Does environmental awareness determine GDP growth ? evidence from Singapore based on ARDL and NARDL approaches

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Abstract

Global environmental pollution has been rapidly growing over the past few years, causing global warming and drastic climate changes. There are efforts carried out by individuals and entities to minimize the level of pollution worldwide. This study attempts to investigate the nexus relationship between carbon emissions, FDI inflows, exports and GDP. Having an open economic setting, heavy reliance on FDI and exports, as well as high rate of carbon emissions, Singapore appears to suit the study. The analysis is carried out using standard time-series techniques, supplemented by ARDL and NARDL tests on annual data spanning from 1970 to 2017. The empirical results tend to suggest that the nexus relationship is statistically significant, the rate of carbon emissions really influences GDP through FDI and that the CO2 emission is the most exogenous among the variables. This study is consistent with the "*no pain all gain*" slogan by which implementation of policies related to carbon emissions is expected to expand GDP growth due to the awareness of investors regarding environmental issues. Our findings are of great importance to the development policies in countries facing similar challenges.

Keywords: environment, GDP growth, ARDL, Nonlinear ARDL, Singapore

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1.0 INTRODUCTION

The fact that carbon emission accounts for the largest portion of environmental pollution, in addition to the drastic increase of global carbon emissions reaching an all time high last year (Carrington, 2018), encourages more studies on the related issue, indirectly, promoting higher level of environmental awareness among the public. The studies, however, are generally not accommodative to the economic state of the samples. In other words, studies on carbon emissions are mostly linked to health problems, thus, involves only health-specific variables such as health expenditure, death rate and cases recorded.

The nexus relationship between GDP, FDI and exports has already been established years back due to their importance in the macroeconomic world. Despite the huge amount of existing studies, the older versions tend to have limitations, thus, the more recent ones come forth to fill-in the missing gaps. Basically, GDP, FDI and exports are regularly being studied as the macroeconomic situation changes from time to time, thus, requiring a more recent and updated information. Simply said, all the four indicators are thoroughly studied from their respective economic and health perspectives, but are scarcely merged into a single economic study. This paper, thus, attempts to examine the four variables from an economic point of view, in addition to the prevalent idea of environmental benefits from reducing carbon emissions.

The next section will briefly explain some existing literature review related to this study. Section 3 explains the theoretical framework for this study. Section 4 outlines the methodology employed in this study and the data sources. Section 5 discusses the results of the tests carried out in the study including time-series techniques, ARDL and NARDL tests. Lastly, section 6 will conclude and briefly outline some policy implications.

2.0 LITERATURE REVIEW

Congruent to the main prevalent idea, a study by Feridun & Sissoko (2011) suggests that FDI positively affect GDP in the long-run. Hansen & Rand (2006) analyses the association between FDI and GDP in a sample of 31 developing countries and they found that the FDI is positively correlated to GDP with causality from FDI to GDP. A study by Tiwari & Mutascu (2011) found that FDI can also have a negative impact on GDP. Thus, the authors suggest an export-led growth path especially at the initial stage of growth.

In relation to carbon emissions, Lean & Smyth (2010) found that electricity conservation policies would reduce exports, but they also found that exports and GDP posit neutrality, thus,

the policies do not bring harm to economic growth. A study by Narayan & Smyth (2009) suggests that causality runs from exports to electricity consumption. Additionally, they also propose increasing investment in electricity infrastructure and stepping up electricity conservation policies.

One of the studies which considers multivariate causalities between the three economic variables in East and Southeast Asia finds that causality runs from FDI to GDP, from FDI to exports, from exports to GDP and also from GDP to exports. This suggests that the causal relationship in a time-series model can also display bicausal association (Hsiao & Hsiao, 2006). Another study which employs ARDL on South Africa finds similar result where it reveals unidirectional causality between GDP growth and FDI running from FDI to GDP, unidirectional causality between FDI and exports running from FDI to exports and bidirectional causality between GDP and exports (Sunde, 2017).

In the empirical studies briefly outlined above, the results tend to be inconclusive for some indicators such as the negative correlation between FDI and GDP. Based on the previous samples of studies carried out on any of the specified variables, we do not find any study which takes into account GDP, FDI, carbon emissions and exports all in a single model. Thus, we find it beneficial to attempt to investigate the long-run relationship between the four indicators as well as the causality chain, which might provide a more comprehensive result.

3.0 THEORETICAL FRAMEWORK

In line with the previous empirical studies, it is generally postulated that FDI and exports affect GDP growth. As FDI increases, the amount of capital increases and promotes higher productivity and development. The lead-lag relationship between exports and GDP growth has also been proven in previous studies, where increase in exports leads to increase in GDP, conversely, decrease in exports or increase in imports leads to decrease in GDP. However, to the best of our knowledge, there is not yet any study which examines the relationship of carbon emissions and the aforementioned three variables. Consideration of carbon emissions would intuitively lead to a more robust model as more variables are involved in the model, limited the probability of omitted variable bias.

In light of the theoretical underpinnings designed for this study, we constructed two theoretical expectations. First, carbon emissions should negatively correlate with FDI inflows as investors are generally cognizant of the environment. The FDI should influence exports as more capital

means more productivity. The exports, in turn, should affect GDP because more exports means more productivity and increased productivity means higher profit and return. Second, the growth of GDP is expected to increase the amount of carbon emissions. This should lead to lower FDI (again assuming investors are mindful of the environment) which in turn, reduces the exports as capital decreases. Based on the above theoretical underpinnings, the long-run cointegration relationship of the four variables will be tested, followed by causality test, mainly through the error correction model and variance decomposition.

4.0 METHODOLOGY AND DATA

The historical data for this study are extracted from the World Bank's *World Development Indicators*, which three missing observations in the carbon emissions are supplemented by Edgar Joint Research Centre database. The limited availability of data restricts the study to annual frequency, spanning from year 1970 to 2017. The table below summarizes the variables employed in this study:

Variable	**Symbol**	**Proxy**
Gross Domestic Product	GDP	GDP per capita (USD)
Foreign Direct Investment	FDI	FDI Inflows (USD)
Carbon emissions	CO2	CO2 per capita (Metric Tons)
Exports	EGS	Exports of Goods and Services (USD)

The methodology adopted in this study is the standard time-series techniques, the ARDL and NARDL approach to cointegration. The long-run equilibrium relationship between the four variables take the following form:

$$GDP_m - \alpha_0 - \alpha_1 FDI_m - \alpha_2 CO2_m - \alpha_3 EGS_m = \varepsilon_m$$

Further elaboration of the methodologies and explanation of the employed tests will be in the following sections.

5.0 EMPIRICAL FINDINGS AND DISCUSSIONS

5.1 Unit Root Tests

Cointegration tests require that the variables to be tested are non-stationary. This is to ensure that the theoretical components of the variables are captured. If a variable is stationary, it is said to have constant mean, variance and covariance, thus, does not encompass theoretical

information. The non-stationary variables will then be converted into their level form by making their variance stationary, followed by differenced level form to make their mean stationary. In order to test for the stationarity and non-stationarity of variables, we proceeded with three different types of unit root tests.

5.1.1 Augmented Dickey-Fuller

	VARIABLE	ADF	VALUE	T-STAT.	C.V.	RESULT
LOG FORM	*LGDP*	AIC: ADF (1)	47.9738	-2.1601	-3.5189	Non-Stationary
		SBC: ADF (1)	44.4985	-2.1601	-3.5189	Non-Stationary
	LFDI	AIC: ADF (4)	-28.8188	-2.7829	-3.5189	Non-Stationary
		SBC: ADF (4)	-34.9007	-2.7829	-3.5189	Non-Stationary
	LCO2	AIC: ADF (1)	8.9776	-2.8383	-3.5189	Non-Stationary
		SBC: ADF (1)	5.5023	-2.8383	-3.5189	Non-Stationary
	LEGS	AIC: ADF (1)	31.2688	-2.4724	-3.5189	Non-Stationary
		SBC: ADF (1)	27.7934	-2.4724	-3.5189	Non-Stationary

	VARIABLE	ADF	VALUE	T-STAT.	C.V.	RESULT
1ST DIFF. FORM	*DGDP*	AIC: ADF (1)	44.5458	-3.7314	-2.9339	Stationary
		SBC: ADF (1)	41.9755	-3.7314	-2.9339	Stationary
	DFDI	AIC: ADF (3)	-30.8388	-4.4664	-2.9339	Stationary
		SBC: ADF (3)	-35.1227	-4.4664	-2.9339	Stationary
	DCO2	AIC: ADF (1)	8.1671	-6.5305	-2.9339	Stationary
		SBC: ADF (1)	5.5968	-6.5305	-2.9339	Stationary
	DEGS	AIC: ADF (1)	27.5915	-4.0168	-2.9339	Stationary
		SBC: ADF (1)	25.0212	-4.0168	-2.9339	Stationary

The null hypothesis of the ADF test is, the variables are non-stationary. The first table shows that the four variables are non-stationary in their level form as their relative T-values are lower than the critical value, implying that we cannot reject the null. After taking their first difference, the variables are all integrated at 1 as the T-values go above the critical value.

5.1.2 Phillips-Perron

The main difference of the PP test and the ADF test is that the latter only takes care of autocorrelation, the former on the other hand, takes care of both autocorrelation and heteroscedasticity.

	VARIABLE	T-STAT.	C.V.	RESULT
LOG FORM	LGDP	-2.3697	-3.5066	Non-Stationary
	LFDI	-4.4137	-3.5066	Stationary
	LCO2	-2.5679	-3.5066	Non-Stationary
	LEGS	-1.2621	-3.5066	Non-Stationary

	VARIABLE	T-STAT.	C.V.	RESULT
1ST DIFF. FORM	DGDP	-3.5052	-2.9256	Stationary
	DFDI	-12.8818	-2.9256	Stationary
	DCO2	-8.0443	-2.9256	Stationary
	DEGS	-4.6739	-2.9256	Stationary

Similar to the previous test, the null hypothesis for PP is the variables are non-stationary. Based on the results from the tables, all the variables are non-stationary in their level form or I(1) except for FDI which is I(0). A possible explanation for this is that the PP test takes care of both autocorrelation and heteroscedasticity which is beneficial in large sample size, but as our sample size is small, using the ADF test appears to be a better fit.

5.1.3 Kwiatkowski-Phillips-Schmidt-Shin

According to Kwiatkowski et al. (1992), KPSS test can distinguish variables which appear to be stationary, or appear to have unit roots, or lack adequate information, to validate whether

they are indeed I(0) or actually I(1). Therefore, we find it complementary to include this approach in the unit root test. Unlike the previous two tests, the null hypothesis for this test is, the variables are stationary.

	VARIABLE	T-STAT.	C.V.	RESULT
LOG FORM	LGDP	0.14944	0.17546	Stationary
	LFDI	0.14905	0.17546	Stationary
	LCO2	0.1197	0.17546	Stationary
	LEGS	0.16225	0.17546	Stationary

	VARIABLE	T-STAT.	C.V.	RESULT
1ST DIFF. FORM	DGDP	0.45565	0.37868	Non-Stationary
	DFDI	0.36429	0.37868	Stationary
	DCO2	0.15484	0.37868	Stationary
	DEGS	0.47986	0.37868	Non-Stationary

The test, however, reveals mixed results where all the variables are stationary in their level form, two variables are stationary after taking their first difference and the other two non-stationary. Based on these inconsistent results, we only consider the ADF test.

5.2 VAR Order Selection

The selection of order of lags is based on the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC). The main difference between both is that the AIC focuses on large value of likelihood and is less concerned about over-parameter, thus, it tends to choose higher order of lags. The SBC on the other hand, is more concerned about over-parameter, thus, it

tends to choose lower order of lags. However, in this case, the AIC and SBC both agree on the order of 1 as the optimum lag order.

Order	AIC	SBC	P-Value	C.V.
1	91.7165	74.1045	[.417]	5%

5.3 Cointegration Tests

5.3.1 Engle-Granger

After knowing the optimum lag order, we can now proceed with Engle-Granger's model of cointegration test. The EG test essentially examines the error term for cointegration. In other words, if the residuals of variables are stationary, cointegration exists among them. The table below shows the result:

VARIABLE	ADF	VALUE	T-STAT.	C.V.	RESULT
LGDP	AIC: ADF (1)	64.3597	-2.9098	-4.3681	No Cointegration
	SBC: ADF (1)	62.6220	-2.9098		
LFDI	AIC: ADF (3)	-19.9647	-3.7935	-4.3681	No Cointegration
	SBC: ADF (5)	-24.6509	-3.0400		
LCO2	AIC: ADF (1)	12.8719	-3.8571	-4.3681	No Cointegration
	SBC: ADF (1)	11.1343	-3.8571		
LEGS	AIC: ADF (1)	50.6479	-2.6143	-4.3681	No Cointegration
	SBC: ADF (1)	48.9103	-2.6143		

The null hypothesis for this test is, the error term is non-stationary. As the T-values for all the variables are lower than the critical value, we fail to reject the null of non-stationarity, thus, no cointegration among the variables. However, there are some limitations of EG which might have influenced this result. First, the EG test only identifies a single cointegration movement which prioritizes the 'first' variable in the model estimation. Second, it is a two-step procedure involving regressions to estimate the residual series and to test for a unit root. Thus, any errors in the first estimation will also be transmitted to the other. Third, it estimates cointegration relation independent of the variables' vector error correction model. This leads to a two-step procedure of the model estimation which might lead to misspecification.

5.3.2 Johansen

As the previous EG test exhibits results which are counter-intuitive to our theoretical framework, possibly due to its limitations, we proceed with Johansen's model of cointegration test. The test essentially makes the error term stationary by giving hypothetical coefficients to the variables, therefore, rendering it easier to get cointegration in this model.

Cointegration LR Test Based on Maximal Eigenvalue of the Stochastic Matrix

Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r = 1	40.3112	31.7900	29.1300
r<= 1	r = 2	15.8435	25.4200	23.1000
Cointegration LR Test Based on Trace of the Stochastic Matrix				
Null	**Alternative**	**Statistic**	**95% Critical Value**	**90% Critical Value**
r = 0	r>= 1	75.3186	63.0000	59.1600
r<= 1	r>= 2	35.0074	42.3400	39.3400

Johansen test involves Maximal Eigenvalue and Trace of the Stochastic Matrix. The results suggest that there is one cointegration among the variables. The null hypothesis of no cointegration is rejected as the T-values for both Eigenvalue and Trace go above their corresponding critical values. This implies that the variables are proven to be moving together in the long-run, congruent to our theoretical intuition.

5.3.3 Autoregressive Distributed Lag (ARDL)

Statistically, both the EG and Johansen tests have common limitations such as: first, the assumption of all variables are non-stationary or I(1). Second, sensitivity of results on the order of lags, constant term and trend. Third, pre-bias, i.e. the P-value test is in favor of accepting the null. Accordingly, we proceed with ARDL approach to cointegration test as introduced by Pesaran et al. (2001) to further corroborate our results. The ARDL test essentially tests for long-run relationship of I(0) and I(1) variables using F-statistic.

DEP. VARIABLE	VARIABLE	F-STAT.	95% Critical Value		RESULT
			LOWER C.V.	UPPER C.V.	
DGDP	F (LGDP | LFDI, LCO2, LEGS)	.66309[.624]	3.539	4.667	Insignificant
DFDI	F (LFDI | LGDP, LCO2, LEGS)	5.2821[.004]	3.539	4.667	Significant
DCO2	F (LCO2 | LGDP, LFDI, LEGS)	.96400[.477]	3.539	4.667	Insignificant
DEGS	F (LEGS | LGDP, LFDI, LCO2)	.52062[.722]	3.539	4.667	Insignificant

The result suggests that there exist no long-run cointegration of variables except when FDI is made the dependent variable. The null hypothesis for this test is the variables are jointly insignificant. As the F-values (other than FDI as dependent variable) fall under the lower critical value extracted from Pesaran's table, we fail to reject the null. However, we reject the null when FDI is the dependent variable, which its F-value indicates that there is actually an unspurious long-run relationship between the variables.

5.4 Long-Run Structural Modelling

At this point, we have already established that there is a long-run cointegration among the variables. We now attempt to test the long-run coefficients of the variables against the theoretically expected values, to examine whether the variables are statistically significant or not. The LRSM involves two steps: first, exact-identification where the coefficient of a variable is normalized; made equal to one. Second, over-identification where the insignificant coefficient of any other variables, if any, is excluded. The null hypothesis for the over-identification step is, restriction is correct.

VARIABLE	PANEL A	PANEL B	PANEL C	PANEL D	PANEL E	PANEL F	PANEL G
LGDP	1.0000	1.0000	1.0000	-.47438	-1.0025	-.70393	0.00
	(*NONE*)	(*NONE*)	(*NONE*)	(.85103)	(.24151)	(.60440)	(*NONE*)
LFDI	-2.1080	-.99752	-1.4203	1.0000	1.0000	1.0000	1.0000
	(3.7818)	(.24126)	(1.1884)	(*NONE*)	(*NONE*)	(*NONE*)	(*NONE*)
LCO2	.28210	.0068174	0.00	-.13382	-.0068388	-.0000	-.27167
	(1.1433)	(.28421)	(*NONE*)	(.34708)	(.28318)	(*NONE*)	(.25500)
LEGS	.83907	.0000	.36834	-.39804	0.00	-.25947	-.72621
	(2.7719)	(*NONE*)	(.98188)	(.61441)	(*NONE*)	(.49400)	(.17785)
Trend	.12571	.060477	.078840	-.059633	-.060628	-.055509	-.062271
	(.23901)	(.035434)	(.065216)	(.020990)	(.021011)	(.017875)	(.020965)
CH SQ(1)	NONE	.42371[.515]	.15261[.696]	NONE	.42371[.515]	.15261[.696]	.29974[.584]

(S.E in Parentheses)

The result shows that when GDP is normalized, the other variables turn out to be insignificant. We then exclude EGS from the model and found out that FDI is significant, which the new model exhibits a P-value of 51.5 percent for its Chi-square value, thus, we fail to reject the null. On the other hand, exclusion of CO2 does not bring about any difference as the other two variables remain insignificant. However, when we attempt to exclude FDI, the LRSM iterations

exceeded 1500 without any given result. Hence, we find it inquisitive to proceed with normalizing FDI's coefficient. We find that the EGS is significant when GDP is excluded from the model with a P-value of 58.4 percent. Nevertheless, we chose not to exclude any variable from the model due to two reasons: first, we aim to find out whether the causal-relationship between the variables is congruent to our theoretical expectation and intuition. Second, our expected theory is supported by the previous cointegration tests where there exists long-run relationship between all the four variables.

5.5 Vector Error Correction Model

5.5.1 Standard VECM

Starting from this stage onwards, the tests are technically to examine the long-run causality chain between the variables. The VECM essentially identifies which variable is the leader (exogenous) and which is the follower (endogenous), based on a null hypothesis of exogeneity.

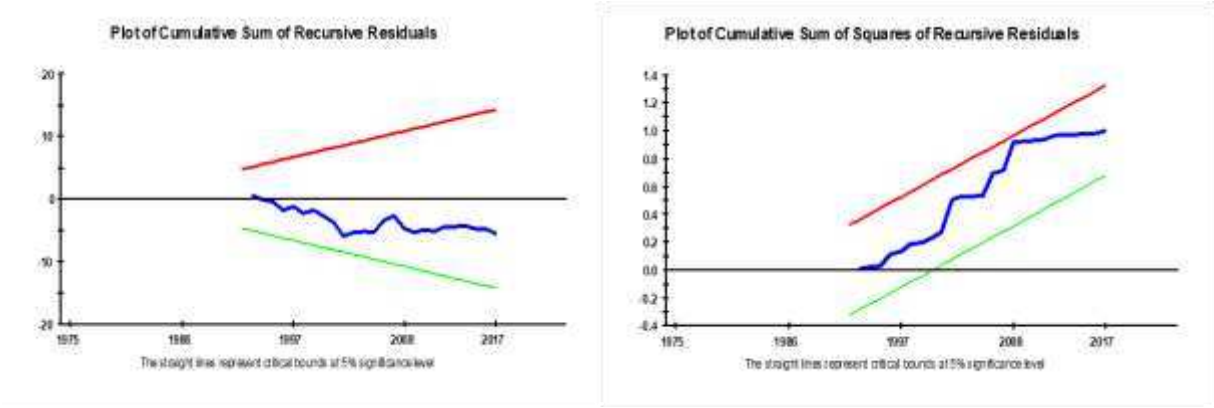
Ecm1(-1)	Coefficient	Standard Error	T-Ratio [Prob.]	C.V.	Result
dLGDP	.064562	.036360	1.7757[.083]	5%	Exogenous
dLFDI	-.76361	.15855	-4.8161[.000]	5%	Endogenous
dLCO2	-.0073697	.075784	-.097246[.923]	5%	Exogenous
dLEGS	.10795	.054659	1.9749[.054]	5%	Exogenous

The result suggests that only FDI is endogenous while the other three variables are exogenous in the long-run. This can be observed in FDI's T-value where it is more than 2 (in absolute term), implying that we have to reject the null. Alternatively, the P-value is less than 5 percent, thus, we reject the null.

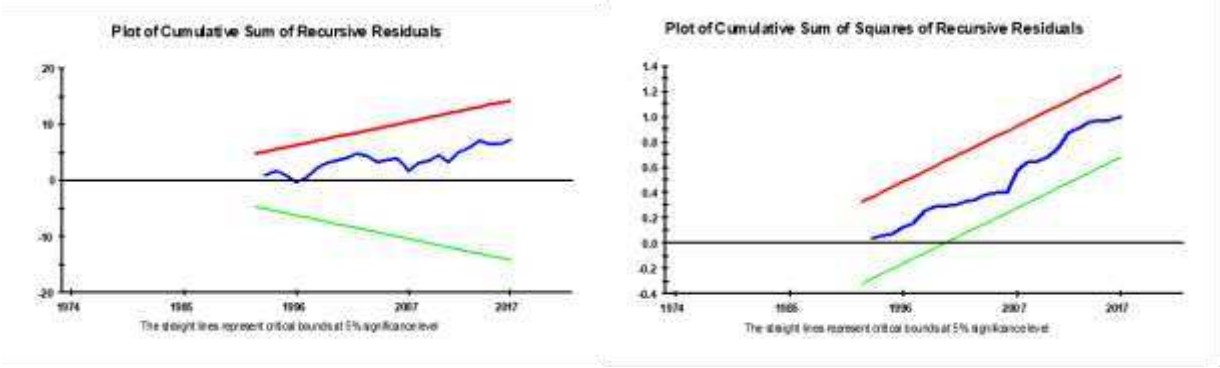
Interestingly, GDP appears to be exogenous and its T-value is close to two. A possible intuitive explanation for this is that GDP might also be endogenous, but due to the inclusion of CO2 and EGS variables, the effect seems to be diverted mostly towards FDI. This also seems to explain the previous ARDL test where cointegration is found when FDI is made the dependent variable. Additionally, the nature of Singapore economy also explains this result, the FDI happens to be one of the most attractive and appealing features in the country due to its open economic setting and stable growth. Thus, a growth in GDP would actually attract more investors to place their capital in the lucrative country.

As we find that FDI appears to be endogenous, we proceed with CUSUM and CUSUM SQUARE tests to examine the model's functional form, whether there is any structural break which might have occurred during the sample period. Additionally, we also test on EGS as its T-value is really close to endogeneity. We find that the two models are appropriate as the distribution of their recursive residuals fall within the boundaries.

CUSUM and CUSUM SQ on FDI



CUSUM and CUSUM SQ on EGS



5.5.2 ARDL Approach to VECM

This section focuses on the extension of the ARDL cointegration test carried out earlier. The ARDL approach to VECM can be segmented into two parts, namely, the long-run and short-run effects of independent variables on the dependent variable.

Static Long-Run Results

The estimation of the ARDL model for the static long-run effect is based on the Akaike Information Criterion (AIC). The two tables below show the results when GDP and FDI are made the dependent variable in two different scenarios.

Regressor	Coefficient	Standard Error	T-Ratio [Prob.]
LFDI	.10629	.056398	1.8847[.070]
LCO2	.30074	.050909	5.9073[.000]
LEGS	.63596	.068023	9.3492[.000]
INPT	-9.5892	.56025	-17.1159[.000]
Regressor	**Coefficient**	**Standard Error**	**T-Ratio [Prob.]**
LGDP	1.8194	.47752	3.8100[.001]
LCO2	-.75031	.22273	-3.3687[.004]
LEGS	-.18248	.36928	-.49415[.628]
INPT	11.5928	5.2401	2.2123[.041]

The first table shows that CO2 and EGS are significantly and positively correlated to GDP. An increase of 1 percent of CO2 and EGS would lead to increase of approximately 0.301 percent and 0.6636 percent of GDP respectively. This suggests that carbon emissions and exports determine the growth of GDP. As consumption of electricity and fuels increases, the productivity and exports also increase, thus, bring about GDP expansion. However, we find no significance of FDI in this case, possibly due to the factor stated earlier.

The second table shows that GDP and CO2 are significantly correlated to FDI. The former posits positive relationship while the latter exhibits negative relationship. An increase of 1 percent of GDP would lead to an increase of 1.819 percent of FDI while the same amount of increase in CO2 would lead to a decrease of 0.750 percent of FDI. This suggests that investors are generally concern about the environment, in addition to their consideration of a country's economic stability and growth.

Short-Run Dynamics

Dependent Variable	dLGDP	dLFDI	dLCO2	dLEGS
dLGDP(1)	.25082	3.8800*	.90733*	1.4058*
	(.14312)	(1.4221)	(.37130)	(.12965)
dLFDI(1)	.016351	1.0134*	-.12215	.0034646
	(.015593)	(.31252)	(.073278)	(.024712)
dLCO2(1)	.050877	-.64470*	.41868	-.066509
	(.030697)	(.30835)	(.55424)	(.048909)
dLEGS(1)	.57265*	-.36819	-.55285	.54242*

	(.053648)	(.76259)	(.30630)	(.16422)
Ecm(-1)	-.43899*	-2.0177*	-.47517*	-.52242*
	(.094451)	(.36877)	(.13255)	(.11505)
SC CHSQ(1)	.29098[.594]	.75886[.397]	.14678[.704]	.047472[.829]
FF CHSQ(1)	10.3859[.003]	.10171[.754]	2.3945[.130]	4.2148[.051]
N CHSQ(2)	.15816[.924]	1.1837[.553]	11.5226[.003]	.86035[.650]
HS CHSQ(1)	.0055279[.941]	2.8686[.099]	5.1519[.028]	.0019228[.965]

(*Indicates significance at 5% level or less)

The table above shows different sets of result based on the consideration of different dependent variables. The result suggests that FDI as a dependent variable tends to be significantly dictated by two other variables in the short-run. On the other hand, when GDP, CO2 and EGS are made dependent variable, they are only dictated by one other variable in their relative specifications. The result also exhibits similar concept to the previous long-run effect where increase in GDP and CO2 would lead to increase and decrease of FDI respectively.

Additionally, an increase in EGS leads to an increase in GDP, an increase in GDP leads to increase in CO2 and EGS in two separate models. Interestingly, in the Singapore context, we find that GDP and EGS display a bicausal relationship in the short-run. In our humble opinion, we think that Singapore is highly reliant on export activities due to its lack of natural resources. Basically, the country imports raw products such as petroleum, electrical appliances, machineries, chemicals and others, then refine those products before exporting them to other countries. The same goes to water supply; Singapore imports water from Johor Bahru, treats the water and exports it back to the Malaysian state. As Singapore's exports increase, its GDP and productivity increase, thus, allowing it to export more. This signifies a strong bicausal relationship between the two variables. The bicausal relationship between GDP and exports is in line with the findings of Hsiao & Hsiao (2006).

5.6 Variance Decompositions

The fact that VECM is not able to discern relative exogeneity or endogeneity of variables, we proceed with VDC test. The VDC essentially decomposes the variance of forecast errors of each variable and indicates the amount of information in the variable which is explained by

other variables. In other words, if a variable is mostly explained by itself, this signifies that the variable is highly exogenous. On the other hand, if a variable is mostly explained by other variables, then it appears to be the most endogenous.

For this step, first, we perform the generalized approach of VDC on the variables. This process does not depend on the particular ordering of the variables in the VAR and does not switch-off the other variables when a variable is shocked. Second, we perform the orthogonalized approach of VDC where the particular ordering of the variables influences the result, in addition to all the other variables are switched-off when a variable is shocked. The table below only shows the result for a time horizon of 4 and 8 years. A detailed information of the result over a ten-year period can be obtained from the appendix.

Generalized Approach

Horizon	Variable	LGDP	LFDI	LCO2	LEGS	Unadj. Total	LGDP	LFDI	LCO2	LEGS
4 Years	LGDP	95.29%	53.85%	4.36%	73.54%	227.05%	41.97%	23.72%	1.92%	32.39%
	LFDI	44.18%	87.28%	7.04%	42.33%	180.82%	24.43%	48.27%	3.89%	23.41%
	LCO2	1.86%	9.75%	99.98%	3.60%	115.19%	1.61%	8.46%	86.80%	3.13%
	LEGS	77.98%	51.55%	7.13%	93.80%	230.47%	33.84%	22.37%	3.09%	40.70%
	Exogeneity	95.29%	87.28%	99.98%	93.80%		41.97%	48.27%	86.80%	40.70%
	Ranking	2	4	1	3		3	2	1	4

Horizon	Variable	LGDP	LFDI	LCO2	LEGS	Unadj. Total	LGDP	LFDI	LCO2	LEGS
8 years	LGDP	94.68%	55.97%	4.66%	72.96%	228.27%	41.48%	24.52%	2.04%	31.96%
	LFDI	49.32%	78.34%	6.26%	49.67%	183.59%	26.87%	42.67%	3.41%	27.05%
	LCO2	1.87%	9.84%	99.98%	3.62%	115.31%	1.63%	8.53%	86.70%	3.14%
	LEGS	77.86%	53.99%	7.54%	93.00%	232.38%	33.50%	23.23%	3.24%	40.02%
	Exogeneity	94.68%	78.34%	99.98%	93.00%		41.48%	42.67%	86.70%	40.02%
	Ranking	2	4	1	3		3	2	1	4

Orthogonalized Approach

Horizon	Variable	LGDP	LFDI	LCO2	LEGS
	LGDP	95.29%	4.55%	0.07%	0.09%
4 Years	LFDI	44.18%	50.38%	2.52%	2.93%
	LCO2	1.86%	8.23%	89.92%	0.00%
	LEGS	77.98%	6.72%	0.74%	14.56%
	Exogeneity	95.29%	50.38%	89.92%	14.56%
	Ranking	1	3	2	4

Horizon	Variable	LGDP	LFDI	LCO2	LEGS
	LGDP	94.68%	5.14%	0.08%	0.10%
8 years	LFDI	49.32%	41.41%	4.28%	4.99%
	LCO2	1.87%	8.31%	89.82%	0.00%
	LEGS	77.86%	7.55%	0.78%	13.81%
	Exogeneity	94.68%	41.41%	89.82%	13.81%
	Ranking	1	3	2	4

The causal relationship can be summarized as follows:

Generalized Approach

Orthogonalized Approach

In both cases, the result corresponds to our theoretical expectation. Although the generalized approach indicates that GDP affects EGS, congruent to the ARDL approach of VECM, their

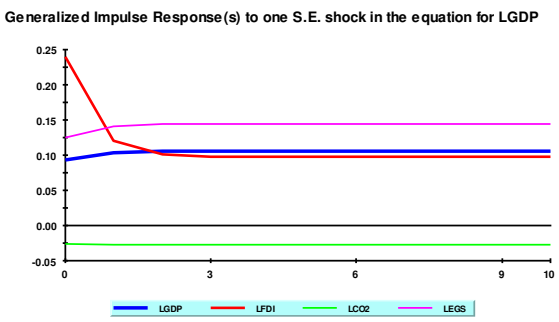
relationship is bicausal. Basically, when GDP affects EGS, it is indirectly inferring that EGS affects GDP due to the fact that higher growth caused by exports, actually means more prospect of increasing the exports. Furthermore, an increase in FDI implies that more capital can be allocated for exports.

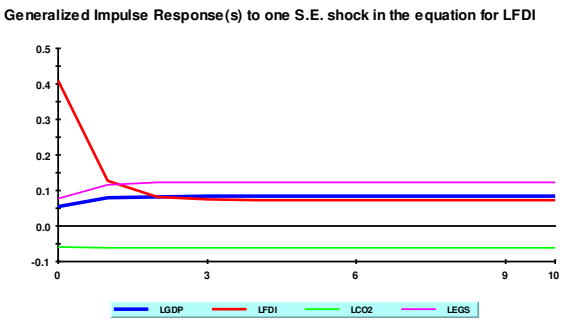
The orthogonalized approach on the other hand, shows that an increase in GDP would lead to more consumption of energy. This signifies more productivity, thus, attracts more investors to invest in the country. As the capital inflow increases, an increase in the amount of exports can be observed. Statistically however, the second approach tends to be contradictory to the previous result which indicates that FDI and CO2 are negatively correlated. Therefore, we consider the first approach to be more accurate.

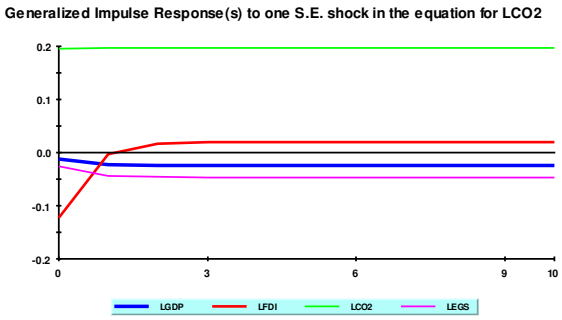
Nevertheless, the VDC results appear to be inconsistent with the standard VECM result which states that the FDI is endogenous. A possible explanation to this is that the standard VECM is based on the results from Johansen test. Thus, the limitations of Johansen are also elevated to VECM, further aggravated by the small sample size which restricts proper error correction model. However, the VDC results seem to be in tandem with the ARDL's VECM results; CO2 and EGS significantly affect GDP while GDP and CO2 affect FDI. This corresponds to generalized and orthogonalized VDC respectively.

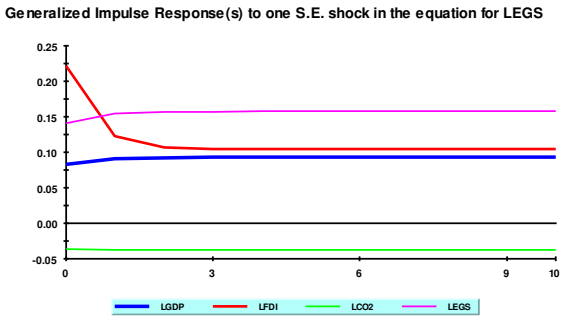
5.7 Impulse Response Functions

The IRF is technically similar to the VDC, but it is represented by graphs unlike VDC which is represented by numerical values. As CO2 is the most exogenous variable, the graphs show that CO2 does not react much from the shocks of other variables. However, all the other variables can be seen to respond to the variable-specific shocks.



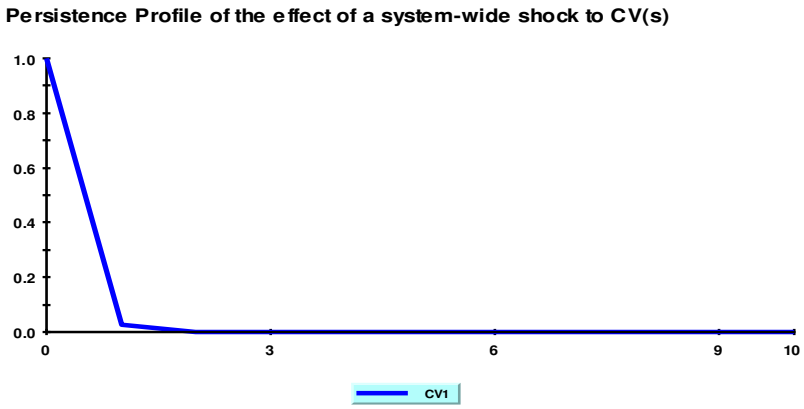






5.8 Persistence Profiles

Moving on to the final step of the standard time-series technique, we proceed to PP process. It is conceptually similar to the IRF, however, it involves shocking the cointegrating vectors using a system-wide shock from an external source. The main purpose for this is to examine the time horizon required for the variables to get back to equilibrium. The graph below suggests that it only takes one year for the variables to equalize.



5.9 Nonlinear Autoregressive Distributed Lag (NARDL)

In addition to the previous tests, we perform an NARDL test to complement this study. As the ARDL assumes symmetric and linearity despite having many advantages over the other cointegration tests, the application of NARDL would produce more insightful results as it does not assume the same. The variables of our interest are the FDI and CO2; we intent to examine whether they exhibit symmetrical relationship or not.

5.9.1 Cointegration Test Statistics

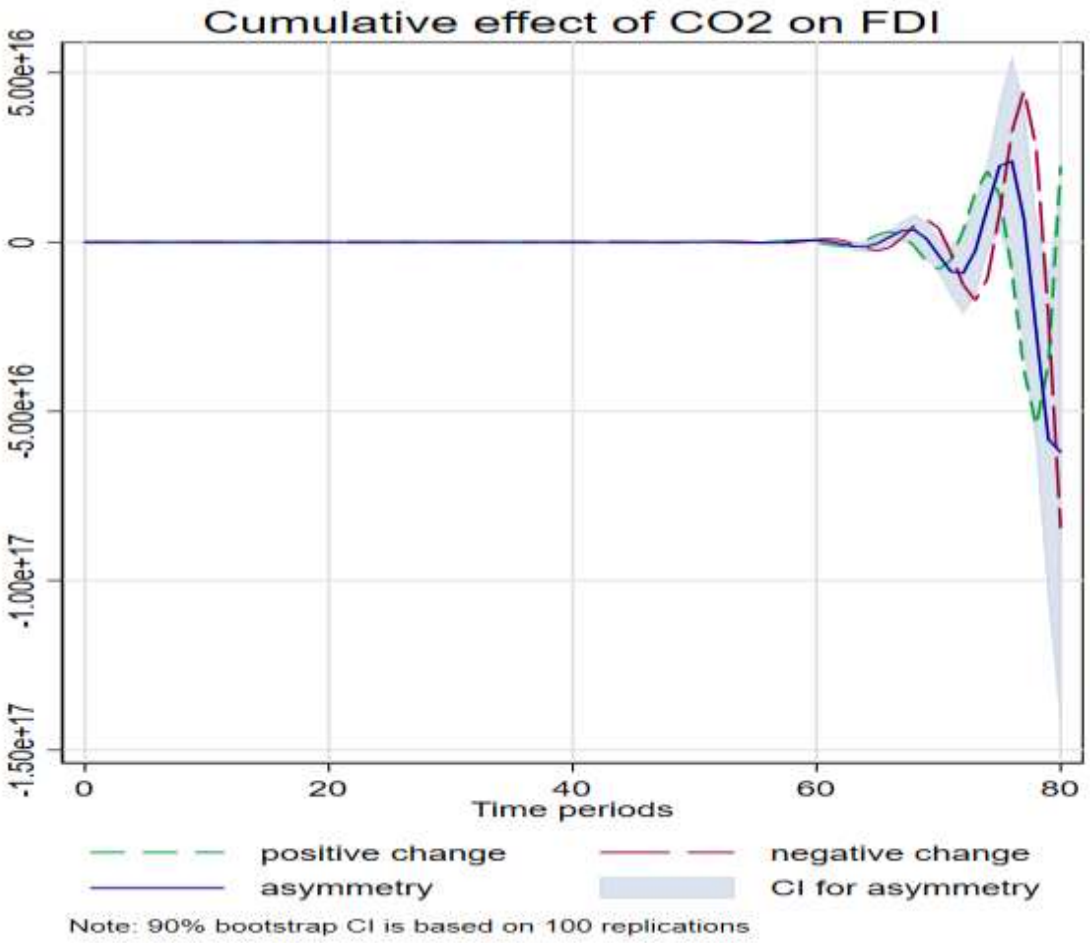
VARIABLE	F-STAT.	99% Critical Value		RESULT
		LOWER C.V.	UPPER C.V.	
CO2	9.9093	5.15	6.36	Cointegration

The table above shows that the two variables are cointegrated in the long-run. Similar to the ARDL test, it adopts F-statistic to determine the result. The null hypothesis is that the variables are jointly insignificant. As the F-value is higher than the upper critical value, we reject the null; the variables are statistically proven to be jointly significant or cointegrated.

5.9.2 Long-run and Short-Run Symmetric Test

INDEP. VARIABLE	EFFECT	F-STAT.	SPECIFICATION
CO2	Short-Run	.001154[.973]	Symmetry
	Long-Run	.7852[.392]	Symmetry

Using the Wald test, we examine the relationship between FDI and CO2, whether or not they are asymmetric. The table above reveals that they are both symmetrically related in the long-run and short-run, thus, a symmetric model (ARDL) turns out to be more appropriate. The null hypothesis for this test is, the variables are significantly indifferent. As the P-values of the F-statistic exceed 5 percent in both long-run and short-run models, we fail to reject the null.



The graph above shows the cumulative effect of carbon emissions on FDI inflows. The positive and negative changes can be observed to lie within the confidence interval or the shaded are, implying that the symmetrical relationship is statistically significant. The changes also reveal symmetric patterns where the positive changes move in the opposite direction of the negative changes and vice-verse.

6.0 CONCLUSION AND POLICY IMPLICATIONS

This study examines the theoretical and causal relationships between GDP, FDI, CO2 and EGS. The results revealed that all the variables are cointegrated in the long-run, but inconclusive results are obtained in the short-run. The study also suggests that carbon emission appears to be the most exogenous variable while exports of goods and services turn out to be the least. In addition, we found out that CO2 and FDI are symmetrically cointegrated in the long-run. Objectively, the study corroborates that investors and multinational corporations are generally mindful of the environment, thus, influencing their investment decisions in a particular country. This, in turn, affects the GDP and net exports of the country.

We humbly propose that every country moves toward reducing its carbon emissions by any means necessary. After all, this effort does not only protect the environment, it also provides higher prospect of FDI inflows and profits, in addition to other benefits. This is especially true for countries which are highly reliant on FDI due to their open economic setting. The fact that carbon emission is the most exogenous variable, it implies that Singapore or other countries can hit the variable to aim for GDP growth. This can be observed in Singapore's attempt to reduce its carbon emissions by enacting the Carbon Pricing Act early this year, which imposes carbon tax on a certain rate of carbon emissions (National Environment Agency, 2019). Thus, it is an operation which walks in line with the saying, "*no pain, all gain*".

The study, however, has some limitations which might have had an influence on the overall result. Firstly, the data employed in this study is based on annual intervals, thus, the accuracy and sensitivity of the results are debatable. Second, the limited availability of data restricts the study to only 48 observations, thus, inflicts small sample size issues. Third, the model considers four variables which are assumed to be of importance in this study, thus, some potentially more important indicators might have been excluded. Taking into account these limitations, further studies might consider a larger dataset, specify the sources of carbon emissions to only high emissions such as factories and industries, or might also consider to include the ageing population's contribution to the carbon emissions.

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