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The exposure-response of air pollution and climate change to chronic respiratory diseases: Does residential energy efficiency matter?

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ABSTRACT

Promoting energy efficiency is crucial for reducing energy consumption, yet its impact on human health remains discussed. This study examines the relationship between household energy efficiency, ambient air pollution, climate change, and mortality risk from chronic respiratory diseases. The study collected observational data in six major cities in Taiwan from 2008 to 2020. The energy efficiency level was determined using the input demand function derived from the stochastic frontier analysis (SFA). Subsequently, analysis was conducted employing a dynamic panel data model and a pooled mean group estimator. The study's findings indicate that enhancing household energy efficiency decreases the mortality rate associated with chronic respiratory diseases. Specifically, at the highest level of energy efficiency (99%), the relative risk reaches its lowest value of 0.639 (95% CI: 0.58–0.70). Additionally, a positive exposure-response relationship is observed between degree days and ambient air pollution ($PM_{2.5}$, PM_{10}, and SO_2), associated with an increased risk of death from chronic respiratory diseases. These results underscore the importance of initiatives to enhance energy efficiency programs in households, particularly in metropolitan areas.

1. Introduction

Many studies have shown that global energy consumption will continue to increase over time; it will further increase the potential for energy and health crises in the future (Krishnan et al., 2021). In their study, Moodley and Trois (2021) stated that the energy demand would increase up to 48% in the next twenty years, along with the growth of the human population. It is also considered that this increase in energy demand will continue to occur substantially in the next few decades (Zohuri, 2020). This increase is also

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inseparable from industrial activity in both developing and developed countries, where the use of energy is still dominated by fossil energy (Rafiee and Khalilpour, 2019). Recent reports show that global electricity demand is growing faster than renewables, which shows a significant increase in the consumption of fossil fuels (IEA, 2021).

Based on the Bureau of Energy (BOE) reports, energy consumption in Taiwan has increased by 12.48% from 2004 to 2020. Until 2020, most of the energy in Taiwan is produced from fossil fuels in the form of coal and crude oil, i.e., by 30% and 44.17%, respectively. In addition, energy consumption is inseparable from energy demand arising from the transportation and household sectors, which are the sectors with the highest energy demand in Taiwan apart from the industrial sector (BOE, 2020). Specifically for the transportation sector, until the end of 2021, the number of motorized vehicles in Taiwan reached 22.6 million units, with 92.5% still using gasoline (MOTC, 2022). It raises the potential for air pollution in Taiwan, posing health risks (Adha et al., 2022; von Schneidemesser et al., 2019). The study results prove that exposure to air pollution such as fine particles ($PM_{2.5}$) can cause respiratory and cardiovascular diseases (Al-Kindi et al., 2020; B. Chen and Kan, 2008; WHO, 2013).

According to the report from WHO, respiratory diseases such as asthma and chronic obstructive pulmonary disease (COPD) cause the death of more than four million people globally each year, and specifically for COPD is projected to be the fifth leading cause of death in the world by 2030 (WHO, 2007; Zafirah et al., 2021). In the Taiwan case, asthma and COPD prevalence has increased to 15–20% (Hayes et al., 2012; Zafirah et al., 2021). Based on data released by the Ministry of Health and Welfare of Taiwan, in 2020, the number of deaths caused by chronic lower respiratory diseases such as COPD, chronic bronchitis, emphysema, and asthma (ICD-10 No. J40-J47) amounted to 5657 cases of death, with the average death rate increased by 0.7% since 2008. This number makes deaths caused by respiratory diseases is the seventh-highest cause of death in Taiwan (MOHW, 2021).

Environmental factors such as air pollution and climate change have long been associated with chronic respiratory diseases (Zafirah et al., 2021). The study conducted by Y.-C. Wang et al. (2012) showed that extreme heat or cold increases emergency room visit (ERV) risks significantly in Taiwan. Several other studies have examined the phenomenon of asymmetric fluctuations in daily temperature (Shen et al., 2014; Shen et al., 2018), particularly focusing on the diurnal temperature range, and some studies have found its significant associations with chronic respiratory diseases (Lim et al., 2012; Z. Wang et al., 2020). The study results from Cheng and Kan (2012) also showed that PM_{10} and the extremely low temperature significantly impacted daily mortality in Shanghai, China. A similar situation was found in Europe, where heatwaves have consistently shown a synergistic effect of air pollution and high temperatures (De Sario et al., 2013). Then, these extreme weather conditions are closely related to climate change caused by air pollution (OECD, 2019), where air pollution is the highest cause of diseases and premature death in the world today (Landrigan et al., 2018). Aside from particulate matter, sulfur dioxide (SO_2) is a known cause of respiratory diseases (Yu et al., 2018). SO_2 causes a decrease in pulmonary function, according to the research of X. Chen et al. (2020) and Gao et al. (2020). This is also linked to the effect of SO_2, which can increase the mortality rate from respiratory diseases (J. Chen et al., 2021; Orellano et al., 2021).

In addition to environmental factors, the results of a study by Faizan and Thakur (2019) show that energy consumption such as solid fuels for cooking has a strong relationship with respiratory diseases in India. The results of the study from Jessel et al. (2019) also show a link between energy consumption, poverty, and climate change on health. Reducing health risks caused by energy consumption, one of the efforts is to encourage energy-efficient technology in households (Westfall and Markowska, 2019). However, a study from Sharpe et al. (2015) showed the opposite result, where increased household energy efficiency may increase the risk of current asthma.

In contrast to previous studies that used property data, residency periods, indices of multiple deprivations (IMD), and household energy efficiency ratings to measure energy efficiency (Sharpe et al., 2015), this study will use an energy efficiency frontier based on the input demand function with SFA, stochastic frontier analysis method (Adha et al., 2021; Filippini and Hunt, 2011, 2012). This approach makes it possible to obtain energy efficiency based on socio-economic factors. Thus, this study can capture the socio-economic impact of households' energy efficiency on chronic respiratory diseases in Taiwan. In addition, this study will use $PM_{2.5}$ levels and changes in cooling and heating degree days as factors that indicate climate change. To our knowledge, there are no previous studies using energy efficiency frontiers in analyzing the impact of energy efficiency on chronic respiratory diseases. Therefore, this study can contribute to the literature that measures the impact of energy efficiency and environmental quality on respiratory diseases.

The significance of this study lies in its scientific contribution to understanding the complex connection between energy efficiency, climate change, and respiratory diseases in Taiwan. By employing a two-stage approach that utilizes the energy efficiency frontier based on the input demand function, this study offers a comprehensive assessment of the impact of energy efficiency on chronic respiratory diseases. Furthermore, incorporating indicators such as $PM_{2.5}$, PM_{10}, and SO_2 levels and differences in cooling and heating degree days allows for a holistic examination of climate change.

The findings of this research hold several scientific contributions. Firstly, this study provides valuable insights into the association between energy consumption patterns, energy efficiency, and respiratory health outcomes. By analyzing the specific context of Taiwan, this study expands the existing literature on the health risks posed by energy consumption and contributes to a deeper understanding of the underlying mechanisms. Secondly, the study adds to the scientific knowledge of the interplay between environmental factors and respiratory diseases. By considering air pollution and climate change as influential factors, this research sheds light on the complex relationship between environmental quality and public health. Including fine particles and sulfur dioxide (SO_2) emissions further enhances understanding of the impact of specific pollutants on respiratory health.

Moreover, by utilizing socio-economic factors, the research procedure captures a more comprehensive understanding of the socio-economic impact of energy efficiency on respiratory diseases. This methodological contribution enhances the scientific toolkit for analyzing energy efficiency in the context of public health. Practically, the findings of this study have significant policy implications. It can inform the development of targeted interventions and strategies to mitigate health risks associated with energy consumption and improve respiratory health outcomes. The results may guide policymakers in designing energy planning initiatives that prioritize

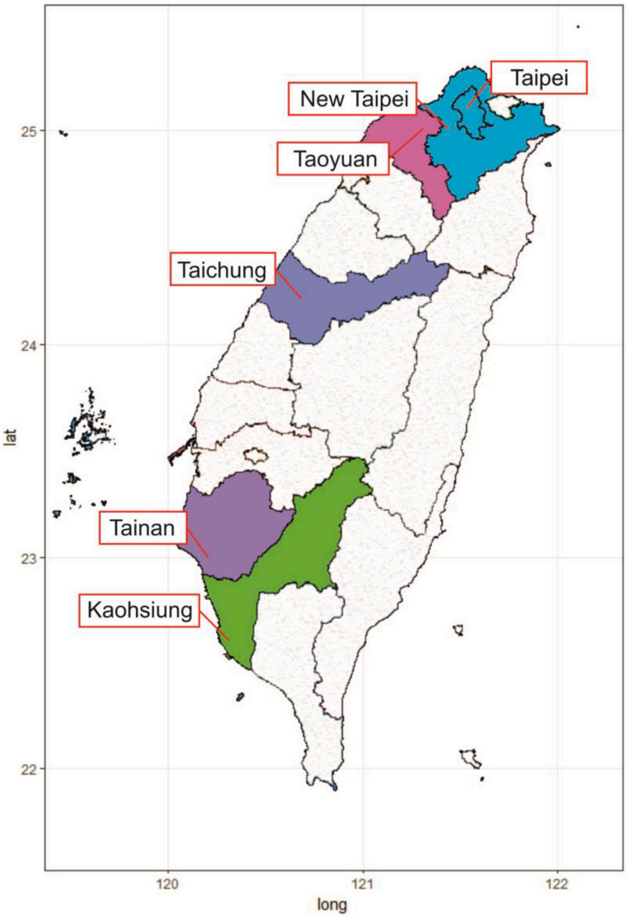

Fig. 1. Geographical distribution of study sites within the six major cities in Taiwan.

efficiency and environmental sustainability, leading to improved public health and reduced respiratory disease burdens.

The remaining paper has been organized as follows. Section 2 presents the data and methodology. Section 3 provides the results of the study, section 4 offers the discussions, and section 5 presents the conclusions and policy implication.

2. Data and methodology

2.1. Data

Several data preprocessing steps will be undertaken to ensure the reliability and accuracy of the data used in this study. The study will focus on Taiwan's six major cities: Taipei, New Taipei, Taoyuan, Taichung, Tainan, and Kaohsiung. The geographical distribution of the study can be seen in the Fig. 1. The data on household energy consumption will be obtained from the annual statistics provided by the Urban and Regional Development Statistics, published by the National Development Council in Taiwan. This data will be used to measure household energy efficiency, which is crucial in understanding the impact on chronic respiratory diseases.

In addition, climate change factors will be considered by utilizing heating and cooling degree days, which will be calculated based on the average daily temperature data obtained from the Taiwan Central Weather Bureau. This information will provide insights into the climate change and its potential effects on respiratory health. Degree days (DD) represent the prevailing temperature conditions in the external environment surrounding a specific location. DD is derived by combining two fundamental components: Heating Degree Days (HDD) and Cooling Degree Days (CDD) (Adha et al., 2022; Adha et al., 2021).

$$HDD = \sum_{i=1}^{n} (T_{base} - T_n)M \tag{1}$$

$$CDD = \sum_{i=1}^{n} (T_n - T_{base})M \tag{2}$$

Table 1
Descriptive statistics.

Description	Var	Mean	Std. dev.	Min	Max
Electricity Consumption (10^9 kWh)	*EC*	7.35	1.96	4.53	11.4
Family Income (NT$)	*I*	1,017,886	162,361.8	740,706	1,422,856
Population	*Pop*	2,681,138	665,749.2	1,873,005	4,030,954
Space per household (ping)	*Space1*	43.25	8.39	30.82	53.02
Space per person (ping)	*Space2*	13.56	2.68	9.27	17.89
Population per household (Person)	*Size*	3.09	1.03	2.45	6.34
Mortality rate from respiratory diseases	*Res*	575.83	117.41	334	860
Degree Days	*DD*	74.81	8.28	62.7	97.1
Particulate matter/$PM_{2.5}$ (μg/m^3)	*PM25*	25.28	6.45	12.5	33.5
Particulate matter/PM_{10} (μg/m^3)	*PM10*	49.31	13.67	23.6	77.8
Sulfur dioxide/SO_2 (ppb)	*SO2*	3.5	1.18	1.87	7.4

Table 2
Cross-sectional dependence test.

CD Test	Pesaran CD Test	Frees	Friedman
H_0	5.225***	0.891**	33.626***

Note: *, ** and *** denote 10%, 5% and 1% levels of significance respectively.

Table 3
Panel unit root test.

Variables	Levels CIPS	First Differences CIPS
EC	−2.301*	−4.484***
I	−2.461**	−4.303***
Pop	−1.274	−2.177*
Space1	−3.475***	−3.869***
Space2	−2.105	−2.739***
Size	0.480	−2.375**
Res	−2.576**	−4.203***
DD	−2.414**	−4.054***
PM25	−2.340**	−3.360***
PM10	−2.324*	−3.790***
SO2	−2.428**	−4.154***

Note: *, ** and *** denote 10%, 5% and 1% levels of significance respectively, and optimum lag determined by AIC.

The base temperature, denoted as T_{base}, represents the threshold temperature used as a reference point for calculating degree days. To compute degree days, the average daily temperature, denoted as T_n, is determined by taking the mean of the daily maximum and minimum temperatures. Consequently, the degree day value is derived by summing the heating degree days (HDD) and cooling degree days (CDD) together. For environmental factors, data on fine particulate matter with a diameter lower than 2.5 μm ($PM_{2.5}$), PM_{10}, and sulfur dioxide (SO_2) will be incorporated into the analysis. These data, which are important in assessing air pollution levels, will be obtained from reliable sources to ensure their accuracy and relevance to the study.

Furthermore, to examine the relationship between chronic respiratory diseases and energy efficiency, data on the number of deaths caused by chronic respiratory diseases will be collected from the National Health Insurance database, which is maintained by the

Table 4
Panel cointegration test.

Pedroni		Westerlund		Kao	
Test	Statistic	Test	Statistic	Test	Statistic
Panel v	3.197***	Gt	−4.082***	Modified DF	−1.952**
Panel rho	−0.216	Ga	−0.437	DF	−3.067***
Panel t	−3.262***	Pt	−3.163*	ADF	−0.911
Panel ADF	−2.263**	Pa	−0.367	UMDF	−3.051***
Group rho	2.185**			UDF	−3.480***
Group t	−0.401				
Group ADF	−2.726***				

Note: *, ** and *** denote 10%, 5% and 1% levels of significance respectively.
The lag lengths are selected using AIC.

Table 5
Determinant of energy efficiency frontier.

	Persistent		Transient	
	Coefficient	Std. error	Coefficient	Std. error
lnI	0.144**	0.063	0.151***	0.092
lnPop	0.739***	0.154	0.573***	0.095
lnSpace1	−0.005	0.136	−0.176*	0.075
lnSpace2	0.213**	0.105	0.398***	0.052
lnSize	−0.045***	0.016	−0.053***	0.019
Constant (α)	9.282***	2.090	11.949***	2.132
σ_u	−16.049*	1.641	−6.248***	0.160
σ_v	−7.620***	0.160	−22.765**	9.210
Regional effects	No		Yes	
log-likelihood	186.526		187.088	
R^2	0.954		0.962	

Note: ***, ** and * denotes statistical significance at 1%, 5% and 10% level respectively.

Table 6
Energy efficiency estimations.

	Mean	Std. Dev	Min	Max
Persistent	0.841	0.094	0.718	1.000
Transient	0.965	0.094	0.902	0.999
Overall efficiency	0.812	0.089	0.681	0.999

Table 7
Estimation results.

Dependent var.: Mortality rate of respiratory diseases	DOLS	DFE	MG	PMG
Long Run				
Efficiency rate	−2.386**	2.016**	6.339	−10.028**
	(1.027)	(0.875)	(14.106)	(4.159)
Degree days	0.007	−0.003	−0.063	0.035***
	(0.004)	(0.008)	(0.113)	(0.006)
$PM_{2.5}$	0.013**	−0.017***	−0.085	0.104***
	(0.006)	(0.005)	(0.146)	(0.029)
PM_{10}	0.011**	0.022*	0.210*	0.065*
	(0.004)	(0.012)	(0.112)	(0.037)
SO_2	0.025	−0.117	−2.527**	0.581*
	(0.038)	(0.087)	(0.998)	(0.330)
Short Run				
ECT		−0.454**	−0.140	−0.037
		(0.202)	(0.665)	(0.062)
Δ Efficiency rate		−1.721	−13.442*	−3.011
		(1.529)	(9.803)	(2.393)
Δ Degree days		0.009**	0.044	0.012***
		(0.004)	(0.036)	(0.004)
Δ $PM_{2.5}$		−0.003	−0.026***	0.001
		(0.007)	(0.006)	(0.007)
Δ PM_{10}		−0.012***	−0.081***	0.027***
		(0.002)	(0.025)	(0.006)
Δ SO_2		0.109	1.456**	0.207*
		(0.084)	(0.604)	(0.124)
Cons		2.145	−16.196	0.372
		(1.492)	(10.020)	(0.470)
R^2	0.811	–	–	–
Observations	54	72	72	72
Cities	6	6	6	6
Hausman test (MG-DFE)		–	0.79	–
Chi2 (MG-DFE)		–	0.9397	–
Hausman test (PMG-MG)		–	–	2.79
Chi2 (PMG-MG)		–	–	0.5396

Note:*, ** and *** denote 10%, 5% and 1% levels of significance respectively.
The lag lengths are selected using Andrews-Lu Model and Moment Selection Criterion; MBIC, MAIC, MQIC.

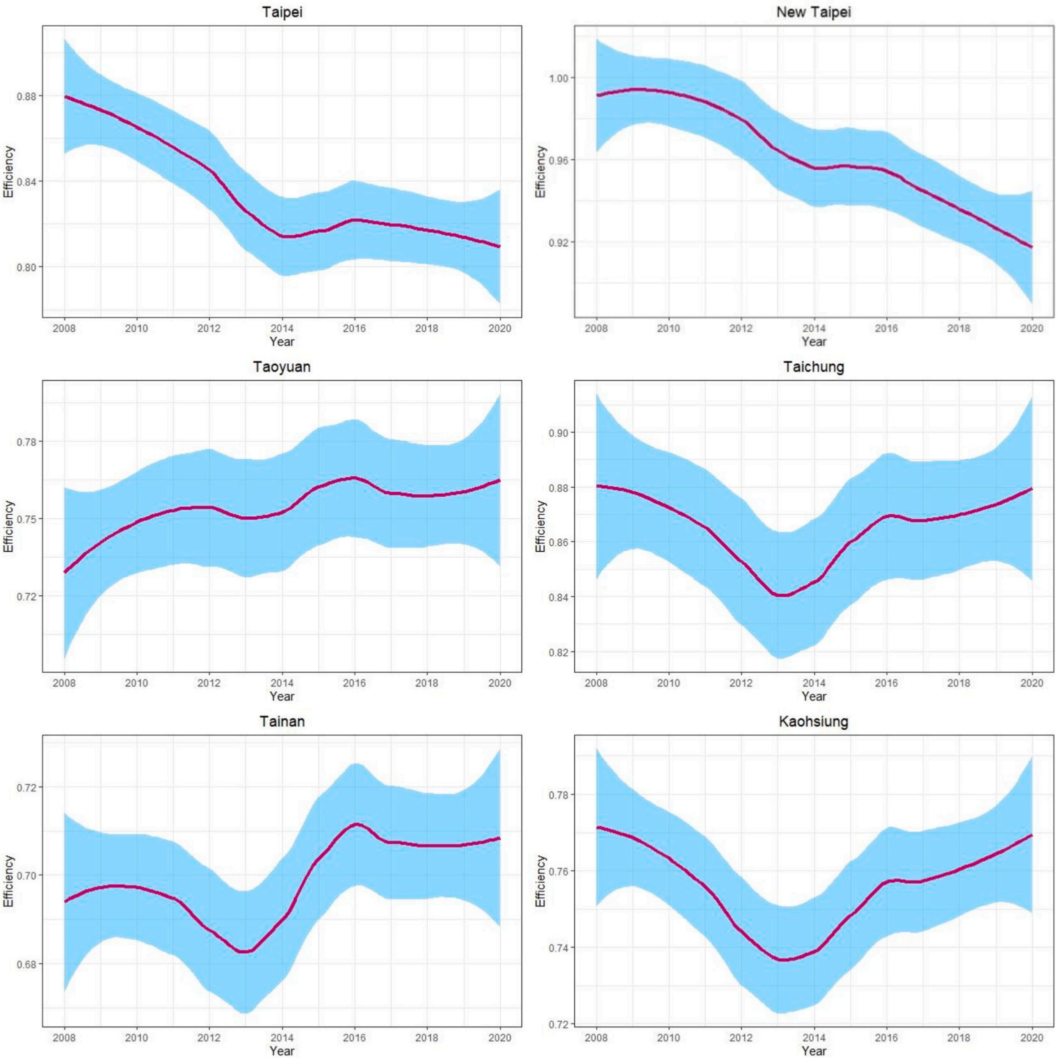

Fig. 2. Overall efficiency rate.

Ministry of Health and Welfare. The 10th revision of the international classification of diseases (ICD-10) will be utilized to identify cases of chronic lower respiratory diseases (ICD-10 No. J40-J47) within the dataset.

The study will employ a balanced panel data approach, utilizing observations from the six major cities in Taiwan over a period spanning from 2008 to 2020. This panel data format allows for analyzing longitudinal changes and trends in chronic respiratory diseases and their association with energy efficiency, climate changes, and environmental factors. Table 1 presents descriptive statistics, with column 1 providing descriptions of the variables, column 2 indicating their respective abbreviations, and columns 3 to 6 displaying the average, standard deviation, minimum, and maximum values, respectively. Through these rigorous data preprocessing steps, the research data will be cleaned, aggregated, and prepared for subsequent analysis. This study aims to provide valuable insights into the relationship between energy efficiency, environmental factors, and chronic respiratory diseases in Taiwan's major cities by ensuring data accuracy and reliability.

2.2. Methodology

Energy efficiency measurement will use the energy demand frontier approach with the stochastic frontier analysis (SFA) method proposed by Filippini and Hunt (2011, 2012, 2015). This method commonly used for estimating household energy efficiency (Adha et al., 2021). This energy efficiency value was obtained from two models, namely the True Fixed Effect Model (TFEM) from Greene (2005a, 2005b) to obtain the value of transient efficiency, and the Fixed Effect Model from Kumbhakar and Heshmati (1995) to obtain the value of persistent efficiency. After getting the efficiency value of the two models, the total efficiency calculation is carried out.

The function of residential energy demand in this study is as follows:

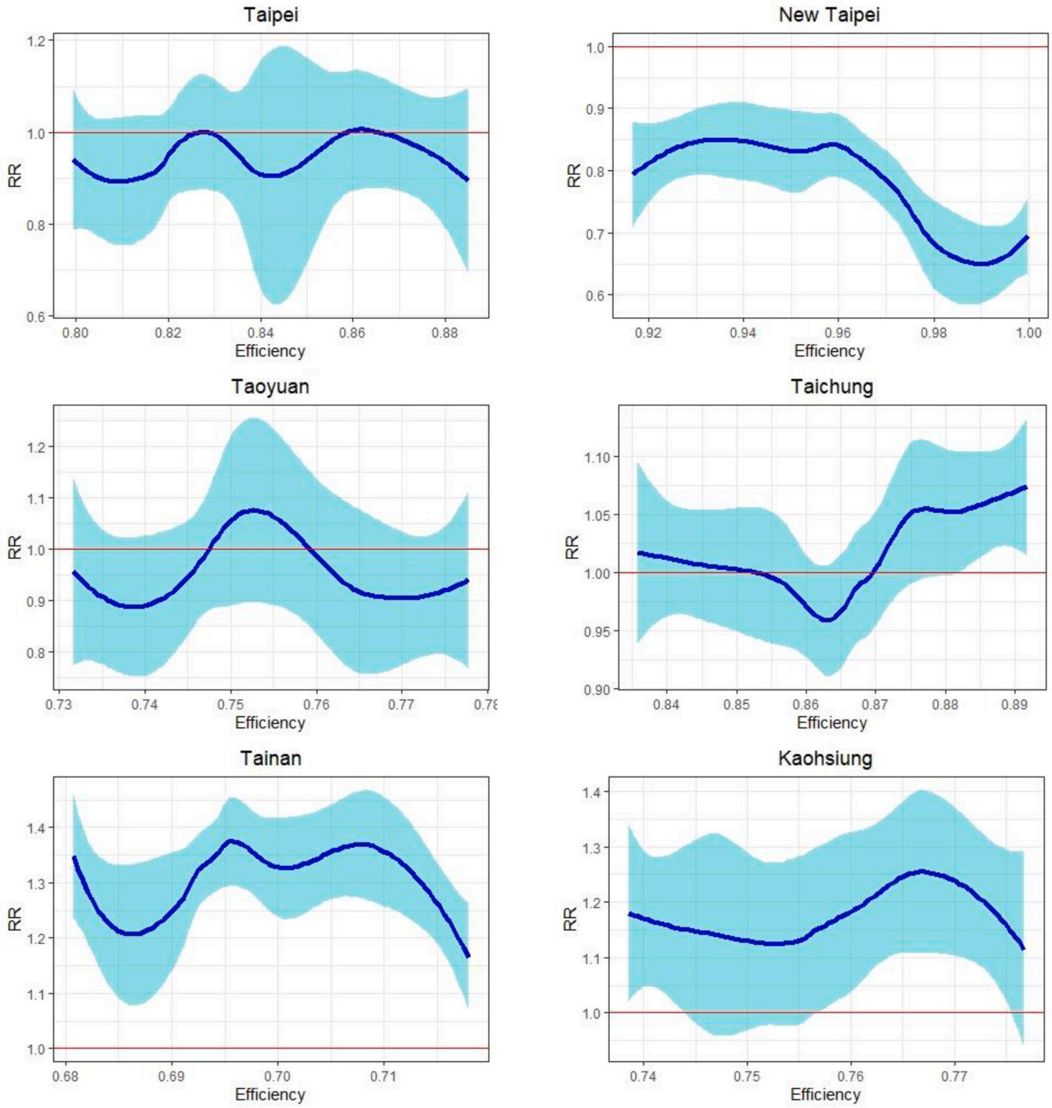

Fig. 3. Relative risk of respiratory diseases associated with energy efficiency.

$$EC_{it} = f(I_{it}, Pop_{it}, Space1_{it}, Space2_{it}, Size_{it}) \tag{3}$$

Where EC_{it} is energy consumption at location *i* and time *t*. I_{it} is income per capita, Pop_{it} is population in study location, notably in six major cities in Taiwan. $Space1_{it}$ is space per household, additionally $Space2_{it}$ is space per person to describe housing condition. $Size_{it}$ is the population size per household energy user.

Based on the approach used in this study, the logarithmic panel function of Eq. (3) will adopt a stochastic frontier function, as shown below:

$$lnEC_{it} = \alpha + \alpha_I lnI_{it} + \alpha_{Pop} lnPop_{it} + \alpha_{S1} lnSpace1_{it} + \alpha_{S2} lnSpace2_{it} + \alpha_{SZ} lnSize_{it} + v_{it} + u_{it} \tag{4}$$

In Eq. (4), the *ln* is the natural logarithm applied to each variable, α representing the estimated parameter and indicates the constant parameter. The error term in Eq. (4) consists of two parts. The first part is v_{it}, which is a symmetric disturbance. The second part is u_{it} which denotes the level of energy efficiency or information that confers the distance between the frontier value and the actual input. This function is a one-sided random disturbance that can change over time and is assumed to follow a half-normal distribution.

Furthermore, the conditional mean of efficiency is used to estimate the level of energy efficiency adopted from Jondrow et al. (1982), as below:

$$E[u_{it} | v_{it} + u_{it}] \tag{5}$$

Besides, in calculating the energy efficiency level, it is given using the following equation:

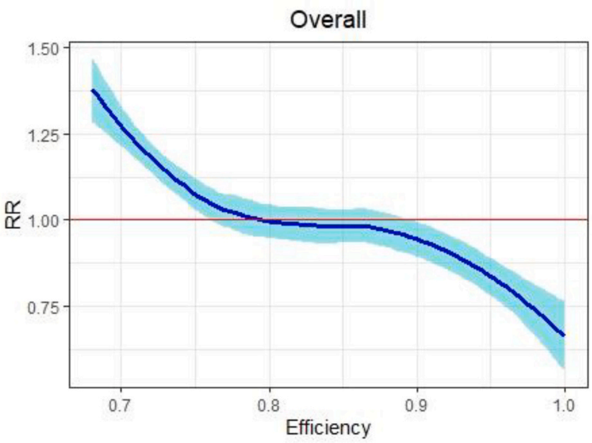

Fig. 4. Relative risk of respiratory diseases and overall efficiency rate.

$$Ef_{it} = \frac{E_{it}^{f}}{E_{it}} = exp(-\hat{u}_{it}) \tag{6}$$

Where the E_{it} is energy consumption in city i and year t and E_{it}^{f} is frontier energy demand.

After getting the value of energy efficiency using the energy demand frontier, the next step is to estimate the impact of energy efficiency and environmental quality on chronic respiratory diseases using autoregressive distributed lag (ARDL) model. The ARDL model (Adha et al., 2022) is written as follows:

$$Y_{it} = \sum_{j=1}^{m} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{n} \vartheta_{ij} X_{i,t-j} + \mu_i + e_{it} \tag{7}$$

The Eq. (7), Y_{it} denotes the growth of the subject of study in location i and time t. i represents the location with $i = 1, \ldots,$ N, and t represents the time with $t = 1, \ldots,$ T. Besides, X_{it} is the vector of $K \times 1$ regressors. λ_{ij}, ϑ_{ij} is the short-run dynamic coefficients, and μ_i is effect-specific group. The error correction model from the equation above is:

$$\Delta Y_{it} = \theta_i \left[y_{i,t-j} - \varphi_i X_{i,t-j} \right] \sum_{j=1}^{m-1} \lambda_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{n-1} \vartheta_{ij} \Delta X_{i,t-j} + \mu_i + e_{it} \tag{8}$$

In the Eq. (8), ΔY_{it} denotes the delta growth of the subject of study in location i and time t. θ_i is a specific group from the speed of adjustment coefficient, and φ_i is a vector long-run relationship. Hence, the model specification in this study with the ARDL parameter (1,0,0,0,0,0,0,0), then the error correction model of our model as follows:

$$\begin{aligned} \Delta lnRes_{it} = & \\ & \theta_i \left(lnRes_{i,t-1} - \varphi_{1i} Eff_{it} - \varphi_{2i} DD_{it} - \varphi_{3i} PM25_{it} - \varphi_{4i} PM10_{it} - \varphi_{5i} SO2_{it} \right) + \sum_{j=1}^{m-1} \lambda_{i1} \Delta lnRes_{i,t-1} + \sum_{j=0}^{n-1} \vartheta_{1i} \Delta Eff_{it} + \sum_{j=0}^{n-1} \vartheta_{2i} \Delta DD_{it} \\ & + \sum_{j=0}^{n-1} \vartheta_{3i} \Delta PM25_{it} + \sum_{j=0}^{n-1} \vartheta_{4i} \Delta PM10_{it} + \sum_{j=0}^{n-1} \vartheta_{5i} \Delta SO2_{it} + \mu_i + e_{it} \end{aligned} \tag{9}$$

In the Eq. (9), $\theta_i = -(1 - \delta_i)$, Δ is the model's first-difference operator, i is the location, t is the time period, e_{it} is a disturbance term assumed to be normally distributed white noise, Res_{it} is mortality of respiratory diseases cases in specific location and time, Eff_{it} is the value of residential energy efficiency from the previous estimation, DD_{it} is the sum of heating and cooling degree days value which showed the climate change, and the rest $PM25_{it}$, $PM10_{it}$ and $SO2_{it}$ are the air pollution which measured from fine particulate matters $PM_{2.5}$, PM_{10}, and sulfur dioxide.

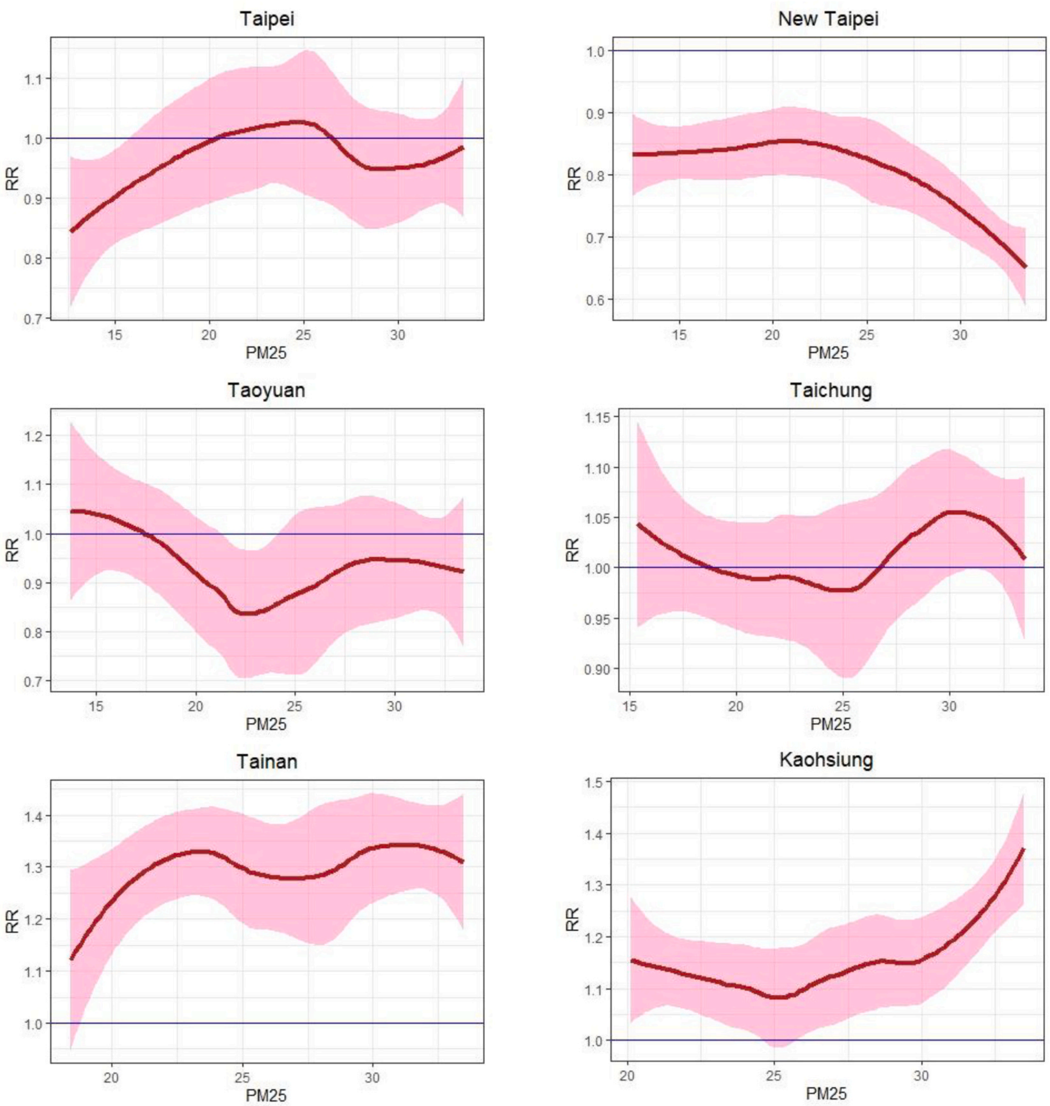

Fig. 5. Relative risk of respiratory diseases associated with $PM_{2.5}$.

2.3. Diagnostics

Before making a measurement, specifically to detect the causality between the mortality rate from chronic respiratory diseases, energy efficiency, and air pollution, the data must be tested for feasibility. This test is performed to reduce problems commonly encountered when estimating causality, such as cross-sectional dependence, series stationary, and data cointegration.

According to the cross-sectional dependence (CD) test shown in Table 2 using the model from Pesaran (2004), Frees (1995), and Friedman (1937) adapted from De Hoyos and Sarafidis (2006), all models strongly reject the null hypothesis of cross-sectional independence. This means that the model in this study has a problem with residual correlation under the fixed effect specification, indicating the presence of cross-sectional dependence. As a result, the panel unit root test will be analyzed using the cross-sectionally augmented IPS (CIPS) test proposed by Pesaran (2007).

The unit root test results from the CIPS model in Table 3 show that all variables are stationary in the first difference. The optimal lag is determined using AIC estimation. The estimation shows that the population variable has a 10% significance level, the size variable has a 5% significance level, and the rest has a 1% significance level. In the first difference CIPS, all variables have significant values. The panel cointegration test comes next.

According to the panel cointegration test shown in Table 4, the majority of the tests produced satisfactory results for the three proposed models. The Pedroni (1999) and Pedroni (2004) models are used in this study, and the results show that the panel v (modified Phillips-Perron t), panel t (augmented Dickey-Fuller t), and ADF group have a significance level of 1%. The ADF panel parameter displaying the modified variance ratio and the group rho value displaying the modified Phillips-Perron t has a significance level of 5%,

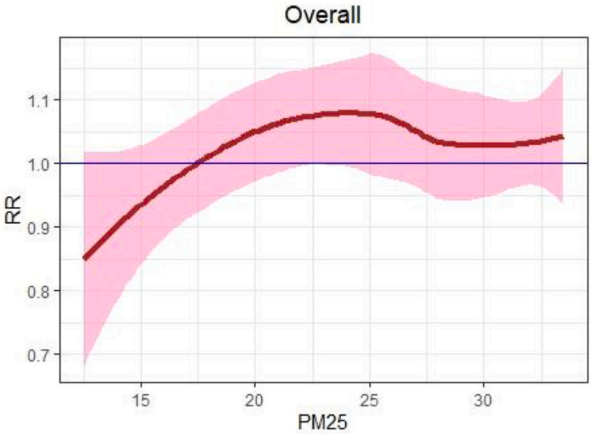

Fig. 6. Relative risk of respiratory diseases and overall $PM_{2.5}$ level.

while the rest shows no significance. This means that five of the seven tests used strongly reject the null hypothesis of the no-cointegrated series. The second model is based on Westerlund (2005, 2007) models. The estimation results show that the Gt parameter has a significance level of 1%, the Pt parameter has a significance level of 10%, and the rest is insignificant. The third model is based on Kao (1999). The parameters Dickey-Fuller t, Unadjusted modified Dickey-Fuller t, and unadjusted Dickey-Fuller t are significant at 1% alpha, modified Dickey-Fuller t is significant at 5% alpha, and the rest are not significant. Overall, this test yields a satisfactory result because most parameters show a significant value at the 1% level. To put it another way, the null hypothesis of no cointegration is strongly rejected. Hence, this study uses panel cointegration regression based on ARDL model.

3. Results

3.1. Energy efficiency estimation

This study calculates the efficiency rate of households in six Taiwanese metropolitan cities to estimate the causality between energy efficiency, environmental quality, and respiratory diseases. In the first stage, this study assesses efficiency by utilizing the input demand function in the stochastic frontier analysis proposed by Filippini and Hunt (2011, 2012, 2015). The level of energy efficiency is determined by the factors that influence household energy consumption. Table 5 shows the estimated energy efficiency results. Based on these estimates, it is clear that family income has a positive impact on energy consumption in Taiwanese urban households. The tendency to use electrical energy increases with higher family income.

The population size factor is another factor that shows a positive impact. According to the SFA estimation results, the population is the factor with the highest coefficient value in the proposed model, with every 1% increase in population in Taiwan's urban areas causing an increase in energy consumption ranging from 57.3 to 73.9%. Space per person is another factor that has a positive influence, which means that the greater the ratio of space to family members, the more energy is required in the household.

Table 6 shows the results of the energy efficiency frontier estimation for both persistent and transient efficiency. According to the results of these calculations, the value of persistent efficiency is less than the value of transient efficiency. Persistent efficiency in Taiwan's urban areas has a mean value of 0.841, while transient efficiency has a value of 0.965. According to the estimation results, the overall efficiency value is 0.812, implying that increasing overall energy efficiency will save 18.8% of total energy consumption. This demonstrates that the level of residential energy inefficiency in Taiwan's urban areas is relatively low. This indicates that the government's energy efficiency policy resulted an effective response (Adha et al., 2022).

3.2. Energy efficiency, climate change, air pollutions and chronic respiratory diseases

After estimating the household energy efficiency rate in six major Taiwanese cities, the next step is to calculate the impact of energy efficiency, climate change, and air pollution on chronic respiratory disease mortality rates. The climate change factor in this study is based on daily temperature changes, which are measured in degree days. Particulate matter 2.5, particulate matter 10, and sulfur dioxide (SO_2) were the pollution factors used in this study. Table 7 displays the statistical test results.

For all models in Table 7, the dependent variable is the logarithm of the mortality rate from chronic respiratory diseases. Based on the dynamic OLS (DOLS) estimation results, the energy efficiency coefficient value is −2.216, which is statistically significant at a 5% level. This means that energy efficiency has a negative impact on chronic respiratory disease mortality rates. It can also be seen in this dynamic OLS model that the climate change variable indicated by degree days and the air pollution factor have a positive effect on the mortality rate.

In addition to DOLS, the dynamic fixed effect model (DFE), the mean group model (MG), and the pooled mean group model (PMG)

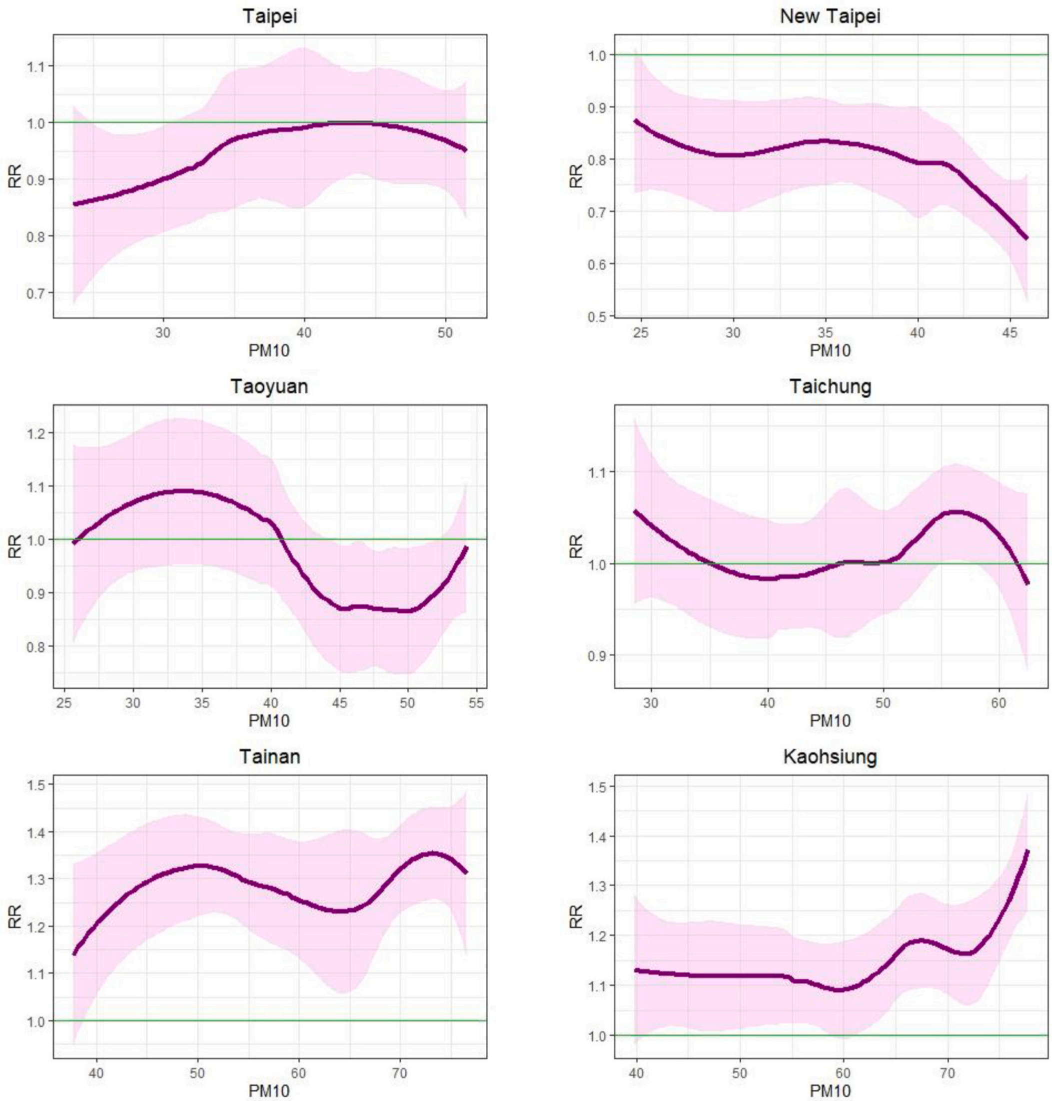

Fig. 7. Relative risk of respiratory diseases associated with PM_{10}.

were used in this study (PMG). According to the DFE estimation results, the energy efficiency variable has a positive long-term effect with a coefficient value of 2.016 and is significant at the 5% level on the mortality rate from chronic respiratory diseases. The positive impact of energy efficiency can also be seen in the MG estimation results, where the energy efficiency variable has a coefficient value of 6.339 in the MG model but has no significant effect on the mortality rate. However, in the short term, energy efficiency has a negative effect on mortality rate in the DFE and MG models, with coefficient values of −1.721 and − 13.442, respectively.

The DFE and MG models also show that the climate change factor indicated by degree days harms respiratory diseases in the long run, with coefficient values of −0.003 and − 0.063, respectively. In the short term, however, these two variables have a positive impact on respiratory diseases. Air pollution factors indicated by $PM_{2.5}$, PM_{10}, and SO_2 indicate that in both the DFE and MG models, PM_{10} has a positive effect on respiratory diseases, while $PM_{2.5}$ and SO_2 have a negative effect on respiratory diseases. In addition, the Hausman test procedure was used to test the models in this study. The PMG estimation results outperform other models according to the Hausman test. As a result, the following interpretation will be based on the PMG estimation results.

The PMG estimation yields the expected sign. According to the PMG estimation, energy efficiency in households has a negative long-term impact with a coefficient value of 10.028 and is significant at the 5% level for the mortality rate from respiratory diseases. It also shows that energy efficiency harms respiratory diseases not only in the long term, but also in the short term. Climate change, as measured by degree days, has a positive long-term and short-term impact on mortality, with coefficients of 0.035 and 0.012, respectively, and is significant at the 1% level. The air pollution factors indicated by $PM_{2.5}$, PM_{10}, and SO_2 in this study show that air pollution has a positive and significant impact on respiratory diseases in the long term, with coefficient values of 0.104, 0.065, and 0.581, respectively.

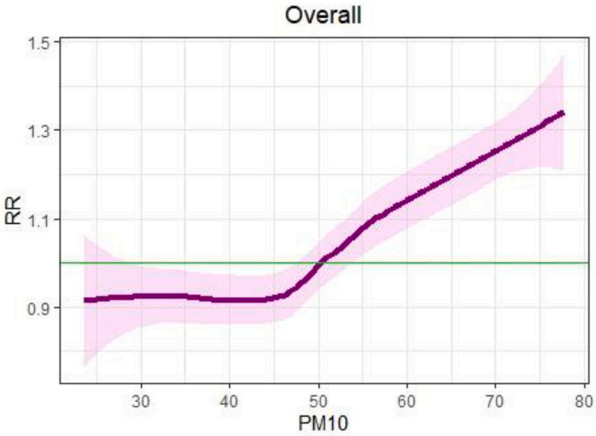

Fig. 8. Relative risk of respiratory diseases and overall PM_{10} level.

4. Discussions

Overall energy efficiency estimation results show that the level of household energy efficiency in Taiwan's six major cities is relatively high. According to the estimation results shown in Table 6, Taiwan's persistent efficiency value is 0.841. Measuring persistent efficiency is critical because it provides an overview and explanation of the impact of various inputs in each region while remaining constant over time (Kumbhakar et al., 2015). The factors of space per person and space per household are important in determining the amount of persistent efficiency in this study.

According to the estimation results, the space per household factor reduces household energy consumption, but it has no effect on the persistent efficiency model. In contrast to space per person, which shows the average building area for each individual in the household, it shows a positive relationship on household energy consumption ranging from 0.213 to 0.398, and significant at the 1% level. It means that every one ping or 3.305m^2 increase in space per person raises household electrical energy consumption by 21.3% to 39.8%.

The average overall value of energy efficiency in Taiwan's six major cities is 0.812. In comparison to previous research on energy efficiency estimation using the SFA with input demand function approach, the overall efficiency value in Taiwan's major cities is higher than the overall efficiency value in Chinese provinces, with an average value of 0.786 (Filippini and Zhang, 2016), and overall efficiency in Indonesia's provinces, with an average value of 0.537 (Adha et al., 2021), and significantly higher than the overall efficiency in African countries, with an average value of 0.075 (Adom et al., 2021). However, when compared to the average overall efficiency in the United States, the average overall efficiency in the United States is higher at 0.826 (Filippini and Hunt, 2012).

This study, in addition to providing an estimate of overall efficiency, also provides an overview of changes in energy efficiency in each city in Taiwan from 2008 to 2020. Fig. 2 depicts the estimated efficiency in each Taiwanese city. Fig. 2 shows that efficiency levels in Taipei and New Taipei decreased during the study period. Aside from these two cities, Taoyuan, Taichung, Tainan, and Kaohsiung have increased their efficiency. However, based on those figures, New Taipei has the highest efficiency level when compared to other cities.

Furthermore, PMG estimates show that household energy efficiency has a negative effect on the mortality rate from chronic respiratory diseases in six major Taiwanese cities. This means that improving household energy efficiency lowers the risk of mortality from chronic respiratory diseases. Indeed, the estimation results show that energy efficiency has the highest coefficient value in influencing respiratory diseases when compared to other variables. The findings of this study support the previous studies by Maidment et al. (2014), which state that even if the impact is small, an intervention on energy efficiency in the household will have a significant effect on the health of the house occupants. Moreover, the findings of this study back up a study conducted by Faizan and Thakur (2019) that demonstrated the negative impact of energy consumption, particularly solid fuel in the home, on respiratory disease in India.

However, the findings of this study are not fully consistent with previous research indicating that energy efficiency interventions may have a smaller impact on health, such as respiratory diseases (Bone et al., 2010). S several studies have found that energy efficiency interventions in residential buildings, such as reducing ventilation, are detrimental to health (Weschler, 2011). However, it should be noted that the measurement of energy efficiency in this study is not specifically based on the characteristics of the house building, but rather on social and economic factors, so that the estimation results reflect the existing demand in the energy market.

Further analysis was performed on the relative risk with 95% confidence interval of mortality rate from chronic respiratory diseases associated with energy efficiency and air pollution in each major city in Taiwan to prove the findings in this study.

Fig. 3 depicts the relative risk (RR) of death from chronic respiratory diseases in Taiwan's major cities associated with household energy efficiency. When compared to other cities in Taiwan, New Taipei has the lowest risk of death from respiratory diseases, with RR value of 0.639 (95% CI: 0.58–0.70), and Tainan has the highest RR value of 1469 (95% CI: 1.34–1.61). At the city level, Taipei,

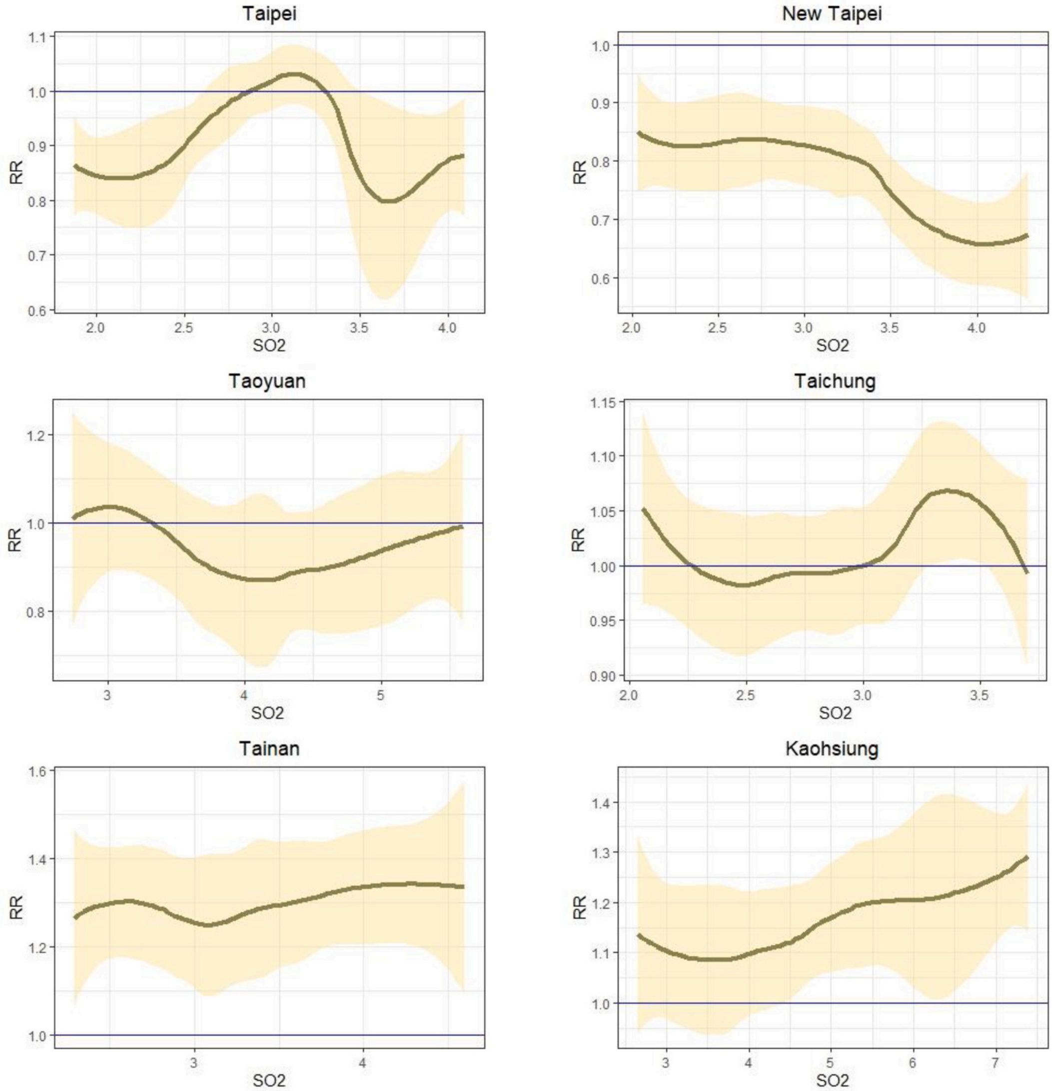

Fig. 9. Relative risk of respiratory diseases associated with SO_2.

Taoyuan, Taichung, and Kaohsiung showed that the value of the risk of death from respiratory diseases was significant when the energy efficiency value was 86.2% with RR 1070 (95% CI: 0.97–1.17), 74.9% with RR 1.154 (95% CI: 1.05–1.26), 89.1% with RR 1115 (95% CI: 1.01–1.22), and 76.7% with RR 1403 (95% CI: 1.28–1.52), respectively.

When the results of energy efficiency estimate in each city are compared, the city with the highest energy efficiency level is New Taipei, with a value of 99%, and the city with the lowest efficiency rate is Tainan, with a value of 68.1%. This finding validates the PMG estimation results, which show a negative relationship between energy efficiency and chronic respiratory diseases. Fig. 4 depicts the relationship between energy efficiency and the relative risk of chronic respiratory diseases in Taiwan's major cities.

Fig. 5 depicts the risk of death due to chronic respiratory diseases in relation to daily mean particulate matter 2.5. According to Fig. 4, the RR in Taipei is significant when $PM_{2.5}$ levels reach 33 g/m^3, indicating that $PM_{2.5}$ increases the risk of death from respiratory diseases. This is in contrast to New Taipei, where an increase in $PM_{2.5}$ levels in the air had no effect on the risk of death in patients with chronic respiratory diseases. The RR value in New Taipei was significant when $PM_{2.5}$ was at 12.5 g/m^3, with an RR value of 0.883. (95% CI: 0.81–0.96). In Kaohsiung, $PM_{2.5}$ had a positive and significant impact on the risk of death from chronic respiratory diseases. When $PM_{2.5}$ levels reach 33.5 g/m^3, the RR value in Kaohsiung becomes significant.

According to the estimation results in Fig. 6, an increase in overall ambient $PM_{2.5}$ increases the risk of chronic respiratory diseases. This finding supports many previous studies that show that the pollutant $PM_{2.5}$ in the environment can increase the risk of death from chronic respiratory diseases (Zafirah et al., 2021). Several previous studies have also found that ambient PM2.5 has a significant impact on the risk of asthma (Fan et al., 2016; Lee et al., 2006). This is due to the presence of toxic materials in $PM_{2.5}$, such as metals, acids, and nitrates, which are carried by combustion. Furthermore, due to its small size, it will be easily inhaled into the respiratory

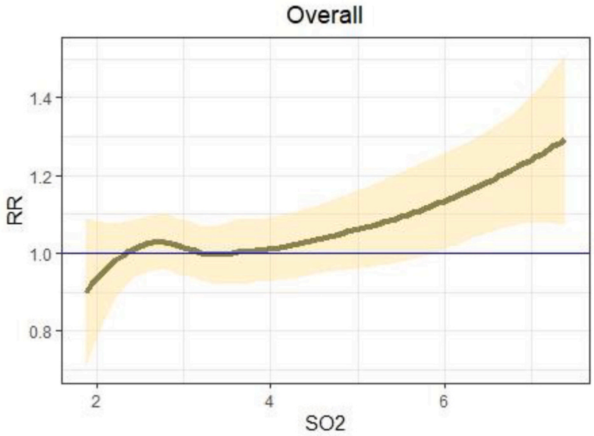

Fig. 10. Relative risk of respiratory diseases and overall SO_2 level.

tract and lungs, causing allergies and inflammation and increasing the risk of developing other respiratory diseases (Liu et al., 2017).

This study investigates the effect of ambient pollutant PM_{10} on the risk of death from chronic respiratory diseases in addition to $PM_{2.5}$. Fig. 7 depicts the impact of pollutant PM_{10} on relative risk in each Taiwanese city based on historical data. Based on this graph, it is clear that the ambient pollutant PM_{10} has the potential to increase the risk of death from respiratory diseases. This was especially noticeable in cities like Taipei, Taoyuan, Tainan, and Kaohsiung. Meanwhile, in New Taipei and Taichung, ambient pollutant PM_{10} does not appear to have a significant impact on chronic respiratory diseases. However, when the overall ambient pollutant in all cities in Taiwan is examined, as shown in Fig. 8, the risk of death from chronic respiratory diseases increases significantly when PM_{10} levels reach 50 g/m^3. According to the estimation results, the value of the risk of death is significant when PM_{10} is at 77.8 g/m^3 with an RR value of 1.328. (95% CI: 1.21–1.45).

Sulfur dioxide (SO2) is the next ambient pollutant examined in this study. Fig. 8 depicts the estimation results in each city, which vary. According to Fig. 9, Kaohsiung has the highest SO_2 level at 7.4 ppb, with an RR value of 1.403 (95% CI: 1.28–1.52), and historical data from Kaohsiung shows that an increase in SO_2 levels in the air increases the risk of death from chronic respiratory diseases.

Furthermore, the overall ambient pollutant SO_2 shown in Fig. 10 demonstrates a positive relationship between an increase in ambient pollutant SO_2 and the relative risk of chronic respiratory diseases in Taiwan's six major cities. This finding supports main findings of a previous study from Ganzhou, China (Zhou et al., 2022), which found a positive exposure-response relationship between SO_2 concentrations and the relative risk of respiratory inpatient visits.

This study calculates the impact of climate change as measured by changes in degree days, in addition to measuring the impact of household energy efficiency and ambient air pollution on the relative risk of chronic respiratory diseases. Degree days are commonly defined as the minimum temperature required in a room to feel comfortable without the use of air conditioners or heating. The degree days are calculated by comparing the daily mean temperature to the temperature standard in the region (Shiau et al., 2022). Degree days are commonly used in measuring a room's energy use and are closely related to measuring energy efficiency. According to the estimation shown in Fig. 11, Kaohsiung has the highest degree days value of 97.1 with an RR value of 1.141 (95% CI: 1.04–1.24). The lowest is in Taoyuan with 62.7 62.7 with an RR value of 1.028 (95% CI: 0.93–1.13).

Fig. 12 depicts the overall impact of degree days on the risk of death from chronic respiratory diseases. When the degree days range from 70 to 85, the relative risk of death increases significantly. More than that, and the relative risk appears to have decreased. This study's findings back up the findings of a previous study by Yang et al. (2018), which found an inverse relationship between average temperature rate and respiratory mortality in Taiwan, and a study by Guo et al. (2022) using Mianyang City observational data. Furthermore, the study of Zafirah et al. (2021) found that temperature rate was significantly associated with COPD (chronic obstructive pulmonary disease) but not with asthma.

Degree days serve as an indicator of the temperature conditions that influence indoor energy use and comfort levels without the need for additional heating or cooling. In the context of this research, changes in degree days reflect shifts in temperature patterns and can have implications for respiratory health. Climate change, characterized by alterations in temperature patterns, can exacerbate respiratory conditions due to its influence on air quality, allergens, and the spread of infectious diseases. Higher degree day values, indicating increased heating or cooling requirements, may contribute to elevated indoor air pollution levels, which can trigger respiratory symptoms and exacerbate existing conditions.

Additionally, variations in temperature and degree days can affect the dispersion of airborne pollutants, such as particulate matter ($PM_{2.5}$ and PM_{10}) and sulfur dioxide (SO_2), which are known to be detrimental to respiratory health (Manisalidis et al., 2020). Changes in temperature patterns may lead to the accumulation of pollutants, especially in urban areas (D'Amato et al., 2014), further increasing the risk of chronic respiratory diseases. By examining the relationship between degree days, household energy efficiency, ambient air pollution, and the relative risk of chronic respiratory diseases, this study provides a new insight into the complex interplay between

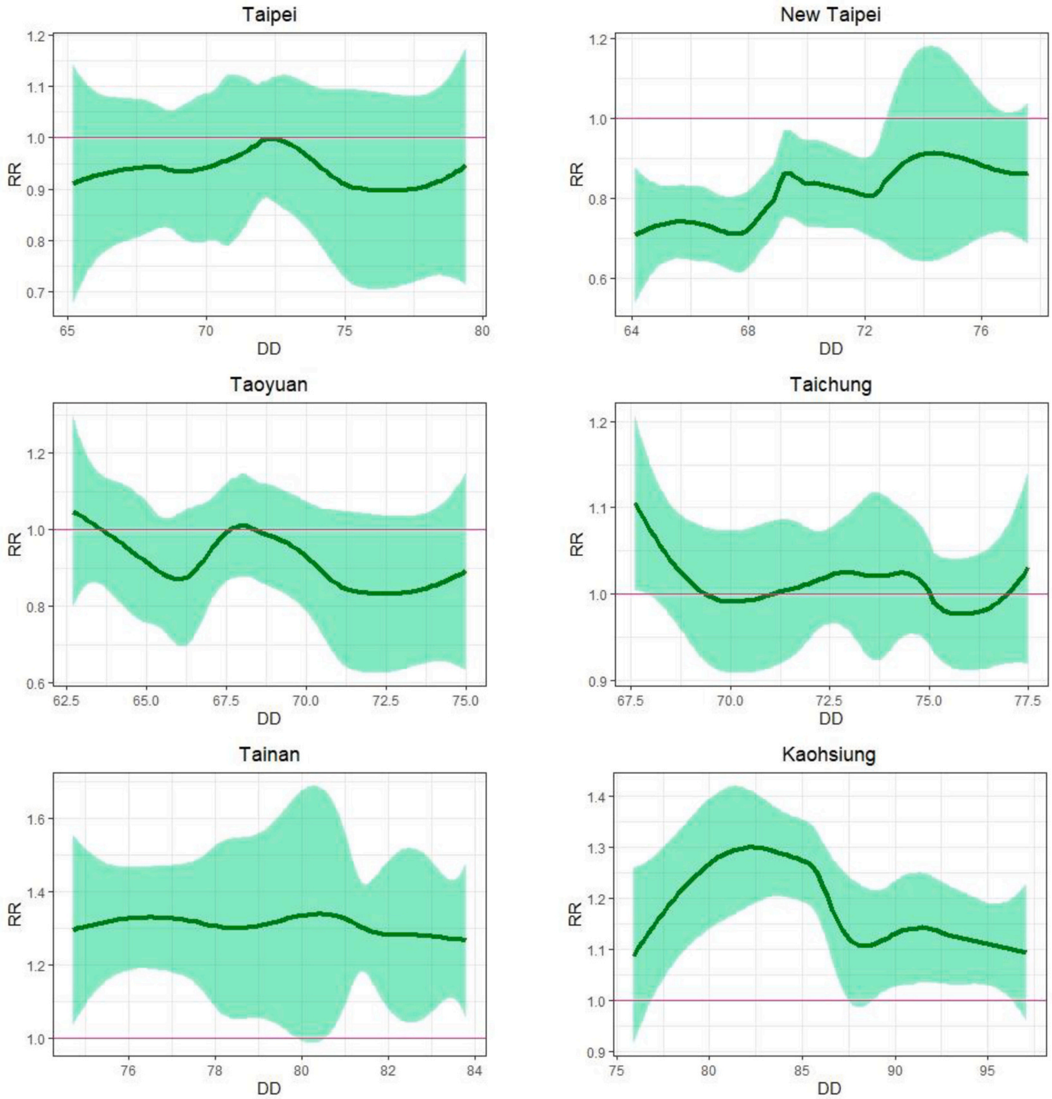

Fig. 11. Relative risk of respiratory diseases associated with degree days.

climate change, indoor environments, and respiratory health outcomes. Understanding these associations can inform the development of targeted interventions and policies to mitigate the adverse health effects of climate change on vulnerable populations.

5. Conclusions

This study examines the impact of household energy efficiency, ambient air pollution, and degree days on chronic respiratory disease mortality. To the best of our knowledge, this is the first study to evaluate the effect of the energy efficiency frontier on chronic respiratory disease mortality rates. The input demand function from the stochastic frontier analysis is used to calculate energy efficiency. After calculating the energy efficiency value for each city, an analysis of the impact of energy efficiency on respiratory disease mortality rates is performed. These measurements were made with the ARDL, dynamic panel data model. The PMG ARDL model was used, which was chosen based on the best model testing using the Hausman test. This study also investigates the relative risk of mortality from chronic respiratory diseases associated with household energy efficiency, degree days, and ambient air pollution, such as $PM_{2.5}$, PM_{10}, and SO_2, to support the findings of the PMG analysis.

The results of energy efficiency measurements using SFA show that household energy efficiency in Taiwan's major cities is relatively high. This estimation is also supported by a low level of persistent inefficiency. According to the measurements, New Taipei has the highest energy efficiency level when compared to other cities. At the same time, Tainan has the lowest level of efficiency. It should be noted, however, that the level of energy efficiency in New Taipei has gradually decreased year after year.

Following the determination of the energy efficiency value, the impact of the efficiency on the death rate caused by chronic

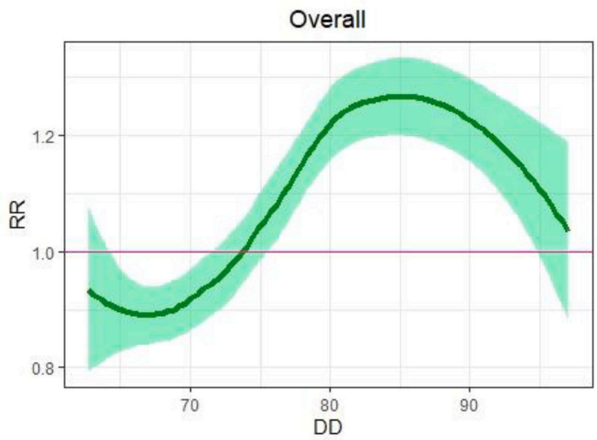

Fig. 12. Relative risk of respiratory diseases and overall degree days level.

respiratory diseases is assessed. Longitudinal data measurements using PMG show that household energy efficiency reduces the risk of death from chronic respiratory diseases. Then, degree days and ambient air pollution, specifically $PM_{2.5}$, PM_{10}, and SO_2, were found to have a positive impact on the risk of death from chronic respiratory diseases. This means that improving household energy efficiency significantly reduces the risk of death from respiratory diseases. On the other hand, worsening climate change and rising levels of ambient air pollution elevate the risk of death from respiratory diseases even further. To support these findings, this study compares the relative risk of death from chronic respiratory diseases in Taiwan's major cities based on energy efficiency, degree days, and ambient air pollution. As a result, these measurements support the PMG estimation findings of this study.

Several policy implications can be drawn from the discussion's explanation. First, the Taiwan government should focus its attention to household energy efficiency policies in the metropolitan area. This is due to the study's estimation results, which show that improving energy efficiency in housing will reduce the risk of death from chronic respiratory diseases. To improve household energy efficiency, the government should begin restricting housing development in the metropolitan area because this study shows that increasing housing density in urban areas encourages household energy consumption while decreasing energy efficiency. Second, encourage more stringent efforts to control air pollution in Taiwan's urban areas. This is based on the findings of this study, which found that $PM_{2.5}$, PM_{10}, and SO_2 levels in the environment increase the risk of death from chronic respiratory diseases. Some efforts that can be made include encouraging the use of environmentally friendly vehicles such as electric vehicles, maximizing the use of public transportation, and encouraging energy conservation programs.

In addition to the valuable insights provided, this study is subject to certain limitations that should be considered in future research. Firstly, the reliance on observational data from only six major cities in Taiwan stems from limited data availability in other locations. Future studies should incorporate a broader range of data sources encompassing various geographical regions to enhance the generalizability of findings. Furthermore, given the observational nature of this study, establishing a causal relationship between energy efficiency, environmental factors, and chronic respiratory diseases presents a challenge. Unmeasured confounding variables or other factors influencing the relationship may exist that should have been accounted for in this study.

Secondly, it is important to acknowledge that the study's time frame, spanning yearly from 2008 to 2020, captures a specific period, and the observed relationships may not necessarily reflect long-term trends or changes. Temporal variations in energy efficiency practices, environmental policies, and disease patterns could impact the findings. Therefore, future research should explore extended periods to gain a more comprehensive understanding of long-term implications. Moreover, while this study focuses on energy efficiency, climate change, environmental factors, and respiratory diseases, it does not fully account for other external factors that may influence respiratory health, including individual lifestyle choices, genetic predispositions, and access to healthcare. Future studies should consider incorporating these additional variables into the research framework to provide a more comprehensive analysis.

CRediT authorship contribution statement

Yuo-Hsien Shiau: Conceptualization, Methodology, Supervision, Funding acquisition. **Su-Fen Yang:** Conceptualization, Validation, Investigation, Writing – review & editing, Supervision. **Rishan Adha:** Conceptualization, Methodology, Software, Resources, Formal analysis, Writing – original draft, Writing – review & editing. **Syamsiyatul Muzayyanah:** Data curation, Software, Resources. **Giia-Sheun Peng:** Conceptualization, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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