Is Greenhouse Gas Emission a New Player in Corporate Bankruptcy Prediction?

Shaonan Tian*
San José State University, San Jose, California, USA

Xu Hartling
Salem State University, Salem, Massachusetts, USA

In this work, we explore how a company's sustainability performance may affect its financial performance in terms of its distress risk using a comprehensive bankruptcy database in the manufacturing sector. We adopt a discrete hazard model to examine the linkage between the Greenhouse Gas (GHG) emission and the corporate default risk at different prediction horizons. Our limited empirical study shows that when the prediction horizon is shorter than 2-years, higher value of the GHG emission predictor variable would correlate to a lower default risk. On the other hand, when the prediction window is longer than 2-years, high default risk is usually linked with high GHG emission values or poor sustainability performance. Such results may suggest that the financial return on being sustainable is rather long term. The investment on being green might present some financial hurdles in a short term. But in a long run, companies with better environmental performance demonstrate lower default risk.

* Corresponding Author. E-mail address: shaonan.tian@sjsu.edu

I. INTRODUCTION

Sustainability has become increasingly important in today's competitive business world since it was first introduced by the United Nations in 1987 (United Nation, 1987). Economic, environmental, and social are three dimensions of sustainability. In the past 30 years, companies have developed corporate strategies to integrate their financial performance, environmental performance and corporate social responsibility (CSR). Take manufacturing industry as an example. To protect the environment and fulfill their social responsibility, manufacturing companies have produced more new or redesigned environmentally friendly products and have "greened" their manufacturing processes to reduce greenhouse gas emissions. Early evidence showed strong environmental performance leads to lower manufacturing costs by eliminating waste (Schmidheiny, 1992). Also, the financial performance at these companies has increased as a result of expanding the market and superseding competitors who fail to demonstrate strong environmental performance (Klassen & McLaughlin, 1996). Later on, the movement of integrating three dimensions of sustainability was facilitated by Kyoto Protocol that entered into force in 2005

(United Nations, 1997). Kyoto Protocol, adopted in Kyoto, Japan in 1997, underlines the key role of industrialized countries in battling climate change and highlights the responsibility of companies towards the natural environment and sustainable development.

It becomes clear that CSR is among various reasons including legislation, eco-efficiency, consumers, international market, public tenders and purchases, retailers/distributers, investors, financial and insurance entities, competitive pressures, pressure groups, employees, and internal pressures that companies adopt an environmental perspective in their corporate strategies (Mera & Palacios, 2004). For many companies, being environmentally sustainable has gone from an add-on function to an integral part of business operations as it is often viewed as central to a corporate mission and thus integrated into all levels of strategies. Having strong environmental performance can eventually be the best way of pursuing competitive strategy (Orsato, 2006; Roy & Vezina, 2001).

Although CSR is viewed as the ultimate motivation for better environmental performance in many companies, early strategy literature suggested that theoretically companies could improve their financial performance as a result of revenue increase (McGuire, Sundgren, & Schneeweis, 1988). This suggested benefit serves as the theoretical starting point for early research such as Klassen and McLaughlin (1996). Recent research on the linkage of environmental performance and financial performance has been extensively studied. However, there is no concrete conclusion to classify this relationship. Although some research suggests no differences in the financial performance for environmentally sustainable companies (Santis, Albuquerque, & Lizarelli, 2016), a number of studies support the positively correlated relationship between environmental performance and financial performance (Charlo, Moya, & Muñoz, 2015; Jackson & Singh, 2015; Lucas & Noordewier, 2016). This is the first motivation of this paper that is to explore the relationship of environmental performance and financial performance. Specifically, we are interested in using corporate greenhouse gas emission as one measurement of environmental performance among many others such as air pollutants, toxic releases, and water withdrawal.

Additionally, existing literature pays close attention to relatively clean and proactive companies that adopt an environmental perspective and their financial performance. Little or no attention has been given to companies failed to bring environment factor to their business planning. These companies may suffer from losing the market driven by environmentally conscious consumers and eventually fail in such competitive business setting. Furthermore, much of the literature focuses on evaluating the financial performance in terms of corporate profit either through revenue gains or cost savings (Klassen & McLaughlin, 1996). Existing literature suggests a need for exploring other financial performance metrics (e.g., default risk) and new linkages to existing corporate bankruptcy literature. This is our second motivation.

In this paper, we explore the possibility of linking greenhouse gas emission to negative financial performance expressed as corporate bankruptcy. Specifically, we introduce greenhouse gas (GHG) emission to the U.S. bankruptcy database. We find adding the GHG variable would improve the model's prediction performance in forecasting default. For one-year ahead prediction, the GHG emission variable enters the bankruptcy prediction model with weak negative sign. This indicates that low GHG emission would not help in reducing its financial distress risk for

12-month prediction window. This may be due to the financial hurdle presented by the investment in the "greening" process. However, the GHG emission variable changes behavior when the prediction horizon extends to 3-years or more. In particular, the GHG emission enters the model with more significant positive sign for 36-month, 48-month and 60-month ahead prediction. Such finding may suggest the return on being green is rather long term. For companies that maintain decent environmental performance with moderate greenhouse gas emission, the risk of being default would be considerably lower comparing to others in a long run.

The remaining of the paper is organized as follows. Section 2 summarizes the literature review. Section 3 describes our bankruptcy database. Section 4 presents the methodology we used in terms of the bankruptcy prediction model and the sustainability performance measure we used in this work. Section 5 shows our empirical results. Section 6 concludes the paper and points out our future direction.

II. LITERATURE REVIEW

2.1. Environmental Performance and Financial Performance

Does a company that strives to gain or maintain positive environmental performance have financial advantages over its competitors, or is environmental performance just an extra cost hurting the financial performance of these companies? The need for rigorous research into the linkage between environmental performance and financial performance could be traced back 20 years ago (Klassen & McLaughlin, 1996). Klassen and McLaughlin (1996) defined environmental performance as a measurement of "how successful a firm is in reducing and minimizing its impact on the environment". Significant positive stock returns were observed following positive environmental events (such as environmental performance awards), but significant negative returns for weak environmental management as indicated by environmental crises. Additional analysis on manufacturing firms suggested that first-time award winners had smaller return increase compared to firms in other industries. This suggested market skepticism in evaluating historically environmentally dirty industries such as manufacturing. The time frame used in the event study was 200 days (short term, less than one year).

Stefan and Paul conducted a systematic overview and provided empirical evidence of improving a company' environmental performance can lead to better economic or financial performance, and not necessarily to an increase in cost (Stefan & Paul, 2008). They systematically analyzed the mechanism involved in each of the following channels of potential revenue increase or cost reduction because of better environmental practices: (a) better access to certain markets; (b) differentiating products; (c) selling pollution-control technology; (d) risk management and relations with external stakeholders; (e) cost of material, energy, and services; (f) cost of capital; and (g) cost of labor.

A recent study of 941 publicly traded U.S. manufacturing firms suggests that within dirty and non-proactive industries there is a positive marginal effect on firm performance as a result of engaging in environmental management practices (Lucas & Noordewier, 2016). The effect on financial performance of implementing environmental management practices is greater in relatively dirty and non-proactive industry contexts than in relatively clean and proactive contexts. Another study using sustainability index shows that socially responsible companies obtain higher profits for the same level of systematic risk and show greater sensitivity to market changes, leverage levels, and company size (Charlo, Moya, & Muñoz, 2015). Multidimensional scaling technique is used to examine the relationship of environmental and financial performance of firms in the U.S. food and beverage supply chain (Jackson & Singh, 2015). Findings suggest that firms with higher environmental rankings tended to perform better financially than those ranked lower.

Another study reports on a new objective data set detailing the environmental performance of the Standard and Poor's 500 companies (Cohen, Fenn, & Naimon, 1995). The study uses two “portfolios” consisting of the “low pollution” and “high pollution” firms in their respective industries. The main finding is that the “low pollution” portfolio does as well as - and often better than - the “high pollution” group.

On the other hand, many previous research studies that attempt to relate environmental performance to financial performance have often led to conflicting results due to small samples and subjective environmental performance criteria (Shameek & Cohen, 2001).

Also, many studies suggest there is no directly positive relationship between corporate environmental performance and financial performance. There is merely an indirect relationship that relies on the mediating effect of a firm's intangible resources. This conclusion is supported by a database comprising 599 companies from 28 countries (Surroca, Tribo, & Waddock, 2010).

Even if there is a link between environmental performance and financial performance, the relationship is quite weak. Using a time series fixed effects statistical approach, the relation between environmental performance and financial performance is much weaker than previously thought (Nelling & Webb, 2009).

There are many reasons that lead to various previous conflicting conclusions. For example, shortcomings exist in the methods applied in most previous quantitative empirical studies on effects of environmental performance on financial performance of firms (Telle, 2006). The conclusion to the claim of “it pays to be green” is unwarranted.

It is critical to understand the relationship between environmental performance and financial performance. Previously, researchers attempted to establish a positive correlation between environmental performance and financial performance to invoke environmental awareness (Telle, 2006). A positive effect of environmental performance on financial performance could also be used to argue that certain environmental regulations could be relaxed (Orlitzky, Schmidt, & Rynes, 2003). That is, if company management perceives “it pays to be green”, they have economic incentives to implement environmentally sensitive production methods, which reduces the need for further government interventions to sustain good environmental performance (Telle, 2006).

A meta-analysis of 52 studies over a 35-year period confirms a positive relationship between environmental performance and financial performance, however, this relationship varies according to the environmental management variables used by researchers, which confirms the need to address the environmental performance measurement problem in order to obtain consistent results across studies (Albertini, 2013). The analysis also pointed out that this relationship is not significant when financial performance is measured by market-based indicators. Another important conclusion drawn from the meta-analysis is that a short period of time may not be the best way to consider and to address the environmental issue.

It becomes clear that existing literature cannot answer whether "it pays to be green" or whether "it pays to operate in green industries" (King & Lenox, 2001). It was discussed that how a firm's attributes and different strategies for environmental improvement may jointly cause both pollution reduction and financial gain and thereby create the appearance of a direct relationship between the two. However, there is still lack of confidence to verify the direction of causality: do more profitable firms invest more in environmental performance or does environmental performance lead to profit? It may be that it pays to reduce environmental impact by certain means and not others. Alternatively, it may be that only firms with certain attributes can profitably reduce their environmental impact. The study suggests that "when does it pay to be green?" may be a more important question than "does it pay to be green".

The literature suggests both environmental performance and financial performance could be measured using various factors. Environmental performance awards (Klassen & McLaughlin, 1996), environmental management practices (Lucas & Noordewier, 2016), conventional pollutions (Cohen, Fenn, & Naimon, 1995), and GHG emissions (CDP, 2016) are among many examples to measure environmental performance. Similarly, financial performance can be evaluated in many ways. The literature focuses on evaluating the financial performance in terms of corporate profit either through revenue gains or cost savings (Klassen & McLaughlin, 1996). Existing literature suggests a need for exploring other financial performance metrics especially from the negative aspect. Default risk has been considered as one of the most commonly used measures of negative financial performance. We chose to use default risk to represent financial performance from a negative point of view. Therefore, we narrow down our interests to default risk bringing the sustainability aspect (GHG emissions) to corporate bankruptcy literature.

2.2. Corporate Bankruptcy Prediction

Forecasting a company's health status has long been an important issue in the literature. Earlier studies have routinely adopted a variety of accounting-based and market-based variables. For example, in Beaver (1966), Altman (1968), Ohlson (1980), and Zmijewski (1984), they have adopted accounting-based predictor variables constructed from reported accounting data to estimate the default risk. Recent work including Shumway (2001), Campbell, Hilscher, and Szilagyi (2008) and Tian, Yu and Guo (2015) added market-based variables in an attempt to improve the empirical performance of the default prediction model. It has been very popular to consider market-based variables and accounting-based variables in the bankruptcy literature as candidate default-risk predictors. However, sustainability has never been studied in corporate bankruptcy prediction model. This work allows us to shed light on this issue by including an approximate measure of the company's environmental performance, greenhouse gas emission, for the first time in bankruptcy prediction model. To the best of our knowledge, this is the first work to explore the link between a company's GHG emission and its default risk. Our analysis shows interesting findings to answer, "when does it pay to be green".

III. BANKRUPTCY DATABASE

In our study, we construct the bankruptcy database by merging daily and monthly CRSP equity data with annually updated accounting data from COMPUSTAT for all companies in manufacturing sector from 1980 to 2015. In total, we observe 2,397 companies with 241,278 firm-month records.

In order to estimate the default risk, we need a binary indicator of the company's default status and a set of explanatory predictor variables. For the binary response variable, we define a company defaulted if the company filed the bankruptcy protection code under Chapter 7 or Chapter 11. If a company exits the database due to other reasons, for example, merger & acquisition, we consider it as "non-default" case. As a result, our bankruptcy database covers 41 default cases in the manufacturing sector during the sampling period.

To construct the explanatory predictor variables, we adopt the most popular bankruptcy prediction model proposed by Campbell et al (2008) as our benchmark model for demonstration purpose. Specifically, we construct eight explanatory variables, including profitability ratio of net income divided by market-valued total assets (NIMTA), leverage ratio of total liability over market-valued total assets (TLMTA), liquidity ratio of a company's cash and short-term assets to the market-valued total assets (CASHMTA), market-to-book ratio (MB), excess return over the S&P500 index (EXRET), stock return volatility over the past 3-month (SIGMA), log of market capitalization standardized by the S&P500 index (RSIZE) and log of price per share truncated at the $15 (PRICE). To study how greenhouse gas emission is linked with a company's financial status, we include GHG emission measure when estimating future default risk. This variable is calculated by multiplying sector-wise GHG emission level, estimated through the Economic Input-Output model (see more details in Section 4.1) with firm-specific economic activity, approximated by the cost of goods (COGS).

IV. METHODOLOGY AND MODEL

4.1. Environmental Performance Evaluation Using Economic Input-Output Life Cycle Assessment

Greenhouse gas emission is considered as one of the major measurements of corporate environmental performance. In our study, we define environmental performance as the amount of GHG emission at the corporate level. GHG emission has been reported voluntarily by a growing number of companies in recent years. Carbon Discloser Project (CDP), an organization based in the United Kingdom, motivates companies and cities to disclose their carbon footprint, giving decision makers the data they need to change market behavior (CDP, 2016). In 2015, there are more than 5,500 companies disclosed to CDP, which generates the world's largest database of corporate environmental performance information (CDP, 2015). However, GHG emisson data is not a reporting item in any accounting or financial report to date, such information has to be derived and converted from a separate source in our research.

Methodologically, there are two approaches to calculate this measure: bottom-up approach based on process analysis and top-down approach based on environmental input-output analysis (Wiedmann, 2009). Process based approaches focus on using primary and secondary process data to achieve high precision calculations. But process-based approaches are usually limited by cost, effort, and data availability and tend to have reduced system boundaries. On the other hand, environmental input-output model was developed by the economist Wassily Leontief in the 1970s based on his earlier input-output work from the 1930s for which he received the Nobel Prize in Economics (EIO-LCA, 2016). It provides an economy-wide approach using Leontif analytical techniques, to economically calculate GHG emission for product groups, companies or countries without sacrificing scope.

The Economic Input-Output Life Cycle Assessment (EIO-LCA) is a technique used to perform a life cycle assessment, an evaluation of the environmental impacts of a product or process over its entire life cycle. It converts the materials and energy resources required for, to the environmental emissions resulting from the activities in our economy (Hendrickson,, Horvath, Joshi, & Lave, 1998). As Hendrickson, Horvath, Joshi, & Lave (1998) described, this method uses information about industry transactions - purchases of materials by one industry from other industries, and the information about direct environmental emissions of industries, to estimate the total emissions throughout the supply chain. It is a robust approach to obtain environmental performance using monetary information. Since its inception in 1995, the method has been applied to economic models of the United States for several different time periods, as well as Canada, Germany, Spain, and some selected US states. The on-line tool has been accessed over 1 million times by researchers, LCA practitioners, business users, students, and others (EIO-LCA, 2016).

To develop a methodology for evaluating company's environmental performance and explore the relationship between environmental performance and financial performance, we applied EIO-LCA and added the output of GHG emission to the U.S. bankruptcy database. For each company i we used, we calculated the total environmental performance in terms of total GHG emission,

$$GHG_i = e_j \times C_{i,j}$$

where e_j is the GHG emission as a result of \$1 million dollars monetary input in sub-sector j in manufacturing sector and $C_{i,j}$ is the cost of goods sold of company i which belongs to sub-sector j. We obtained e_j at each sub-sector in manufacturing sector using the online EIO-LCA tool by hand. For example, using the EIO-LCA tool, we find 1 million dollars economic activity for the iron and steel mills sector in the ferrous and nonferrous metal production industry may yield a total of 3,660 CO_2 emissions on average. Here the amount of CO_2 emissions is the output from the EIO-LCA model. Combining the cost of goods sold reported by each company in the same sector, we compute the GHG emission. In this work, we map the industry and sector information provided by the EIO-LCA model to the Standard Industry Classification (SIC) codes[1]. For industries that contain multiple sectors, we use the average of their reported GHG values for each sector. The full list is reported in Table A1 in the Appendix.

4.2. Corporate Bankruptcy Prediction Model With Added Environmental Sustainability Measurement

To estimate the default probability, we adopt the state-of-the-art reduced-form model, the discrete hazard model (Shumway (2001)). The discrete hazard model implies a logistic link between the binary bankruptcy event and the predictor variables. The advantage of using the discrete hazard model over the static model is that all the companies' historical accounting and market information has been considered in the bankruptcy prediction process. Coping with the time-varying data would be helpful in providing more consistent estimate. Following Shumway (2001), we estimate the default

[1] See Appendix A in http://www.eiolca.net/docs/full-document-2002-042310.pdf for details.

risk over the next 12 months by establishing a logistic link between the binary response and the set of the explanatory variables. Mathematically, the discrete hazard model is expressed as

$$P\left(Y_{i,t+12}=1 \middle| Y_{i,t+12-1}=0, X_{i,t}\right)=\frac{e^{\beta_0+\beta' X_{i,t}}}{1+e^{\beta_0+\beta' X_{i,t}}}, \quad (1)$$

where $X_{i,t}$ is a covariate vector of time-varying firm-specific explanatory variables at time *t*, β is a vector of covariate effect parameters and β_0 is a scalar parameter. The dependent variable $Y_{i,t+12}$ is a default indicator, which is one if firm *i* files for bankruptcy protection after 12 month given it survives through 11 months from time t and zero otherwise. Thus, for bankrupted companies, the default indicator is set to unity only at the time of twelve months before the default event. Any other time would be set to “0”s for the default indicator. For companies that are financially healthy or exit the database due to other reasons, the default indicator is set to 0 at all times.

In addition to the popular 12-month ahead prediction horizon, it is also common to consider other prediction horizons. Mathematically, different prediction horizons simply indicate different lags between the set of predictor variables and the default indicator. In this work, we explore different prediction horizon including 1-month, 12-month, 24-month, 36-month, 48-month and 60-month ahead model prediction performance, in order to find how sustainability performance contributes to the default risk at shorter or longer prediction horizons. Such results would be helpful in providing some insights to the question “when it pays to be green”.

V. EMPIRICAL RESULTS

To investigate how GHG emission contributes to the default risk estimation, we fit a discrete hazard model as in equation (1) on the bankruptcy database to predict the bankruptcy probability in next twelve months. Table 1 summarizes results. In specific, the first two columns report the coefficients estimates from fitting the Campbell et al. (2008)’s model (CHS 2008, thereafter) on our bankruptcy database and the last two columns report the coefficients estimates when adding the GHG emission environmental performance to the CHS model. We note the GHG emission enters the model with a weak negative effect (-0.0404 with an absolute z-statistics of 0.6739). This shows that the company with high GHG emission or equivalently the company with poor environmental performance would have a low default risk. Our conclusion is in line with Klassen and McLaughlin (1996)’s work. They concluded that in manufacturing industry first-time environmental award winner companies usually had smaller return increase compared to other industries (Klassen & McLaughlin, 1996). Because the financial return is so small that manufacturing companies do not gain ambitious motivation to mitigate GHG emission, but to pursue a promising financial performance with their limited budget.

On the other hand, most of the predictor variables used in CHS 2008’s work enters our model with expected signs. For example, a firm suffering from high market volatility (SIGMA) and/or high liability (LTMTA) is often more likely to go bankruptcy, whereas a firm with a promising earning performance (NIMTA) usually indicates a good financial health, thus a low default risk.

For model comparison purpose, we report each model’s McFadden’s Pseudo-R2. McFadden’s Pseudo-R2 is a log-likelihood based information measure. It is one of the most popular goodness of fit measure for the discrete hazard model used in many bankruptcy prediction studies such as CHS (2008) and Tian et al. (2015). The model with higher McFadden's pseudo-R2 value is often more desirable. Results from the last row of Table 1 show a slight improvement on the model's McFadden's Pseudo-R2 when the environmental performance included of 0.0857 over the benchmark CHS (2008)'s model of 0.0846.

TABLE 1. DISCRETE HAZARD MODEL FITTING RESULTS FOR 12-MONTH AHEAD PREDICTION

Variables	Coefficient Estimate	P-value	Coefficient Estimate	P-value
Observations: 241,178				
GHE			-0.0404 (0.6739)	0.5004
PRICE	-0.3483 (1.5731)	0.1157	-0.3445 (1.5439)	0.1226
SIGMA	0.287 (0.7339)	0.463	0.2828 (0.7204)	0.4713
NIMTA	-2.661 (2.9484)	0.0032	-2.6606 (2.9551)	0.0031
LTMTA	1.9517 (2.6173)	0.0089	2.1354 (2.7327)	0.0063
EXCESSRETURN	-0.7835 (0.8603)	0.3896	-0.7815 (0.8583)	0.3908
CASHMTA	-0.2059 (0.2071)	0.836	-0.1307 (0.1327)	0.8946
RSIZE	-0.0134 (0.1212)	0.9034	0.0119 (0.1026)	0.9183
MBE	-0.2581 (1.6797)	0.093	-0.2587 (1.6834)	0.0923
Intercept	-9.2137 (5.9300)	<0.0001	-9.0045 (5.6735)	<0.0001
Pseudo R^2		0.0846		0.0857

This table reports the coefficient estimates from fitting a discrete hazard model on Campbell et al. (2008) and with added GHG emission predictor variables on the companies in the manufacturing sector from 1980 to 2015. The first two columns summarize the coefficient estimates (absolute z-statistics in the parenthesis), p-values and McFadden's Psedudo-R^2 for the CHS 2008 model. The last two columns summarize the coefficient estimates (absolute z-statistics in the parenthesis), p-values and McFadden's Psedudo-R^2 for the CHS 2008 model with added GHG emission predictor variable.

Forecasting default risk at different prediction horizons has received much attention in recent years. To further investigate how GHG emission affects a firm's default risk at both short-term and long-term level, we extend our analysis at different prediction horizons. Table 2 highlights the estimation results of the environmental predictor variable only when we fit the discrete hazard model with the GHG emission variable included in the CHS 2008's model for 1-month, 12-month, 36-month, 48-month and 60-month ahead prediction. It is quite interesting to observe the changing signs of the environmental performance predictor variable at varying prediction horizons. In specific, we note the GHG emission enters the model with a negative effect at shorter prediction horizon (less than 2 years). But such effect changes to a positive effect at longer prediction horizon for three-or-more-years ahead prediction. Such finding is quite interesting. It may suggest that for shorter term, company's default risk would increase when the company's GHG emission is low, or being environmentally sustainable. But for longer term, being environmentally sustainable or having a low GHG emission would decrease the default risk. This result definitely shed lights on the issue of "when it pays to be green". Investing on the company's sustainability process or being green might face some financial hurdles for a short term. But in a long run, maintaining a good environmental performance helps in improving its financial standing. In addition, our limited empirical study shows that the scale of the coefficient estimates for the GHG emission at different prediction horizons increases and p-values decrease monotonically from 36-month onwards. Such steady trend may provide some initial evidence for the claim that the effect of environmental performance on a company's financial performance becomes stronger for longer prediction horizons and the financial return of being green or sustainable is rather long-term. Such preliminary finding is also consistent to Albertini (2013)'s work, stating that it may not be the best way to consider and to address the environmental issue for a short period of time (Albertini, 2013).

To save space, full results are summarized in the appendix. Table 2A summarizes the results for 1-month ahead prediction, and Table 3A, 4A, 5A, and 6A report the results for 24-month, 36-month, 48-month and 60-month ahead prediction. In addition to the changing behavior from GHG variable, we find most of the financial predictor variables including stock volatility (SIGMA), profitability ratio (NIMTA), liability ratio (LTMTA), excess return (EXCESSRETURN) and the size variable (RSIZE) enter the prediction model with consistent signs when different prediction horizons are presented. For example, a large company with high profitability ratio but low liability ratio tends to be financially healthy at both short-term and long-term level, whereas a more volatile firm with low excess return usually indicates a high default risk. On the other hand, the stock price variable (PRICE) switched signed from negative in the short-term to positive in long-term. This may suggest that the stock price variable rather be a short-term predictor of default risk than long-term.

Although in the current regression analysis, we adopted a popular set of accounting-based and market-based variables as control variables, it is still possible that our results could be confounded by omitted variables in other aspects, such as regulation or governance variables. Given the limited scope of this work, we leave this important topic for future research.

TABLE 2. MODEL FITTING RESULTS ON GHG EMISSION FOR DIFFERENT PREDICTION HORIZONS

	COEFFICIENT ESTIMATES	P-VALUE	PSEUDO $R^{2,*}$
1 MONTH (247,439)	-0.0168 (0.3610)	0.7182	0.1621
12 MONTH (241,178)	-0.0404 (0.6739)	0.5004	0.0857
24 MONTH (234,600)	-0.0076 (0.2490)	0.8033	0.0425
36 MONTH (227,945)	0.0091 (0.9182)	0.3585	0.0646
48 MONTH (220,330)	0.0095 (1.0938)	0.2740	0.0239
60 MONTH (210,443)	0.0137 (1.5596)	0.1189	0.0190

This table reports the coefficient estimates (with standard error in the parenthesis), the p-value and McFadden's Psedudo-R^2 from fitting a discrete hazard model on Campbell et al. (2008) with added GHG emission predictor variable on the companies in the manufacturing sector from 1980 to 2015 at different prediction horizons. The rows summarize the estimation results for 1-month, 12-month, 24-month, 36-month, 48-month and 60-month ahead model prediction.
* Comparison on Pseudo R^2 among models requires further cautions due to the change in the size of the dataset used for each prediction horizons.

VI. CONCLUSIONS

In this paper, we investigate how environmental performance affects a company's financial distress risk. We carefully chose GHG emission as an indication of corporate environmental performance. Using EIO-LCA and adding the GHG emission output to the U.S. bankruptcy database, we adopt the discrete hazard model to manufacturing company data. We explore 1-month, 12-month, 24-month, 36-month, 48-month and 60-month ahead model prediction performance in order to find how GHG emission contributes to the default risk at shorter or longer prediction horizons.

For shorter prediction horizons (less than two years), the results show that higher value of the GHG emission predictor variable would lead to a lower default risk. This finding is in line with Klassen and McLaughlin (1996)'s work. On the other hand, when the prediction window is longer than 2-years, our results show that high default risk is usually linked with high GHG emission values or poor environmental performance. Such results may suggest that the financial return on being environmentally sustainable is rather long term. The investment on being green might present some financial hurdles in a short term. But in a long run, companies with better environmental performance demonstrate lower default risk.

Future research is needed to demonstrate the robustness of the results obtained in this paper. Currently, only manufacturing industry data is analyzed in the models. One possibility is to look into other environmentally notorious industries and historically "green" industries to perform cross-industry analysis. We could also consider modifying the current corporate environmental performance measure or include other environmental sustainability indicators in the model to expand the content of environmental performance. Examples of alternative environmental sustainability indicators include conventional air pollutants and energy usage. Furthermore, our research could be expanded to include default data of other international countries.

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APPENDIX A

Table A1: List of Standard Industry Classification codes and its Greenhouse Gas emission

SIC	GHG	SIC	GHG	SIC	GHG
3050	795	3555	633	3724	352
3080	1144	3559	568	3728	511
3086	1195	3560	638	3730	480
3089	1250	3561	563	3743	563
3100	851	3562	711	3751	760
3140	846	3564	653	3760	326
3211	2050	3567	504	3790	646
3220	1390	3569	602	3812	316
3221	1550	3570	426	3821	503
3231	946	3571	284	3822	518
3241	11600	3572	366	3823	449
3250	1830	3575	362	3824	458
3260	1080	3576	339	3825	458
3270	1995	3577	336	3826	310
3272	1735	3578	465	3827	438
3281	624	3579	465	3829	343
3290	1407	3580	590	3841	335
3310	3660	3585	592	3842	536
3312	1965	3590	624	3843	636
3317	2030	3612	606	3844	378
3320	1060	3613	423	3845	352
3330	1800	3620	636	3851	323
3334	3340	3621	660	3861	623
3341	3490	3630	644	3873	371
3350	1397	3634	615	3910	724
3357	762	3640	486	3911	746
3360	1180	3652	565	3931	308
3420	755	3661	358	3942	581
3430	705	3663	358	3944	671
3433	660	3669	332	3949	613
3440	564	3670	513	3950	558
3443	771	3672	572	3960	499
3460	1072	3674	469	3990	643
3470	1110	3677	609	4011	603
3480	565	3678	586	4100	1870
3490	806	3679	392	4210	984
3510	614	3690	535	4213	1400
3523	726	3695	533	4400	2780
3524	697	3711	618	4412	2780
3530	747	3713	570	4512	1980
3531	699	3714	630	4522	505
3537	793	3715	764	4610	4400
3540	582	3716	644	4812	309
3541	546	3720	352	4899	322
3550	633	3721	370	4924	563

This table provides the list of the greenhouse gas emission output for each SIC industry code from the EIO-LCA model.

Table A2: Discrete Hazard Model Fitting Results for 1-month Ahead Prediction

Variables	Coefficient Estimate	P-value	Coefficient Estimate	P-value
Observations: 247,439				
GHE			-0.0168 (0.3610)	0.7182
PRICE	-0.7730 (3.5356)	0.0004	-0.771 (3.5168)	0.0004
SIGMA	0.3046 (0.8876)	0.3748	0.3015 (0.8769)	0.3805
NIMTA	-2.0867 (2.5245)	0.0116	-2.0949 (2.5360)	0.0112
LTMTA	2.4888 (3.1366)	0.0017	2.5612 (3.1420)	0.0017
EXCESSRETURN	-0.1501 (0.1866)	0.8520	-0.1516 (0.1884)	0.8506
CASHMTA	1.2043 (1.5724)	0.1159	1.2223 (1.5983)	0.1100
RSIZE	0.0501 (0.3981)	0.6906	0.0626 (0.4817)	0.6300
MBE	-0.3116 (1.8563)	0.0634	-0.3115 (1.8590)	0.063
Intercept	-8.7537 (5.1010)	<0.0001	-8.6337 (4.9474)	<0.0001

This table reports the coefficient estimates from fitting a discrete hazard model on Campbell et al. (2008) and with added GHG emission predictor variables on the companies in the manufacturing sector from 1980 to 2015. The first two columns summarize the coefficient estimates (absolute z-statistics in the parenthesis) and p-values for the CHS 2008 model. The last two columns summarize the coefficient estimates (absolute z-statistics in the parenthesis) and p-values for the CHS 2008 model with added GHG emission predictor variable.

Table A3: Discrete Hazard Model Fitting Results for 24-month Ahead Prediction

Variables	Coefficient Estimate	P-value	Coefficient Estimate	P-value
Observations: 234,600				
GHE			-0.0076 (0.2490)	0.8033
PRICE	-0.2924 (1.3166)	0.1880	-0.2918 (1.3113)	0.1898
SIGMA	-0.0138 (0.0316)	0.9751	-0.0142 (0.0316)	0.9743
NIMTA	-1.4106 (1.2598)	0.2078	-1.4092 (1.2590)	0.2080
LTMTA	2.2271 (3.2468)	0.0012	2.2718 (3.2156)	0.0013
EXCESSRETURN	-0.7207 (0.7215)	0.4706	-0.7192 (0.7201)	0.4715
CASHMTA	0.0759 (0.0721)	0.9425	0.0921 (0.0878)	0.9301
RSIZE	-0.1086 (0.9862)	0.3240	-0.1028 (0.9133)	0.3611
MBE	0.1000 (1.0810)	0.2797	0.1002 (1.0830)	0.2788
Intercept	-10.5817 (6.8035)	<0.0001	-10.5351 (6.7144)	<0.0001

This table reports the coefficient estimates from fitting a discrete hazard model on Campbell et al. (2008) and with added GHG emission predictor variables on the companies in the manufacturing sector from 1980 to 2015. The first two columns summarize the coefficient estimates (absolute z-statistics in the parenthesis) and p-values for the CHS 2008 model. The last two columns summarize the coefficient estimates (absolute z-statistics in the parenthesis) and p-values for the CHS 2008 model with added GHG emission predictor variable.

Table A4: Discrete Hazard Model Fitting Results for 36-month Ahead Prediction

Variables	Coefficient Estimate	P-value	Coefficient Estimate	P-value
Observations: 227,945				
GHE			0.0091 (0.9182)	0.3585
PRICE	0.1200 (0.4737)	0.6357	0.1143 (0.4520)	0.6513
SIGMA	0.3836 (0.8195)	0.4125	0.3758 (0.8037)	0.4216
NIMTA	-3.3331 (3.3919)	0.0007	-3.3496 (3.4028)	0.0007
LTMTA	2.5131 (3.3009)	0.0010	2.4106 (3.1324)	0.0017
EXCESSRETURN	1.5960 (1.5890)	0.1121	1.5992 (1.5911)	0.1116
CASHMTA	-0.0105 (0.0100)	0.9918	-0.0385 (0.0374)	0.9700
RSIZE	-0.1245 (1.1599)	0.2461	-0.1355 (1.2591)	0.2080
MBE	-0.0999 (0.6978)	0.4853	-0.0992 (0.6938)	0.4878
Intercept	-11.6814 (7.4190)	<0.0001	-11.7459 (7.4708)	<0.0001

This table reports the coefficient estimates from fitting a discrete hazard model on Campbell et al. (2008) and with added GHG emission predictor variables on the companies in the manufacturing sector from 1980 to 2015. The first two columns summarize the coefficient estimates (absolute z-statistics in the parenthesis) and p-values for the CHS 2008 model. The last two columns summarize the coefficient estimates (absolute z-statistics in the parenthesis) and p-values for the CHS 2008 model with added GHG emission predictor variable.

Table A5: Discrete Hazard Model Fitting Results for 48-month Ahead Prediction

Variables	Coefficient Estimate	P-value	Coefficient Estimate	P-value
Observations: 220,330				
GHE			0.0095 (1.0938)	0.2740
PRICE	0.1327 (0.6129)	0.5399	0.1275 (0.5907)	0.5547
SIGMA	0.2368 (0.5603)	0.5753	0.2272 (0.5375)	0.5909
NIMTA	-1.7828 (1.7063)	0.0880	-1.7966 (1.7195)	0.0855
LTMTA	1.4911 (2.5418)	0.0110	1.3965 (2.3503)	0.0188
EXCESSRETURN	-1.2876 (1.4392)	0.1501	-1.2894 (1.4402)	0.1498
CASHMTA	0.2939 (0.3497)	0.7266	0.2688 (0.3170)	0.7513
RSIZE	-0.1221 (1.4083)	0.1590	-0.1314 (1.5147)	0.1299
MBE	-0.0524 (0.4808)	0.6306	-0.0526 (0.4828)	0.6292
Intercept	-10.5089 (8.0858)	<0.0001	-10.5579 (8.1467)	<0.0001

This table reports the coefficient estimates from fitting a discrete hazard model on Campbell et al. (2008) and with added GHG emission predictor variables on the companies in the manufacturing sector from 1980 to 2015. The first two columns summarize the coefficient estimates (absolute z-statistics in the parenthesis) and p-values for the CHS 2008 model. The last two columns summarize the coefficient estimates (absolute z-statistics in the parenthesis) and p-values for the CHS 2008 model with added GHG emission predictor variable.

Table A6: Discrete Hazard Model Fitting Results for 60-month Ahead Prediction

Variables	Coefficient Estimate	P-value	Coefficient Estimate	P-value
Observations: 210,443				
GHE			0.0137 (1.5596)	0.1189
PRICE	0.0014 (0.0000)	0.9944	-0.0027 (0.0141)	0.9896
SIGMA	0.0894 (0.2154)	0.8295	0.0759 (0.1830)	0.8548
NIMTA	-0.4328 (0.3422)	0.7322	-0.4722 (0.3738)	0.7086
LTMTA	1.6576 (3.0222)	0.0025	1.5428 (2.7785)	0.0055
EXCESSRETURN	-0.6541 (0.7475)	0.4548	-0.6586 (0.7520)	0.452
CASHMTA	-0.5747 (0.5444)	0.5862	-0.6283 (0.5876)	0.5568
RSIZE	-0.1616 (1.8266)	0.0678	-0.1737 (1.9687)	0.049
MBE	0.1416 (1.9237)	0.0544	0.1408 (1.9092)	0.0562
Intercept	-10.7789 (8.3168)	<0.0001	-10.8511 (8.4121)	<0.0001

This table reports the coefficient estimates from fitting a discrete hazard model on Campbell et al. (2008) and with added GHG emission predictor variables on the companies in the manufacturing sector from 1980 to 2015. The first two columns summarize the coefficient estimates (absolute z-statistics in the parenthesis) and p-values for the CHS 2008 model. The last two columns summarize the coefficient estimates (absolute z-statistics in the parenthesis) and p-values for the CHS 2008 model with added GHG emission predictor variable.