718	12.060
Investment (million IDR)	845.213	629,000	744.191
N-subsectors	44	44	44

Note: Unbalanced panel data with $N = 1464$.
Source: Authors' calculation. IDR = Indonesian Rupiah (1 US$ = IDR 12,440, in 2014).

Oude Lansink (2018). The dynamic directional input distance function also assumes variable returns to scale as well as directional vectors of inputs and investment as applied by Kapelko et al. (2014) and Setiawan (2019a).[5]

This research covers 44 subsectors of the Indonesian food and beverage industry classified at the five-digit level of the International Standard Industrial Classification system. Some subsectors were constructed by combining subsectors at the four-digit level with fewer than 30 firms. Technical inefficiency is estimated using firm-level data over the period 1980–2014 from the Annual Manufacturing Survey provided by BPS. Table 1 presents the descriptive statistics of the variables used in the analysis. The value of gross output is defined as the output of the firm, deflated by the wholesale price index (WPI) of the Indonesian food and beverage industry. Labor efficiency units represent labor input, following Setiawan (2019a). Raw materials include total costs of domestic and imported raw materials, deflated by the WPI for raw materials.[6] Fixed capital is measured as the value of fixed assets deflated by the WPI of fixed assets. Furthermore, investments are measured as purchases of additional fixed assets minus sales of fixed assets, deflated by the WPI of fixed assets.

4 | RESULTS

Based on Table 2, the average dynamic technical inefficiency was 0.284 during the period 1980–2014, indicating that firms in the industry could have reduced their variable inputs by 28.4% and expanded investment by 5.68% (20% of 28.4%) of the size of the capital stock, while still producing the same quantity of output.[7] Dynamic technical inefficiency increased during the period from 1980 to 2014 at an average rate of 1.878%. Although HHI exhibited decreasing trends, its average values were relatively stable after 1985 and high (see also Setiawan & Effendi, 2016).[8]

The panel VAR model was estimated using the Arellano–Bond estimator to account for the endogeneity problem stemming from the lagged endogenous variables on the right-hand side of the equation. The estimated models fulfilled the orthogonality condition with all variables being stationary at the level form. Two lags were used in the model based on the modified Akaike information criterion.

[5]The directional vector of investments indicates how the adjustment costs can be adjusted in the technical efficiency estimation.
[6]Other costs related to the production, such as electricity and fuel costs, are included in the domestic raw material.
[7]The subsector of corn cleaning, corn milling, corn flour, and rice flour had the lowest DTI, while the subsector of processed coffee, herbs, and tea had the highest DTI during the period 1980–2014.
[8]HHI remained high and above 0.20 during the period of estimation. This classified the industry into highly concentrated industry (HHI > 0.18) (see US Department of Justice and Federal Trade Commission, 2010).

TABLE 2 Average DTI, industrial concentration (HHI) and their changes, by subperiod

Period	DTI	DTI changes (%)	HHI	HHI changes (%)
1980–1984	0.227	7.670	0.573	−16.583
1985–1989	0.260	−1.079	0.307	−7.838
1990–1994	0.282	3.283	0.255	−2.107
1995–1999	0.306	1.335	0.262	4.694
2000–2004	0.319	−2.133	0.272	−3.671
2005–2009	0.317	9.787	0.240	4.885
2010–2014	0.279	−5.715	0.206	−5.962
1980–2014	0.284	1.878	0.302	−3.797

Note: Unbalanced panel data with $N = 1464$.
Abbreviation: DTI, dynamic technical inefficiency; HHI, Herfindahl–Hirschman Index.
Source: Authors' calculation.

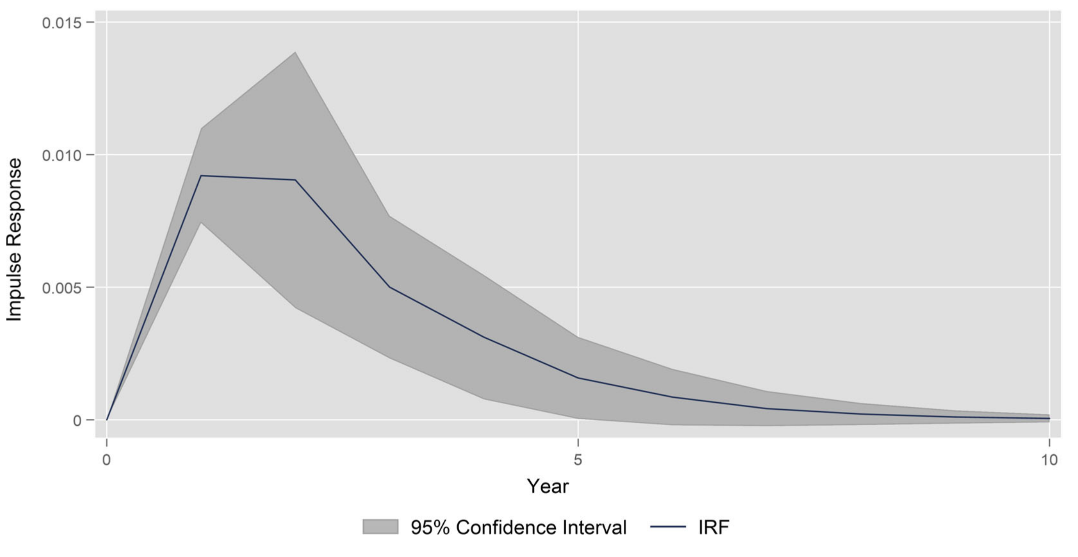

FIGURE 1 Impulse response function (IRF) of Herfindahl–Hirschman Index shock on dynamic technical inefficiency

Figure 1 shows the impulse response suggesting that a one standard deviation shock in HHI had a significant impact on dynamic technical inefficiency in the second year, and the impact diminished after the third year. The impact of the shock was positive, which suggested that higher HHI increased dynamic technical inefficiency in the short run. However, the impact of HHI *on* dynamic technical inefficiency was limited, that is, only 0.7% and 1.65% of the total variance during the 2- and 10-year simulations, respectively. The impact completely vanished after 10 years.

The impact of a one standard deviation shock of dynamic technical inefficiency on HHI was not significant (see Figure 2). These results support a unidirectional relationship between the two variables in line with the quiet-life hypothesis, where highly concentrated industry impedes the firms to be efficient, and not vice versa. The results imply that policymakers should strictly monitor the development of industrial concentration in the short run.

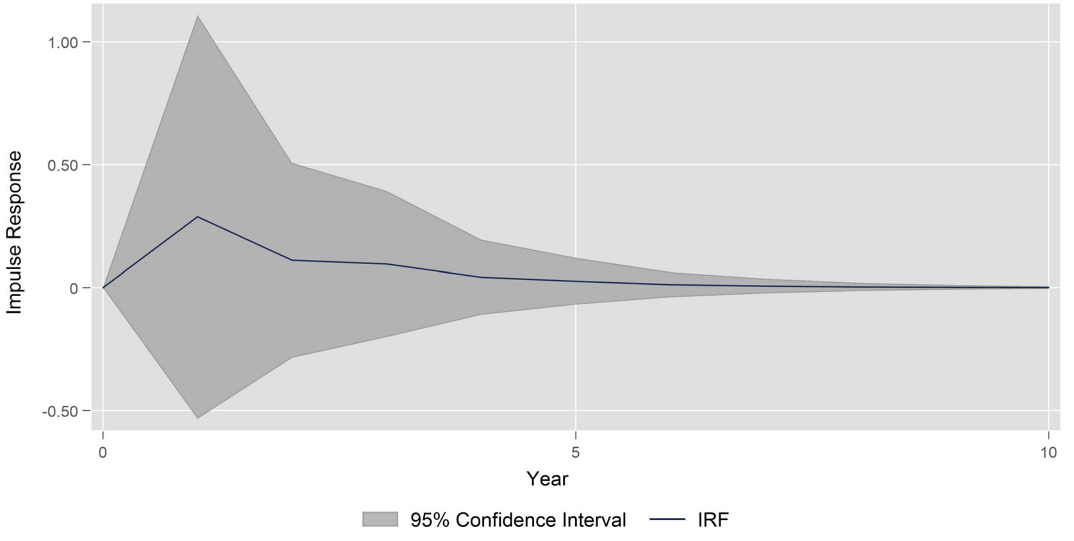

FIGURE 2 Impulse response function (IRF) of dynamic technical inefficiency shock on Herfindahl–Hirschman Index

5 | CONCLUSIONS

This research showed that industrial concentration in the Indonesian food and beverage industry was relatively high. The analysis of the relationship between industrial concentration and dynamic technical inefficiency suggested that the impact of a shock in HHI significantly increased dynamic technical inefficiency in the short run. This implies that industrial concentration should be routinely monitored, as a higher technical inefficiency will ultimately have a negative effect on the welfare of consumers.

This research empirically predicts the impulse response partially on the relationship between industrial concentration and technical efficiency. Nevertheless, the model may still be valid by having a covariance stationary that fits the prediction. Future studies may look into the impact of other variables, such as international trade variables, which may increase competitive pressure.

AUTHOR CONTRIBUTIONS

Maman Setiawan contributed to writing the paper, data collection, econometrics modeling, and estimation.

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REFERENCES

Hirsch, S., Schiefer, J., Gschwandtner, A., & Hartmann, M. (2014). The determinants of firm profitability differences in EU food processing. *Journal of Agricultural Economics*, *65*(3), 703–721.

Indonesian Central Bureau of Statistics. (2016). *Economy and trade report*. https://www.bps.go.id

Kapelko, M., Oude Lansink, A., & Stefanou, S. A. (2014). Assessing dynamic inefficiency of the Spanish construction sector pre- and post-financial crisis. *European Journal of Operational Research*, *237*(1), 349–357.

Leibenstein, H. (1966). Allocative efficiency vs “X-Efficiency”. *The American Economic Review*, *56*(3), 392–415.

Oude Lansink, A., & Silva, E. (2004). Non parametric production analysis of pesticides use in the Netherlands. *Journal of productivity analysis*, *21*(1), 49–65.

Setiawan, M. (2019a). Persistence of price-cost margin and technical efficiency in the Indonesian food and beverages industry. *International Journal of the Economics of Business*, *26*(2), 315–326.

Setiawan, M. (2019b). Dynamic productivity growth and its determinants in the Indonesia food and beverages industry. *International Review of Applied Economics*, *33*(6), 774–788.

Setiawan, M., & Effendi, N. (2016). Survey of industrial concentration and price-cost margin of the Indonesian manufacturing industry. *International Economic Journal*, *30*(1), 123–146.

Setiawan, M., Emvalomatis, G., & Oude Lansink, A. (2012). The relationship between technical efficiency and industrial concentration: Evidence from the Indonesian food and beverages industry. *Journal of Asian Economics*, *23*(4), 466–475.

Setiawan, M., & Oude Lansink, A. (2018). Dynamic technical inefficiency and industrial concentration in the Indonesian food and beverages industry. *British Food Journal*, *120*(1), 108–119.

US Department of Justice and Federal Trade Comission. (2010). *Horizontal merger guidelines*.