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Analyses of topical policy issues

Did the policy responses influence credit and business cycle co-movement during the COVID-19 crisis? Evidence from Indonesia

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ABSTRACT

This paper examines the responses of credit and business cycle to various policy actions of the Government of Indonesia during the COVID-19 crisis. Specifically, the paper addresses two key questions (1) How do the credit and business cycle behave during the COVID-19 crisis in Indonesia? (2) Do the central bank and government policy responses effectively stabilize the credit and business cycle? Using the concordance Index and DCC-GARCH methodology, we found that the COVID-19 crisis increased Indonesia's credit and business cycle co-movements. Similarly, using the mixed data sampling regression technique, our findings suggest fiscal policy measures and government support help the business cycle revival during the COVID-19 pandemic. However, the monetary policy transmission is weak during the pandemic

1. Introduction

This paper examines the responses of the credit and business cycle to various policy actions of the Government of Indonesia during the COVID-19 crisis. The outbreak of COVID-19 in China in December 2020 and its subsequent spread across the world induced countries to adopt strict policies, such as lockdowns, to curb the spread of the virus. Evidence suggests that the pandemic led to excessive unemployment, a drastic reduction in economic growth, a fall in the stock market, depreciation of the exchange rate, and disruption in trade (Baldwin and Di Mauro, 2020; Iyke, 2020a; IMF, 2020a; Phan and Narayan, 2020; Narayan et al., 2020; Vidya and Prabheesh, 2020). The consequent global recession induced many economies to follow aggressive countercyclical policies, such as monetary and fiscal policies, to revive from recession. However, the overall impact of these policies on recovery is not yet known, especially for emerging market economies (EMEs).

It is argued that understanding business and credit cycle co-movements is crucial for policy formulations. For instance, if the recession coincides with the contraction phase of a financial or credit cycle, then the impact of the recession will be severe (Borio, 2014; Reinhart and Rogoff, 2011). In other words, if the credit cycle is in the contraction phase before COVID-19, then the pandemic-induced recession will worsen (Liu et al., 2020). At the onset of the pandemic, there was a short squeeze in liquidity in the global financial markets due to the investors' behavior of fire sale of risky assets and rush towards safety and liquidity (IMF, 2020b). As the global financial, product and input markets are well integrated in recent years, the contraction in the financial markets amplifies economic fluctuations via a reduction in consumption demand and

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supply-side disruptions. Thus, the pandemic outbreak would have increased the nexus between credit and the business cycle. In such a scenario, i.e., the contraction stage of the credit and business cycle, much stronger macroeconomic policies are required for recovery compared to regular times. Thus it is vital to know the phases of these cycles for the effectiveness of the policies.

Thus, the present study analyses the issues related to Indonesia's business and financial cycles and the policy effectiveness during the COVID-19 crisis. Specifically, the paper addresses the following questions: (1) How do the credit and business cycle behave during the COVID-19 crisis in Indonesia? (2) Are the central bank and government policy responses effective in stabilizing the credit and business cycle? We address these questions for the following reasons: (1) Indonesia, the fourth largest populist country in the world, experienced a high level of COVID-19 cases in 2020. The number of cases reached 0.6 million in Dec 2020 and increased to 6 million in June 2022. (2) Due to the pandemic, the country's economic growth declined from 5.02% in 2019 to −2.00% in 2020.[1] (2) The country experienced a severe credit crunch during the pandemic outbreak. For instance, banks' credit growth rate declined from 9.45% in 2019 to 2.39% in 2020.[2] (3) Similarly, the government of Indonesia promptly intervened by supporting measures to mitigate the crisis by spending around 9.33 per cent of GDP, which is the largest among the G20 emerging market economies (IMF, 2021).

The existing research shows that credit expansion and contraction are the main drivers of economic fluctuations, and thus, the financial cycle driven by credit growth is the key determining force of the business cycle (Smets and Wouters, 2007; Justiniano et al., 2010; Jermann and Quadrini, 2012; Iacoviello, 2015). Borio (2012) defines the financial cycle can be best thought as "the self-reinforcing interactions between perceptions of value and risk, attitudes towards risk, and financing constraints, which translate into booms followed by busts". These interactions can magnify economic fluctuations and possibly lead to serious financial distress. The existing studies also show that the EMEs' credit cycle is often determined by the monetary policy of the advanced economies (Guo and Stepanyan, 2021; Brauning and Ivashina, 2020). Thus, the EMEs policymakers face many challenges to maintaining macroeconomic stability. These economies' financial cycle often deviates from the economic cycle due to excessive credit boom/bust, subsequently affecting financial stability (Warjiyo and Juhro, 2019; Lubis et al., 2019). It is also argued that monetary policy may not be effective in maintaining both macroeconomic and financial stability during credit cycle expansion (Badarau and Popescu, 2014).

In recent years there have been many studies on the economics of COVID-19.[3] There are studies on monetary policy and its effectiveness by measuring its impact on the stock market (Narayan et al., 2021, 2020; Phan and Narayan, 2020; Chundakkadan and Sasidharan, 2021), and on the exchange rates in EMEs (Yilmazkuday, 2021), on long-term interest rates in the US (Bhar and Malliaris, 2021). Further, the studies revealed that COVID-19 and its uncertainty relevels affected the stock market (Haroon and Rizvi, 2020; Iyke and Ho, 2021), exchange rates (Iyke, 2020a,b; Rai and Garg, 2021), oil market (Devpura and Narayan, 2020; Narayan, 2020), and trade and economic growth (Vidya and Prabheesh, 2020; Vidya, 2021; Zainuddin et al., 2021). However, there have been few studies in recent days on the effectiveness of policy response to the COVID-19 crisis. For instance, Yilmazkuday (2022) found that emerging markets without zero bounds could reduce the reaction of economic activity and exchange rate volatility. In contrast, advanced economies with zero bounds could not mitigate the effect caused by COVID-19. Zhou et al. (2021) affirm that the conventional monetary policy causes depreciation during the COVID-19 pandemic crisis. Conversely, Wei and Han (2021) affirmed that the emergence of this pandemic had weakened the transmission of monetary policy. Similarly, Prabheesh et al. (2022) found that the monetary policy transmission during the COVID-19 crisis period is weak in emerging economies due to the "cautionary" or "wait and see" approach followed by the economic agents.

Likewise, there have been many studies on the Indonesian context in recent years on economic growth (Juhro et al., 2022, 2020a; Juhro, 2015; Sharma et al., 2018), business cycle (Dutu, 2015; Prabheesh et al., 2021), financial sector and policies (Juhro and Iyke, 2019; Prabheesh and Rahman, 2019), the impact of COVID-19 pandemic and policy responses (Malahayati et al., 2021; Rizvi et al., 2021; Juhro et al., 2020b). However, none of the above studies addresses the business and financial cycle phase during the COVID-19 period and the impact of the policy responses on these cycles.

In order to address the research questions discussed earlier, we constructed the concordance indices of Indonesia's credit cycles with the business cycle to measure the degree of cycle synchronization. Second, we apply the dynamic conditional correlation-generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model to assess the evolution of the business and credit cycle. Third, we use two indices to capture the policy responsiveness to the COVID-19 pandemic s, such as the economic support index and the government support index. We also estimate an equation using the mixed data sampling regression technique (MIDAS) to examine the impact of policy responses on the business and credit cycle. Finally, as a robustness test, we used an alternative technique to measure the business and credit cycle and confirm the findings on the effectiveness of policy responses.

Our empirical findings show that (1) there has been an increased convergence between business and credit cycles in Indonesia during the COVID-19 outbreak. (2) Credit and business cycles were in the contraction phases before the pandemic outbreak. (2) The government's economic and supporting policies have the desired effect on the recovery of the business cycle but not the credit cycle. (3) The monetary policy transmission is weak to revive both credit and business cycles during the pandemic.

[1] Data source CEIC, growth rate in gross domestic product at 2010 price level.

[2] Data source CEIC, commercial banks annual credit growth rate.

[3] Refer to Padhan and Prabheesh (2021) and Narayan (2021) for a review of papers related to the economics of COVID-19.

Thus, we contribute to the existing literature in the following ways. (1) this is one of the first attempts to analyze the effectiveness of various policy measures, such as monetary policy and various government supports initiatives. (2) This paper is one of the first papers examining the relationship between credit and business cycle during the COVID-19 crisis. (3) We used the MIDAS methodology to estimate the impact of policy response on the credit and business cycle to accommodate the data related to policies available in different frequencies into the analysis. (4) This study is one of the first attempts to examine the effectiveness of various policy responses of the government of Indonesia adopted during the COVID-19 pandemic.

The rest of the paper is as follows. Sections 2 and 3 discuss the empirical model and data. Section 4 discusses the empirical methodology and Section 5 reports empirical findings. Section 6 concludes.

2. Empirical model

Following Adrian et al. (2010), Yan and Huang (2020) and Prabheesh et al. (2021), we specify the following five empirical models to examine the effectiveness of policy responses to the COVID-19 crisis in Indonesia.

$$y_t = \beta_0 + \beta_1\, i_t + \beta_2\, er_t + \beta_3\, vix_t + \epsilon_t \tag{1}$$

$$y_t = \beta_0 + \beta_1\, i_t + \beta_2\, er_t + \beta_3\, vix_t + \beta_4 covid19\_dummy + \epsilon_t \tag{2}$$

$$y_t = \beta_0 + \beta_1\, i_t + \beta_2\, er_t + \beta_3\, vix_t + \beta_4 covid19\_dummy * i_t + \epsilon_t \tag{3}$$

$$y_t = \beta_0 + \beta_1\, i_t + \beta_2\, er_t + \beta_3\, vix_t + \beta_4 covid19\_dummy * i_t + \beta_5\, ESI_t + \epsilon_t \tag{4}$$

$$y_t = \beta_0 + \beta_1\, i_t + \beta_2\, er_t + \beta_3\, vix_t + \beta_4 covid19\_dummy * i_t + \beta_5\, GSI_t + \epsilon_t \tag{5}$$

where y_t *includes business and credit cycle*. Similarly, $\beta_1, \ldots \beta_5$ are the parameters to be estimated. β_0 is the intercept; t denotes time and ε_t stands for error term. Similarly, *i* indicates the interest rate, and *er* indicates the exchange rate. Likewise, *vix* is the indicator of global risk conditions. The variable *covid*19*_dummy* captures the period of COVID-19 crisis, which takes a value of 0 during the pre-COVID-19 crisis period and one during the crisis period (March 2020 onwards). Likewise, the variable *ESI* and *GSI* are the economic support and the government support index, respectively. Where all variables are measured in logarithmic form except interest rate, *ESI and GSI*.

The variables such as *i and vix* are *expected to have a* negative effect on impact *y* as an increase in the domestic interest rate, and global uncertainty reduces the credit availability and output and, thus, we expect $\beta_1 < 0$ and $\beta_3 < 0$. Whereas, the exchange rate (*e*) can have a positive impact on output as the depreciation of domestic currency leads to higher output through a higher trade balance ($\beta_2 > 0$). Whereas its impact on the credit cycle may not be known as the depreciation or appreciation of domestic currency can lead to an increase in credit availability ($\beta_2 < 0$). For instance, depreciation can lead to higher credit availability through higher savings due to higher output. Whereas an appreciation of domestic currency also leads to higher credit availability through risk-taking behavior of the financial institutions as domestic currency appreciation strengthens the balance sheet of the financial institutions that borrow in foreign currency, as their liabilities fall relative to assets, which makes the borrower appear more creditworthy and attract creditors to extend more credit Hofmann et al. (2017). Similarly, the variable *x* is expected to have a positive impact y_t as an increase in economic support and government support indices are expected to have a positive effect on output and credit ($\beta_4 > 0$). Finally, the *covid_dummy* is captures the impact of the COVID-19 crisis on credit and business cycle. Similarly, $covid\_dummy * i$ is the interactive dummy that captures the effectiveness of monetary policy during the COVID-19 period.

3. Data

Data have been drawn from various sources such as Bank Indonesia, China Economic Information Center (*CEIC*) database, and Bank for International Settlement (BIS). To construct the business and credit cycle, we use the growth of the Industrial Production Index (IIP) and commercial banks credit to the economy, respectively. Similarly, we draw the policy and exchange rates to measure the policy responses related to the COVID-19 crisis. Monetary policy response data has been collected from BIS. For volatility, data has been collected from St. Louis Federal Bank. Similarly, to examine the other policy responses of the Government of Indonesia to the COVID-19 pandemic, we use the economic support index (*ESI*) and government response index (*GRI*)[4] developed by Hale et al. (2020). The ESI includes income support, debt/contract relief for households, fiscal measures, and international support during the COVID-19 period. In contrast, GRI includes the various measures taken by the government to contain the spread of COVID-19. Details of measurements of the variables and data sources are reported in Appendix. Our period of analysis is restricted to 2010M01 to 2022M03. We utilize both monthly and daily data for the analysis. For instance, the key macroeconomic variables such as IIP and credit are in monthly frequency. At the same time, the other policy variables such as exchange rate, interest rate, ESI and GRI are in daily frequency. As converting monthly data into daily (or another way around) may lose the crucial information contained in the data, we use the mixed data sampling (MIDAS) regression technique for the analysis.

[4] For more information, data related to what are variables considered in the construction of the ESI and GRI index see China information economic center (CEIC) and Hale et al. (2020). See (https://www.bsg.ox.ac.uk/research/publications/variation-government-responses-covid-19).

4. Econometric methodology

We adopt various econometric methodologies to address the research questions. First, we construct business and credit cycles by retrieving the cyclical components of the time series data using the Hodrick–Prescott (H–P Filter) method. Second, a concordance index is constructed to examine the degree of credit cycle co-movement between credit and business cycle. This also helps to understand the level of synchronization between two cycles. Third, we calculated the time-varying co-movement index using dynamic conditional correlation through GARCH to understand credit and business cycle co-movements trends. Fourth, we adopt the MIDAS technique to estimate the effectiveness of government policy responses on credit and business cycle. Finally, as a robustness test, we retrieved the cyclical components of the time series data using the Christiano–Fitzgerald (CF) Filter (2003) and repeated the estimation.

4.1. Concordance index

The concordance index is used to identify the turning points of the business cycle, and we follow Harding and Pagan (2002) quarterly version of the BB algorithm[5] to construct the index. The concordance index developed by Harding and Pagan (2002, 2006) measures the proportion of time two cycles are in the same phase of their business cycle.[6] There is a perfect concordance, when the value of concordance is unity. Whereas in the case of perfect disconcordance, when the value of concordance is zero, indicating both cycles are always in the opposite direction. The concordance index will have the maximum value of unity when $S_{X,t} = S_{Y,t}$ and zero when $S_{X,t} = \left(1 - S_{Y,t}\right)$. The concordance index value between 0.5 to 1 reveals weak to perfect synchronization, and the value 0 to 0.5 reveals perfect to weak disconcordance. The concordance index shows the average number of periods in which two business cycle occurs at the same phase of the cycle.

First, we identify the turning points of the business cycle and define a variable $S_{X,t}$ as follows:

$$S_{X,t} = \begin{Bmatrix} 1, \textit{if } X \textit{ is in expansion in time } t \\ 0, \textit{Otherwise} \end{Bmatrix} \tag{6}$$

Similar way we defined $S_{Y,t}$.

$$S_{Y,t} = \begin{Bmatrix} 1, \textit{if } Y \textit{ is in expansion in time } t \\ 0, \textit{Otherwise} \end{Bmatrix} \tag{7}$$

The concordance index between the two series X and Y can be constructed as follows:

$$C_{XY} = \frac{1}{T}\sum_{t=1}^{T}\left[S_{X,t}S_{Y,t} + \left(1 - S_{X,t}\right)\left(1 - S_{Y,t}\right)\right] \tag{8}$$

For series X we can say it is pro-cyclical with Y series for concordance index value between 0.5 and 1, and countercyclical for the value between 0 to 0.5. Further, the index value close to 1 would indicate perfect procyclicality, where an index value of 0 would indicate perfect counter-cyclicality.

Further, the test of the null hypothesis of the two series are synchronized can be estimated as:

$$\frac{S_{Y,t}}{\sigma s_Y} = \upsilon + \rho_s\left(\frac{S_{X,t}}{\sigma s_X}\right) + \varepsilon_t \tag{9}$$

The null hypothesis states that two cycles are not synchronized i.e. $\rho_s = 0$. The value of $\rho_s = 1$ indicating the value of the concordance index is unity and $\rho_s = -1$ indicating the value of the concordance index is zero. The Newey–West heteroscedasticity and autocorrelation consistent (HAC) adjusted standard error is used to estimate the t-statistics to avoid extensive serial correlation as identified by Harding and Pagan (2006).

4.2. Dynamic Conditional Correlations (DCC)

We use the DCC-GARCH model to calculate the evolution or the time-varying nature of synchronization between the credit cycle and business cycle over time. The relationship between cycles is not constant for a long period of time, and thus, a time-varying relationship will have explanatory power to explain the evolution of synchronization. To determine the time-varying correlation between the cycles, we use Engle's (2002) DCC model. The DCC model is a multivariate generalized autoregressive conditional heteroscedastic (MGARCH) model and has advantages over other multivariate GARCH models because of its limited parameter estimation and varying conditional correlation matrix.

[5] Bry and Boschan (1971) have developed an algorithm to explore the turning points of the business cycle and the algorithm is famously known as BB algorithm. Later, it was developed by Harding and Pagan (2002, 2006).

[6] We follow the similar approach to Padhan and Prabheesh (2020) and Prabheesh et al. (2021) for construction of concordance index for Indonesia.

In this study, we have considered the following dynamic conditional correlation (DCC) specification of the M dimensional multivariate GARCH (1, 1) model to determine the dynamic conditional correlation.

$$Y_t = \varnothing_0 + \varnothing_1 Y_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim (0, H_t) \tag{10}$$

$$H_t = \Gamma_t R_t \, \Gamma_t \tag{11}$$

$$\Gamma_1 = diag \left\{ \sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \ldots . \sqrt{h_{MM,t}} \right\} \tag{12}$$

$$h_{ii,t} = w_i + \beta_1 h_{ii,t-1} + \gamma_i \varepsilon^2_{i,t-1} \; i = 1, 2 \ldots \ldots M \tag{13}$$

$$R_t = (diag\,\{Q_t\})^{-1/2} Q_t (diag\,\{Q_t\})^{-1/2} \tag{14}$$

$$Q_t = (1 - \alpha - \beta)\,\overline{Q} + \alpha u_{t-1} u^{'}_{t-1} + \beta Q_{t-1} \tag{15}$$

where, $Y_t = (Y_{1,t}, Y_{2,t} \ldots .., Y_{M,t})'$ and $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t} \ldots \ldots, \varepsilon_{M,t})$ are the $Mx1$ vectors. H_t is the conditional covariance matrix of the random vector ε_t and $u_t = \left(\frac{\varepsilon_{1,t}}{\sqrt{h_{11,t}}}, \frac{\varepsilon_{22,t}}{\sqrt{h_{22,t}}} \ldots \ldots \frac{\varepsilon_{it}}{\sqrt{h_{MM,t}}} \right)'$ is a vector that contains the standardized values of ε_t. R_t is the time varying correlation matrix and Q_t is the positive definite symmetric matrix. $\overline{Q}$ represents the unconditional variance matrix of u_t. α and β are scalars, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$, for the positive definiteness of a conditional correlation matrix. The time varying elements of Y_1, $\rho_{ij,t}$ are as follows:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}, q_{jj,t}}} \tag{16}$$

where $q_{ij,t}$ is the $i - j$th element of Q_t. For estimating the unknown parameters, the following likelihood function is maximized:

$$L(\theta) = -\frac{1}{2} \sum_{t=1}^{T} (M \log(2\pi) + 2\log(|\Gamma_t|) + \log(|R_t|) + u_t' R_t^{-1} u_t) \tag{17}$$

Here, T is the number of observations, and M is the number of the variables in the system; θ represents all the parameters to be estimated.

4.3. Mixed Data Sampling (MIDAS)

MIDAS regression technique is highly parameterized, reduced form regression that has the ability to incorporate the samples at different frequencies, and is proposed by Ghysels et al. (2004, 2005). In this context, the response of the higher frequency of independent variables is modeled through highly parsimonious distributed lag polynomials, which reduce the incidence of the proliferation of the parameters and resolve the lag-order selection issues (Foroni and Marcellino, 2013). Further, MIDAS helps to reduce the loss of information and bias in modeling and forecasting.

The use of MIDAS is advantageous over the traditional techniques in the midst of a number of coefficients for each high and low frequencies as it reduces the number of coefficients by applying larger weights on near lags than the far away contemporaneous value. Following Ghysels et al. (2004), the MIDAS equation can be provided as:

$$Y_t = \alpha_0 + \alpha_1 A\left(L^{\frac{1}{q}}; \eta\right) R_t^{(q)} + \epsilon_t^{(q)} \tag{18}$$

In our model, the dependent variable is Y_t is sampled at a monthly frequency. The term t is the time for model estimation up to $1, \ldots, T$. The independent variables $R_t^{(q)}$ are sampled q time faster than dependent variable, here $q = 29$. The term $\mathrm{A}(L^{\frac{1}{q}}) = \Sigma_{p=0}^{Pmax} A(P)\, L^{\frac{P}{q}}$ is a polynomial of length P^{max} in the $L^{\frac{1}{q}}$ a lag operator that can be defined as $L^{\frac{P}{q}} R_t^{(q)} = R_{t-p/q}^{(q)}$. The lag operator $L^{\frac{P}{q}}$ produces the value of $R_t^{(q)}$ lagged by p/q Periods. A monthly\daily example would explain Eq. (1) is a projection of monthly Y_t onto daily data $R_t^{(q)}$ using unto P^{max} daily lags.

A regression model can be explained as follows:

$$Y_t^L = \Sigma_{i=0}^{P} \alpha_i V_{t-1}^L + \delta f\left(\theta, R_{p,t}^H\right) + \epsilon_t \tag{19}$$

The variable Y_t^L is the dependent variable samples at monthly low frequency. The term V_{t-1}^L is the set of independent variables samples at the same frequency as the dependent variable. $R_{p,t}^H$ is the set of explanatory variables sampled at a higher frequency. The term α_i, δ and θ are the parameters that need to estimate. The $f(.)$ is the process of converting the higher frequency variable into lower or equal to dependent variable frequency and the term ϵ_t is a white noise process.

The following equation can be used to take the average of the high-frequency data that occur between dependent and independent variables.

$$R_t^L = \frac{1}{q} \Sigma_{J=0}^{q-1} R_{t-j}^H \tag{20}$$

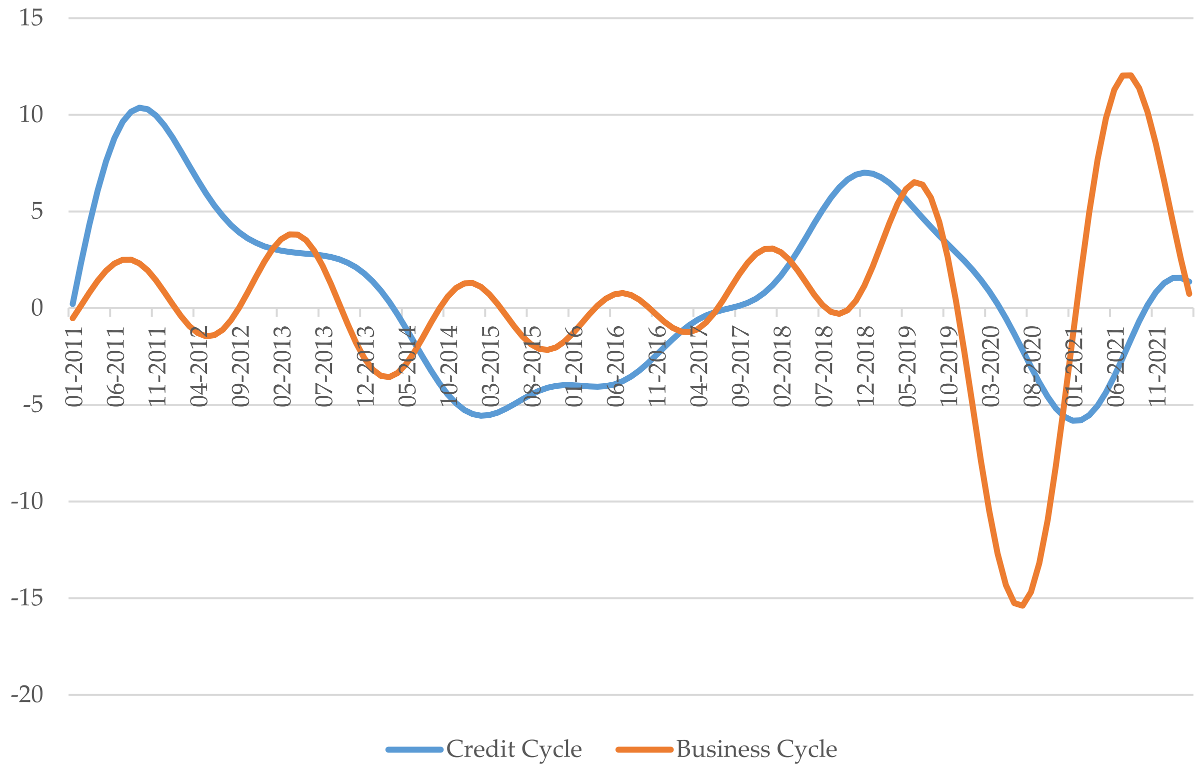

Fig. 1. Trends in credit and business cycles. This figure shows the Trends in credit cycle and business cycle for Indonesia. The cyclical series are obtained from HP filter method.

The term q is the number of periods in the higher frequency corresponding to a single period in the lower frequency. The R_t^H are the high-frequency variables corresponding to the last observation in period t of the lower frequency. The final model we estimate allows the non-equal weights for each lag of high frequency-independent variable $(t-j)$ and but will lead to a number of coefficients quite large. However, it is better to put larger weight on the near lags than those that are far from the contemporaneous value through a parsimonious model. The final equation of the MIDAS model is to be estimated as follows:

$$Y_t^L = \Sigma_{i=1}^q \alpha_i V_{t-1}^L + \eta \Sigma_{j=0}^{q-1} w_{t-j}(\gamma) R_{t-j}^H + \xi_t \tag{21}$$

where weighting function $w_{t-j}(\gamma) R_{t-j}^H$ transform high-frequency variables into low-frequency variables. The parameterization of the lagged coefficient of $w_{t-j}(\gamma)$ is one of the main abilities of the MIDAS regression technique. In our estimation, we estimate the MIDAS technique by using the Almon Lag Weighting Function (Almon, 1965) as it is useful in the presence of high-frequency mismatch from monthly to daily series.

5. Empirical findings

5.1. Findings from concordance index and dynamic conditional correlation

Fig. 1 exhibits the trends in credit and business cycle measured from the HP filter technique. It can be observed that both cycles are moving together. However, the length of the credit cycle is larger than the business cycle. It is also interesting to note that both cycles were in a downward trend just before the pandemic, indicating a recession phase. During the pandemic, the business cycle exhibited a steep decline and recovery compared to the credit cycle. Further, Table 1 reports the findings from concordance index estimation. The findings show that the concordance index of the credit cycle with the business cycle for Indonesia is 0.469, which implies that 46.9% of the time, Indonesia's credit cycle and the business cycle are in the same phase. However, the concordance index is statistically insignificant. This implies that the cyclical movement between Indonesia's credit and business cycles is not synchronized during the study period. Further, Fig. 2 shows Indonesia's time-varying correlation between the credit and business cycles observed from the DCC-GARCH model. It shows an increasing trend, especially after 2014, where the correlation has increased from −0.005 in 2014M08 to 0.31 by 2022M03. We can also observe a fall in the co-movements in mid-2018. However, during the COVID-19 period, post-march 2020 period, the co-movement between credit and business cycle increased and reached

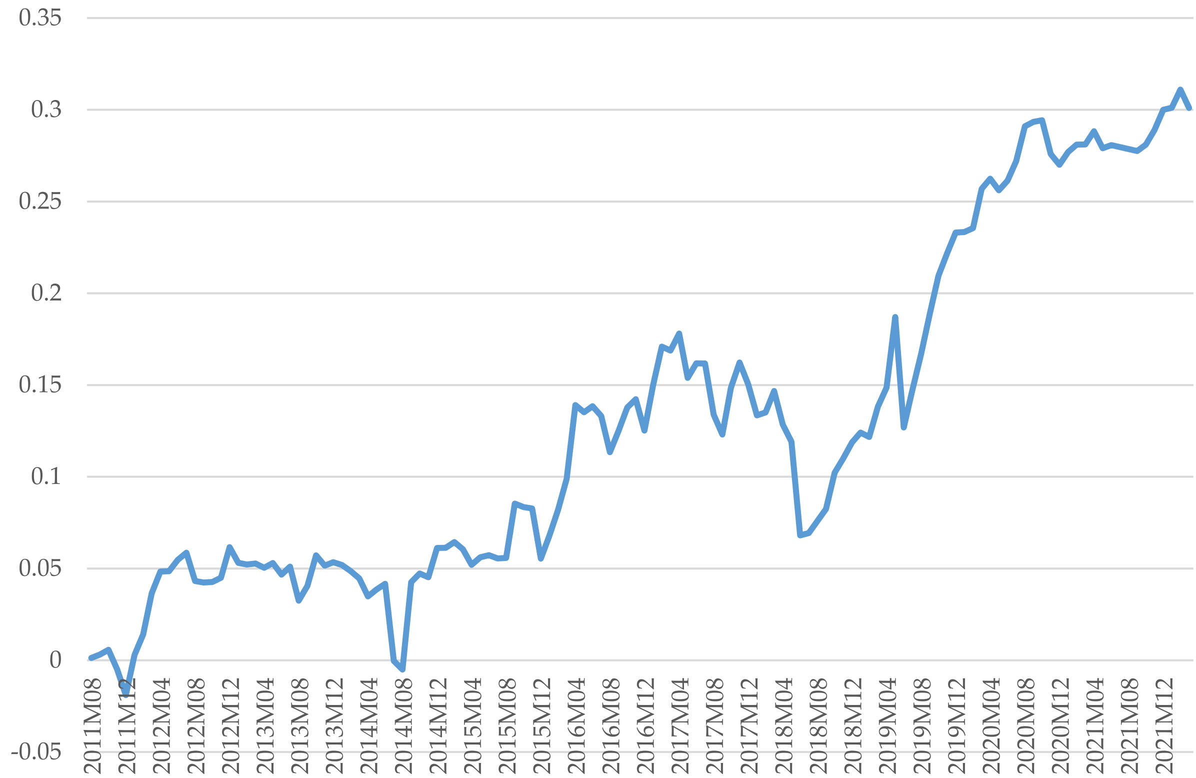

Fig. 2. Dynamic conditional correlation. This figure shows the time-varying correlation between credit cycle and business cycle for Indonesia. The results are calculated using DCC-GARCH model.

Table 1
Descriptive statistics.

Variables	Mean	Maximum	Minimum	S.D.	Skewness	JB
Credit cycle	0.8933	10.368	−5.817	4.412	0.257	0.08 (0.080)*
Business cycle	0.305	12.04	−15.38	4.852	−0.541	226.44 (0.000)*
i	5.67	7.75	3.502	1.352	−0.091	8.28 (0.020)
er	9.432	9.672	9.051	7.629	−0.770	17.40 (0.00)*
vix	17.88	57.745	10.135	6.691	2.45	628.73 (0.000)
GSI	55.142	71.200	0.000	15.813	−1.878	818.022 (0.000)*
ESI	30.968	37.500	0.000	11.961	−1.836	607.757 (0.000)*

This table reports the descriptive statistics of the variables used in the study. Where, *i*, *er*, *vix* denote interest rate, exchange rate and volatility index to capture the global risk condition, respectively. Similarly, GSI and ESI are govt. support index and economic support index respectively. The number in parentheses is the level of significance and asterisk * indicate the significance at 1% level and S.D denotes standard deviation.

the highest value of 0.29 in 2020M10. This clearly states that COVID-19 strengthened the co-movements between credit and business cycle in Indonesia. The decline in economic activities and low credit intake (due to the weak macroeconomic fundamentals) could be the reasons for strengthening the correlation between cycles.

5.2. Results from MIDAS estimation

Before reporting the estimation results, we present the descriptive statistics of the variables in Table 2. Similarly, As MIDAS regression assumes all variables in the models are stationary in nature, we first check stationary properties of variables by employing the conventional unit root tests such as Augmented Dicky Fuller (ADF) and Phillips and Perron

Table 2
Concordance index.

Variables	Concordance index	Coefficient	*t*-statistic	Probability
Credit and Business Cycle	0.469	−0.050	−0.426	0.670

The table shows the concordance index results between credit cycle and business cycle for Indonesia. The cycles are retrieved using Hodrick-Prescott (HP) filter.

Table 3
Unit root test results.

Variable	ADF		PP	
	Level	First Diff.	Level	First Diff.
Credit cycle	−3.911	−7.201	−7.603	−10.133
	(0.000)*	(0.00)***	(0.000)*	(0.000)*
Business cycle	−4.142	−13.121	−8.932	−20.223
	(0.000)*	(0.000)*	(0.000)*	(0.000)*
i	−0.710	−7.922	−0.812	−7.200
	(0.822)	(0.000)*	(0.625)	(0.000)*
er	−0.911	−9.001	−0.921	−8.151
	(0.721)	(0.000)*	(0.761)	(0.000)*
vix	−4.621	−12.123	−4.711	−13.122
	(0.000)*	(0.000)*	(0.000)*	(0.000)*
GSI	0.599	−9.011	1.101	−61.111
	(0.961)	(0.000)*	(0.988)	(0.000)*
ESI	−8.912	−68.111	−8.011	−65.111
	(0.000)*	(0.000)*	(0.000)*	(0.000)*

The table shows the unit root test of the variables based on Augmented Dickey–Fuller (ADF), Phillips–Perron (PP). The null and the alternative hypotheses are series is non-stationary (contains unit root) and series is stationary (no-unit root), respectively. The test statistic of ADF and PP are compared with critical values tabulated by MacKinnon (1996), respectively. Lags are selected automatically using Schwarz Information criterion (SBC). Where, The number in parentheses is the level of significance and * denotes rejection of unit root at 1%. Where, *i, er, vix* denote interest rate, exchange rate and volatility index to capture the global risk condition, respectively. Similarly, GSI and ESI are govt. support index and economic support index respectively.

(PP) test. The findings of the unit root test are presented in Table 3. The finding shows that the credit cycle, business cycle, *vix*, and ESI are stationary in levels, whereas the variables such as *i, er* and *GSI* are stationary at first difference. The non-stationary variables are converted into stationary by differencing method to make the data amenable for MIDAS estimation.

The findings from the MIDAS regression while considering credit cycle as a dependent variable are given in Table 4. The findings suggest that the domestic interest rate (*i*) is negative and statistically significant in Model 1 and 5, indicating the increase in interest rate reduces the credit growth in the economy. This finding suggests that the monetary policy effectively stabilizes the credit cycle in Indonesia, which is consistent with the findings of Prabheesh et al. (2021).

It is also interesting to note that the exchange rate *(er)* has a negative sign and is statistically significant in all models (1 to 5), indicating an exchange rate appreciation leads to an increase in credit boom in the country. This negative relationship between the exchange rate and credit cycle can be attributed to the risk-taking behavior of the financial institutions in response to the exchange rate appreciation, as domestic currency appreciation reduces the foreign liabilities of the financial institutions and thereby strengthens their balance sheet. In other words, when a home currency appreciates, its value of foreign currency-denominated liabilities falls in terms of domestic currency as compared to the assets side, which increases the net worth of the bank as a borrower and which subsequently increases leverage and risk-taking behavior (Hofmann et al., 2017). Similar findings are reported in the context of EMEs by Kalemli-Ozcan et al. (2018) and Kearns and Patel (2016). Similarly, the global uncertainty index, *vix*, also shows a negative sign and is statistically significant in all models, indicating the role of global uncertainty in determining the country's credit cycle.

The variable that captures the COVID-19 crisis (*covid19_dummy*) is found to have a negative and significant impact on the credit cycle (model 2, 4 and 5), implying the pandemic has an adverse impact on credit availability in the country. The existing studies also find a similar finding, such that the pandemic adversely impacted the banking sector of Indonesia through declining credit delivery to the real sectors (Darjana et al., 2022).

The monetary policy responses during the COVID-19 period captured the interaction dummy (*i*covid19_dummy*) shows an expected sign but is not statistically significant. This shows the weak monetary policy transmission to the credit market during the pandemic. This finding is in line with the existing studies that find conventional monetary policies yield little effect on the targeted variables during the COVID-19 pandemic due to the 'wait and see approach followed by the economic agent (Prabheesh et al., 2021).

It is also interesting to see that the Economic Support Index (*ESI*) and Government support index (*GSI*) positively impact the credit cycle (model 4 and 5). However, the effects are not found to be statistically significant. These findings further

Table 4
Results from MIDAS.

Dependent variable: *Credit cycle* (HP filtered)					
Variable	Model-1	Model-2	Model-3	Model-4	Model-5
i	−0.305	−0.244	−0.249	−0.236	−0.169
	(−1.910)***	(−1.565)	(−1.457)	(−1.501)	(−1.941)***
er	−3.633	−1.044	−3.142	1.196	−0.259
	(2.257)**	(2.662)**	(1.929)***	(0.750)	(−0.149)
vix	−0.539	−0.759	−0.571	−0.749	−0.501
	(−5.067)*	(−7.025)*	(−5.308)*	(−6.958)*	(−4.448)*
covid19_dummy		−1.241		−0.917	−0.817
		(4.842)*		(7.186)*	(6.122)*
*i*covid19_dummy*			−1.378		
			(−1.599)		
ESI				0.0117	
				(1.326)	
GSI					0.088
					(1.63)
Constant	16.521	17.126	16.611	17.100	16.448
	(55.395)*	(56.747)*	(55.057)*	(56.817)*	(51.738)*
Adjusted R^2	0.227	0.343	0.236	0.340	0.149
AIC	0.769	0.612	0.764	0.618	0.872
SIC	0.879	0.744	0.896	0.749	1.004

The table shows the results obtained from MIDAS regression. Where, *i, er, vix* denote interest rate, exchange rate and volatility index to capture the global risk condition, respectively. Similarly, GSI and ESI are govt. support index and economic support index respectively. The number in parentheses is t-statistics and asterisk *, **, *** show the significance at 1%, 5% and 10% level, respectively.

Table 5
Results from MIDAS.

Dependent variable: *Business cycle* (HP filtered)					
Variable	Model-1	Model-2	Model-3	Model-4	Model-5
i	−0.046	−0.052	−0.0449	−0.043	−0.045
	(−1.972)***	(−2.267)**	(−1.868)***	(−1.885)***	(−1.904)***
er	0.720	0.882	0.711	0.735	0.751
	(3.264)**	(3.839)*	(3.182)**	(3.429)*	(3.472)*
vix	−0.023	−0.010	−0.024	−0.0140	−0.020
	(−1.537)	(−0.673)	(−1.558)	(−0.882)	(−1.393)
covid19_dummy		−0.104		−0.0197	−0.0216
		(−2.175)**		(−2.002)**	(−2.122)**
*i*covid19_dummy*			−0.033		
			(−0.284)		
ESI				0.0034	
				(2.217)**	
GSI					0.0118
					(1.848)***
Constant	0.064	0.029	0.066	0.039	0.0557
	(1.519)		(.540)	(0.888)	(1.363)
Adjusted R^2	0.067	0.094	0.061	0.090	0.084
AIC	−3.174	−3.196	0.061	−3.192	−3.185
SIC	−3.064	−3.064	−3.028	−3.060	−3.053

The table shows the results obtained from MIDAS regression. Where, *i, er, vix* denote interest rate, exchange rate and volatility index to capture the global risk condition, respectively. Similarly, GSI and ESI are govt. support index and economic support index respectively. The number in parentheses is t-statistics and asterisk *, **, *** show the significance at 1%, 5% and 10% level, respectively.

reveal that the economic support actions of the government of Indonesia, such as the income and debt relief support to households, were insufficient to create an economic environment to revive the credit market.

Table 5 shows the responses of the business cycle. It can be observed that the domestic interest rate (i) is negative and statistically significant in all the models, indicating the monetary policy transmission is strong to revive the business cycle. Similarly, the exchange rate *(er)* shows a positive sign and is statistically significant, implying domestic currency depreciation improves output growth and thereby revives the business cycle. However, the variable *vix* does not significantly affect business cycle movements, although it shows the expected negative sign. This finding shows that the country's real sector is less exposed to global risk conditions.

The table also shows that the COVID-19 crisis has an adverse effect on the country's business cycle movements, as the variable *covid19_dummy* is statistically significant in all models. However, the monetary policy actions of the central bank during COVID-19 do not have a significant effect on the business cycle as the interaction term is not statistically

Table 6
Robustness test.

Dependent variable: *Credit cycle* (CF filtered)					
Variable	Model-1	Model-2	Model-3	Model-4	Model-5
i	−0.211	−0.222	−0.411	−0.273	−0.221
	(−1.912)***	(−1.663)	(−1.322)	(−1.322)	(−1.921)***
er	−2.129	−1.112	−3.912	1.011	−0.153
	(2.607)**	(2.522)**	(2.611)**	(0.650)	(−0.122)
vix	−0.321	−0.322	−0.411	−0.521	−0.537
	(−6.742)*	(−6.123)*	(−5.221)*	(−4.977)*	(−4.222)*
covid19_dummy		−1.011		−0.512	−0.671
		(5.172)*		(6.227)*	(5.222)*
*i*covid19_dummy*			−1.112		
			(−1.424)		
ESI				0.049	
				(1.326)	
GSI					0.011
					(1.811)
Constant	13.142	15.223	15.231	16.721	15.222
	(45.221)*	(43.001)*	(53.222)*	(52.941)*	(41.112)*
Adjusted R^2	0.392	0.321	0.393	0.359	0.3231
AIC	0.621	0.732	0.824	0.823	0.890
SIC	0.612	0.722	0.817	0.622	0.904

The table shows the results obtained from MIDAS regression. Where, *i, er, vix* denote interest rate, exchange rate and volatility index to capture the global risk condition, respectively. Similarly, GSI and ESI are govt. support index and economic support index respectively. The number in parentheses is t-statistics and the asterisk *, **, *** show the significance at 1%, 5% and 10% level, respectively.

significant *(i*covid19_dummy) in* model 3. This finding shows that the monetary policy actions of the central banks are weak in influencing the real sector. However, the variables such as *ESI* and *GSI* show a positive and statistically significant effect, indicating that overall government economic policies and supportive actions during the pandemic attained the desired effect as they helped the real sector recover from the recession due to the COVID-19 crisis. Our overall findings suggest that the policy responses of the Indonesian government to the COVID-19 pandemic helped to recover economic activities, thereby reviving the economic cycle; however, its impact on the credit cycle was feeble. The responsiveness of the economic cycle may be attributed to the direct income support, debt/contract relief for households, fiscal measures, etc., which helped recover the economic activities. However, the weak responsiveness of the credit market could be due to the low credit offtake of the private sector due to the presence of a high level of uncertainty.

As a robustness test, we used Christiano–Fitzgerald (CF) Filter (2003) method to retrieve the cyclical components to measure the economic and credit cycle. Then repeated, the estimation using the MIDAS approach and results are reported in Tables 6 and 7. It can be observed that the findings are consistent with earlier conclusions based on HP-filtered cycles.

6. Conclusion

The COVID-19 outbreak, and subsequently locked down across the countries, dragged most countries into recession. Many adopted various policies to recover from this crisis and consequent recession, including monetary and fiscal measures. However, the degree of effectiveness of these policies on the economic revival largely depends upon the co-movements of the business and credit cycles. If the credit cycle is in the contraction phase during the crisis, then much stronger macroeconomic policies are required to mitigate the adverse effect than in normal times. Given this presumption, this paper analyses the effectiveness of economic policies for the revival of credit and business cycles in Indonesia. Our findings suggest that both cycles were in the contraction phase before the pandemic. Moreover, the pandemic intensified the co-movement between them.

Further, our empirical findings suggest that monetary policies are ineffective in reviving credit and business cycles in the country, indicating the weak transmission of monetary policy during the COVID-19 period. However, the fiscal policy initiatives of the government are found to have a significant positive effect on the revival of the business cycle. This indicates that the policies such as income support, debt/contract relief for households, fiscal measures, etc., helped recover the economic activities. However, the effect of the policy initiatives on the credit cycle is found to be weak, which could be partially attributed to the private sector's inadequate responsiveness to the policies due to the high level of uncertainty.

Further, our findings also reveal that the government's overall supportive policies have helped the economy recover from a recession caused by the COVID-19 crisis. However, the weak monetary policy transmission during the pandemic period suggests a strong policy initiative from the Bank of Indonesia for economic revival during the crisis. Further, monetary and fiscal coordination is required for a fast recovery, as banking credit to the business sector is more effective

Table 7
Robustness test.

Dependent variable: *Business cycle* (CF filtered)					
Variable	Model-1	Model-2	Model-3	Model-4	Model-5
i	−0.019 (−2.221)**	−0.032 (−3.111)**	−0.011 (−1.701)	−0.012 (−1.922)***	−0.034 (−1.911)***
er	0.642 (4.122)*	0.717 (4.109)*	0.722 (4.100)*	0.728 (4.487)*	0.736 (3.99)*
vix	−0.011 (−1.302)	−0.021 (−0.222)	−0.011 (−1.362)	−0.0137 (−0.232)	−0.011 (−0.912)
covid19_dummy		−0.106 (−3.911)*		−0.023 (−2.142)**	−0.019 (−2.211)**
*i*covid19_dummy*			−0.018 (−0.828)		
ESI				0.112 (2.913)**	
GSI					0.096 (2.243)**
Constant	0.011 (1.230)	0.019 (0.322)	0.034 (0.293)	0.021 (1.154)	0.453 (1.509)
Adjusted R^2	0.124	0.139	0.135	0.189	0.196
AIC	−2.231	−2.205	3.206	−3.331	−3.220
SIC	−2.111	−2.012	−3.610	−3.325	−3.309

The table shows the results obtained from MIDAS regression. Where, *i, er, vix* denote interest rate, exchange rate and volatility index to capture the global risk condition, respectively. Similarly, GSI and ESI are govt. support index and economic support index respectively. The number in parentheses is t-statistics and the asterisk *, **, *** show the significance at 1%, 5% and 10% level, respectively.

with budgetary expansion. This is mainly because the monetary policy transmission mechanism takes via credit channel (Warjiyo and Juhro, 2019). Thus, quantitative easing from the central bank and widening the budget may help to recover the credit and business cycle from the crisis.

Appendix

Variable measurement and data sources

Variables	Definition	Measurement	Data sources
Credit cycle	Credit cycle	HP filtered on the growth of commercial banks credit	*CEIC*
Business cycle	Business cycle	HP filtered on the growth of Index of Industrial Production	*CEIC*
i	Interest rate	*Policy rate of BI*	*CEIC*
er	Exchange rate	Nominal exchange rate of Indonesian rupiah to USD	*CEIC*
vix	Volatility Index		St. Louis Federal Bank.
GSI	Government response index	GRI includes the various types of measures taken by the government to contain the spread of the COVID-19	Hale et al. (2020). https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker
ESI	Economic support index	The ESI includes income support, debt/contract relief for households, fiscal measures, and international support during the COVID-19 period.	Hale et al. (2020). https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker

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