Junior Management Science 4(3) (2019) 422-432

Junior Management Science

journal homepage: www.jums.academy

Measuring the Impact of Carbon Emissions on Firm Value Using Quantile Regression

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Abstract

A fundamental transformation of the global economy towards a low-carbon economy is inevitable in order to achieve the climate targets set by the United Nations. Hence, it becomes increasingly important to understand how firm level carbon mitigation affects the value of a company. The purpose of this thesis is not only to estimate the average relationship between carbon emissions and firm value but to investigate whether this relationship is heterogeneous and thus whether the effect of carbon emission on firm value depends on the value of the respective company. A quantile regression approach with firm value measured as Tobin's Q as the dependent variable is applied. The estimation outcomes clearly indicate that higher carbon emissions reduce firm value for all quantiles. However, the extent of the effect depends strongly on the value of the respective company suggesting that the value-enhancing effect of reduced carbon emissions is higher for firms with relatively high firm value.

Keywords: carbon emission; firm value; quantile regression.

1. Introduction

In 2017, the annual average amount of carbon dioxide in earth's atmosphere reached an all-time peak of more than 400 parts per million (ppm). This corresponds to an alarming increase in atmospheric carbon dioxide concentration of about 25% in the last 50 years (Lindsey, 2018). Evidence suggests that this man-made increase has contributed significantly to progressive global warming (Williams et al., 2017) and thereby intensified the associated problems in financial, social, and environmental aspects on a global scale (United States Environmental Protection Agency, 2017). To avoid a worsening of the impacts and to reduce the risks of global warming, 195 nations devoted themselves to hold the increase in the global average temperature well below 2°C compared to pre-industrial levels by reducing greenhouse gas emissions, especially carbon dioxide emissions (United Nations, 2015). However, in a very recent report, the intergovernmental panel on climate change (IPCC) shows that the measures taken so far are not sufficient. The report finds that limiting global warming to 1.5°C - 2°C would still require a reduction of carbon emissions of about 45% by 2030, reaching net zero by 2050. The achievement of this ambitious objective calls for far-reaching and rapid changes in every aspect of human activities (IPCC, 2018). Consequently, firm level adaption and carbon emission mitigation are essential, because the corporate sector is responsible for a significant amount of overall carbon emissions. Hence, it is most likely that companies will face increased shareholder and public pressure to reduce carbon emissions as well as more stringent climate change regulations (Aggarwal and Dow, 2011). Moreover, the direct financial impact of carbon emissions becomes increasingly relevant due to the resolutions made during the world climate conference in Paris 2015 (Union Investment, 2016). These developments mean that firm level reduction of carbon emissions becomes increasingly important, not only for companies but for all parts of an economy. In order to take appropriate measures, corporate managers, investors and regulators have to deal with how the inevitable transition to a low-carbon economy and the associated mitigation of carbon emissions affects a firm's value and financial performance (Lee and Min, 2015; Union Investment, 2016). Therefore, it is essential to provide these decision-makers with an accurate and reliable estimation of the relationship. In prior research, it is generally suggested that environmental and economic performance are positively correlated. Nevertheless, as only mean regression techniques have been applied to investigate this issue, the relation between carbon emissions and firm value is solely estimated with respect to the 'average firm' (Mosteller and Tukey, 1977). This lead to the presentation of an incomplete picture of the relationship (Koenker and Bassett Jr, 1978). By applying the concept of quantile regression, this study explores the possibility of dif-

DOI: https://doi.org/10.5282/jums/v4i3pp422-432

ferent effects of carbon emissions on firm value depending on the value of the respective firm. Hence, more detailed results and more reliable estimators (Koenker and Hallock, 2001) on the relationship are provided.

The remainder of this study is structured as follows: In section two, a short overview of the current state of research on the relation between carbon emissions and firm value is given and the hypothesis to be tested in this study is developed. In section three, the theoretical concept of quantile regression is presented. In section four, the examined data set is introduced. In section five, a mean and quantile regression analysis is conducted and the results are presented. In section six, the results are discussed and possible implications are presented. Moreover, limitations of the study and suggestions for further research are provided. In the last section, the study is briefly summarized.

2. Literature review and development of hypothesis

2.1. Overview of the current state of research

As was to be expected, a considerable amount of work has been done to analyse the impact of a firm's environmental performance on its valuation. Most studies examined the relationship based on the hypothesis, that better (worse) environmental performance increases (decreases) firm value or financial performance. Indicators most often used as a proxy for environmental performance include the amount of carbon emissions, greenhouse gas emissions and aggregated environmental performance indices (e.g. Aggarwal and Dow, 2011; Al-Najjar and Anfimiadou, 2012; Nishitani and Kokubu, 2012; Matsumura et al., 2014). As carbon dioxide is reported to be the principal source of global warming, it is directly associated with the most impending global environmental issue (Lee and Min, 2015). Therefore, carbon emission is used as the indicator for a firm's environmental performance in this study. Regardless of the specific definition of environmental performance, an overwhelming majority of research on this issue found a positive impact of environmental activities on firm value. Especially with increased public perception of the negative consequences of global warming (Capstick et al., 2015), a discernible trend in recent research, suggesting that companies can improve its financial performance by reducing emissions, can be observed. For example, Matsumura et al. (2014) conducted a study with a sample of S&P 500 firms and found that, on average, firm value decreases by \$212.000 for every additional thousand metric tons of carbon dioxide emitted. In another study on South African companies, Ganda and Milondzo (2018) focused on the impact of carbon emissions not on firm value but on corporate financial performance in general using multiple regression techniques. They found strong evidence that supports the idea of a negative relation between carbon emissions and financial performance. In a similar study on Japanese manufacturing firms, Nishitani and Kokubu (2012) exploited a random effects model to investigate the relationship between a firm's greenhouse gas emissions and firm value measured as Tobin's Q. Their observations were in line with former results as they found that firms are more likely to increase in value when reducing greenhouse gas emissions. King and Lenox (2008) applied a panel data regression to analyse the relation between carbon emissions and firm value with a sample of 614 US manufacturing firms. They found that lower emissions are significantly associated with higher Tobin's Q results. Furthermore, several other studies including Aggarwal and Dow (2011) and Al-Najjar and Anfimiadou (2012) found evidence of a negative relationship between carbon emissions and firm value in particular or a positive relationship between environmental and economic performance in general.

A common approach to explain why environmental activities improve firm value is based on the assumption that stakeholders and investors consider environmental performance as a form of intangible value. This is because successful emission mitigation decreases the exposure to global warming risks and generates new profit opportunities. Thus, a competitive advantage over rivals in a low-carbon future is generated (Nishitani and Kokubu, 2012). Moreover, especially with increased public perception of global warming issues, the positive reputational effect of green investment activities becomes more important, and thus more valuable. Besides, increased energy efficiency (Sprinkle and Maines, 2010) and the possibility to charge higher prices for environmentally friendly products (Aggarwal and Dow, 2011) are presumed to be firm value-enhancing effects of increased environmental performance.

2.2. Purpose of this bachelor's thesis

Although the above-mentioned studies generally suggest that environmental activities and performance are positively correlated with firm value, the informativeness of this major finding is limited by the fact that the relation is always estimated by applying different mean regression techniques (e.g. Aggarwal and Dow, 2011; Al-Najjar and Anfimiadou, 2012; Matsumura et al., 2014; Ganda and Milondzo, 2018). Consequently, prior research focused on measuring the average effect, which is, according to Koenker and Hallock (2001), likely to provide an incomplete picture of a relation between two variables. It is not considered, that this average effect of carbon emissions on firm value may not necessarily be representative for all firms. This reduces the reliability of the provided results (Koenker and Hallock, 2001).

Due to the lack of research on this issue, the focus of this study is to shed light on the heterogeneity of the effect of carbon emissions on firm value. Thereby, a quantile regression model as introduced by Koenker and Bassett Jr (1978) is applied and the following hypothesis is to be tested:

> H: The effect of carbon emissions on firm value depends significantly on the value of the respective firm, and thus the average effect is not informative.

3. Theoretical background on quantile regression

3.1. Motivation of quantile regression

To provide an estimation on the relationship between a set of independent variables and a dependent variable, standard ordinary least squares regression is one of the most popular statistical methods (Huang et al., 2017). However, this approach, as well as other mean regression techniques, gives a rather incomplete picture of the covariate effects just as a sample's mean gives an incomplete picture of a single distribution (Mosteller and Tukey, 1977). This is because mean regression models quantify the effects of the explanatory variables only at the conditional mean and assume that this effect is constant, and thus representative, for the entire conditional distribution of the dependent variable (Huang et al., 2017). If one expects the effects of the explanatory variables on the dependent variable to be heterogenous, this average effect is not adequate (Koenker and Hallock, 2001; Huang et al., 2017). As stated by Mosteller and Tukey (1977), it gives an incomplete picture and, moreover, might lead to wrong conclusions and less informative results (Schulze, 2004). Quantile regression addresses this issue as it allows to evaluate the covariate effects separately for each quantile along the entire conditional distribution of the dependent variable instead of only the effects at the conditional mean (Huang et al., 2017). Hence, quantile regression gives a far broader picture of the covariate effects (Koenker and Hallock, 2001) and provides the possibility to detect heteroscedasticity in the examined data (Schulze, 2004). However, if the relation between an dependent and an independent variable is highly homogenous amongst the entire conditional distribution, quantile regression does not provide any added value (Koenker and Hallock, 2001). Beside the possibility to capture heterogenous effects, quantile regression has other favourable characteristics. It is well known that, when asymmetries and heavy tails exist, the sample median provides a better summary of centrality than the mean (Koenker and Hallock, 2001). Consequently, compared to standard mean models, quantile regression is far more robust to outliers (Huang et al., 2017). Moreover, there is no need for an assumption about the parametric distribution of the dependent variable and the constant variance of the observation-specific error terms (Huang et al., 2017).

3.2. Cross-sectional quantile regression

The original quantile regression model as introduced by Koenker and Bassett Jr (1978) is based on

$$y_i = x_i\beta_\tau + \epsilon_i \; ; \; i = 1,\dots,n \; ; \; \tau \in (0;1) \tag{1}$$

where x denotes a vector of explanatory variables, y is the dependent variable and ϵ presents the observation-specific disturbance term. β_τ denotes the vector of quantile-specific regression parameters to be estimated for the τ-th quantile of the conditional distribution of the dependent variable (Koenker and Hallock, 2001). The estimation of the parameters is based on solving a least asymmetric absolute deviation problem:

$$\begin{aligned}\hat{\beta}_\tau = & argmin_{\beta_\tau}\Big(\sum_{i\in\{i|y_i\geq x_i\beta_\tau\}} \tau * |y_i - x_i\beta_\tau| + \\ & \sum_{i\in\{i|y_i< x_i\beta_\tau\}} (1-\tau) * |y_i - x_i\beta_\tau|\Big)\end{aligned} \tag{2}$$

To paraphrase it, all observations above the hyperplane $x_i\beta_\tau$ are multiplied with τ, all observations below with $(1-\tau)$. Then, β_τ shall be chosen such that the sum of these asymmetrically weighted absolute deviations is minimized. This minimization problem can mostly be solved efficiently by linear programming methodologies (Schulze, 2004). As the problem depends on τ, the solution to the problem yields a distinct set of regression coefficients for each desired quantile level. Hence, instead of estimating solely one conditional mean function as in standard mean regression models, a quantile regression model provides a set of conditional quantile functions (Schulze, 2004). The τ-th conditional quantile of x_i with respect to x_i can then be written as

$$Q_\tau(y|x) = x\hat{\beta}_\tau \tag{3}$$

Thereby, the obtained τ-specific regression coefficients $\hat{\beta}_\tau$ can be interpreted as the effect of the explanatory variables at the τ-th quantile of the conditional distribution of the dependent variable (Koenker and Bassett Jr, 1978).

3.3. Quantile regression on panel data

As the data set that is exploited in the following empirical analysis has both a cross-sectional and a time dimension, the cross-sectional quantile regression approach of Koenker and Bassett Jr (1978) ought to be extended in order to capture unobserved individual-specific effects (Koenker, 2004). However, models combining the quantile regression framework with panel data analysis are based on very strong assumptions that are rarely satisfied. Especially with a rather small amount of time series, as in the present data, it is difficult to provide any meaningful results with most approaches (Powell, 2015). Besides, the interpretation of the estimation outcomes of most approaches varies significantly compared to cross-sectional quantile regression coefficients (Powell, 2016). Due to these difficulties in estimating a quantile regression model for panel data, the time dimension of the data set used in this study is eliminated in the following empirical analysis. Thus, the cross-sectional quantile regression approach introduced earlier in this section can be applied. Nevertheless, the combination of quantile regression and panel data analysis provides some favourable features as it allows to control for unobserved individual-specific effects and to expose heterogenous covariate effects simultaneously (Huang et al., 2017). Therefore, a very recent quantile regression approach for panel data introduced by Powell (2015) is attached to the study.

4. Variables & sample research

4.1. Data sources

The following empirical models are based on firm observations for the years 2010 to 2016. Financial data were obtained from the Thomson Reuters Datastream and are measured in U.S. dollars. Carbon emission data were collected from two different databases: the Carbon Disclosure Project (CDP) and Thomson Reuters ESG. The amount of carbon emissions for each firm and year is expressed in tonnes. The disclosure of data on carbon emissions to these databases is voluntary. For firms that did not disclose data voluntarily, the amount of carbon emissions was estimated if reliably possible (CDP Worldwide, 2017). Due to this estimation approach, some of the obtained measurements of a firm's carbon emission do differ slightly depending on the respective database. Thus, when data on carbon emission for one firm and year are available in more than one database, the average measurement is used.

4.2. Independent variables

The relevant variable of interest in this study is carbon emission. For each firm and year, overall carbon emissions, Scope 1 carbon emissions and Scope 2 carbon emissions are reported. Whereas Scope 1 refers to carbon emissions from sources that are controlled or owned by the company (direct carbon emissions), Scope 2 accounts for carbon dioxide that is emitted by generation of purchased electricity consumed by the firm (indirect carbon emissions). Overall carbon emission accounts for both Scope 1 and Scope 2, as well as for all other carbon emissions not covered by these two categories (World Resources Institute, 2014). To provide a picture as detailed as possible, the effect of Scope 1, Scope 2 and overall carbon emissions on firm value is estimated separately. Hence, at each step of the following empirical analysis, three models are estimated. The first model estimates the effect of direct carbon emissions on firm value. The second model focuses on the relation between indirect carbon emissions and firm value. In the third model, the relation between a firm's overall carbon emissions and firm value is analysed. For the purpose of improved representation of the estimation outcomes, the amount of a firm's carbon emissions in each category is divided by 1,000,000.

4.3. Dependent variable

To follow prior research in this area, firm value measured as Tobin's Q denotes the dependent variable. A firm's Tobin's Q is calculated as the ratio of the market value of assets to the replacement value of assets. Market value of assets is calculated as the sum of market value of equity and market value of liabilities. The replacement value of assets is calculated as the sum of book value of equity and book value of liabilities (Vermunt, 2013). Hence, the formulation to calculate a firm's Tobin's Q is:

$$Q_i = (\text{market value of equity} + \text{market value of liabilities}) / (\text{book value of equity} + \text{book value of liabilities}) \tag{4}$$

In literature, some more elaborate calculation approaches may be found. However, the simplified approach used in this study significantly reduces the computational effort. It is widely used in recent research and presents a sufficient approximation of most more complex approaches (Dowell et al., 2000; King and Lenox, 2008). The use of Q as the measurement of firm value allows to directly compare accounting data and financial valuation data. This offers the opportunity to expose the market evaluation of management performance. Moreover, it allows considering both a firm's results produced in the past and potential future growth opportunities (Lindenberg and Ross, 1981). A value of Q above 1 suggests that an investment in the respective firm would be profitable, because the value of the capital investments exceeds the costs (King and Lenox, 2008). It indicates good management performance as the outputs (market value) exceed the inputs (book value) (Lindenberg and Ross, 1981). A Q value below 1 indicates that the market assumes the future cash flows provided by the firm to be lower than the amount of money invested in its assets (King and Lenox, 2008).

4.4. Control variables

Several control variables are considered in this study which are commonly included in financial performance analysis and known to impact Tobin's Q (e.g. Konar and Cohen, 2001; King and Lenox, 2008; Aggarwal and Dow, 2011; Lee and Min, 2015; Iskandar, 2016). The control variables are 1) capital intensity calculated as the ratio of capital expenditures to net sales, 2) growth rate calculated as the percentage change in net sales, 3) leverage measured as the ratio of total debt to total assets, 4) profitability calculated as the ratio of net income to total assets, 5) R&D intensity calculated as the ratio of R&D expenditures to total assets and 6) liquidity measured as the ratio of cash to total assets. Table 1 provides an overview of all variables included in the following regression analysis.

4.5. Sample

As a cross-sectional regression analysis is conducted in the following empirical section, the time dimension of the data was eliminated. Thereby, for each firm and variable, the average value across all years was calculated. For a firm to be included in the sample, Tobin's Q, measurements of all three carbon emission categories as well as the introduced control variables must be available for at least two years in the period of 2010-2016. To ensure that the regression results are not unduly sensitive to outliers, all variables are 'winsorized'. Thereby, 2.5% of the measurements are modified at each tail of the respective distribution (Cox, 1998). After excluding firms that lacked sufficient financial or carbon emission data, a sample of 3,570 firms remained. Testing for multicollinearity of the explanatory variables by calculating the correlation

Table 1: Overview of all variables and the respective definition

Dependent Variable	
Tobin's Q	Market value over replacement value of assets
Independent Variables	
Scope 1	Direct carbon emissions divided by 1 million
Scope 2	Indirect carbon emissions divided by 1 million
Overall	Overall carbon emissions divided by 1 million
Control Variables	
Capital Intensity	Capital expenditures over net sales
Growth Rate	Percentage change in net sales
Leverage	Total debts over total assets
Profitability	Net Income over total assets
R&D Intensity	R&D expenditures over total assets
Liquidity	Cash over total assets

matrix and the variance inflation factors, which are presented in the appendix, did not reveal any problem. In Table 2, the descriptive statistics of all variables employed for the empirical models are displayed.

5. Empirical models

5.1. Classical mean regression analysis

Before conducting a quantile regression analysis to address potential heterogenous effects, standard ordinary least squares regression is applied. Hence, the average relationship between the three categories of carbon emission (Scope 1, Scope 2, Overall) and firm value is estimated (Mosteller and Tukey, 1977). This allows to give a reference point for the following quantile analysis and to obtain an initial overview of the relationship. Moreover, it is evaluated whether the predominant finding of a negative average effect of carbon emissions on firm value in recent research can be supported. Thereby, one regression model is estimated for each of the three carbon emission categories. Each model includes Tobin's Q as the dependent variable and the respective carbon emission measurement and all control variables as the explanatory variables. For all three models, an adjusted R2 value of approximately 0.4 was observed. The F-test approved the overall model significance for all mean regression models. The models were re-estimated using robust standard errors. However, the outcomes were not significantly different from the results presented below. In the first model, a firm's direct carbon emissions are included as the relevant variable of interest. Table 3 presents the estimation results.

The major finding of the first model is that the mean effect of direct carbon emissions on firm value is found to be negative and statistically significant. This indicates that firms are, on average, more likely to increase Tobin's Q when reducing direct carbon emissions. In contrast to Scope 1 carbon emissions, all control variables impact Tobin's Q positively. According to Bartram et al. (2011), profitability and growth are likely to increase firm value, because they lead to higher cash flows to equity holder. Du et al. (2016) found that sufficient liquidity also increases firm value measured as Tobin's Q, because it increases the financial scope and reduces the risk of insolvency. High research and development intensity might promise future comparative advantages and is therefore positively linked with firm value (Gupta et al., 2017; Du et al., 2016). Leverage and capital intensity were not found to impact firm value significantly.

The second mean regression model estimates the average relation between indirect carbon emissions and firm value. The observed regression coefficients as well as the associated p-values are presented in Table 4.

The estimation outcomes of the second model show that the coefficient carried by Scope 2 is negative and statistically significant. Thus, the model suggests that companies can increase firm value by reducing indirect carbon emissions. As expected, the estimated coefficients of the control variables do not change remarkable in sign, value or significance when compared to the first model.

Table 5 provides information on how firm value is affected by a company's overall carbon emissions. These include Scope 1 and Scope 2 carbon emissions as well as all other carbon emissions not covered by these two categories.

As was to be expected with respect to the first two models, the coefficient of the relevant explanatory variable shows that the effect of overall carbon emissions on firm value is negative and statistically significant. Thus, one can conclude that a company is, on average, likely to increase firm value when reducing carbon emissions regardless of the specific source of emission. The effects of the control variables on firm value are similar to those observed in the first two models.

Table 2: Summary statistics for sample companies

Variable	Mean	Median	Standard Dev.
Tobin's Q	2.110	1.605	1.363
Scope 1	0.792	0.035	2.256
Scope 2	0.215	0.048	0.384
Overall	1.105	0.105	2.779
Capital Intensity	0.115	0.044	0.241
Growth Rate	0.113	0.047	0.244
Leverage	0.217	0.199	0.171
Profitability	0.028	0.040	0.095
R&D Intensity	0.042	0.012	0.070
Liquidity	0.126	0.090	0.117

Table 3: Mean regression estimators – Direct Carbon Emission

Variable	Coefficient	p-value
Scope 1	- 0.0318	0.000
Capital Intensity	0.1194	0.133
Growth Rate	1.4040	0.000
Leverage	0.0128	0.911
Profitability	4.2904	0.000
R&D Intensity	8.4910	0.000
Liquidity	2.7320	0.000

Table 4: Mean regression estimators – Indirect Carbon Emission

Variable	Coefficient	p-value
Scope 2	- 0.3332	0.000
Capital Intensity	0.9426	0.233
Growth Rate	1.3722	0.000
Leverage	0.0541	0.637
Profitability	4.3020	0.000
R&D Intensity	8.4626	0.000
Liquidity	2.6616	0.000

Table 5: Mean regression estimators – Overall Carbon Emission

Variable	Coefficient	p-value
Overall	- 0.0282	0.000
Capital Intensity	0.1171	0.141
Growth Rate	1.3997	0.000
Leverage	0.0188	0.870
Profitability	4.2870	0.000
R&D Intensity	8.4820	0.000
Liquidity	2.7198	0.000

5.2. Quantile regression analysis

As described in section 3, the results obtained from the above conducted mean regression analysis provide only a rough summary of the effects of carbon emissions on firm value as only the effect at the condition mean is estimated (Koenker and Hallock, 2001). To expose potential heterogeneity of the effects, quantile regression estimators as introduced by Koenker and Bassett Jr (1978) are calculated. Analogue to the mean regression models, one quantile regression model is estimated for each carbon emission category. Thereby, the obtained quantile-specific regression coefficients indicate how the respective carbon emission category affects firm value at the τ-th quantile of the conditional distribution of firm value measurements (Koenker and Hallock, 2001). Tables 6-8 provide an extract of the estimation outcomes. For each emission category, the estimated regression coefficient and the associated p-value are given for each decile of the conditional distribution. To stay within the scope of the paper, the coefficients carried by the control variables are not displayed at this point of the study. However, the complete estimation outcome including the coefficients of the control variables and the related p-values are attached to this study. To illustrate the statistical variation of the coefficients carried by the variables of interest along the entire conditional distribution of the dependent variable, a graphic display is provided. In each graph, the estimated quantile regression coefficients of the respective carbon emission category are plotted against the quantiles of the conditional distribution. The solid horizontal line denotes the mean regression estimate which does obviously not vary with the quantiles. The two dashed lines depict the conventional 95% confidence interval for the respective mean regression estimator.

Looking at the graphical depiction presented above reveals that carbon emissions from all sources affect firm value similarly along the conditional distribution. However, it should be noted that the coefficients obtained from the second model, referring to the impact of Scope 2 carbon emissions on firm value, are much higher at each specific decile than the estimators provided by the first and the third model. Nevertheless, at the bottom of the conditional distribution, the quantile estimators carried by the variable of interest are close to zero, but always negative, in all three models. The effect of direct carbon emissions on firm value at the lowest decile is not found to be statistically significant at the 10% level. From the conditional distribution's bottom until approximately the median, the quantile-specific coefficients in all models are roughly constant as they show only minor changes with a tendency to decrease (increase in absolute value). In contrast, at the right side of the conditional distribution, the coefficients carried by the independent variables diminish strongly reaching the lowest (highest absolute) value at the highest quantiles. Except the mentioned insignificance, all quantile estimators in all three models are significant at the 10% level.

However, the described shift of the quantile estimators along the conditional distribution of firm value measurements does not justify a quantile regression model as long as the results are not compared to the mean regression estimator, especially to its confidence interval (Koenker and Hallock, 2001). Hence, the main important result from this quantile regression analysis is that the obtained quantile-specific regression coefficients from all three models lie predominantly outside the 95% confidence interval of the mean regression estimator. This clearly indicates that the least squares confidence interval does a poor job representing the range of covariate effects along the conditional distribution (Koenker and Hallock, 2001). The average effect is neither representative for the quantiles below the median nor for the effects at top of the conditional distribution. Solely between approximately the sixth and the ninth decile, the quantile effects are adequately expressed by the mean regression models. This range is even smaller for the quantile effects provided by the second model. This clearly demonstrates that the quantile regression approach improves the informativeness and reliability of the results compared to the classical OLS regression. Moreover, it can be seen that the median estimator lies significantly above the mean estimator in all three models. This emphasizes the robustness of the quantile regression approach towards outliers. In contrast, the mean effect of carbon emissions on firm value is likely to be distorted by the very strong quantile effects at the top of the conditional distribution.

The coefficients carried by the control variables are, as well as in the mean regression analysis, mostly constant across the three models. However, the quantile regression approach revealed significant heterogeneity of the effects along the conditional distribution of firm value measurements for most of the control variables. Hence, it would be worth investigating the impact of financial performance indicators on firm value using quantile regression in further research.

6. Discussion

6.1. Comparison and interpretation of the regression results

The mean regression models support the trend in recent research suggesting that firms can, on average, increase firm value when reducing carbon emissions. The estimation outcomes clearly show that lower direct, indirect and overall carbon emissions are significantly associated with higher Tobin's Q results. Thus, the reduction of carbon emissions is likely to improve firm value regardless of the specific source of emission. Thereby, the value-enhancing effect of reduced Scope 2 carbon emissions is estimated to be stronger than the effect of reduced direct carbon emissions along the entire conditional distribution. Moreover, the effect of overall carbon emissions on firm value is lower than the effects of Scope 1 and Scope 2 carbon emissions. This may suggest that all carbon emissions not covered by Scope 1 and Scope 2, but included in the overall emission measurement, have a lower negative or even positive impact on firm value. As well as the mean regression models, the quantile approach generally suggests that lower carbon emissions are significantly associated with higher firm value measurements. Regardless of the specific source of emission and the specific quantile of the conditional distribution of the dependent variable, carbon emission reduction is likely to improve firm value. However, the extent to which a firm can benefit from carbon emission mitigation varies significantly along the conditional distribution. The models suggest that firms with relatively low Tobin's Q results cannot improve firm value by reducing carbon emissions as much as suggested by the average effect. In contrast, for firms at the top of the conditional distribution of firm value measurements, the value-enhancing effect of reduced carbon emissions is significantly higher and therefore strongly underestimated by the average effect. This applies to Scope 1, Scope 2 and overall carbon emissions.

As can be seen from the empirical results, the underlying hypothesis of this study is clearly proven. It is shown that

Table 6: Quantile regression estimators – Direct Carbon Emission

Decile	1	2	3	4	5	6	7	8	9
Coeff.	-0.004	-0.008	-0.008	-0.010	-0.012	-0.016	-0.021	-0.031	-0.055
p-value	0.127	0.007	0.004	0.000	0.000	0.000	0.000	0.000	0.000

Table 7: Quantile regression estimators – Indirect Carbon Emission

Decile	1	2	3	4	5	6	7	8	9
Coeff.	-0.087	-0.144	-0.164	-0.156	-0.162	-0.189	-0.220	-0.260	-0.409
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 8: Quantile regression estimators – Overall Carbon Emission

Decile	1	2	3	4	5	6	7	8	9
Coeff.	-0.004	-0.010	-0.008	-0.010	-0.010	-0.014	-0.019	-0.025	-0.045
p-value	0.081	0.007	0.008	0.000	0.000	0.000	0.000	0.000	0.000

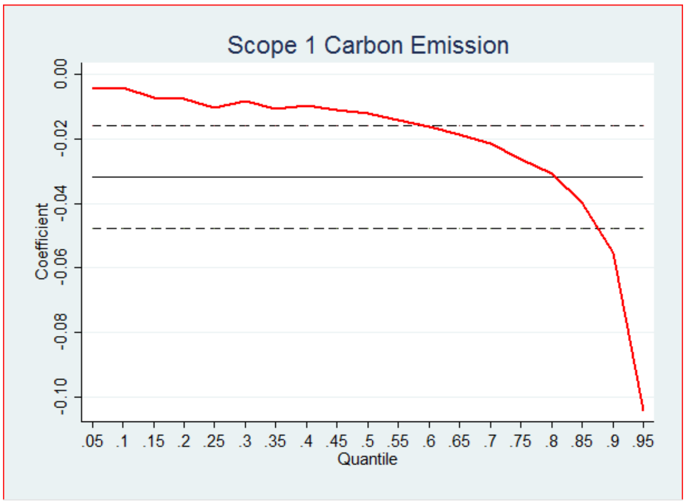

Figure 1: Quantile Regression Estimators - Direct Carbon Emission

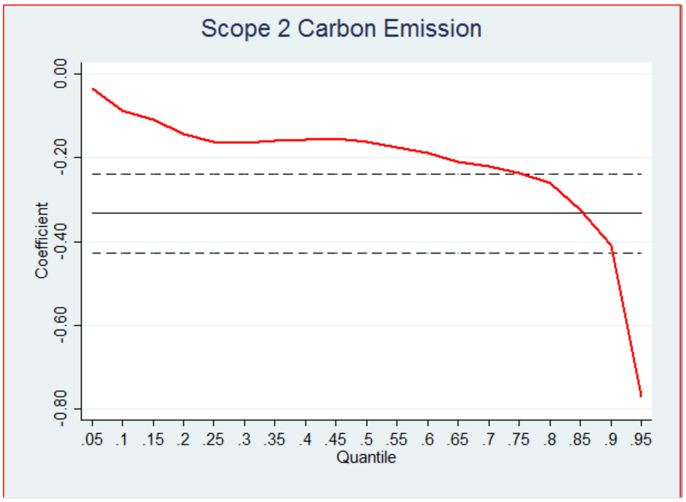

Figure 2: Quantile Regression Estimators - Indirect Carbon Emission

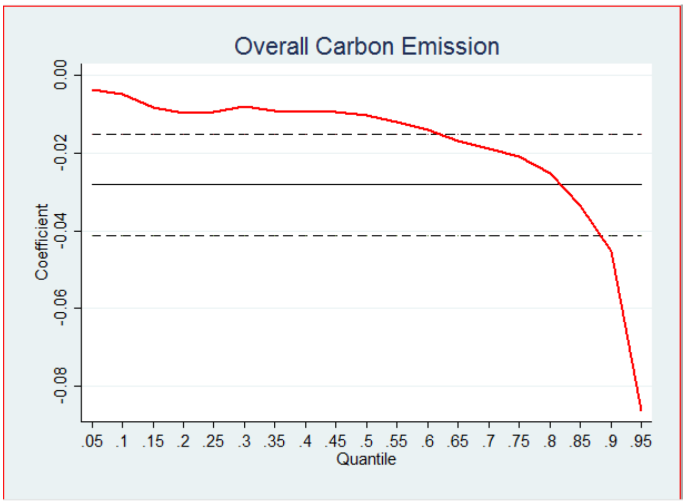

Figure 3: Quantile Regression Estimators - Overall Carbon Emission

the impact of carbon emissions on firm value depends significantly on the relative value of the respective firm. This indicates that the average effect is not informative and does not provide a reliable basis for taking adequate measures. However, as the relation between carbon emissions from all sources and firm value is estimated to be negative at the conditional mean as well as at the entire conditional distribution of Tobin's Q measurements, both approaches indicate that the market places high value to a firm's environmental performance.

The observed shift of the quantile estimators along the conditional distribution might be explained by the higher interest of investors in firms with higher Tobin's Q. As a high Tobin's Q indicates good management performance and returns that exceed the costs, such a firm is more attractive to potential investors (Lindenberg and Ross, 1981). Thus, the interest in the firm in general and therefore the interest in its environmental performance is higher. Consequently, one might conclude that, as well as it is likely that the effect of CSR on firm value depends on customer awareness (Servaes and Tamayo, 2013), the effect of carbon emissions on firm value depends on investor awareness and is therefore higher for firms with relatively higher Tobin's Q results.

6.2. Implications of the findings

The main result of the empirical analysis, suggesting that the effect of carbon emissions on firm value is significantly heterogenous, should be considered at all levels affected by the inevitable firm level carbon mitigation. In the following, some considerations on how the findings of this study may be taken into account at different levels are presented.

It has been shown that for a firm that is interested in increasing its value, carbon emission reduction is an adequate measure regardless of the value of the respective firm. This alone is an important finding for corporate managers who are hesitant about engaging in emission mitigation activities as they are sceptical about its effect on firm value. However, when referring to the average value-enhancing effect, an incorrect impression is given, because, for most firms, the real effect is either over- or underestimated. Hence, when evaluating to what extend firm value can be increased with carbon emission reduction and when comparing the value-enhancing effect to other 'value-increasing measures', the quantile estimators provide a more reliable base. Moreover, investors might also benefit from taking the quantile regression results into consideration. When being aware that a firm's engagement in emission mitigation activities does not increase firm value equally along the entire conditional distribution of firm value measurements, investment decisions can be designed accordingly and future profits can be estimated more reliable. Finally, the results might improve the efficiency of measures taken by regulators in order to encourage companies to reduce carbon emissions. By taking quantile effects into consideration, a focus can be set on firms that do not yet benefit from voluntary carbon emission reduction as much as others, namely relatively less valuable firms.

6.3. Limitations and suggestions for further research

A major limitation of this study is the application of a cross-sectional quantile regression model instead of a quantile regression model for panel data. As mentioned above, this is mainly due to the limited amount of time series in the present data. The cross-sectional approach reduces the informativeness of the results as it does not control for individual-specific unobserved heterogeneity (Huang et al., 2017). Further research might address this issue by exploiting data sets with a larger amount of time series or by applying improved quantile regression models for panel data.

Another question that should be answered by further research is why the value-enhancing of carbon emission mitigation is higher for relatively more valuable firms. As this study only estimated the nature of the relationship but did not analyse what causes the effects to increase with rising firm value, such a study would strongly improve the understanding of the connection between carbon emissions and firm value.

In addition, future research might also analyse and compare the long-term effects of carbon mitigation activities on firm value. Finally, an issue that might be investigated in further research is whether the effect of carbon emissions on other financial performance indicators than firm value is heterogenous as well. Especially corporate managers might be interested in the quantile-specific effects of carbon emissions on accounting-based measures.

7. Summary

In past decades, carbon dioxide emission has become a major environmental concern. To limit global warming and the associated negative consequences, the amount of carbon dioxide emitted from firms must be reduced (United Nations, 2015), because the corporate sector is responsible for significant quantities of overall carbon emissions (Aggarwal and Dow, 2011). To take appropriate measures, policy makers, investors and corporate managers have to deal with how the firm level mitigation of carbon emissions affects a firm's value (Lee and Min, 2015). In order to provide more reliable estimators on this relationship, a quantile regression approach was applied. In contrast to mean regression models, this approach addresses potential heterogenous effects and provides a more complete picture (Koenker and Hallock, 2001) of the relationship between carbon emissions and firm value. To improve the informativeness of the results, the effect of a firm's direct, indirect and overall carbon emissions on firm value was estimated separately. The estimation outcomes show that lower carbon emissions from all sources are significantly associated with higher Tobin's Q results. However, the quantile regression estimators revealed significant heterogeneity of the effects. It was found that a firm with relatively high firm value can benefit much more from reducing carbon emissions than a firm below the median of the conditional distribution of firm value measurement. By taking the results of this study into consideration, all levels affected by firm level emission mitigation might take more appropriate measures and improve the efficiency of those.

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