Panel Dataset to Assess Proactive Eco-Innovation in the Paradigm of Firm Financial Progression

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Abstract: Recently, eco-innovation has received a lot of attention in the academic and corporate world due to its potential to accelerate firm financial progression. To measure eco-innovation, mostly primary data and a reactive approach were employed. By emphasising the proactive approach and utilising a secondary panel dataset, this study fills the existing research gap. Data presented in this paper comprise 31 energy firms from Bursa Malaysia for the years between 2015 and 2019. Panel data associated with eco-innovation proactiveness and firm financial progression were collected from three different sources such as company websites, annual reports, and sustainability reports using content analysis. For data collection, an index was adapted comprising five dimensions of eco-innovation, named as product, process, technology, organizational, and marketing. In addition to that, Tobin's Q was considered as a proxy dimension for firm financial progression because it considers both market value as well as book value. Following a unit root test, six specific data diagnostic tests were performed to ensure data reliability and validity for future potential usage. The results reveal that the panel dataset was organised and is eligible for further statistical model analysis.

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Dataset: <https://data.mendeley.com/datasets/335vpkktm3/1>.

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1. Summary

Recently, the awareness and understanding of eco-innovation among all stakeholders have created pressure on firms to act proactively. The role of proactiveness in eco-innovation has received increased attention across a number of disciplines in the new normal era due to its potential towards increasing firm financial progression. In the light of recent events such as Agenda 2030 and billion-dollar projects in eco-innovation, it is becoming tremendously hard to overlook the reality of proactiveness. However, it is interesting to note that most of the studies in the eco-innovation domain were conducted reactively and using primary data [1–4]. By emphasising a proactive eco-innovation approach and utilising a secondary panel dataset, this study fills a research gap that currently exists.

It is argued that panel data produce highly reliable information with greater flexibility and efficiency. Furthermore, panel data eliminate the drawbacks of primary data, cross-sectional data, and time series data. Additionally, firm financial progression is considered as one of the prime yardsticks for future investment. Therefore, this study collected panel data for both proactive eco-innovation and financial progression.

For the collection of panel data, an index based on proactiveness was adapted comprising five dimensions of eco-innovation, named as product, process, technology, organizational, and marketing. In addition to that, Tobin's Q was considered as a proxy

dimension for firm financial progression because it considers both market value as well as book value. A reflection of market value is important for future probable investors to justify their investment.

The dataset in this study comprised of 31 publicly traded energy firms from Bursa Malaysia between the years of 2015 and 2019. There were twofold reasons to choose the publicly traded energy companies. First, publicly traded firms have high market capitalization and prospective investors may be more interested in investing in those companies in the stock exchange [5]. Furthermore, they disclose their financial and sustainability reports regularly, in addition to their initiatives concerning eco-innovation [5,6]. Second, energy resources such as crude oil and coal have long been acknowledged to be some of the most important components for economic progress for an emerging country such as Malaysia [7–9].

Panel data for this study were collected and accumulated from company websites, annual reports, and sustainability reports using a content analysis approach. Generally, the annual reports and sustainability reports of publicly listed firms are audited and certified [4–6,10,11]. As a result, general investors may rely on the audited papers for future investments, and these reports are reliable sources of information that are available to prospective investors. In addition, publicly listed companies acknowledge their eco-innovation initiatives and activities in both annual reports and sustainability reports.

2. Data Description

As discussed in the previous section, this study focused on publicly traded energy companies in Malaysia. According to the Bursa Malaysia website, there are 31 energy firms. Data were collected for a total of 5 years (2015, 2016, 2017, 2018, and 2019) for 31 companies from three different sources, such as a respective company's website, their sustainability reports, and most importantly, company annual reports. All the data were accumulated into a Microsoft Excel file (Supplementary Materials), followed by their input into STATA 14.2 for further analysis. For further data analysis, five econometric models were developed on the basis of eco-innovation proactiveness and firm financial progression, as illustrated in Table 1. The first model was based on product eco-innovation, the second model was based on process eco-innovation, the third model was based on technology eco-innovation, the fourth model was based on organizational eco-innovation, and the fifth model was based on marketing eco-innovation.

Table 1. Econometric Model.

Model	Explanation
Model 1 (Product eco-innovation)	$TQ = \beta_0 + \beta_1 \text{prod_eii} + \varepsilon$
Model 2 (Process eco-innovation)	$TQ = \beta_0 + \beta_1 \text{proc_eii} + \varepsilon$
Model 3 (Technology eco-innovation)	$TQ = \beta_0 + \beta_1 \text{tech_eii} + \varepsilon$
Model 4 (Organizational eco-innovation)	$TQ = \beta_0 + \beta_1 \text{org_eii} + \varepsilon$
Model 5 (Marketing eco-innovation)	$TQ = \beta_0 + \beta_1 \text{mark_eii} + \varepsilon$

Note.

TQ = Tobin's Q

$TQ = (MVE + PS + DEBT) / \text{Book Value of total Assets of firm}$

MVE = Firm's Share Price $\times$ Common Shares outstanding

PS = Liquidating Value of Preferred Stock

DEBT = Value of Short-Term Liabilities

β = (Beta) or Drift Element

$\beta_1, 2 \dots k$ = Slope Coefficients (Coefficient of independent variables)

ε = Epsilon (Error Term)

prod_ei = Product eco-innovation;

proc_ei = Process eco-innovation;

tech_ei = Technology eco-innovation;

org_ei = Organizational eco-innovation;

mark_ei = Marketing eco-innovation.

2.1. Descriptive Statistics

To begin, descriptive statistics are given for 155 observations (31 businesses $\times$ 5 years) from the panel data. The average values in the descriptive study of proactive eco-innovation dimensions were positive. With a mean of 1.48 and a standard deviation of 0.77, and a low of 0.43 and a high of 3, product eco-innovation had a mean of 1.48 and a standard deviation of 0.77. Process eco-innovation had a mean of 1.52 and a standard deviation of 0.70, with a low of 0.64 and a maximum of 3. It had a mean of 1.52 and a standard deviation of 0.70, with a minimum of 0.64 and a maximum of 3. With a minimum of 0.5 and a high of 2.88, technology eco-innovation had a mean of 1.39 and a standard deviation of 0.72. The mean of organisational eco-innovation was 1.39, with a standard deviation of 0.76, and a minimum of 0.33 and a maximum of 3. The marketing eco-innovation dimension had a mean of 1.29, a standard deviation of 0.80, and a minimum and maximum value of 0.0 and 3. The marketing eco-innovation dimension had a mean of 1.29, a standard deviation of 0.80, and a minimum and maximum value of 0.0 and 3. The mean of proactive eco-innovation dimensions was 1.41, with a standard deviation of 0.72, a minimum value of 0.44, and a maximum value of 2.84. For the five aspects, process eco-innovation had the highest average value of 1.52, while marketing eco-innovation had the lowest average of 1.29.

Tobin's Q had a mean of 1.14 and a standard deviation of 0.60, with a minimum of 0.30 and a high of 3.47. Firm size (log value of total assets) had a mean of 6.20, a standard deviation of 0.53, a minimum of 5.01, and a maximum of 7.57. Table 2 presents a summary of the statistics.

Table 2. Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max
Product eco-innovation	1.4789	0.7736	0.43	3.00
Process eco-innovation	1.5192	0.7014	0.64	3.00
Technology eco-innovation	1.3905	0.7227	0.50	2.88
Organization eco-innovation	1.3860	0.7584	0.33	3.00
Marketing eco-innovation	1.2945	0.7995	0.00	3.00
Tobin's Q	1.1423	0.6052	0.30	3.47

Source: Authors' own analysis.

2.2. Unit Root Analysis

Before performing a unit root test, the dataset was first defined as panel data. The unit root test determines whether a variable in panel dataset is stationary or nonstationary. The primary purpose for performing a panel unit root test is to determine whether a time series is stationary, or whether a change in time does not induce a change in the distribution's shape. Unit roots are one of the causes of non-stationarity. This test is known to have low statistical power. Simply, stationarity means the statistical properties of a particular time series data do not change over time. It is considered to be an important part of the analysis of panel data because many relevant and appropriate analytical tools, statistical tests, and model analyses largely depend on it. Because of the limited sample size, Hardri's (2002) test was used in this research [12]. Table 3 indicates that for this test, all null hypotheses were accepted and alternative hypotheses were rejected. As a result, it can be shown that all of the panels in this research have stationarity. The p -values for product eco-innovation, process eco-innovation, technological eco-innovation, organizational eco-innovation, and marketing eco-innovation were less than 0.05, suggesting that all variables are stationary. Furthermore, Tobin's Q yielded the same result, indicating that all variables in this panel dataset are stationary.

Table 3. Result of unit root test.

Ho: Panels Are Stationery and Ha: Panels Comprise Unit Roots		
	Statistic	
product eco-innovation	z	7.2292
	p-value	0.000
process eco-innovation	z	7.9354
	p-value	0.000
technology eco-innovation	z	7.1884
	p-value	0.000
Organizational eco-innovation	z	7.6754
	p-value	0.000
Marketing eco-innovation	z	6.9343
	p-value	0.000
Tq (Tobin's Q)	z	7.6510
	p-value	0.000

Source: Authors' own analysis.

2.3. Data Diagnostics Tests

Data can be divided into parametric and nonparametric data. Parametric data rely on regression assumptions, while no such assumption applies to nonparametric data. Moreover, previous studies have reported that parametric data must fulfil all the assumptions before regression and model analysis can be performed [13–16]. Therefore, without verifying these fundamental assumptions, results may be ambiguous and unsatisfactory. Following the previous discussion, the panel dataset was diagnosed by the following tests to fulfil the fundamental regression assumptions.

2.3.1. Outlier Identification

An outlier is defined as an observation that differs from the rest of the sample by a substantial amount [15–18]. When a panel dataset contains outliers, regression analysis becomes problematic. The best techniques for removing outliers from a data collection are the box plot practice and Cook's distance assessment [16,17,19]. The box plot method aids in the visualisation of outliers, whereas Cook's distance analysis depicts the extra effects of outliers on the dataset. Cook's distance analysis has a thresh-old range of 3 metres [20,21]. Table 4 shows the results of the Cook's distance test, which shows that the residual results for smallest and maximum, inside the border, and not above the threshold of 3. Figure 1 depicts the results of outlier identification for the dependent dimension.

Table 4. Result of Cook's distance assessment.

	Minimum	Maximum	Mean	Std. Deviation
Cook's distance for TQ (Tobin's Q)	0.000	0.084	0.007	0.013

Figure 1. Cook's distance result box plot.

2.3.2. Test for Normality

Normality is assumed and considered for different statistical analyses, such as t-tests, regression, and ANOVA. This clarifies that the sample of the research should be drawn from a normally distributed population which is in the form of a bell or an inverted-U shape. Therefore, after the elimination of outliers from the dataset, normality needs to be ensured in the dataset for further analysis. There are several techniques to test the normality in data, such as P–P plot (probability–probability plot), skewness and kurtosis tests, frequency distribution (histogram), boxplot, and Q–Q plot (quintile–quintile plot). Before conducting the regression analysis, skewness and kurtosis examination were used to validate the assumption of normality [17,18]. Skewness and kurtosis should be used to determine aspects of data normality. The statistics for each dimension in eco-innovation should be between 1.96 and 2.58 at an alpha of 0.05 and 0.10 [16,21]. Table 5 shows that the threshold range (1.96 at alpha of 0.05 and 2.58 at alpha of 0.10) did not contradict the basic assumption of normality, demonstrating that the dataset for this panel data study had ensured normality.

Table 5. Statistics of skewness and kurtosis.

	Statistics of Skewness	Statistics of Kurtosis
Product eco-innovation	0.577	−1.111
Process eco-innovation	0.704	−0.889
Technological eco-innovation	0.750	−0.864
Organizational eco-innovation	0.593	−1.090
Marketing eco-innovation	0.410	−0.774
Tobin's Q	1.648	2.090

2.3.3. Multicollinearity Test

After illustrating the data for normality, the next phase was to investigate multicollinearity. The parameters and projected findings could be skewed and inconsequential due to the presence of a high-level multicollinearity in the data. [21,22]. As a result, prior to conducting the regression, it is necessary to detect the presence of a strong correlation [23]. The variance inflation factor (VIF) is a method for detecting multicollinearity among variables that was carried out in this research using STATA 14.2 [24]. As indicated in Table 6, none of the models in this study had VIF values that were higher than the threshold range (average value of VIF = 3.96).

Table 6. Result of VIF.

	Statistics (VIF)	Statistics (1/VIF)
Model 1 (product eco-innovation)	1.051	0.9515
Model 2 (process eco-innovation)	1.035	0.9662
Model 3 (technological eco-innovation)	1.069	0.9355
Model 4 (organizational eco-innovation)	1.070	0.9346
Model 5 (marketing eco-innovation)	1.046	0.9560

2.3.4. Test for Heteroscedasticity

This research examined the heteroscedasticity in the data after multicollinearity analysis to guarantee non-bias and a significant regression model analysis. As a result, the Breusch–Pagan test was used to detect a heteroscedasticity issue in the dataset. If the p -value is less than 0.05, the panel dataset has a heteroscedasticity issue, according to the universal rule [25]. The findings of testing with the five models that used the heteroscedasticity test to describe the nature of data are discussed in the next section. The p -value (probability > chi2) for all five models was less than 0.05, suggesting that the panel data for this study had a heteroscedasticity problem [26]. Tables 7–11 provide the specifics of each model outcome. The random effect robust model, on the other hand, may be used to remove heteroscedasticity from the data in order to conduct model analysis [27]. As a result, the panel dataset's heteroscedasticity may be eliminated by employing a random effects model.

Table 7. Product eco-innovation (Model 1).

$tq[Company,t] = Xb + u[Company] + e[Company,t]$		
Estimated Results:		
	Var	sd = sqrt(Var)
tq	0.366305	0.6052313
e	0.0825608	0.287334
u	0.2396043	0.4894939

Test: Var(u) = 0; chibar2(01) = 151.83; Prob > chibar2 = 0.0000.

Table 8. Process eco-innovation (Model 2).

$tq[Company,t] = Xb + u[Company] + e[Company,t]$		
Estimated Results:		
	Var	sd = sqrt(Var)
tq	0.366305	0.6052313
e	0.0820641	0.2864682
u	0.2229383	0.4721634

Test: Var(u) = 0; chibar2(01) = 149.06; Prob > chibar2 = 0.0000.

Table 9. Technological eco-innovation (Model 3).

$tq[Company,t] = Xb + u[Company] + e[Company,t]$		
Estimated Results:		
	Var	sd = sqrt(Var)
tq	0.366305	0.6052313
e	0.0830915	0.288256
u	0.2348743	0.4846383

Test: Var(u) = 0; chibar2(01) = 145.75; Prob > chibar2 = 0.0000.

Table 10. Organizational eco-innovation (Model 4).

$tq[Company,t] = Xb + u[Company] + e[Company,t]$		
Estimated Results:		
	Var	sd = sqrt(Var)
tq	0.366305	0.6052313
e	0.080285	0.2833461
u	0.2381306	0.4879863

Test: Var(u) = 0; chibar2(01) = 159.12; Prob > chibar2 = 0.0000.

Table 11. Marketing eco-innovation Model 5.

$tq[Company,t] = Xb + u[Company] + e[Company,t]$		
Estimated Results:		
	Var	sd = sqrt(Var)
tq	0.366305	0.6052313
e	0.0830817	0.288239
u	0.2342102	0.4839527

Test: Var(u) = 0; chibar2(01) = 140.26; Prob > chibar2 = 0.0000.

2.3.5. Test for Serial Correlation

The error terms from various time periods are linked in serial correlation analysis. Serial correlation is most often seen in time series and panel data investigations. If a serial correlation is found in a dataset, it results in a biased model that is unsuitable for advanced data analysis. As a consequence, the Durbin–Watson investigation was employed to detect the problem of serial correlation. Table 12 shows the Durbin–Watson outcome for serial correlation for five models on eco-innovation developed under this study. If the statistical values in regression model analysis are either two (2), near two (2), or less than two (2), then there is no serial correlation in the dataset, according to the universal rule for Durbin–Watson analysis. [14,28]. The following Table 12 shows that this research had no serial association based on this threshold level range.

Table 12. Result of Durbin–Watson test.

	Statistics
Model 1 (product eco-innovation)	0.738
Model 2 (process eco-innovation)	0.767
Model 3 (technological eco-innovation)	0.736
Model 4 (organizational eco-innovation)	0.703
Model 5 (marketing eco-innovation)	0.773

2.3.6. Test for Endogeneity

If an explanatory variable is correlated with the error term, then endogeneity is considered to exist in the data. Endogeneity is a problematic issue for further analysis, which deems the findings of the regression model analysis biased and insignificant. Endogeneity issues arise either due to measurement error or reverse causality of an omitted variable [14]. The Hausman test was used in this research to identify endogeneity in the data. If the p statistics of the Hausman analysis result is greater than 0.05, the dataset is not endogenous. Table 13 shows the outcomes of the Hausman examination, which indicate the panel dataset to be free of endogeneity [29].

Table 13. Result of Hausman test.

	Test Result	
	Statistics	p -Value
Model 1 (product eco-innovation)	1.18	0.120
Model 2 (process eco-innovation)	1.28	0.163
Model 3 (technological eco-innovation)	2.52	0.340
Model 4 (organizational eco-innovation)	0.33	0.062
Model 5 (marketing eco-innovation)	2.59	0.370

3. Methods

Data collection methods are an indispensable part of every empirical study. Data were collected from secondary sources, named as company websites, company annual reports, and company sustainability reports. There are two parts to this panel dataset. First, proactive eco-innovation data which were collected through four categorical content analyses, and second, firm financial progression data which were collected through using Tobin's Q ratio. However, there are some limitations of this method. First, this study only focused on energy sector data, and second, financial data access was very limited. Table 14 illustrates more about the data collection instruments regarding eco-innovation proactiveness and financial progression.

Table 14. Summary of instruments for panel data collection.

Variable	Dimensions of Eco-Innovation	Instrument/Index	Content Analysis
Proactive Eco-innovation	Product	Seven indicators recommended in García-Granero et al. (2018). [30]	0 = information not available, 1 = only brief information, 2 = Detailed information 3 = Detailed description with future strategies on innovation.
	Process	Eleven indicators recommended in García-Granero et al. (2018) [30]	
	Technological	Eight indicators proposed in Arundel and Kemp (2009) [31]	
	Organizational	Nine indicators proposed in García-Granero et al. (2018) [30]	
	Marketing	Three indicators proposed in García-Granero et al. (2018). [30]	
Firm Financial Progression	Tobin's Q	$TQ = (MVE + PS + DEBT) / \text{Book Value of total Assets of firm}$	

Source: Authors' own analysis.

4. User Notes

The panel dataset will be useful for a future comparative study between proactive eco-innovation and reactive eco-innovation. Furthermore, it is the first-ever data collection regarding proactive eco-innovation. Additionally, this dataset can be reused for further insights through investigating cross-country findings in comparison with another emerging economy. Finally, this dataset can also be useful for meta-analysis and bibliometric analysis in an eco-innovation study, and due to the nature of this panel dataset, it will be used for empirical investigation in a subsequent proactive eco-innovation study.

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