The impact of air pollution, health, productivity on welfare in Indonesia

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Abstract

This article examines the impact of air pollution on health, productivity, and welfare in Indonesia, using a vector autoregression (VAR) model. Air pollution can cause various diseases and deaths, reduce labor supply and output, increase health care costs, and lower quality of life. Indonesia is one of the developing countries that suffers from high levels of air pollution, especially in urban areas. The main sources of air pollution in Indonesia are forest fires, transportation, industry, power generation, and household burning. The article reviews the current evidence on the health, productivity, and welfare effects of air pollution in developing countries. The article also applies a VAR model to estimate the effect of government consumption expenditure (GCG) on PM2.5 concentration (REC), labor force participation rate (LFP), and health expenditure per capita (CHE). The article finds that GCG has a negative and significant impact on itself, no significant impact on LFP, and positive and significant impacts on REC and CHE. The article concludes that air pollution has complex and heterogeneous effects on health, productivity, and welfare in Indonesia, and that policy makers should adopt a comprehensive and context-specific approach to reduce air pollution levels and protect vulnerable populations.

Keywords: Air pollution, Health, Productivity, Welfare, Indonesia
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Background

Indonesia is a developing country in Southeast Asia, with a population of about 273 million people and a GDP per capita of $4,174 in 20201. Indonesia faces various challenges and opportunities in achieving economic growth and social welfare, especially in the context of environmental degradation and climate change. One of the major environmental and health problems that Indonesia has to deal with is air pollution, which affects millions of people across the country (Sopiana & Harahap, 2023 ; Prabowo, Sasongko, & Damayanti, 2022). In particular, air pollution in poor nations is one of the most pressing environmental and health concerns of our day. Particulate matter (PM), ozone (O3), nitrogen dioxide (NO2), sulphur monoxide (SO2), carbon monoxide (CO), and volatile organic compounds (VOCs) are all examples of air pollutants. Wildfires, volcanoes, dust storms, burning fossil fuels, industry, agriculture, and even home heating with wood or charcoal can all be producers of these compounds. People's health, productivity, and well-being can be negatively impacted by air pollution due to its potential to cause a wide range of adverse health outcomes, including but not limited to: respiratory and cardiovascular illnesses; cancer; early death; cognitive impairment; decreased labour supply and production; higher healthcare expenditures; and a worse quality (Organization & others, 2021).

Numerous epidemiological and experimental research throughout the world have examined the effects of air pollution on human health. Nearly seven million fatalities in 2019 were attributed to air pollution, or more than 10% of all deaths, according to the World Health Organisation (WHO). Most of these fatalities occurred in LMICs, where air pollution levels frequently exceed WHO recommendations (Baumgartner et al., 2020). Air pollution has been linked to a wide range of health problems, including acute and chronic respiratory diseases like asthma, bronchitis, pneumonia, chronic obstructive pulmonary disease (COPD), and lung cancer; cardiovascular diseases like ischemic heart disease, stroke, and heart failure; neurological disorders like Alzheimer's disease, Parkinson's disease, and cognitive decline; negative pregnancy outcomes like preterm birth, low birth weight, and congenital anomalies; and increased mortality rates (Jiang et al., 2016).

The impact of air pollution on productivity has also been investigated by several economic and social studies. Air pollution can affect productivity through various channels, such as reduced labor supply, impaired labor performance, increased absenteeism and presenteeism, lower human capital accumulation, higher health care expenditure, and lower consumer demand. PM2.5 exposure reduced global labor supply by about 0.8 billion days in 2013. Ozone exposure reduced worker productivity by 5.5% in California. Moreover, we found that PM2.5 exposure reduced cognitive test scores by 0.64 standard deviations in China (Rentschler & Leonova, 2023).

Air pollution's toll on human well-being has been measured in a number of ways. The term "welfare" encompasses a wide range of ideas related to people's happiness and contentment in society as a whole. Gross domestic product (GDP), adjusted net savings (ANS), the happiness index (HI), disability-adjusted living years (DALYs), and willingness to pay (WTP) for improved air quality are all indices of welfare. In 2013, air pollution was responsible for an estimated $5.11 trillion in welfare losses worldwide, according to a research by the World Bank (2016). In Indonesia, the air pollution caused a 0.23 point drop in the happiness index. In addition, we discovered that Chinese households were prepared to spend roughly $30 annually to see a 10% decrease in PM2.5 concentration (Basoglu & Uzar, 2019).

In point, air pollution is a serious threat to human health, productivity, and welfare in developing countries. Air pollution can cause various diseases and deaths, reduce labor supply and output, increase health care costs, and lower quality of life. Therefore, policy makers should adopt a comprehensive and context-specific approach to design and implement policies that can reduce air pollution levels, protect vulnerable populations, and promote green growth. Some possible policies include setting emission standards, imposing environmental taxes or subsidies, promoting renewable energy sources, improving public transportation systems, enhancing monitoring and enforcement mechanisms, and raising public awareness and participation (Gunningham & Sinclair, 2019 ; Widarni, Irawan, Harnani, Rusminingsih, & Alim, 2022).

Research Method

We proxied Labor force participation rate, Renewable energy consumption, with Current health expenditure variables. For the GDP per capita growth variables. We use secondary data from the world bank. Our research period is from 2005 to 2020. We use the following equation:

$GCG_t = \beta_0 + \beta_1 LFP_t + \beta_2 REC_t + \beta_3 CHE_t + e_t$ eql 1

$LFP_t = \beta_0 + \beta_1 GCG_t + \beta_2 REC_t + \beta_3 CHE_t + e_t$ eql 2

$REC_t = \beta_0 + \beta_1 GCG_t + \beta_2 LFP_t + \beta_3 CHE_t + e_t$ eql 3

$CHE_t = \beta_0 + \beta_1 GCG_t + \beta_2 LFP_t + \beta_3 REC_t + e_t$ eql 4

Description:

GCG : GDP per capita growth
LFP : Labor force participation rate
REC : Renewable energy consumption
CHE : Current health expenditure
β : the magnitude of the effect of causality
e = Error term
t = Time period
eql: equation

Table 1. Variable Description

Variable	Explanation	Data type	Source
GDP per capita growth	Annual percentage increase in GDP per capita at current exchange rates. The gross domestic product divided by the population at midyear gives us the GDP per person. Gross domestic product (GDP) at purchaser's prices is the total of (a) all product taxes and (b) all subsidy payments deducted from the value of all final goods and services produced inside the economy by all resident producers. Depreciation of manufactured assets and wear and tear on natural resources are not factored into the calculation.	Percent	World Bank
Labor force participation rate	The percentage of the population aged 15-64 who are economically	Percent	World Bank

	active, defined as providing labour for the production of goods and services, is known as the labour force participation rate.		
Renewable energy consumption	The percentage of final energy consumption that comes from renewable sources is known as renewable energy consumption.	Percent	World Bank
Current health expenditure	Current health care spending as a proportion of gross domestic product. The annual consumption of healthcare products and services is factored into current health expenditure estimates. Health care investments including hospitals, medical equipment, computers, and emergency vaccination supplies are not included in this metric.	Percent	World Bank

Result and Discussion

Table 2. Root Test Results

Variabel	Unit Root	Statistics for the Augmented Dickey Fuller	Probability	Description
GDP per capita growth (GCG)	Level	-0.379281	0.8897	Tidak Stationary
	First Different	-1.427073	0.5390	Tidak Stationary
Labor force participation rate (LFP)	Level	-4.662065	0.0028	Stationary
	First Different	-5.157635	0.0016	Stationary
Renewable energy consumption (REC)	Level	-0.631446	0.8354	Tidak Stationary
	First Different	-3.310356	0.0346	Stationary

Current health expenditure (CHE)	Level	-1.074276	0.6967	Tidak Stationary
	First Different	-2.973537	0.0661	Tidak Stationary

*the limit value used at the significance level of 0.05

Based on the findings shown on Table 2. The fact that GCG, LFP, REC and CHE stationary data are not at the same level, so that the first differencing is put into action. The results of the first differencing show that the data is stationary with a probability value < 0.05. After knowing the stationarity of the data held, then testing is carried out to calculate the best lag duration to utilize. The method used determining the optimal lag duration LogL, LR, FPE and AIC. The smaller the value of LogL, LR, FPE, AIC, the lag is the most optimum lag. The outcomes of the test are shown on the next table

Table 3. Maximum Lag Test

Lag	LogL	LR	FPE	AIC
0	-308.7571	NA	1.52e+13	41.70094
1	-275.0425	44.95279*	1.59e+12*	39.33900*

Table 3. Shows the optimum lag testing of the VAR model using the LogL, LR, FPE and AIC criteria. Based on these results, it is known that the optimum model is found in Lag 1 because the LogL, LR, FPE and AIC values in Lag 1 are the smallest compared to the previous Lag.

Table 4. Cointegration Test

Hypothesized at Most	Eigenvalue	Trace Statistic	0.05 Critical Value	Probability
None	0.847959	28.25412	27.58434	0.0410
1	0.524634	11.15505	21.13162	0.6318
2	0.415464	8.054057	14.26460	0.3733
3	0.000628	0.009419	3.841466	0.9223

* Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

The cointegration test results are shown in table 4 above explain one probability value is under 0.05. It means that there is one significant probability. Analysis of VAR for identify connection among the researched variables studied that one variable have influence other variables in short term. The coefficients on the VAR analysis can be used to determine the influence between variables. If the coefficient value is less than the t-statistic value, then there is an influence relationship between these variables.

Table 5. VECM Estimation Results

	D(GCG)	D(LFP)	D(REC)	D(CHE)
D(GCG(-1))	-0.950568	-11966.17	110.8786	0.038281
	(1.02511)	(6576.54)	(142.339)	(0.08728)
	[-0.92729]	[-1.81952]	[0.77897]	[0.43860]
D(LFP(-1))	-1.58E-05	0.218555	0.006889	3.30E-06
	(2.6E-05)	(0.16437)	(0.00356)	(2.2E-06)
	[-0.61732]	[1.32968]	[1.93649]	[1.51229]

D(REC(-1))	0.002631	-112.7979	0.344944	-0.000733
	(0.00365)	(23.4440)	(0.50741)	(0.00031)
	[0.71992]	[-4.81139]	[0.67981]	[-2.35538]
D(CHE(-1))	8.675616	-114795.4	-574.9095	-0.450855
	(5.15108)	(33046.6)	(715.244)	(0.43857)
	[1.68423]	[-3.47374]	[-0.80380]	[-1.02800]
C	-38.93305	6591.785	-1337.535	4.743619
	(21.9704)	(140951.)	(3050.67)	(1.87061)
	[-1.77207]	[0.04677]	[-0.43844]	[2.53587]

Considering what the VAR analysis revealed, could be said that relationship between GCG and GCG has a non positive significant impact because the coefficient value's at -0.950568, this value more than the -0.92729 t-statistic's value. The non significant correlation exists between GCG and LFP, meaning that the two variables are not related to each other because the coefficient value is at -11966.17 way much more than the -1.81952 t-statistic value. The significant correlation also found exists between GCG and REC, because the coefficient value is at 110.8786 way more than the 0.77897 t-value statistic. The significant association between GCG and CHE was spotted, we found that the coefficient value is at 0.038281 much less than the 0.43860 t-value statistic.

Conclusion

Reducing GCG levels further reduces GCG levels, suggesting that GCG has a negative and large self-reinforcing feedback loop. There is a statistically significant impact for GCG at the 5% level, since the coefficient value of -0.950568 exceeds the t-statistic value of -0.92729. It is obvious from the VAR analysis that there is no direct correlation between GCG and LFP. When comparing the t-statistic of -1.81952 to the coefficient value of -11966.17 for GCG on LFP, we see that the impact is not statistically significant at the 5% level. VAR analysis, however, reveals that GCG has a positive and substantial influence on REC and CHE, with higher levels of GCG leading to higher levels of REC and CHE. When comparing the coefficient value of 110.8786 for GCG on REC to the t-statistic value of 0.77897, the latter is much larger, indicating that the impact is significant at the 5% level of statistical significance. Since the t-statistic for GCG on CHE is 0.43860 and the coefficient value is 0.038281, the impact is significant at the 5% level of statistical significance.

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