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Performance Evaluation of The Industrial Resilience Index by Using Cross-Correlation Method

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Abstract. This paper shows how resilience-based measurements, Industrial Resilience Index (IRI), is able to indicate the performance trend of general manufacturing, measured in Gross Domestic Product (GDP), impacted by shocks represented by the value drops of the Rupiah to the US Dollar. This paper argues that IRI is able to measure not only the resilience of the Metal Product Manufacturing Sector (MPMS) but also the performance dynamic of the general manufacturing industry. This study evaluates the IRI performance by using the cross-correlation method. The cross-correlation process consists of a comparison between IRI and the GDP of the manufacturing industry, as well as a comparison to other indices related to manufacturing sectors, such as the Purchasing Manager Index (PMI), the Production Index of Large and Medium Manufacturing Industry (PII), the Competitiveness Industrial Performance (CIP), and the Global Competitiveness Index (GCI). The positive and high value of the correlations in this study shows IRI's ability to reflect the sector resilience and the GDP of the general manufacturing industry trend. The result of this study suggests that IRI can be utilized as a dynamic indicator of the general manufacturing industry. Through its data series and trend analysis, decision or policymakers may employ IRI to forecast how resilient MPMS, as well as the general manufacturing industry trend, is when the sector faces shocks in the future. The result of the study shows that cross-correlation coefficient of IRI is 0.74. The coefficient value indicates that IRI is a coincident indicator within the business cycles of the general manufacturing industry. Therefore, as an alternative of resilience-based measurement, the study suggests that IRI is able to demonstrate its significance in predicting the resilience of MPMS and the general manufacturing industry, in anticipating a dynamic shock is in the future.

Keywords: Analysis; Cross-correlation; Evaluation; Industrial resilience index; Performance

1. Introduction

In recent years, studies related to resilience or risk-adjusted performance measurement have received significant attention among scholars (Fauzi and Jahidi, 2022; Sambowo and Hidayatno, 2021; Berawi, 2018). The capability to analyze the impact of the dynamic environment on a system and to respond any disturbance correctly determines how well the system performs and sustain in the long run. This study explores such phenomenon by evaluating Metal Product Manufacturing Sector (MPMS), representing a system, and the exchange rate fluctuation, representing a shock, that impacts the system

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performance dynamically. Like a system, the output of MPMS is dependent on various internal and external disturbances. The production process in the MPMS requires some of the economic transactions for inputs are based on the foreign exchange (Jandhana, Zagloel, and Nurcahyo, 2018; 2017). For example, some of the raw materials cannot be fully obtained from local vendors, so producers have to import it directly or via trade agents that import them from overseas. Additionally, the energy costs for production process can fluctuate and are often affected by foreign exchange rates, particularly the exchange rate between the Indonesian Rupiah and the US Dollar (Narayan, Falianty, and Tobing, 2019). As a result, MPMS in Indonesia heavily depends on the movements of this exchange rate.

This study is a further exploration of developing and evaluating a composite index, the Industrial Resilience Index (IRI) or *Indeks Ketahanan Industri* (Jandhana, 2019; Jandhana, Zagloel, and Nurcahyo, 2018). The index measures the resilience as well as the performance trend of the MPMS in Indonesia, in Gross Domestic Product (GDP), adjusted by the impact of exchange rate shock (Rupiah to US Dollar) caused by drastic macroeconomic disturbances. Although the study uses statistical data of MPMS to measure its resilience, the same calculation method can be used to measure resilience in any system schemes. Other than measuring the current performance, IRI also provides the simulated stress test for decision and policymakers to find out about the impact of the future exchange rate shock on the sector. The previous study also shows a strong correlation between IRI and GDP of MPMS as shown in Figure 1.

Based on previous studies in the field of resilience (Barrett *et al.,* 2021; Jandhana, 2019; Bradtmöller, Grimm, and Riel-Salvatore, 2017; Carlson *et al.,* 2012), this study defines resilience in the industrial sector as the property or the character of the industrial sector that reflects the sector's ability to anticipate disturbances and absorb the impact of disturbances in the form of shock or stress, that may spoil the performance of the industrial sector, and to recover from various the disruption and to return to the normal state of production, and to compete in the market soon. The IRI value measures how resilience of the sector. According to Jandhana (2019) there are four dimensions in the formation of IRI, such as Basic Production Dimensions, Industrial Environment Carrying Capacity Dimensions, Innovation Dimensions and Efficiency, and Macroeconomic Dimensions. The four dimensions consist of nineteen variables. IRI is the result of combining several concepts in building industrial resilience measurement methods based on the Production Theory. To see the impact caused by the shock dynamically, IRI employs Vector Autoregressive (VAR) and Vector Autoregressive modeling systems with exogenous variables (VARX). This modeling system can capture the presence of changes in IRI due to the shocks.

The strong correlation between IRI and the GDP of MPMS, as shown in Figure 1, raises another question. The question is whether IRI, as the MPMS' performance indicator, has the ability to predict the trend of the business cycle of the general manufacturing sector in Indonesia. Any variables within an economic indicator move together to create a certain condition, which becomes the building block of business cycles (Diebold and Rudebusch, 2020; Harding and Pagan, 2002; Burns and Mitchell, 1946). This is the foundation of the development of business cycles known today. In this study, IRI is evaluated its capability to measure business cycle trends in the manufacturing sector in general. This study examines whether the IRI is a leading, coincidental, or lagging indicator in the business cycles. Additionally, this study results not only ensure the IRI calculation accuracy, but also contribute to the research of dynamic performances and risk measurements. This enables IRI to become a viable tool for predicting manufacturing industry conditions. To provide a more comprehensive understanding, this paper elaborates on the theoretical background, methodology, results discussion, and conclusion.

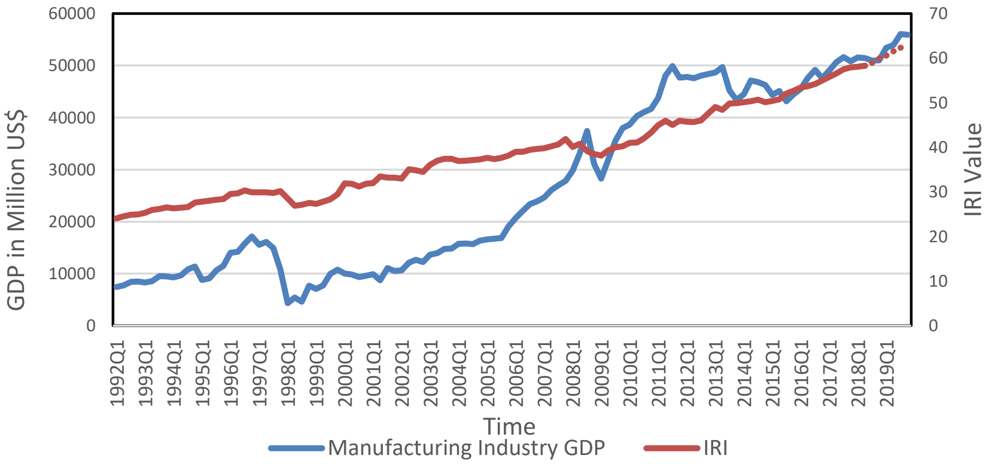

Figure 1 The Comparison of the Industrial Resilience Index (IRI) and Gross Domestic Product (GDP) of MPMS in Billion Rupiah, Quarter I/1992 to Quarter IV/2019

2. Theoretical Background

There have been numerous studies in resilience science in these past recent years. Resilience is defined as the state that describes the capacity of an entity (e.g., individual, asset, organization, community, system, or region) to react by anticipating, adapting, resisting, absorbing, responding, and recovering from both internal or external disturbances (i.e., stressors and shocks), so the entity can limit vulnerability and promote sustainability by maintaining its functional and structural integrity in its new conditions (i.e., the new equilibrium) (Barrett *et al.,* 2021; Carlson *et al.,* 2012; Harding and Pagan, 2002; Burns and Mitchell, 1946). Furthermore, resilience determines how well an entity copes with external and internal risks in order to sustain the operation and return to the pre-event condition or the new equilibrium when it experiences a disturbance. Resilience Engineering (RE) is a field of engineering that studies a system's behavior and capabilities to manage the complexity of a socio-technical system to avoid failure or minimize the impacts of failure by recognizing, responding, and adapting to any variations, changes, disturbances, disruptions, and surprises that fall outside of the system capability (Serfilippi and Ramnath, 2018). Risks in the manufacturing sector may come from various sources, such as rapid changes in processing technology, macroeconomic conditions, raw material prices, energy prices, and exchange rates (Zagloel and Jandhana, 2016). Recently, the rise of the covid 19 pandemic has not only impacted the health sector but also stress-tested the performance of the manufacturing sector as well as the global economy (Hudecheck *et al.,* 2020; Woods and Hollnagel, 2017). Unfortunately, so far, there have been no pragmatic guidelines on how to incorporate risk management into the measurement of the state of resilience. Based on previous resilience studies, such as in the field of the pediatrician (Ahern *et al.,* 2006), sustainable development (Angeon and Bates, 2015), ecology (Van Meerbeek, Jucker, and Svenning, 2021: Walker *et al.,* 2004; Holling, 1973), supply chain management (Mandal, 2014), personal health (Windle, Bennett and Noyes, 2011), and others, there is still a wide gap of knowledge to fill in the field of resilience measurement. Therefore, the purpose of this study is to contribute part of various studies needed to fill in the field of resilience study.

This study also draws on the widely known theory of the business cycle that has been in existence since the industrial era. This theory, subsequently, describes the fluctuation of economic activities in nations, including phases of expansion, recession, contraction, and revival within a certain period of time (Kose, Sugawara, and Terrones, 2020; Harding and Pagan, 2002; Burns and Mitchell, 1946). The fluctuation is diffused over an integrated economic system involving industrial, commercial, finance, and service sectors. Today, there have been several studies conducted to explore uncertainty and measurement related to the business cycle. Those studies led to two main research topics (Ludvigson, Ma, and Ng, 2021; 2020). The first research topic relates to the uncertainty of the prime source of the business cycle. The second research topic concerns the type of uncertainty that is responsible for causing the business cycle. From their literature study, they explained that macro uncertainty is the driver of economic fluctuation that contributes to the business cycle. Despite the findings, the study still finds that a variety of parameterizations and specifications show macro uncertainty rises endogenously in response to business activity shocks (Ludvigson, Ma, and Ng, 2021; 2020). This contributes to the countercyclical behavior that creates financial uncertainty within a system. Therefore, instead of macro uncertainty, financial uncertainty becomes the driver of economic fluctuation. Macro uncertainty may augment the downturn and push it toward a recession. This behavior needs to be studied further. This paper contributes to explaining how uncertainty in financial markets is transmitted to the real economy that, includes the manufacturing industry sector.

This study also incorporates the Theory of Production, which explains the roles of input factors, such as capital, raw materials, and labor, needed to generate output in the industrial sector (Jandhana, 2019; Fuss and McFadden, 2014; Solow, 1956). This model became the foundation of the Growth Model that includes labor and capital as production factors, as well as the government as policy maker (Bajo-Rubio, 2000). Then, the production function included natural resources or sources of raw materials (N) and human capital/capacity (H) as independent variables (Mankiw, 2020; Senhadji, 2000; Ferguson and Gould, 1975). The following equation 1 shows the production function with level of technology implementation in sector (A) considered as a constant:

$$Y = A(t)\, f\,(L, K, H, N) \tag{1}$$

where,

Y = Production output (GDP)
L = Labor employed in the sector
K = Capital invested in the sector
t = Period
A = Total Factor Productivity Constant

Based on the equation, it can be said that as the level of technology implementation (A) increases, the output of the given combination of inputs will increase as well. This model underscores how important technology implementation in improving the production process as well as creating process or product innovations and the sector output growth (Juhász, Squicciarini, and Voigtländer, 2024; Kask and Sieber, 2002; Solow, 1956). Therefore, successful technology implementation, along with the availability of other production factors, will determines the sector's performance and its resilience.

Unlike the previous study (Jandhana, 2019), the measurement of IRI in this study employs more recent data, which was based on the 2019 data that was forecasted previously by the ARIMA method. ARIMA method is employed to forecast each variable which was included in the calculation of IRI. ARIMA is basically an Auto-Regressive method that integrates three principles and processes to find the best fitting forecasting by determining the parameters (Fattah *et al.*, 2018; Bhuiyan, Ahmed, and Jahan, 2008; Box *et al.*, 1976). Those principles are:

- Auto Regression. This is a process of changing a variable that regresses its own lagged values, with p representing the number of lag observations in a model (lag order).

- Differencing. This is a process that converts data to become stationary by differentiating the data values from the previous data, with *d* representing the number of times that data values are differenced (degree of differentiating).
- Moving Average. In order to allow the dependency of data from the residual error, this process applies a moving average method to autoregression, with *q* denoting the order of the moving average.

ARIMA allows a model developer to construct a forecasting tool that simulates the trends, cycles, seasonality, and other dynamic data based on historical data. However, just like any model, the ARIMA model needs to be used with caution. The effectiveness of ARIMA also depends on the time span a future trend will be forecasted (Grogan, 2020). In general, the longer the time span to be forecasted, the less precise the trend forecast.

This study employs cross-correlation analysis to verify the trend similarity between two data series. This method can also be employed to predict the movement of the data in a system (Cowperwait and Metcalve, 2009). To perform the calculation, the two data series must have the data mean and variance in a stationary condition. In other words, through the cross-correlations analysis, one can examine "the degree of similarity between two sets of numbers and can be quantified" (Costa, 2021; Derrick and Thomas, 2004). Like autocorrelation analysis, the cross-correlation method has been used in the field of engineering and science, such as electronic, acoustic, and geophysical (Nelson-Wong *et al.*, 2009). The method will be employed to analyze how noises or signals can be isolated and observe their similarities. It involves correlating different time-varying signals against one another. Cross-correlations have a value between -1 and 1 (Derrick and Thomas, 2004; Sensoy *et al.*, 2013). Furthermore, this value should be accompanied by the degrees of freedom (DOF). A high cross-correlation value with a high DOF is better than a high cross-correlation value with a low DOF (Chao and Chung, 2019).

3. Methodology

To achieve the research objectives, several steps need to be carried out sequentially as shown in the following Figure 2. The first step involved recalculating the IRI to incorporate the latest data adjustments. The study utilized the manufacturing sector data administered by the Statistics Indonesia, as in previous studies. This study includes the input and output data of the MPMS generated from 1992 until fourth quarter of 2019, instead of 2017 from the previous study (Jandhana, 2019). As previously stated, the result of IRI measurement shows that the shock of the Rupiah value against the US Dollar has a negative impact on the MPMS in Indonesia recorded until 2017. The next step is to determine the reference variable that describes and measures the system's value. In this study, the most appropriate variable to use is the Gross Domestic Product (GDP) generated by the manufacturing industry in Indonesia. For comparison, this study incorporates business cycles analysis from three other well-known indicators in the industrial sector, such as the Purchasing Manager Index (PMI), Production Index of Large and Medium Manufacturing Industry (PII), Competitiveness Industrial Performance (CIP) from the United Nations Industrial Development Organization (UNIDO), and the Global Competitiveness Index (GCI) from World Economic Forum (WEF).

The data smoothing process was carried out by eliminating seasonal and trend factors to determine the turning point of IRI. To eliminate seasonal factors, the study utilizes X-12 Autoregressive Integrated Moving Average (ARIMA) model (Mohamed and Mohammed, 2021). Furthermore, to eliminate the trend factor, Hodrick-Prescott (HP) or so-called HP filter is used to remove trend components and short-term cyclical components from the data series. The process is carried out to minimize the following function equation 2 and equation 3 (Nilsson and Gyomai, 2011):

$$y_t = \tau_t + c_t \tag{2}$$

$$\min_{\tau_t} \sum_t (y_t - \tau_t\}^2 + \lambda \sum_t (\tau_{t+1} - 2\tau_t + \tau_{t-1})^2 \tag{3}$$

where,

y_t = original series
τ_t = the trend component
c_t = the cyclical component
λ = smoothing Parameter

Once the data smoothing process is completed, the next step is to do cross-correlation. The purpose of cross-correlation is to separate whether the data series being tested becomes the leading, coincident, or lagging indicator (Podobnik and Stanley, 2008). By conducting the cross-correlation analysis, the movement direction between two or more data series (indicators) can be observed and measured (Dean and Dunsmuir, 2016). The cross-correlation value ranges from -1 to 1. The following is the formula (equation 4, and 5) for cross-correlation analysis (Benazir and Achsani, 2008):

$$r_{xy}(l) = \frac{c_{xy}(l)}{[\sqrt{c_{xy}(l)}][\sqrt{c_{xy}(0)}]} \qquad where : l = 0, \pm 1, \pm 2, \ldots \tag{4}$$

$$c_{xy}(l) = \begin{cases} \sum_{t=1}^{T-1} \frac{[(x_t - \bar{x})(y_{t+1} - \bar{y})]}{T} & where : l = 0, 1, 2, \ldots \\ \sum_{t=1}^{T+1} \frac{[(y_t - \bar{y})(x_{t-1} - \bar{x})]}{T} & where : l = 0, 1, 2, \ldots \end{cases} \tag{5}$$

where:

r = the leading or lagging correlation between the x and y variables
x = candidate variable
y = reference series variable
c = cycle
l = leading or lagging indicator
t = period

The result of cross-correlation analysis also signals which indicators show a positive correlation with the benchmark indicator, the GDP of the manufacturing industry, after the data has been corrected to eliminate the possibility of the seasonal trend. The process of detrending will utilize Hodrick-Prescott (HP) and the ARIMA X-12 Model (Mohamed and Mohammed, 2021). After the detrending process, the following step is to remove any factors related to the seasonal variation, such as the increase in output during the holidays. This step explores the possibility of whether any of the indexes is the leading, coincident, or lagging indicator for estimating the GDP movements of the manufacturing industry. Leading indicator means that the movement of the observed indicator (IRI) precedes the movement of the benchmark indicator (GDP of the manufacturing industry). The indicator that has the highest correlation coefficient indicates that it can be considered a forecasting tool in envisaging the general movement of the GDP of the manufacturing industry. This implies that the observed indicator can be employed as a tool for forecasting purposes under certain measurements. Coincident indicator denotes that both the observed indicator and the benchmark indicator share the same rhythm of movement. Finally, lagging indicator shows that the movement of the observed indicator follows the benchmark indicator.

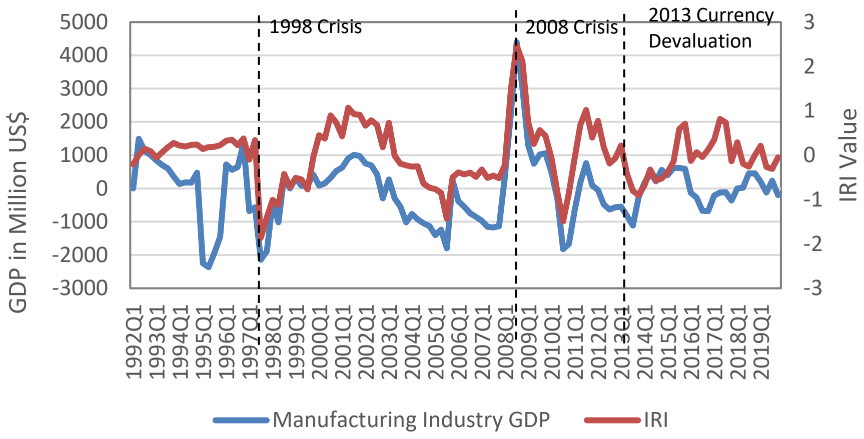

Figure 2 Cycles Comparison: GDP of Manufacturing Industry vs IRI (Quarter 1/1992 - Quarter 4/2019)

4. Results and Discussion

The study explores the correlation between IRI, PMI, PII, CIP, GCI, and GDP of the manufacturing industry. By using the simple correlation calculation, as shown on Table 1, the result seems to demonstrate positive correlation between IRI, PMI, PII, CIP, GCI, and GDP of MPMS. IRI and GDP of the manufacturing industry show the correlation coefficient of 0.98, while the correlation coefficient between PII and GDP of the manufacturing industry is 0.97. Additionally, a correlation coefficient of GCI and GDP of the manufacturing industry indicates 0.95. The high correlation coefficient might be interpreted as such that the increase IRI, GCI, and PII follows the surge of GDP in the manufacturing industry. It also may imply that the lower GDP of the manufacturing industry can correlate to the lower IRI, GCI, and PII, respectively.

Table 1 The Correlation Between Various Indices Related to the GDP of Manufacturing Industry

Indexes	Correlations with GDP of Manufacturing Industry	Correlations with IRI
1. Industrial Resilience Index (IRI)	0.98	
2. Purchasing Managers Index (PMI)	-0.12	-0.01
3. Production Index of Large and Medium Manufacturing Industry (PII)	0.97	0.98
4. Competitiveness Industrial Performance (CIP)	0.50	0.55
5. Global Competitiveness Index (GCI)	0.95	0.96

Since the data still consists of the embedded trend factor, there should be a cross-correlation analysis to align the movement of each index with the GDP of the manufacturing industry. Cross-correlation analysis requires any trend factor to be removed from all of the analyzed data by utilizing Hodrick-Prescott (HP) and the ARIMA X-12 Model. After data detrending, both charts of IRI and GDP of the manufacturing industry show that they move in the same direction (Figure 3). Furthermore, as displayed in Figure 2, IRI is able to display the impact of the Indonesian economic crisis on the manufacturing industry that occurred between 1997 and 1998, as well as the global crisis in 2008. Unlike IRI, the other indices, such as PMI, PII, CIP, and GCI could not capture the shock of the sector's PDB during a crisis as shown in Figure 3. The study result also suggests that those indices could not capture the GDP and the movement of its input variables. Figure 3 also describes the cycle comparison between the manufacturing sector's GDP and PMI, PII, CIP, or GCI. Specifically, based on the correlation coefficient, between GDP and PII indicates a coefficient of 0.97, while between GDP and GCI shows a coefficient of 0.95.

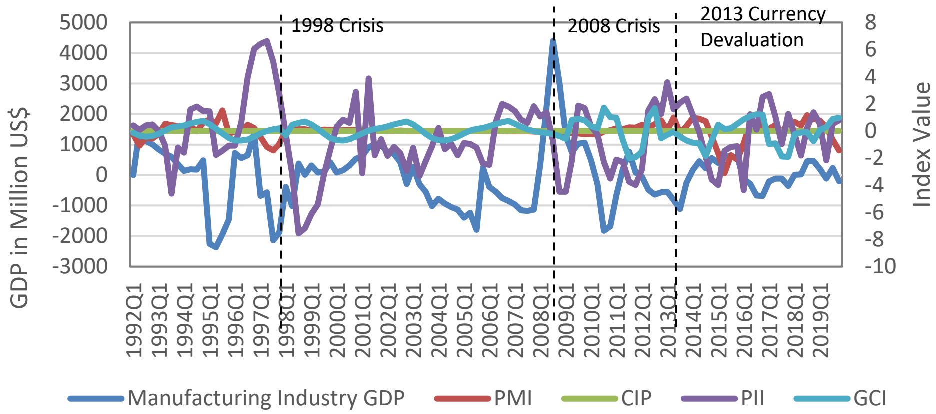

Figure 3 Cycles Comparison: GDP of Manufacturing Industry vs PMI vs CIP vs PII vs GCI (Quarter 1/1992 - Quarter 4/2019)

Based on the cross-correlations analysis, as presented in Table 2, the result suggests that the movement of IRI has the closest match to the movement of the GDP of the manufacturing industry with a coefficient of cross-correlation of 0.74 which is directly significant at lag '0'. This suggests that the IRI movement can be used to forecast the variation in GDP of the manufacturing industry. Therefore, IRI can detect the sector experiencing a recession, stagnation, or contraction in the manufacturing industry in general.

Table 2 The Result of Cross-Correlation Analysis on Multiple Indices in the Indonesian Manufacturing Industry, period 1992/Q1-2019/Q4

No	Variable	Lead/Lag (Quarter)	Coeff
1.	Industrial Resilience Index (IRI)	Lag 0	0.74
2.	Purchasing Managers Index (PMI)	Lead 3	0.20
3.	Production Index of Large and Medium Manufacturing Industry (PII)	Lead 7	0.44
4.	Competitiveness Industrial Performance (CIP)	Lead 5	0.22
5.	Global Competitiveness Index (GCI)	Lag 4	0.53

5. Conclusions

This study is an extension of the previous study in constructing a tool to measure system resilience in the Metal Product Manufacturing Sector (MPMS), the Industrial Resilience Industry (IRI). By using the cross-correlation method, the study compares the results from IRI measurement against the results from the manufacturing industry's GDP, the Purchasing Manager Index (PMI), the Production Index of Large and Medium Manufacturing Industry (PII), the Competitiveness Industrial Performance (CIP), and the Global Competitiveness Index (GCI). Accordingly, this study produces three results. First, the correlation calculation suggests that IRI has a close relationship with the GDP of the manufacturing industry. The correlation coefficient between the two is 0.98 appears to be highest among the correlation coefficient with other manufacturing indices. Secondly, IRI appears to move in line with the movement of the GDP cycle in the manufacturing industry. Additionally, based on the business cycle analysis, the result implies that IRI can be identified as a coincident indicator with a fairly high cross-correlation rate of 0.74. This suggests that the IRI method might be used as a tool to predict the direction or the movement of the general manufacturing industry cycle. Thirdly, however, IRI is not able to see the magnitude of the cyclic movement. Finally, this study contributes to the development of the resilience measurement and the dynamic measurement for analyzing risks and their impact in a system performance. For the future agenda, this study should lead to investigations on how IRI can be implemented in different fields of science.

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References

Ahern, N.R., Kiehl, E.M., Lou Sole, M., Byers, J., 2006. A Review of Instruments Measuring Resilience. *Issues in Comprehensive Pediatric Nursing*, Volume 29(2), pp. 103–125

Angeon, V., Bates, S., 2015. Reviewing Composite Vulnerability and Resilience Indexes: A Sustainable Approach and Application. *World Development*, Volume 72, pp. 140–162

Bajo-Rubio, O. 2000. A Further Generalization of the Solow Growth Model: The Role of the Public Sector. Economics Letters, 2000, Volume 68(1), pp. 79–84

Barrett, C.B., Ghezzi-Kopel, K., Hoddinott, J., Homami, N., Tennant, E., Upton, J., Wu, T., 2021. A Scoping Review of The Development Resilience Literature: Theory, Methods and Evidence. *World Development*, Volume 146, p. 105612

Benazir, A.D., Achsani, M.A., 2008. Composing Early Warning Indicators of Exchange Rate Movements in Indonesia: Development of Business Cycle Analysis. *Journal of Management & Agribusiness,* Volume 5(1), pp. 1–15

Berawi, M.A., 2018. The Role of Technology in Building a Resilient City: Managing Natural Disasters. *International Journal of Technology,* Volume 9(5), pp. 862–865

Bhuiyan, M.N.A., Ahmed, K.S., Jahan, R., 2002. Study on Modeling and Forecasting of the GDP of Manufacturing Industries in Bangladesh. CMU. *Journal of Social Science and Humanities,* Volume 2(2), pp. 143–157

Box, G.E., Jenkins, G.M., Reinsel, G.C., Ljung, G.M., 1976. *Time Series Analysis Forecasting and Control-Rev.* John Wiley & Sons

Bradtmöller, M., Grimm, S., Riel-Salvatore, J., 2017. Resilience Theory in Archaeological Practice–An Annotated Review. *Quaternary International*, Volume 446, pp. 3–16

Burns, A.F., Mitchell, W.C., 1946. *Measuring Business Cycles* (No. burn 46-1). National Bureau of Economic Research

Carlson, J.L., Haffenden, R.A., Bassett, G.W., Buehring, W.A., Collins, M.J., Folga, S.M., Whitfield, R.G., 2012. *Resilience: Theory and Application (No. ANL/DIS-12-1).* Argonne National Laboratory (ANL), Argonne, Illinois, United States

Chao, B.F., Chung, C.H., 2019. On Estimating the Cross-Correlation and Least Squares Fit of One Data Setto another with Time Shift. *Earth and Space Science*, Volume 6, pp. 1409–1415

Costa, L.D.F., 2021. Comparing cross correlation-based similarities. *arXiv preprint arXiv:2111.08513*.

Cowperwait, P.S.P., Metcalve, A.V., 2009. *Time Series Analysis*. New York: Springer

Dean, R.T., Dunsmuir, W.T., 2016. Dangers and Uses of Cross-Correlation in Analyzing Time Series in Perception, Performance, Movement, and Neuroscience: The Importance of

Constructing Transfer Function Autoregressive Models. *Behavior Research Methods*, Volume 48(2), pp. 783–802

Derrick, T., Thomas, J., 2004. Time Series Analysis: The Cross-Correlation Function, In: *Innovative Analyses of Human Movement*, Chapter 7, Stergiau, N. (ed.), Human Kinetic Publishers, Champaign, Illinois, pp. 189–205

Diebold, F.X., Rudebusch, G.D., 2020. *Business Cycles: Durations, Dynamics, and Forecasting.* Princeton University Press

Fattah, J., Ezzine, L., Aman, Z., El Moussami, H., Lachhab, A., 2018. Forecasting of Demand using ARIMA Model. *International Journal of Engineering Business Management*, Volume 10, p. 1847979018808673

Fauzi, P.N.F.N.M., Jahidi, Z., 2022. Identification of Risks Exposed to The Development of Zakat and Wakaf Housing in Malaysia. *International Journal of Technology*, Volume 13(4), pp. 727–739

Ferguson, C.E., Gould., J.P., 1975. *Microeconomic Theory*. Illinois: Richard D. Irwin

Fuss, M., McFadden, D., 2014. *Production Economics: A Dual Approach to Theory and Applications: Applications of The Theory of Production*. Elsevier

Grogan, M., 2020. Limitations of ARIMA: Dealing with Outliers. Available Online at: https://towardsdatascience.com/limitations-of-arima-dealing-with-outliers-30cc0c6ddf33, Accessed on May 30, 2021

Harding, D., Pagan, A., 2002. Dissecting the Cycle: A Methodological Investigation. *Journal of Monetary Economics,* Volume 49(2), pp. 365–381

Holling, C.S., 1973. Resilience and Stability of Ecological Systems. *Annual Review of Ecology and Systematics*, Volume 4(1), pp. 1–23

Hudecheck, M., Sirén, C., Grichnik, D., Wincent, J., 2020. How Companies Can Respond to the Coronavirus. MIT Sloan Management Review. Available Online at: https://sloanreview.mit.edu/article/how-companies-can-respond-to-the-coronavirus/. Accessed on May 30, 2021

Jandhana, I.B.M.P., 2019. Pembangunan Indeks Ketahanan Industri (IKI) Sebagai Alternatif Pengukuran Kinerja Sektor Industri *(The development of the Industrial Resilience Index (IRI) as an Alternative Performance Measurement in the Industrial Sector).* Disertation, Universitas Indonesia

Jandhana, I.B.M.P., Zagloel, T.Y.M., Nurcahyo, R., 2017. Measuring Industrial Resiliency by Using Data Envelopment Analysis Approach. *In:* 3rd International Conference on Business and Engineering Research (ICBER), Osaka, Japan 17th-18th November, 2017

Jandhana, I.B.M.P., Zagloel, T.Y.M., Nurcahyo, R., 2018. Resilient Structure Assessment using Cobb-Douglas Production Function: The Case of the Indonesian Metal Industry. *International Journal of Technology,* Volume 9(5), pp. 1061–1071

Juhász, R., Squicciarini, M.P., Voigtländer, N., 2024. Technology Adoption and Productivity Growth: Evidence from Industrialization in France. *Journal of Political Economy*, Volume 132(10), pp. 1–42

Kask, C., Sieber, E., 2002. Productivity Growth in 'High-tech' Manufacturing Industries. *Monthly Labor Review,* Volume 125, p. 16

Kose, M.A., Sugawara, N., Terrones, M.E., 2020. Global Recessions. *CAMA Working Paper 10/2020,* Centre for Applied Macroeconomic Analysis

Ludvigson, S.C., Ma, S., Ng, S., 2020. COVID-19 and the Macroeconomic Effects of Costly Disasters. *National Bureau of Economic Research,* Volume 2020, p. 26987

Ludvigson, S.C., Ma, S., Ng, S., 2021. Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response? *American Economic Journal: Macroeconomics,* Volume 13(4), pp. 369–410

Mandal, S., 2014. Supply Chain Resilience: A State-Of-The-Art Review and Reandrch Directions. *International Journal of Disaster Resilience in the Built Environment*, Volume 5(4), pp. 427–453

Mankiw, N.G., 2020. *Principles of Macroeconomics*. 9th Edition. Cengage Learning

Mohamed, A.S., Mohammed, N.A., 2021. Forecasting Enhancement Using a Hodrick-Prescott Filter. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, Volume 12(6), pp. 3378–3391

Narayan, S.W., Falianty, T., Tobing, L., 2019. The Influence of Oil Prices on Indonesia's Exchange Rate. *Bulletin of Monetary Economics and Banking*, Volume 21(3), pp. 303–322

Nelson-Wong, E., Howarth, S., Winter, D.A., Callaghan, J.P., 2009. Application of Autocorrelation and Cross-Correlation Analysis in Human Movement and Rehabilitation Research. *Journal of Orthopaedic & Sports Physical Therapy*, Volume 39(4), pp. 287–295

Nilsson, R. and Gyomai, G., 2011. Cycle Extraction: A Comparison of the Phase-Average Trend Method, the Hodrick-Prescott and Christiano-Fitzgerald Filters. *OECD Statistics Working Papers*, No. 2011/4, OECD Publishing, Paris

Podobnik, B., Stanley, H.E., 2008. Detrended Cross-Correlation Analysis: A New Method for Analyzing Two Non-Stationary Time Series. *Physical Review Letters*, Volume 100(8), p. 084102

Sambowo, A.L., Hidayatno, A., 2021. Resilience Index Development for the Manufacturing Industry based on Robustness, Resourcefulness, Redundancy, and Rapidity. *International Journal of Technology*, Volume 12(6), pp. 1177–1186

Senhadji, A. 2000. Sources of Economic Growth: An Extensive Growth Accounting Exercisex. IMF Staff Papers, Volume 47(1), pp. 129–157

Sensoy, A., Yuksel, S., Erturk, M., 2013. Analysis of Cross-Correlations Between Financial Markets After the 2008 Crisis. *Physica A: Statistical Mechanics and its Applications*, Volume 392(20), pp. 5027–5045

Serfilippi, E., Ramnath, G., 2018. Resilience Measurement and Conceptual Frameworks: A Review of the Literature. *Annals of Public and Cooperative Economics*, Volume 89(4), pp. 645–664

Solow, R.M., 1956. A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*, Volume 70(1), pp. 65–94

Van Meerbeek, K., Jucker, T., Svenning, J.C., 2021. Unifying the Concepts of Stability and Resilience in Ecology. *Journal of Ecology*, Volume 109(9), pp. 3114–3132

Walker, B., Holling, C.S.S., Carpenter, R., Kinzig, A., 2004. Resilience, Adaptability and Transformability in Social–Ecological Systems. *Ecology and Society*, Volume 9(2), p. 5

Windle, G., Bennett, K.M., Noyes, J., 2011. A Methodological Review of Resilience Measurement Scales. *Health and Quality of Life Outcomes*, Volume 9(1), pp. 1–18

Woods, D.D., Hollnagel, E., 2017. Prologue: Resilience Engineering Concepts. *In: Resilience Engineering*, CRC Press, pp. 1–6

Zagloel, Y., Jandhana, I.B.M.P., 2016. Literature Review of Industrial Competitiveness Index: Research Gap. *In:* Proceeding of Industrial Engineering and Operations Management (IEOM) Conference. Kuala Lumpur, Malaysia, pp. 613–627