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The Good Guy Game: When Firms Reduce Carbon Emissions, Do Profits Increase?

kEVIN Fortune
Macalester College

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Kevin Fortune

Macalester College Department of Economics

Paper Advisor: Gary Krueger

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I. INTRODUCTION AND LITERATURE REVIEW

This paper examines whether decreases in a firm’s carbon emissions causes that firm’s profit to increase. The premise is that consumers concerned about climate change prefer products that are less carbon intensive. Carbon intensity is the amount carbon emitted due to the production and consumption of one unit of a good. Consumers experience disutility when their actions cause CO2 concentration to rise, harming the environment and other people. Because of this disutility, they are willing to pay a higher price for relatively less carbon intensive products. For example, a consumer may decide to shop for groceries at Whole Foods rather than Cub Foods. Similarly, a consumer may decide to purchase a Tesla Model 3 (an electric car) instead of a Toyota Corolla (a gasoline car). The idea is that consumers can differentiate carbon intensities between otherwise similar products.

Firms have an opportunity to affect the demand curve they face by reducing their carbon intensity, but to do so involves an investment cost. There are many ways a firm may reduce carbon intensity. They could switch to low-carbon energy sources, purchase more energy efficient capital, research new production technology, generate energy onsite, et cetera. The common theme is that all of these options have a cost. Firms must maximize profits by choosing how much to invest in carbon intensity reduction.

Taking such actions to reduce emissions is one form of Corporate Social Responsibility (CSR). CSR is defined as “meeting the needs of a company’s direct and indirect stakeholders (employees, clients, pressure groups, communities, etc.), without compromising its ability to meet the needs of future stakeholders as well” (Dyllick and Hockerts 2002). A stakeholder is “any group or individual who can affect or is affected by the achievement of the organization's objective” (Freeman 1984). In the context of carbon emissions, stakeholders include anyone in the world who experiences the costs of climate change. CSR does not mean that firms act altruistically; a firm that reduces carbon emissions to maximize profits also participates in CSR. That is the concern of this paper: whether reduction in carbon intensity increases profit, holding other determinants of profit constant.

There is a vast economic literature discussing the theoretical and empirical implications of CSR. Motivations for empirical research in CSR today come from theoretical arguments first made 60 years ago. Economists observed that spending on CSR per firm quadrupled between 1950 and 2000 (Caplow 2001). The earliest economic writing criticized this behavior. Levitt (1958) argued on purely theoretical grounds that firms destroyed wealth when they spent resources on objectives other than maximizing their own profits. In a famous New York Times article, Milton Friedman (1970) argued that firms spending resources on CSR was theft from their stockholders, managers, and employees. Friedman's explanation for the increase in CSR spending was "political subversion" of the decision-makers within firms. Margolis (2003) has retroactively called this anti-CSR school of thought "Economic Contractarianism."

Two economic theories, called the Stakeholder Theories, developed in response to Levitt and Friedman's criticisms (Freeman 1984). The first was normative Stakeholder Theory, which argued that firms had an ethical obligation to their stakeholders. The second was descriptive Stakeholder Theory, which argued that firms that spent money on CSR were profit-maximizing, and searched for evidence to support that claim. The descriptive theory said that consumers preferred to purchase products from firms whom they deemed good. Therefore, monopolistically competitive firms could affect demand through investment in CSR. The descriptive theory directly rebutted the Economic

Contractarian argument; by engaging in CSR, firms created wealth. This thesis tests the hypotheses from descriptive Stakeholder Theory, as I seek to learn whether CSR is consistent with profit-maximizing behavior.

The CSR literature changed from a theoretical debate to a search for empirical evidence regarding Stakeholder Theory and Economic Contractarianism. Moskowitz (1972) wrote the first empirical work, finding a positive correlation between CSR and share prices by looking at a panel of 14 firms. Vance (1975) took the same dataset as Moskowitz and showed that these companies grew slower than their non-CSR peers on the S&P 500 and Dow Jones Indices. A meta-analysis by Margolis (2003) found that between 1972 and 2002 there were 127 studies searching for a causal relationship between CSR and financial performance. Margolis concluded that the total results of these studies suggested a weak positive relationship. He found that 70 of the studies concluded that there was a positive relationship, while 57 of the studies found no relationship, a negative relationship, or mixed results. Margolis stipulated, however, that the majority of these studies failed to address problems with empirical estimation that were common across the literature: omitted variables, endogeneity, poor samples, and unreliable measures of CSR and financial performance dependent variables.

Since the late 1990s, the literature has made efforts to address the estimation problems laid out by Margolis. Three dependent variables have become common as measures of financial performance. [1]The most common measure is share prices (Curran and Moran 2007; van Dijken 2007; Consolandi 2009; and Cheung 2010). These papers

[1] In addition to these analyses of high market value companies in the US stock exchanges, there I some studies that use smaller samples. For example, Wagner (2002) looks at the relationship between forest sustainability practices and profit in the paper industry. Curran and Moran (2007) examines at the shocks in stock prices of companies that I recently included or deleted from the FTSE4Good UK 50 Index. Both papers found a positive relationship between CSR and profit.

seek to answer whether CSR creates wealth for investors. But share prices do not necessarily reflect market fundamentals. It could be the case that prices change according to expected future profit and other variables in financial markets. What investors expect to happen to profits in the future may differ from what actually happens to profits in the future. If that's the case, then a positive relationship between share prices and CSR does not necessarily mean that profit increases as a result of the CSR action, meaning that the conclusions of those papers do not fully answer the question posed by this paper[2]. The next most common measure of financial performance is Tobin's Q (Lo and Sheu 2007; Wagner 2010; Garcia-Castro et al. 2010)[3]. This measure falls to some of the same methodological problems as share prices because the numerator is determined by the price of shares. The advantage of Tobin's Q is that it measures expectations of profit against that actual value of assets, therefore controlling for overestimated expectations. The final measures of financial performance are various accounting measures such return on assets and accounting profit (López et al. 2007; Garcia Castro et al. 2010). These dependent variables are less sensitive to forces on financial markets. Conclusions about the relationship between financial performance and CSR vary within all dependent variables, so the choice of dependent variable cannot explain the variation in estimation results.

Some recent work has found that the inclusion of certain control variables affects the results. Specifically, a set of papers found that controlling for firm size, industry, and risk (of investment) changes the results of the effect of CSR on stock price (Aupperle et

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[2] However, if share prices do accurately indicate current period profit, then the conclusions of Curran and Moran (2007); van Dijken (2007); Consolandi (2009); and Cheung (2010) do reveal information about the CSR-profit relationship. The conclusions I mixed.

[3] The Tobin's Q ratio is calculated as the market value of a company divided by the replacement value of the firm's assets (Investopedia 2016).

al., 1985; Coombs and Gilley, 2005; Hillman and Keim, 2001; Pava and Krausz, 1996; Waddock and Graves, 1997b). The results of these papers vary, but they all look at stock price as a dependent variable explained by various measures of CSR. Firm size may matter because it affects the visibility of CSR actions to consumers. People are more likely to notice Target's CSR activities than those of Georgetown Cupcakes. The same reasoning applies to the industry control variable. Consumers and stakeholders are more knowledgeable about downstream industries like retail than upstream industries like iron ore mining.

Wagner (2010) found that including the advertising intensity of the markets of firms in his panel data set increased the positive significance of the relationship between CSR and financial performance. Advertising intensive industries are more sensitive to changes in public perception. CSR has the effect of boosting the company's public image. McWilliams and Siegel (2000) show that including R&D intensity decreases the significance of the relationship, but that it remains positive. The reason may be that R&D intensive companies have higher return investments to make other than CSR, so the R&D intensive companies that do invest in CSR experience lower profit.

I have read one paper that controls for endogeneity between profit and CSR. The argument for endogeneity is that firms that earn more profit can afford to invest more in CSR. Garcia-Castro et al. (2010) use a set of three instrumental variables to predict CSR ratings according to KLD[4] score. The instrumental variables are an industry dummy, corporate governance measures, and inclusion on the S&P 500 (to proxy for visibility). Garcia-Castro et al. observe that when these instruments are included, the

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[4] A stock index that provides social responsibility ratings for all companies included in the index.

relationship goes from significantly positive to insignificantly negative. They conclude that more work must be done to control for endogeneity between profit and CSR.

This paper contributes to the literature by examining whether carbon intensity reductions result in greater profit. I use carbon emissions data from surveys conducted by CDP, a non-profit organization. These surveys are distributed every year to the 500 largest companies in the world measured by market capitalization. Carbon emissions are an objective quantity, unlike many of subjective indices previously used in the literature such as KLD scores and inclusion on the Dow-Jones sustainability index. I can compare and measure the differences in carbon intensities between firms, whereas indices are not as comparable. This characteristic of my data allow me to apply a difference-in-difference method to measure the effect of carbon emissions on profit, a method previously unused in the literature. The difference-in-difference model controls for variables that would otherwise confound the estimation. In addition to the new application of empirical techniques, this paper develops a theoretical model to explain consumer and firm behavior with respect to carbon emissions.

The empirical models all find a significant negative relationship between profit and carbon intensity. Profit increases as a company become less carbon intense. The results also suggest that carbon intensity matters in some industries but not others. Data constraints prevent me from drawing conclusions about specific industry effects due to small numbers of observations in some industries. I conclude that the results are evidence in support of the theory that companies can increase profit by decreasing carbon intensity. There are significant questions about the results addressed in the robustness section.

The rest of the paper proceeds as follows. Section II develops a theoretical model to explain how companies can earn greater profit through reductions in carbon intensity. Section III discusses the data and their advantages and disadvantages. Section IV explains the empirical estimation technique. Section V shows the results. Section VI tests the robustness of results and lays out unaddressed potential weaknesses. Section VII concludes.

II. THEORY

The model developed in this section aims to explain the relationship between changes in carbon intensity and profit in an oligopolistic market. There are two profit-maximizing firms that produce goods (X_1 and X_2) with different carbon intensities for each good. The model occurs over two periods. In the first period, the firms emit the same amount of carbon per unit produced (aka carbon intensity). They may invest *I* to reduce their carbon intensity in the next period. A greater investment results in greater reduction in carbon intensity. In the second period each firm faces a different demand curve (unless they invested nothing in the first period).

Consumers are endowed with income *N* and choose to consume some quantity of the two goods. They maximize utility function $U(X_1, X_2, C)$, subject to their income constraint. The variable C is the total carbon emissions produced by goods consumed, and is a function of X_1 and X_2. The utility function could be expressed only as a function of X_1 and X_2, but keeping the C in the model makes it clear how carbon emissions affect consumer and producer behavior.

The key to the model is that the carbon emissions variable in the utility function enables firms to differentiate themselves and affect demand. Firms make their investment decision based on expectations about what the other firm will invest. The firms achieve Nash Equilibrium when they maximize profits across the two periods given their expectations about the other firm's strategy.

a) Demand

The goal of this subsection is to show how consumer preferences about carbon intensities affect the demand curve. Consumers seek to maximize their utility $U(X_1, X_2, C)$. Assume for the moment that the marginal disutility of carbon emissions does not depend on the quantity of goods and that the marginal utilities of goods do not depend on carbon emission levels. In other words, I am assuming that the utility function takes some additive form $U = f(x_1, x_2) + g(C)$. Then the constrained optimization problem requires the consumer to meet these three first-order conditions:

$$\max \theta_{x_1 x_2 \lambda} = U(X_1, X_2, C) - \lambda(P_1 X_1 + P_2 X_2 - N)$$

$$(1) \qquad \frac{\partial \theta}{\partial x_1} = \frac{\partial U}{\partial x_1} + \frac{\partial U}{\partial C}\frac{\partial C}{\partial x_1} - \lambda P_1 = 0$$

$$(2) \qquad \frac{\partial \theta}{\partial x_2} = \frac{\partial U}{\partial x_2} + \frac{\partial U}{\partial C}\frac{\partial C}{\partial x_2} - \lambda P_2 = 0$$

$$(3) \qquad \frac{\partial \theta}{\partial \lambda} = N - P_1 X_1 - P_2 X_2 = 0$$

The $\frac{\partial U}{\partial x_i}$ terms in each equation represent that marginal utility provided by the good. The $\frac{\partial U}{\partial C}$ terms represent how much the utility changes for each unit of carbon emitted, and $\frac{\partial C}{\partial x_i}$ is the carbon intensity of the good. Combining the three first-order conditions, I get

$$(4) \qquad \frac{\frac{\partial U}{\partial x_1} + \frac{\partial U}{\partial C}\frac{\partial C}{\partial x_1}}{P_1} = \frac{\frac{\partial U}{\partial x_2} + \frac{\partial U}{\partial C}\frac{\partial C}{\partial x_2}}{P_2}$$

The interpretation of equation 4 is that the sum of the marginal utility of the good and the marginal disutility of carbon emissions per dollar must be equal for both goods. This equation can illuminate how changes in carbon intensity can affect the consumption of goods. Suppose that the carbon intensity of x_1 increases. I know that $\frac{\partial U}{\partial C}$ is negative because I have assumed that consumers receive disutility from the carbon emissions of their goods. The sum of marginal utilities decreases.

In order for equation 4 to hold, either the marginal utility of x_1 must increase or marginal utility of x_2 must decrease. The consumer in this model has no control over the price or carbon intensity of either good. For the marginal utility of x_1 to increase, the quantity consumed of x_1 must decrease (assuming that there exists diminishing marginal utility of the good). The end result is that the consumer reacts to the increase in x_1's carbon intensity by decreasing consumption of good x_1 and increasing consumption of x_2.

Suppose that the goods are identical in every way except for carbon intensity. The reason I want to do this is so that I can think about a duopolistic market with identical goods. Now the marginal utilities of the goods must be equal. The only difference between the numerators in equation 4 comes from the marginal disutility of carbon emissions. Equation 4 indicates that the result is a corner solution, because the less carbon intense good always has greater marginal utility per dollar, as long as prices are held constant. Realistically, the less carbon intense good would probably have a greater price than the other, which means that a corner solution is not necessary.

If I specify a function for utility, then I can derive a demand curve for the goods. Suppose that a consumer's utility function is

$$(5) \qquad U = x_1^{\alpha} x_2^{\beta} C^{\gamma}$$

such that $0 < \alpha < 1, 0 < \beta < 1,$ and $\gamma < 0$. I am returning to a utility function in which consumers receive different marginal utilities from each good. Note that this specific utility function does not fit in the general case considered in equations 1-4 because this function does not assume that the utility function is additive. The demand for x_1 is[5]

$$(6) \qquad x_1 = \frac{-P_2 C^{\gamma}(\alpha+\beta)}{P_2 \frac{\partial U}{\partial C}\frac{\partial C}{\partial x_1} - \frac{\partial U}{\partial C}\frac{\partial C}{\partial x_2} * P_1 - \frac{\beta C^{\gamma} P_2 P_1}{I}}$$

It is difficult to interpret the meaning of individual terms in the demand function, but I can understand how quantity demanded changes with the parameters. The two parameters of interest are the carbon intensities of x_1 and x_2. If I derive $x_1$with respect to the carbon intensities, the resulting equations are

$$(7) \qquad \frac{\partial x_1}{\partial \frac{\partial C}{\partial x_1}} = \frac{C^{\gamma}(\alpha+\beta)}{\frac{\partial U}{\partial C}\left(\frac{\partial C}{\partial x_1}\right)^2}$$

$$(8) \qquad \frac{\partial x_1}{\frac{\partial C}{\partial x_2}} = \frac{-P_2 C^{\gamma}(\alpha+\beta)}{\frac{\partial U}{\partial C}\left(\frac{\partial C}{\partial x_2}\right)^2 P_1}$$

Because I have assumed that $\frac{\partial U}{\partial C}$ is negative, I know that the quantity demanded of x_1 decreases with the carbon intensity of x_1 and increases with the carbon intensity of x_2. Note that these derivations assumed that carbon intensity does not change with the quantities demanded. If that were not the case, then I would have to account for the carbon level term remaining inside $\frac{\partial U}{\partial C}$. This assumption may not reflect a market in which companies experience economies of scale. For instance, it may require a certain amount of energy to run a machine for an hour, regardless of the production of that machine.

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5 The derivation of equation 6 is provided in the appendix

Therefore, the company has to consume no additional energy to produce more goods as long as the machine is not at capacity.

The important result of equations 7 and 8 is that changes in carbon intensity can decrease quantity demanded decreases while keeping price constant. Graphically, this is a downward shift of the demand curve. If producers can decrease their carbon intensity by changing production technology, then they can affect the demand curve they face in the future. I have demonstrated that when consumers receive disutility from carbon emissions, changes in carbon intensity cause downward shifts in the demand curve. I showed this generally for the utility functions that are additive ($U = f(x_1, x_2) + g(C)$) and also for a particular non-additive utility function ($U = x_1^{\alpha} x_2^{\beta} C^{\gamma}$). I also had to impose the assumption that carbon intensity does not change with quantity produced. Relaxing these assumptions does not necessarily alter the results of these models, but it depends on the specific utility and carbon emissions functions.

b) Supply

This subsection explains how producers choose the level of carbon intensity investment which maximizes profits. In the first period, the market is a homogenous duopoly. They face the same price which is a function of the sum of their produced quantities. For the sake of simplicity, I assume that the firms face a linear demand function derived from a cumulative utility function which includes a term for carbon emissions.

(9) $$p = A - B * X$$

(10) $$X = \mathrm{x}_1 + \mathrm{x}_2$$

The parameters *A* and *B* are constants. Let each firm faces the same marginal cost of production. Given equations 9 and 10 and that firm 1 maximizes profits, I find that the reaction curve for firms 1 and 2 are

$$(11) \qquad x_1 = \frac{A - B * x_2 - MC}{2B}$$

$$(12) \qquad x_2 = \frac{A - B * x_1 - MC}{2B}$$

The parameter MC is the marginal cost of both firms 1 and 2. The profit maximizing quantities are attained through the reaction curves. Solving for x_1 and x_2 results in

$$(13) \qquad x_1 = x_2 = \frac{A - MC}{3B}$$

Both firms produce the same quantity. The potential difference between firms A and B in period 1 is their expectations about what the other firm will invest. As demonstrated in the discussion of consumer demand, the demand for a good depends on both its own carbon intensity as well as the carbon intensity of the other firm. Therefore, the expected return on investment in carbon intensity may depend on the competitor's investment. The objective of the firms in period 1 is to maximize profits in the period while choosing the level of investment that maximizes period 2 profits minus investment. Since period 1 profit does not depend on investment, the quantity produced in period 1 has no effect on the investment decision.

The market in period 2 becomes a heterogeneous duopoly because the goods are differentiated through different fixed carbon emissions for each firm. Now the firms face their own demand curves. Specifically,

$$(14) \qquad P_1 = A_1 - B_1 x_2 - C_1 x_1$$

$$(15) \qquad P_2 = A_2 - B_2 x_2 - C_2 x_1$$

Note that the price of each good is a function of the quantity of both goods. This reflects that the goods are similar enough that one firm's production decision affects the consumer's willingness to pay for the other. But the goods are different enough to have different prices.

The parameters that characterize the demand curves are A_i, B_i, and C_i. These parameters are determined by the consumer's utility function. As shown in the discussion of consumer demand, an increase in the carbon intensity of x_1 shifts its demand curve downward but shifts the demand for x_2 upward. For example, suppose the consumer's utility function is such that

$$(16) \qquad A_1 = f(\frac{\partial C}{\partial x_1}, \frac{\partial C}{\partial x_2})$$

$$(17) \qquad A_2 = g(\frac{\partial C}{\partial x_1}, \frac{\partial C}{\partial x_2})$$

Under the assumption that consumers receive disutility from carbon emissions, $A_1$and A_2 must increase with their own carbon intensities and decrease with the carbon intensity of the other good. To show how profit changes carbon intensity, I need to know how profit changes with A_1 and A_2. The reaction curves derived from equations (14) and (15) are

$$(18) \qquad x_1 = \frac{A_1 - MC - B_1 x_2}{2C_1}$$

$$(19) \qquad x_2 = \frac{A_2 - MC - C_2 x_1}{2B_2}$$

The optimal quantities attained by substituting equations (18) and (19) are

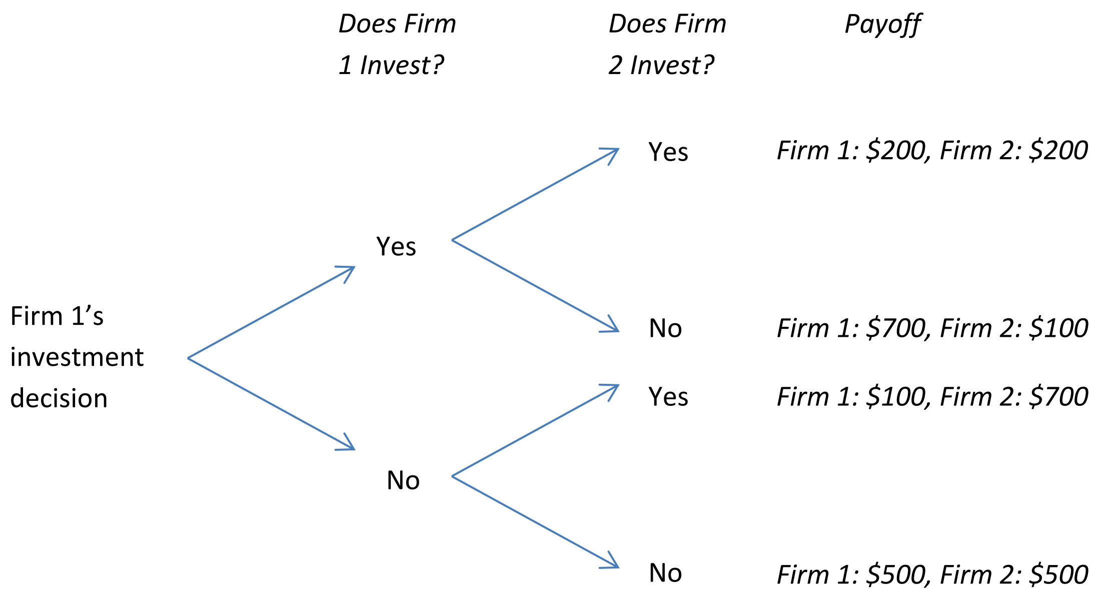
$$(20) \qquad x_1 = \frac{\frac{A_1 - MC}{2C_1} - \frac{B_1 A_2}{4C_1 B_2}}{1 - \frac{B_1 C_2}{2B_2}}$$

$$(21) \qquad x_2 = \frac{\frac{A_2 - MC}{2C_2} - \frac{B_2 A_1}{4C_2 B_1}}{1 - \frac{B_2 C_1}{2B_1}}$$

No definite statement can be made about the relationship between the quantities and the A_i parameters. Taking the derivatives does not add any additional clarity. The direction of the derivatives depends on the other parameters in the demand equations. Therefore, no definite statement can be made about the relationship between profit and A_i, and the conclusions of the model are ambiguous. Conclusions can only be drawn when information about the other parameters are known, which can only be learned empirically.

Even if the profit-carbon intensity relationship is not ambiguous, the behavior of firms is still not clear. If the expected benefit of carbon intensity investment depends on the competitor's carbon intensity, then firms have to make decisions based on the expected outcomes. Suppose that firms can only make a binary investment at a fixed cost. Consider decision tree 1.

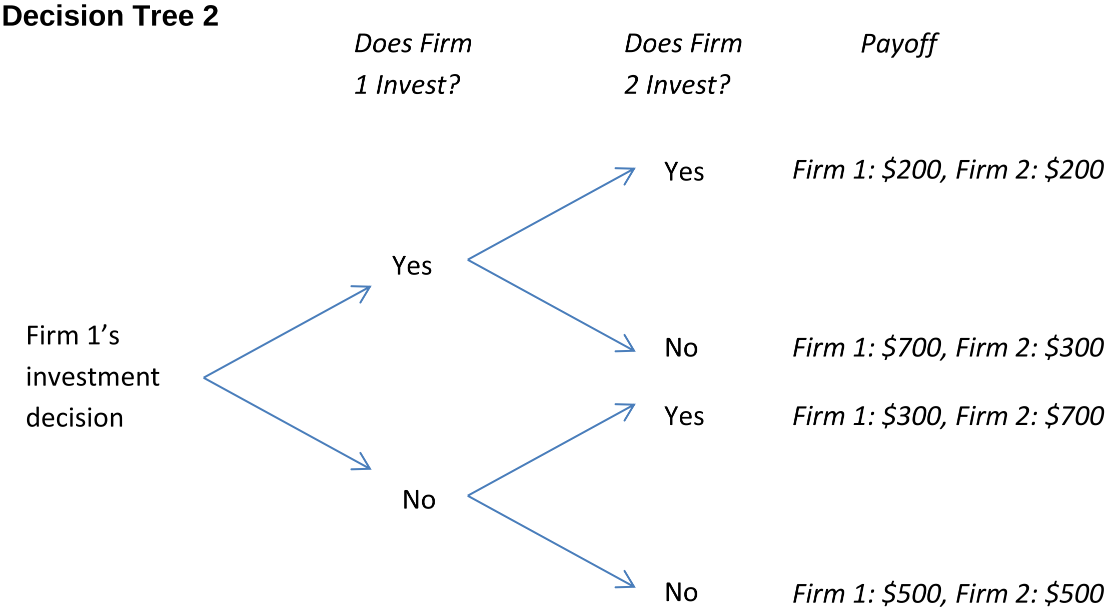
Decision Tree 1



The quantities in parentheses represent the expected net benefits of each decision combination. Both firms investing is the worst total outcome because they spend resources investing in carbon intensity reduction but gain no advantage in carbon intensity over the competitor. Yet both firms still invest because the outcome is better for investing regardless of what the competitor does. In the game with only two time periods, cooperation is impossible because both firms always experience the temptation to break any agreement, and they each know that the other firm has experiences that temptation. In a game with infinite periods, it is possible for the firms to cooperate because there is no definite end period in which firms are tempted to break the agreement.

Because the profit-carbon intensity relationship is theoretically ambiguous, the true payoff structure could differ greatly from decision tree 1. Consider decision tree 2:

Decision Tree 2



In decision tree 2, it is not clear what the firms will do. If firm 2 invests, then firm 1 is better off not investing. If firm 2 does not invest, then firm 1 is better off investing. If the firms cannot coordinate their actions, then the firms will make a decision based on expected outcomes and the expected decision of their competitor. Note that decision tree 2 still maintains the same assumption as in decision tree 1 that an investor has an advantage over a non-investor and that both firms investing is the worst outcome for them.

In summary, the theoretical model makes ambiguous predictions. The ambiguity comes at two levels. First, it is not clear that reductions in carbon intensity necessarily result in greater profit. Second, it is not clear that firms would invest in carbon intensity reduction even if it can increase profits. The model makes many simplifying assumptions that may not reflect the real world. For these reasons, empirical estimation of the profit-carbon intensity relationship is crucial.

III. DATA AND SUMMARY STATISTICS

The carbon emissions data for this paper come from CDP[6], a non-profit organization whose mission is to facilitate transparency of companies' environmental impact around the world. CDP publishes a data set that reports the carbon emissions of the top 500 companies in the world by market capitalization[7]. The data span three years 2011-2013[8]. I use only the data of companies from the United States because my financial data only includes United States companies. There are 343 company-year

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6 CDP was formerly known as the Carbon Disclosure Project.

7 Market capitalization is the total value of a publicly traded company's shares. In other words, the price of its shares times the total number of shares.

8 The CDP survey has been taken for more years than this time span, but I only have access to these years due to my own financial constraints.

observations in the data set. Some companies appear for less than three years because they entered or exited the sample during the collection period. CDP collects the data through survey responses, to which companies respond on a voluntary basis. The US subsample of the survey has 343 respondents and 124 non-respondents, providing a 73% response rate. The number of non-respondents is great enough to cause response bias. The robustness section addresses the possibility and consequences of response bias in the results.

CDP reports two different types of emissions. Scope 1 emissions refer to emissions which happen on-site and under the control of the company. These make up the majority of emissions for most companies. Scope 2 emissions are from purchased energy, heat, and steam. Note that on-site energy generation falls into scope 1 emissions. The advantage of including only scope 1 emissions in the econometric model is that changes in energy prices would not confound the profit-emissions relationship, unless there is heterogeneity in the cost of on-site energy generation. On the other hand, scope 1 emissions would not pick up the effect of reductions in a company's energy intensity, an important source of carbon emissions reduction. Our primary models use the sum of scope 1 and scope 2 emissions as the independent variable, but I also estimate with the separate emissions types for robustness.

Carbon intensity is the emissions divided by revenue[9]. I use carbon intensity instead of carbon emissions because intensity relates the quantity of carbon emissions to the size of the company. Another possible measure of carbon intensity would be carbon emissions per quantity produced. This measure better corresponds with our theoretical model, but there are problems with the quantity measure. Different products

[9] All financial variables are in real terms.

of the same company can have different carbon emissions. I would have to use a weighted average of carbon emissions among different products. The data to perform this calculation at the company level do not exist for most companies in the sample. Carbon emissions divided by revenue is a less data-intensive alternative that should not alter results. Of course, the ideal paper would use both measures.

Figure 1 shows the distribution of carbon intensity. Carbon intensity follows approximately a log-normal distribution with some extreme values along the tail. There are two outliers at 0.9931 and 0.9130 tons CO2e/USD. Both of the outliers are observations of Dominion Resources, a utilities company on the east coast of the United States. All of the values of carbon intensities are reasonable. It is not surprising that there are extremes in carbon intensity because the sample is diverse among industries. Energy utilities naturally have higher carbon intensity than Walmart. It also makes sense that the order of magnitude of carbon intensity is low. For large companies, revenue is in the billions of USD.

The financial data come from EDGAR, the SEC database listing all 10-K and 10-Q filings[10]. All publicly traded companies in the United States are required to submit these filings to the SEC each year. They provide much financial information about each company. I use the revenue, assets, and profit data from each filing. All values are in real terms. Profit is the dependent variable in all regressions. The assets variable refers to the total value of durable goods held by a company. I use this variable as a control in some regressions. Revenue is only used to calculate carbon intensity. Every company in the sample has these data. Figures 2, 3, and 4 show the distributions of the financial data used in this paper.

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10 Thank you to the writers at StockPup (http://www.stockpup.com/data/) for extracting the data from EDGAR and sharing their work for free.

The financial variables also follow a log-normal distribution. This distribution makes sense for revenue and assets because a company must make at least certain amount of revenue to be in the top 500 companies by market capitalization. The minimum cutoff means that by definition all the extremes occur on the right side, instead of the left side.

Table 1: Summary Statistics (Years: 2011-2013)

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Carbon Intensity	343	0.000486	0.1126	0.0000872	0.9931
Revenue (Ten Millions)	343	200	296	8.34	2110
Profit (Ten Millions)	343	20.7	25.9	-3.048	197
Assets (Ten Millions)	343	708	1670	21.1	10500

All of the independent variables have a standard deviation greater than its mean. The high variation in the sample means that the econometric models are more capable of finding a signal in the data. Profit has one less observation because there was one negative value for unlogged profit in the sample. As discussed above, the extremes occur on the right side of the distributions, which explains why the maxima tend to be much further from the means than the minima. The effect of outliers will be discussed in the robustness section.

Figure 1[11]

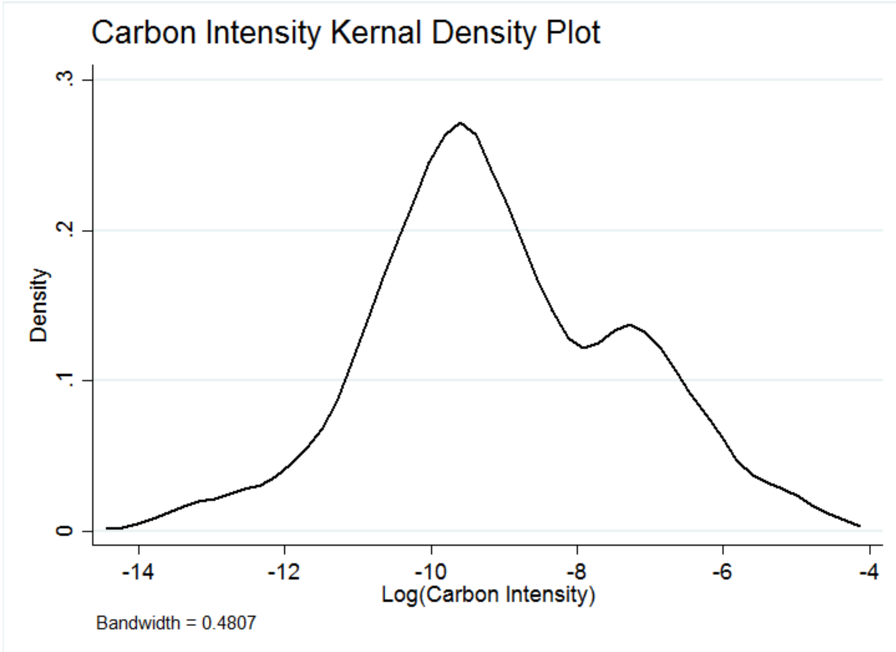
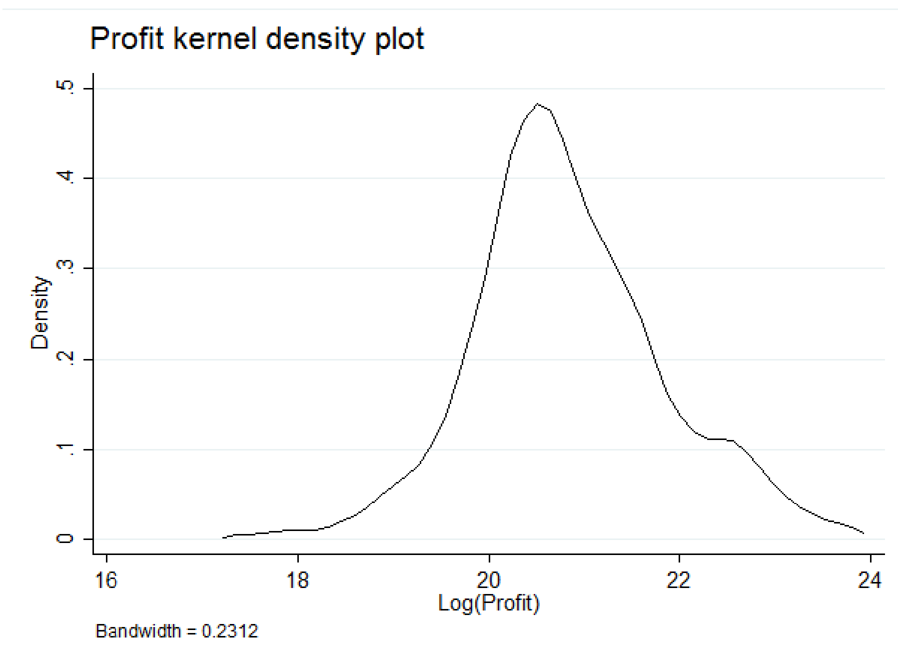


Figure 2[12]



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11 All values for carbon intensity I positive.

12 There I two company-years with negative profit.

Figure 3[13]

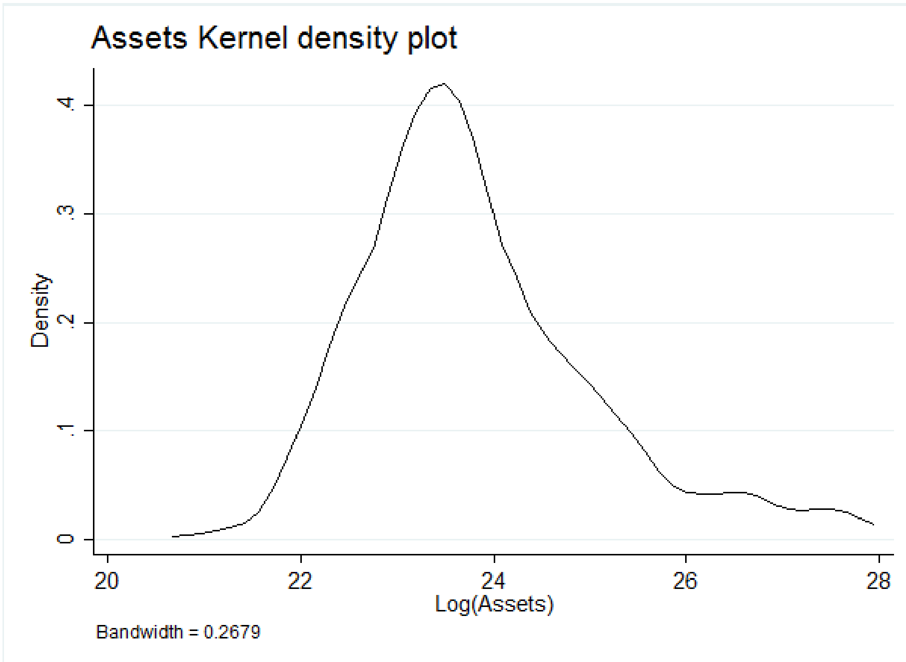
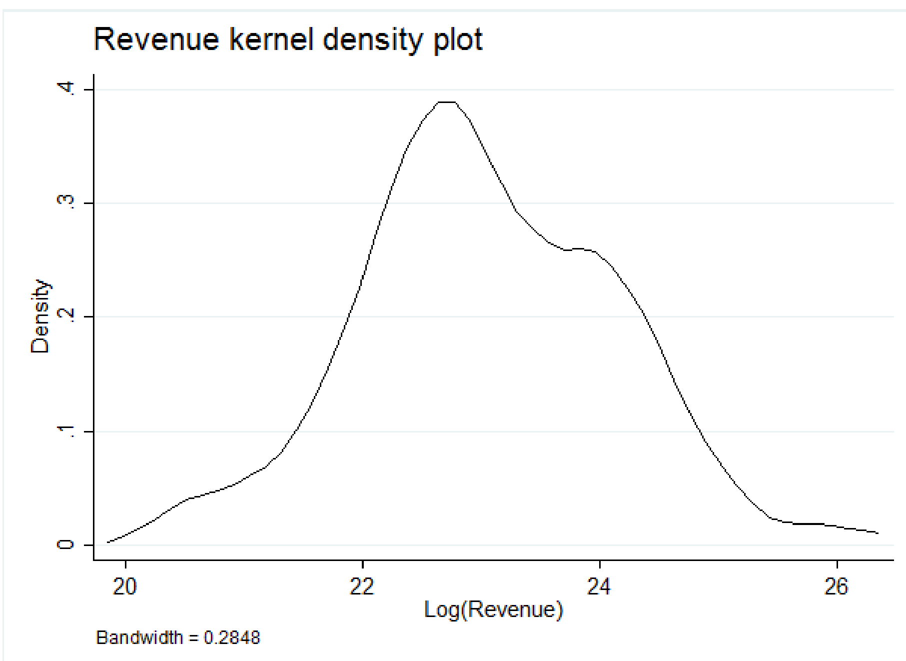


Figure 4[14]



13 All values for assets I positive.
14 All values for revenue I positive.

Table 2 shows the number of observations in each industry. The 5 industries with the greatest number of observations are finance and insurance, information, manufacturing 2, manufacturing 3, and wholesale trade. The differences in the size of industry groups matters for the estimation of models with industry-carbon intensity interaction terms. Small groups will have larger standard errors and smaller t-scores. The model is likely commit type 2 errors when industry groups are small.

These data work well to empirically test the model laid out in the theory section. First, large companies are much more visible to consumers than small consumers. Greater visibility means that consumers can have information by which they may make their consumption choices. In terms of the theoretical model, consumers may place a greater weight on carbon emissions in visible industries (i.e. the gamma parameter is more negative). Second, many of the companies in the sample are in common industries, meaning that I can observe within industry effects of carbon emissions on profit.

The trickiest part of these data is determining whether they represent what consumers actually observe about carbon emissions. It seems unlikely that a significant number of consumers research the specific carbon emissions of the products they purchase. Rather, consumers may make decisions based on general feelings about carbon intensity. For instance, most consumers know and believe that a Toyota Prius emits less carbon than the comparable Toyota Corolla. Another question is where consumers get their information. For example, most companies publish a Corporate Social Responsibility Report[15] detailing their efforts to reduce environmental impact. Consumers may use those as sources of information. This is only a problem if

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[15] Example: http://www.generalmills.com/~/media/Files/GRR/GRR_2016_report.pdf?la=en

companies report different carbon emissions between the CSR report and CDP survey response.

Table 2: Industry tabulation

Industry	Observations
Adminstrative and Waste Management	4
Construction	6
Entertainment	10
Finance and Insurance	66
Food Services	3
Information	34
Manufacturing 1	12
Manufacturing 2	45
Manufacturing 3	45
Mining and Gas Extraction	35
Professional, Scientific, and Technical Services	9
Real Estate	5
Retain Trade 1	27
Retail Trade 2	12
Transportation	15
Utilities	14
Wholesale Trade	30

Another problem is that marketing may matter more than actual carbon emissions performance. I could argue that marketing would not work without actual results to support it, but it would be naive to assume that marketers need evidence to run an effective marketing campaign. If there is a difference between our data and what consumers observe due to marketing, then our models should fail to find a signal of the emissions-profit relationship or find a weaker signal than what I would otherwise find.

IV. ESTIMATION EQUATIONS

Every empirical model in this paper uses a random effects estimator. The data do not contain enough observations for each company to take advantage of fixed effects. The panel contains at most three years for a company. Each model has a fixed effect term for the year of the observation. I use logged profit as the dependent variable because the order of magnitude of profit is much greater than carbon intensity. An unlogged dependent variable would make the model heteroskedastic and may underestimate the statistical significance of the coefficients. The independent variables are unlogged. After calculating the log-level regressions, I derive the carbon elasticity of profit at the mean values of carbon intensity and profit. These elasticities are the results of interest for the models without interactions terms. For the models with interactions terms, I simply use log-log regressions because it is difficult to attain an estimate of the elasticities of individual groups when the groups are small.

I begin with the simplest model for the relationship between profit and carbon emissions:

$$\text{(E1)} \qquad \pi_{it} = B_1 + B_2 c_{it} + \theta_t + \varepsilon_{it}$$

The symbol π_{it} indicates logged profit, c_{it} indicates carbon intensity of a single company-year observation, θ_t is the dummy for year, and ε_{it} is the error term for an observation *it*. The coefficient B_2 signifies the percentage by which profit increases after a one unit change in carbon intensity[16]. This model says little about whether carbon emissions cause the company-year to earn more profit, but subsequent, more informative models build off it.

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[16] I used a specification of the STATA margins command to calculate the elasticity from B_2.

Model E2 controls for the heterogeneity in profit between industries by adding dummies for each industry using 2-digit NAICS codes:

$$\text{(E2)} \quad \pi_{it} = B_1 + B_2 c_{it} + \theta_t + \mu_j + \varepsilon_{it}$$

The symbol μ_i indicates the dummy for the industry of observation *i.* Industry variation could explain a negative elasticity because industries that are characteristically lower carbon intensity could earn more profit. For example, it consumes much more energy for a factory to manufacture a car than a lawyer to try a case, even though the total of lawyer's fees at the end of a trial may sum to the price of a car. The dummies pull out the mean profit for each industry, meaning that the coefficient B_2does not pick up the effect of between industry effects.

This is where the industry definitions matter. If industry definitions are not granular enough – that is, the 2-digit NAICS codes do not capture variation between industries – then the estimation of B_2 may be inconsistent because heterogeneity in carbon intensity and profit between industries biases the coefficient. If the codes are too detailed because a company produces many different products, then the estimation is inefficient because there are more industry groups than necessary for a consistent estimation. Ideally, I would use fixed effects to control for time-invariant characteristics of firms, but the available data do not allow for such a model.

The next model controls for heterogeneity in energy consuming capital by using the value of assets as a proxy for a company's use of capital:

$$\text{(E3)} \quad \pi_{it} = B_1 + B_2 c_{it} + B_3 K_{it} + \theta_t + \mu_j + \varepsilon_{it}$$

The symbol K_{it} indicates the amount of assets owned by a company in year *t*. Heterogeneity in energy consuming capital could positively bias the coefficient B_2 and elasticity. Clearly, not all assets result in carbon emissions. Financial assets do not emit carbon, but manufacturing capital assets do. The assets variable picks up more heterogeneity than necessary, but it is not important to estimate a consistent coefficient for assets.

The fourth model is the same as model E3 but with differences between carbon emissions and profit.

$$\text{(E4)} \quad \pi_{it} - \pi_{i(t-1)} = B_1 + B_2(c_{it} - c_{i(t-1)}) + B_3 K_{it} + \theta_t + \mu_j + \varepsilon_{it}$$

The coefficient B_2 is interpreted differently in E4 than the other models. Here it means when the difference in carbon intensity increases by 1, the percent change in profit increases by B_2 dollars.

The differences model controls for industry level characteristics. As explained above, industry heterogeneity could explain a negative coefficient if not properly controlled in models E1 though E3. In the differences model, industry heterogeneity in the levels of carbon intensity and profit could not explain a negative B_2 coefficient. The story would have to be that some industries gain more profit faster than others and that those same industries tend to decrease their carbon intensity from year to year. That story seems less likely than the industry heterogeneity confounding story in models E1 thorough E3.

The differences model controls for any variable that is confounding in levels but not differences. Heterogeneity in energy efficiency is another example. In the level models, energy efficient companies have higher profit because of lower energy costs but emit less carbon because they can produce the same output while consuming less energy. Therefore, the result is a negative B_2 coefficient. But in the differences model, the confounding story must be that firms which have an increasing rate of profit gains also are becoming more energy efficient each year. Although the differences model made the problem a little better, this still is a believable explanation for a negative coefficient. The robustness section addresses changes in energy efficiency as a confounding variable.

The last two models add industry interaction terms to models E3 and E4:

(E5) $\pi_{it} = B_1 + B_2 c_{it} + B_3 K_{it} + B_4 c_{it}\mu_j + \theta_t + \mu_j + \varepsilon_{it}$

(E6) $\pi_{it} - \pi_{i(t-1)} = B_1 + B_2(c_{it} - c_{i(t-1)}) + B_3 K_{it} + B_4(c_{it} - c_{i(t-1)})\mu_j + \theta_t + \mu_j + \varepsilon_{it}$

The interaction terms reflect variation in the effect of carbon emission on profit between industries. The model described in this paper's theory section suggests that if consumers have less information about a firm, then the effect of carbon emissions on profit is diminished. Consumer information may vary at the industry level.

Profit relationships are difficult to estimate because many variables determine profit. Any of these variables which affects revenue or costs that also decreases energy intensity is a confounding variable. Energy intensity is one example. As a firm becomes more energy intense, carbon intensity decreases because the firm consumes less energy and profit increases because the firm experiences lesser costs. In order to address this problem, in part, I use the same models to estimate the revenue-carbon intensity relationship. Fewer variables confound that relationship. A negative coefficient on carbon intensity for these models is stronger evidence for the consumer-preference model described in section III. If that model is accurate, I expect to see consistent results for both profit and revenue.

Another challenge in empirical estimation is endogeneity. The argument is that profitable companies have more capital to make investments. Some of those investments may be reductions in carbon intensity. Therefore, profit causes lower carbon intensity. The same argument also applies to revenue. I have no empirical tool to address endogeneity concerns. The theoretical arguments made in section III answer endogeneity on theoretical grounds.

V. RESULTS

Table 3 summarizes the most important regression result for profit models 1 through 4 – carbon intensity elasticity of revenue. The elasticities are all significantly negative. The magnitude stays about the same for each model, except for model 4 (the differenced model) which has a different interpretation than models 1 through 3. The elasticities for the first four models seem reasonable. If carbon intensity halves, then profit increases by 10%. I expect to see an inelastic relationship because carbon emissions only makes up one part of consumer preferences. There are many other characteristics of goods about which consumer may care. If the results are robust, then they are evidence in support of the hypothesis that lower carbon intensity results in greater profit.

One notable result is that R-squared is low in the first model without industry or asset controls, but increases five-fold with the controls. The low R-squared and low magnitude on the elasticities mean that carbon intensity explains only a small portion of variation in profit. It would have been concerning if the models suggested that changes in carbon intensity explained a large part of variation in profit.

Table 4 presents the carbon intensity elasticities for revenue. The elasticities in the revenue models are similar to those in the profit models. All elasticities are around -0.10 (except for the differenced models, which are around -0.02). These results are encouraging. They suggest that the changes to profit are occurring mostly through revenue. The empirical results are consistent with consumer preferences being the cause of profit gains.

The industry dummies are significant in the levels models but insignificant in the differenced models. This suggests that there is not much variation in first-order changes in profit between industries. Because there is no variation in profit at the industry level, the differenced model is robust to industry heterogeneity as a confounding explanation for the negative coefficient on carbon intensity. The confounding variables must be heterogeneity in first-order changes. The only surprising result is that the time dummies are not significant for any model except the differenced model. This suggests that profit does not tend to vary across years.

The number of observations changes between the level model and the difference model because the first year for each company has no difference. There is no variation in profit for each year – as shown by the year dummy – so the dropped years should not bias the results in the differences. There are 142 companies in the data and 145 observations dropped in the differenced model. The extra 3 are because 3 companies had observations in 2011 and 2013, so they dropped two observations in the differenced model.

Regressions 5 and 6 add industry interaction terms to regressions 3 and 4. Figures 5 and 6 illustrate the elasticities calculated from the regressions. Regression 5 finds that the coefficient is only significant for finance and insurance, manufacturing 1, manufacturing 2, mining and gas, and retail trade 2. Regression 6, the differenced model, finds that the coefficient is only significant for food service, finance and insurance, manufacturing 3, and mining and gas extraction. The takeaway from these results is that the characteristics of industries affect the profit-carbon intensity relationship. However, these models do not do a good job identifying precisely for which industries it matters because some of the industry groups have fewer observations than the others.

The industries that do have significant coefficients are industries more visible to consumers than other industries. Consumers interact directly with firms in the retail trade, food service, and insurance industries. Ethical consumers would be most concerned with the industries with which they directly interact. Therefore, it makes sense to see a strong effect of carbon intensity in those two industries. Manufacturing, mining, and gas companies do not fit that explanation because consumers do not purchase goods directly from those companies. Rather, these companies may have high consumer perception because they are the “usual suspects” of carbon emissions. Energy companies such as Exxon Mobile fall into these categories.

Figures 7 and 8 show the results of the revenue interacted regressions. The most important result is that every industry that had a significant coefficient in figures 5 or 6 also has a significant coefficient in figures 7 or 8, except for food services. This shows that carbon intensity is affecting profit through revenue. Two industries, retail and wholesale trade, had significant coefficients in the revenue figures but not the profit figure.

Table 2 in summary statistics tabulates the number of observations in each industry. The 5 industries with the greatest number of observations are finance and insurance, information, manufacturing 2, manufacturing 3, and wholesale trade. Out of those 5 industries, only wholesale trade has an insignificant coefficient in neither regression 5 nor 6. Retail trade 2 and food services have a low number of observations but a positive coefficient in one of the models. The low number of observations for some industries means that the model is likely to commit type 2 errors on the carbon intensity coefficients for those industries. This is supported by the fact that the industries with significant coefficients tend to have more observations than the industries with insignificant coefficients. It would not be wise to interpret figures 5 and 6 as showing exactly for which industries carbon emissions matters. Rather, one should conclude that there seems to be heterogeneity in the carbon intensity effect on profit between industries, and more information is needed to determine precisely how they differ.

Table 3: Profit Elasticities [17]

Model	(E1) Base Model	(E2) Industry Fixed Effects	(E3) Asset Control + Industry FE	(E4) Differences
Carbon Intensity Elasticity of Profit[18]	-0.1025***	-0.1126***	-0.1094***	-0.0238***
Observations	343	343	343	197
F-Statistic	8.47	4.42	7.60	2.50
Adj. R-Squared	0.0617	0.1602	0.2791	0.1270

***p<0.01 **p<0.05 *p<0.10

Table 4: Revenue Elasticities [19]

Model	(E1) Base Model	(E2) Industry Fixed Effects	(E3) Asset Control + Industry FE	(E4) Differences
Carbon Intensity Elasticity of Revenue[20]	-0.0910***	-0.1102***	-0.1070***	-0.01669***
Observations	343	343	343	197
F-Statistic	5.30	4.83	8.19	2.98
Adj. R-Squared	0.0363	0.1754	0.2961	0.2413

***p<0.01 **p<0.05 *p<0.10

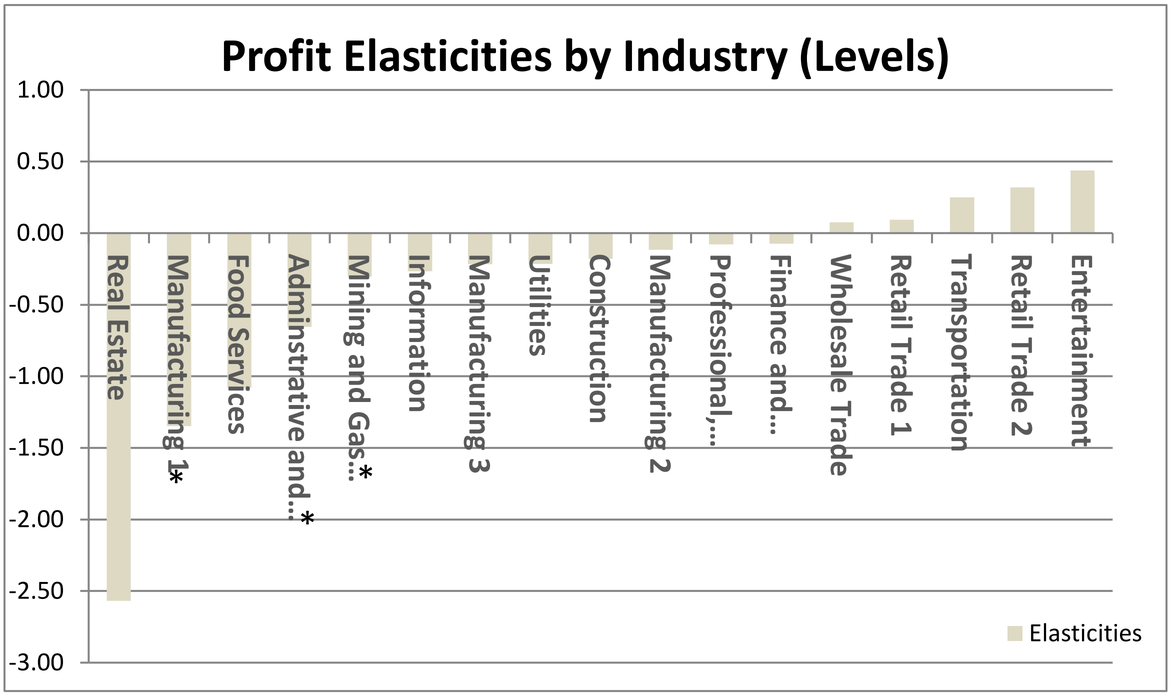
[17] Table 3 summarizes the key results from the non-interacted profit regressions. Beginning from the left, each subsequent model adds one new complexity. The appendix contains the full regression results for each model.

[18] Carbon Elasticity of Profit is the elasticity between profit and carbon intensity.

[19] Table 4 summarizes the key results from the non-interacted revenue regressions. Beginning from the left, each subsequent model adds one new complexity. The appendix contains the full regression results for each model.

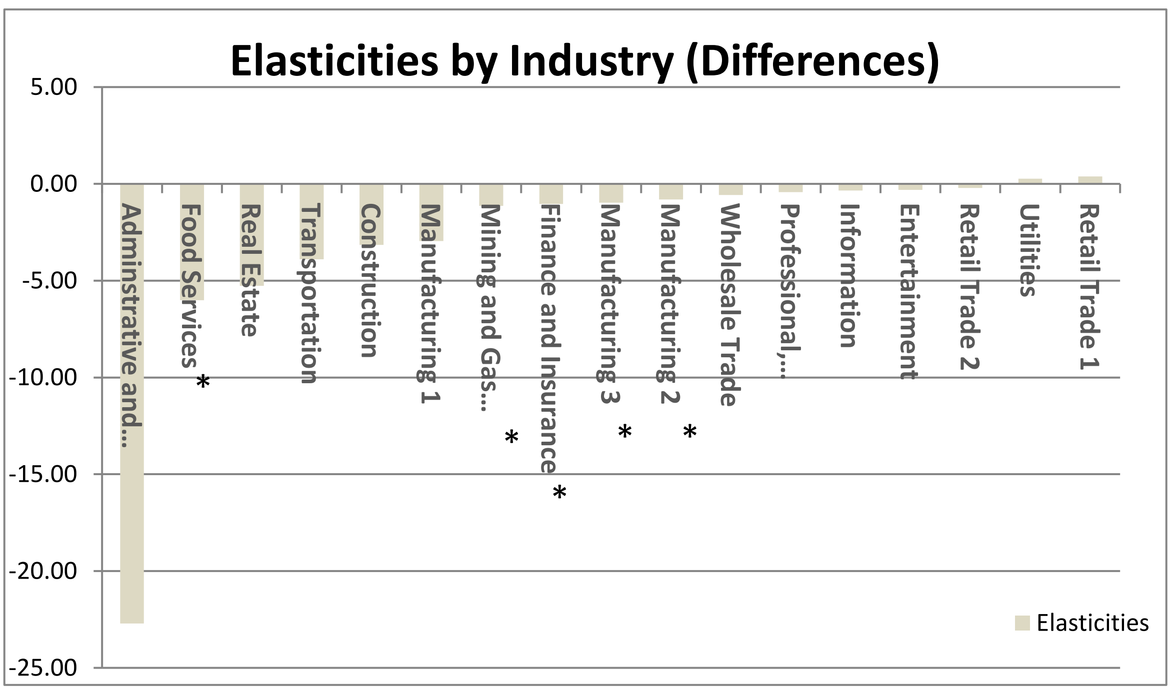
[20] Carbon Elasticity of Revenue is the elasticity between profit and revenue.

Figure 5: Profit Elasticities by Industry (Levels)



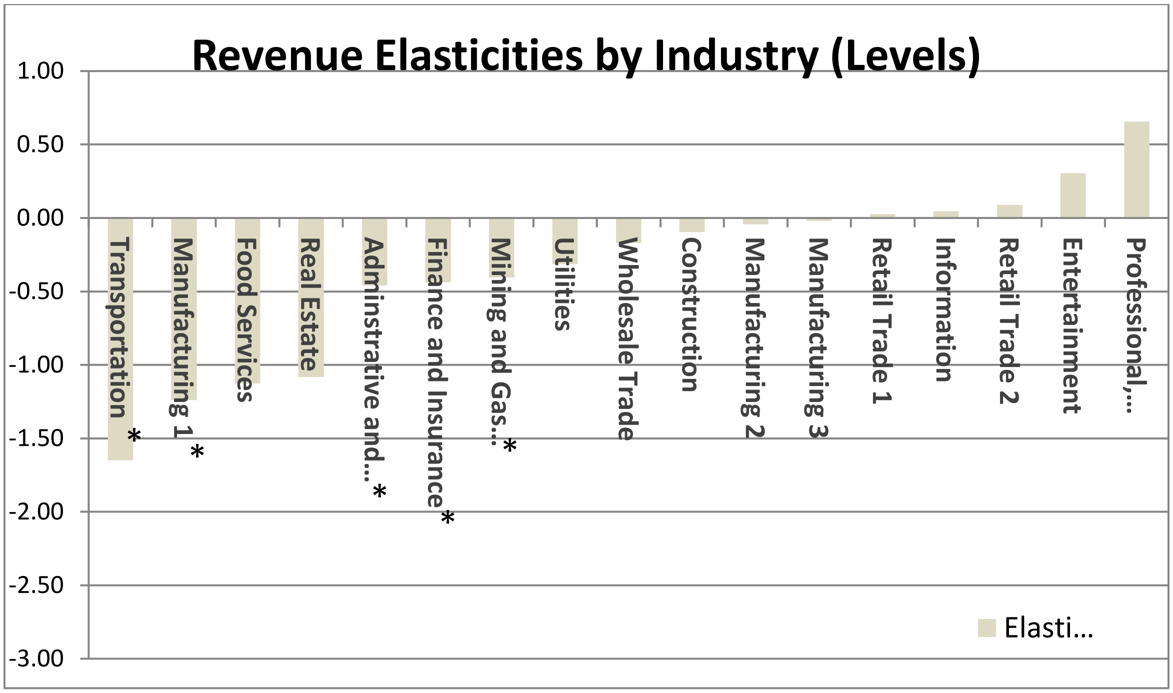
*Indicates significance at p <0.05 level

Figure 6: Profit Elasticities by Industry (Differences)



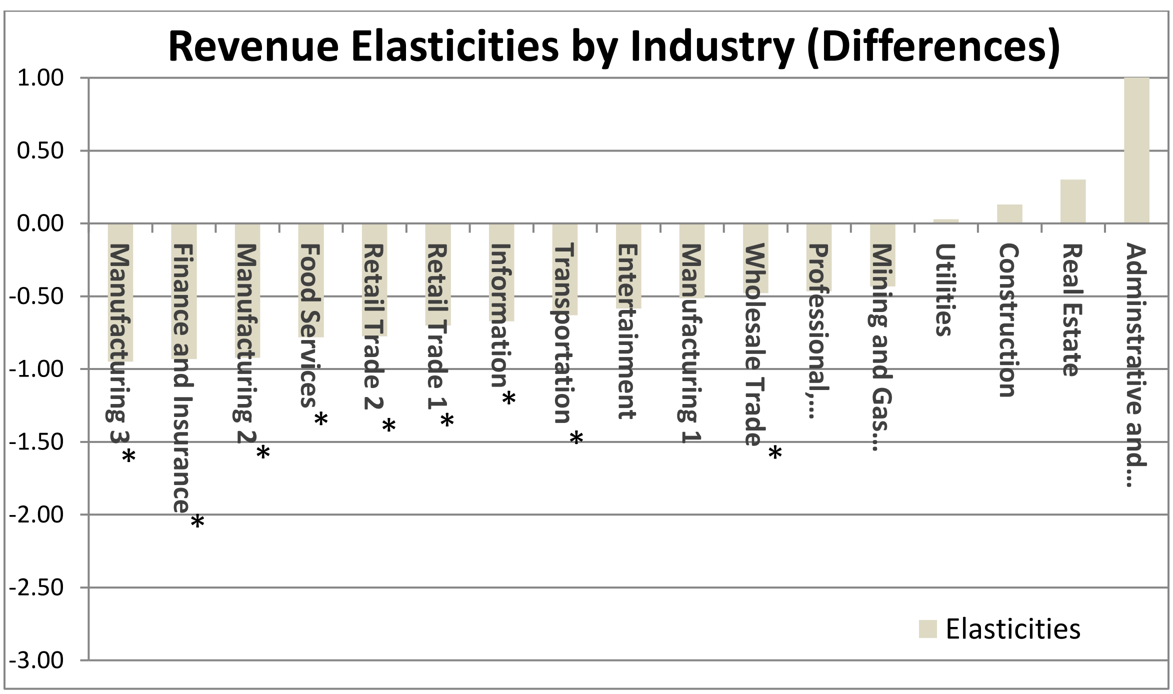
*Indicates significance at p <0.05 level

Figure 7: Revenue Elasticities by Industry (Levels)



*Indicates significance at p <0.05 level

Figure 8: Revenue Elasticities by Industry (Differences)



*Indicates significance at p <0.05 level

VI. ROBUSTNESS

There are a number of potential robustness concerns the results. Table 5 lists each potential robustness problem and its consequence for conclusions.

Table 5: Robustness problems

Robustness problem	Consequences if unaddressed
Within industry energy efficiency heterogeneity	Inconsistent coefficient estimates
Within industry low carbon energy price heterogeneity	Inconsistent coefficient estimates
Time	Conclusions limited to sample time period
Firm size	Conclusions limited to sample firm and comparable firms
Country heterogeneity	Conclusions limited to United States and comparable countries
Sampling bias	Inconsistent coefficient estimates
Results driven by outliers	Conclusions limited out of sample

Some of these robustness problems have already been discussed in previous sections. The differenced model eliminates the effect of energy efficiency heterogeneity, but there could still be a confounding effect if firms that are gaining profit also are becoming more energy efficient. To test whether the results are robust to energy efficiency heterogeneity, I run the differences models (models 4 and 6) using only scope 1 emissions, which do not include emissions from purchases electricity. The result is still a significantly negative coefficient. Scope 1 emissions include emissions generated on-site, meaning that heterogeneity in the differences of on-site energy generation efficiency within industries could explain a negative coefficient. For that to be the case, on-site energy generation would also have to make up a large portion of companies' energy sources, but most electricity is purchased from electric utilities. It seems unlikely that energy efficiency confounds the coefficient in the difference models.

Low carbon energy price heterogeneity could also explain a negative coefficient. If some companies face a lesser carbon energy price than others, and the price of low carbon energy is lower than high carbon energy sources, then those firms could receive higher earnings and emit less carbon. This may be the case in regions where solar energy is cheap and so companies build on-site solar generation. Without information about low carbon energy prices faced by specific companies, I cannot control for heterogeneity at the firm level. Industry controls do allow me to control for heterogeneity at the industry level, and the difference models are only confounded if there is heterogeneity in the differences of low carbon energy prices within industries.

The next three robustness problems constrain the conclusions that can be derived from the results, but do not cause inconsistent coefficient estimates. The relationship between carbon emissions and profit may change over time. For example, people may care less about carbon emissions during recessions than boom periods. The results are robust within the sample time period because of the time dummies, but they are not robust out of sample. The results may also not be robust to firms out of sample. The sample includes only some of the top 500 largest companies in the world by market capitalization based in the United States. This paper's theoretical model assumes that firms are oligarchic. It may not apply to smaller firms in more competitive markets.

Finally, differences in knowledge and opinions about climate change between countries could result in different coefficients, so conclusions must be limited to the United States.

The carbon intensity data come from a survey, and there may be sampling bias in the estimates of the coefficients. The bias would arise if survey respondents tend to earn more profit and decrease their carbon intensity each year, or vice-versa. Low carbon intensity firms may be more likely to respond because they want to publicize their results. There is no way to test that hypothesis about carbon intensity. I can, however, observe that there is no significant difference in the means of profit between the two groups. Table 6 summarizes the profits.

Table 6: Respondents vs Non-respondents

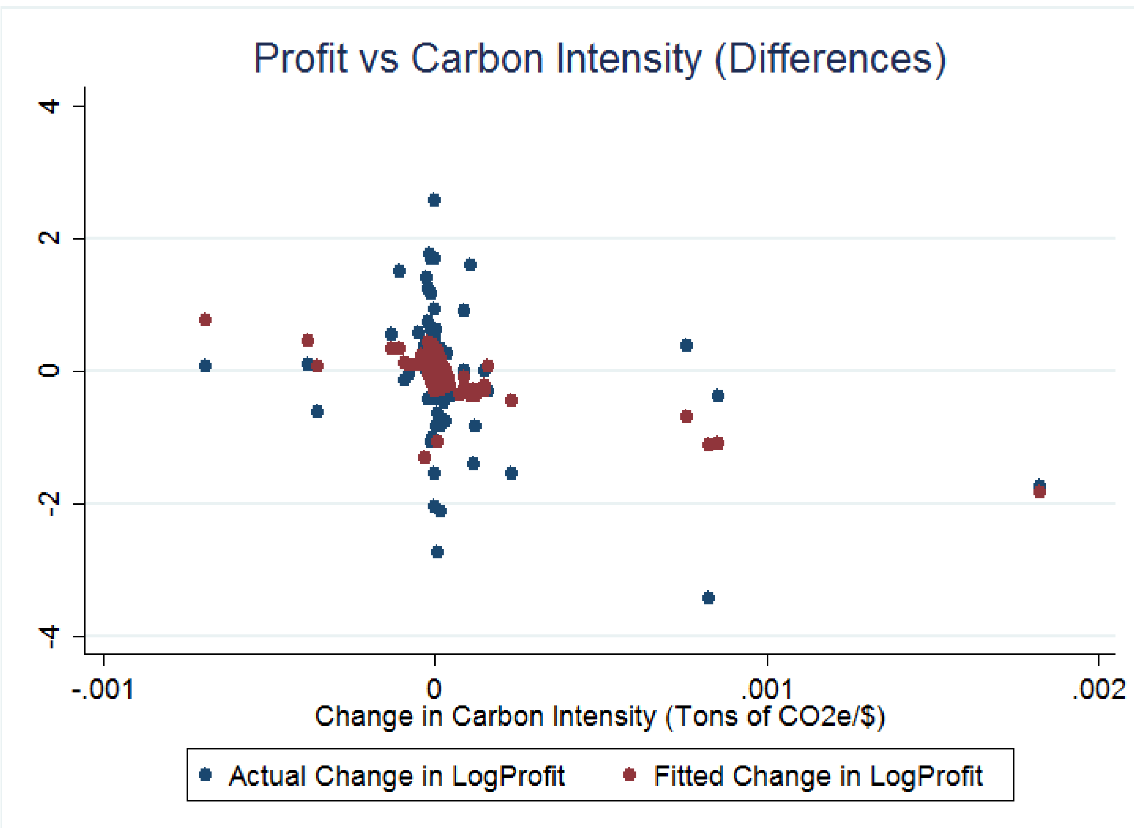
Group	Mean of Logged Profit	Standard Deviation	Observations
Respondents	21.77	0.9845	344
Non-respondents	21.33	0.9586	123

The results may be sensitive to outliers. Figure 9 shows the actual and fitted values of profit versus carbon intensity for model 4 (the differences model with no interaction terms). The farthest outliers have relatively highly positive changes in carbon intensity and highly negative changes in logged profit. The two largest such outliers are Devon Energy Corporation and Newmont Mining Corporation. Removing both of those from the sample results in an insignificant coefficient on change in carbon intensity. On the hand, there are some outliers with highly positive changes in profit and no change or highly negative change in carbon intensity. Removing Marathon Oil Corporation and

Exxon Mobil from the sample at the same time as the other two outliers results in a significantly negative coefficient.

The overall results seem to be sensitive to the addition and removal of outliers. There are two qualifications to that sensitivity. First, results hold if I remove outliers from both sides. Second, the outliers tend to be in the energy sector. In fact, all of the top 4 outliers are from the mining and gas industry. Removing outliers in one industry does not significantly affect the coefficient in other industries.

Figure 9[21]



21 Note that this graph uses colors to differentiate fitted and actual changes.

VII. CONCLUSIONS

I find evidence to support the hypothesis that lower carbon intensity results in greater profit for companies. I develop a theoretical model to explain how consumer preference for low carbon intensity products can increase profit for oligarchic companies with lower carbon intensity than competitors. Companies play a game in which they choose to invest in carbon intensity reduction. The results of the theoretical model are ambiguous, emphasizing the need for empirical evidence.

The empirical evidence supports that carbon intensity decreases profit. The results hold up when the model controls for industry effects and differences. The models with interaction terms complicate the results. My estimates of the carbon intensity elasticity is -0.10. The effect is heterogeneous across industries – I find no effect for some industries but a negative coefficient for others. The insignificant coefficients may be the result of some industries having fewer observations in the data than others. Because of this constraint, I conclude that carbon intensity matters more in some industries than other, but I hesitate to say exactly for which industries carbon intensity does not matter. The results when revenue is used as the dependent variable instead of profit. This means that the results are robust to omitted variables that confound through cost. The greatest cause for concern is endogeneity. If profitable companies can invest more in carbon intensity reduction, then that would explain the negative coefficient. I have no way to address endogeneity other than the theoretical arguments made in section III.

There are potential upgrades to this thesis. While the differenced model does some work to control for confounding variables, a fixed effects model would go a long way to controlling for time-invariant confounding characteristics of firms. This model requires panel data with more observations for each group than currently available. Firm-level data about energy-efficiency and low carbon energy prices would also help to give more confidence that these variables do not cause the negative coefficient in these models. I would also like to see about whether these results hold for similar companies in other countries.

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APPENDIX

Derivation of Equation (6) in the theory section:

The consumer's utility function is

$$U = x_1^{\alpha} x_2^{\beta} C^{\gamma}$$

The consumer chooses $x_1\ and\ x_2$ to maximize U subject to their income.

$$max\vartheta_{x_{1_{x_2\lambda}}} = x_1^{\alpha} x_2^{\beta} C^{\gamma} - \lambda(P_1 x_1 + P_2 x_2 - I)$$

There are three first order conditions:

$$\text{(A1)} \quad \frac{\partial\vartheta}{\partial x_1} = \alpha x_1^{\alpha-1} x_2^{\beta} C^{\gamma} + x_1^{\alpha} x_2^{\beta} \frac{\partial U}{\partial C} \frac{\partial C}{\partial x_1} - \lambda P_1 = 0$$

$$\text{(A2)} \quad \frac{\partial\vartheta}{\partial x_2} = \beta x_1^{\alpha} x_2^{\beta-1} C^{\gamma} + x_1^{\alpha} x_2^{\beta} \frac{\partial U}{\partial C} \frac{\partial C}{\partial x_2} - \lambda P_2 = 0$$

$$\text{(A3)} \quad \frac{\partial\vartheta}{\partial\lambda} = I - P_1 x_1 - P_2 x_2 = 0$$

Combining equations (A1) and (A2),

$$\text{(A4)} \quad \frac{x_1^{\alpha-1} x_2^{\beta} C^{\gamma} + x_1^{\alpha} x_2^{\beta} \frac{\partial U}{\partial C} \frac{\partial C}{\partial x_1}}{P_1} = \frac{\beta x_1^{\alpha} x_2^{\beta-1} C^{\gamma} + x_1^{\alpha} x_2^{\beta} \frac{\partial U}{\partial C} \frac{\partial C}{\partial x_2}}{P_2}$$

With equations (A4) and (A3), there are two unsolved variables with two different equations. By rearranging (A 3) so that only x_2 is on the left hand side, I can substitute x_2 into (A4). Rearranging gives the demand function

$$\text{(A5)} \quad x_1 = \frac{-P_2 C^{\gamma}(\alpha+\beta)}{P_2 \frac{\partial U}{\partial C} \frac{\partial C}{\partial x_1} - \frac{\partial U}{\partial C} \frac{\partial C}{\partial x_2} * P_1 - \frac{\beta C^{\gamma} P_2 P_1}{I}}$$

Regressions Table 1: No interactions

VARIABLES	(E1) logEarnings	(E2) logEarnings	(E3) logEarnings	(E4) D.logEarnings
Carbon Intensity	-210.5***	-231.1***	-224.7***	-445.2***
	(45.9)	(53.7)	(49.7)	(107.6)
Construction		-0.489	-0.781	0.0116
		(0.586)	(0.544)	(0.555)
Entertainment		-0.825	-0.798	0.0560
		(0.586)	(0.543)	(0.523)
Finance and Insurance		-1.091**	-1.649***	0.118
		(0.471)	(0.443)	(0.442)
Food Services		-2.729***	-2.635***	-1.213**
		(0.692)	(0.641)	(0.604)
Information		-0.845*	-0.849*	0.0813
		(0.483)	(0.447)	(0.451)
Manufacturing 1		-1.427**	-1.370***	-0.177
		(0.568)	(0.527)	(0.524)
Manufacturing 2		-0.832*	-0.797*	-0.0441
		(0.473)	(0.438)	(0.442)
Manufacturing 3		-1.398***	-1.347***	0.0632
		(0.476)	(0.441)	(0.445)
Mining and Gas Extraction		-0.971**	-0.961**	-0.153
		(0.478)	(0.443)	(0.450)
Scientific and Technical Services		-1.624***	-1.550***	0.101
		(0.546)	(0.506)	(0.506)
Real Estate		-2.440***	-2.367***	0.238
		(0.609)	(0.564)	(0.552)
Retail Trade 1		-1.191**	-1.156**	-0.0929
		(0.492)	(0.455)	(0.462)
Retail Trade 2		-1.144**	-1.113**	0.0391
		(0.525)	(0.486)	(0.485)

Transportation		-1.299**	-1.238***	0.0129
		(0.509)	(0.471)	(0.468)
Utilities		-1.316**	-1.287***	-0.0918
		(0.524)	(0.486)	(0.485)
Wholesale Trade		-1.635***	-1.562***	0.0478
		(0.484)	(0.449)	(0.453)
Assets			0***	0
			(0)	(0)
2012	-0.199	-0.178	-0.171	
	(0.126)	(0.120)	(0.111)	
2013	0.0280	0.0261	0.0495	0.282***
	(0.128)	(0.122)	(0.113)	(0.0871)
Constant	21.93***	23.10***	22.98***	-0.123
	(0.0940)	(0.459)	(0.425)	(0.430)
Observations	343	343	343	197
Adjusted R-squared	0.0617	0.1602	0.2791	0.1270
F-Stat	8.47	4.42	7.60	2.50

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Regression Table 2: Interaction Models

VARIABLES	(E5) logEarnings	(E6) D.logEarnings
Construction	-1.177*	-0.658
	(0.682)	(1.378)
Entertainment	-1.794**	-0.482
	(0.763)	(1.347)
Finance and Insurance	-1.949***	-0.504
	(0.485)	(1.308)
Food Services	-3.165	-2.604*
	(2.734)	(1.380)
Information	-0.979*	-0.457
	(0.502)	(1.311)
Manufacturing 1	-0.741	-0.752
	(0.702)	(1.336)
Manufacturing 2	-1.277***	-0.583
	(0.484)	(1.309)
Manufacturing 3	-1.748***	-0.534
	(0.495)	(1.309)
Mining and Gas Extraction	-1.062**	-0.665
	(0.502)	(1.310)
Scientific and Technical Services	-2.147***	-0.571
	(0.779)	(1.377)
Real Estate	-0.802	-0.617
	(3.348)	(1.535)
Retail Trade 1	-1.850***	-0.673
	(0.500)	(1.314)
Retail Trade 2	-2.741***	-0.797
	(0.711)	(1.510)
Transportation	-2.335***	-0.554
	(0.882)	(1.316)
Utilities	-2.183***	-0.730
	(0.557)	(1.322)

Wholesale Trade	-2.261***	-0.507
	(0.504)	(1.311)
Administrative and Waste Management#Carbon Intensity	-670***	-22.7
	(228)	(59.4)
Construction#Carbon Intensity	-916	-3.15
	(1804)	(6.77)
Entertainment#Carbon Intensity	10084	-0.319
	(10643)	(200)
Finance and Insurance#Carbon Intensity	-6594***	-1.04***
	(2464)	(0.315)
Food Services#Carbon Intensity	897	-6.00***
	(18356)	(1.42)
Information#Carbon Intensity	-3758***	-0.336
	(1311)	(0.511)
Manufacturing 1#Carbon Intensity	-2442***	-2.95
	(853)	(5.53)
Manufacturing 2#Carbon Intensity	-230***	-0.813
	(79)	(0.379)
Manufacturing 3#Carbon Intensity	-1191	-0.969**
	(1235)	(0.359)
Mining and Gas Extraction#Carbon Intensity	-590***	-1.13***
	(134)	(0.269)
Scientific and Technical Services#Carbon Intensity	2409	-0.423
	(9299)	(3.62)
Real Estate#Carbon Intensity	-9575	-5.26
	(14089)	(5.76)
Retail Trade 1#Carbon Intensity	436	-0.377
	(295)	(0.288)
Retail Trade 2#Carbon Intensity	15446**	-0.203

	(6411)	(0.802)
Transportation#Carbon Intensity	400	-3.89
	(764)	(4.04)
Utilities#Carbon Intensity	-94	-0.265
	(72)	(0.643)
Wholesale Trade#Carbon Intensity	567	-0.582
	(496)	(0.524)
Assets	0***	-0
	(0)	(0)
2012	-0.190*	
	(0.106)	
2013	0.0490	0.311***
	(0.108)	(0.0870)
Constant	23.47***	0.424
	(0.469)	(1.299)
Observations	342	197
F-Stat	6.30	2.84
Adjusted R-squared	0.346	0.2470

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Companies in Sample

	company year
1.	3M Company 2011
2.	3M Company 2012
3.	3M Company 2013
4.	AFLAC Incorporated 2011
5.	AFLAC Incorporated 2012
6.	AFLAC Incorporated 2013
7.	AT&T Inc. 2011
8.	AT&T Inc. 2012
9.	AT&T Inc. 2013
10.	Abbott Laboratories 2011
11.	Abbott Laboratories 2012
12.	Abbott Laboratories 2013
13.	Adobe Systems, Inc. 2013
14.	Aetna Inc. 2012
15.	Air Products & Chemicals, Inc. 2011
16.	Air Products & Chemicals, Inc. 2012
17.	Air Products & Chemicals, Inc. 2013
18.	Allergan, Inc. 2011
19.	Allergan, Inc. 2012
20.	Allergan, Inc. 2013
21.	Allstate Corporation 2011
22.	Allstate Corporation 2013
23.	Altria Group, Inc. 2011
24.	Altria Group, Inc. 2012
25.	American Express 2011
26.	American Express 2012
27.	American Express 2013
28.	American Tower Corp. 2011
29.	Amgen, Inc. 2011
30.	Amgen, Inc. 2012
31.	Amgen, Inc. 2013
32.	Anadarko Petroleum Corporation 2011
33.	Anadarko Petroleum Corporation 2013
34.	Apache Corporation 2011
35.	Apache Corporation 2012
36.	Apache Corporation 2013
37.	Automatic Data Processing, Inc. 2011

38. Automatic Data Processing, Inc. 2012
39. Automatic Data Processing, Inc. 2013
40. BB&T Corporation 2011
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41. Baker Hughes Incorporated 2011
42. Baker Hughes Incorporated 2012
43. Baker Hughes Incorporated 2013
44. Bank of America 2011
45. Bank of America 2012
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46. Bank of America 2013
47. Baxter International Inc. 2011
48. Baxter International Inc. 2012
49. Baxter International Inc. 2013
50. Becton, Dickinson and Co. 2011
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51. Becton, Dickinson and Co. 2012
52. Best Buy Co., Inc. 2011
53. Biogen Idec Inc. 2012
54. Biogen Idec Inc. 2013
55. Boeing Company 2011
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56. Boeing Company 2012
57. Boeing Company 2013
58. Bristol-Myers Squibb 2011
59. Bristol-Myers Squibb 2012
60. Bristol-Myers Squibb 2013
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61. CSX Corporation 2011
62. CSX Corporation 2012
63. CSX Corporation 2013
64. CVS Caremark Corporation 2011
65. CVS Caremark Corporation 2012
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66. CVS Caremark Corporation 2013
67. Capital One Financial 2011
68. Capital One Financial 2012
69. Capital One Financial 2013
70. Caterpillar Inc. 2011
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71. Celgene Corporation 2011
72. Celgene Corporation 2012
73. Celgene Corporation 2013
74. CenturyLink 2012
75. CenturyLink 2013
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76. Chevron Corporation 2011
77. Chevron Corporation 2012

78. Chevron Corporation 2013
79. Cisco Systems, Inc. 2011
80. Cisco Systems, Inc. 2012

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81. Cisco Systems, Inc. 2013
82. Citigroup Inc. 2011
83. Citigroup Inc. 2012
84. Citigroup Inc. 2013
85. Cognizant Technology Solutions Corp. 2011

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86. Cognizant Technology Solutions Corp. 2012
87. Cognizant Technology Solutions Corp. 2013
88. Colgate Palmolive Company 2011
89. Colgate Palmolive Company 2012
90. ConocoPhillips 2011

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91. ConocoPhillips 2012
92. ConocoPhillips 2013
93. Consolidated Edison, Inc. 2012
94. Corning Incorporated 2011
95. Corning Incorporated 2012

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96. Corning Incorporated 2013
97. Costco Wholesale Corporation 2012
98. Costco Wholesale Corporation 2013
99. Cummins Inc. 2013
100. Deere & Company 2011

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101. Deere & Company 2012
102. Deere & Company 2013
103. Dell Inc. 2011
104. Dell Inc. 2012
105. Devon Energy Corporation 2011

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106. Devon Energy Corporation 2012
107. Dominion Resources, Inc. 2011
108. Dominion Resources, Inc. 2012
109. Dow Chemical Company 2011
110. Dow Chemical Company 2012

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111. Dow Chemical Company 2013
112. E.I. du Pont de Nemours and Company 2011
113. E.I. du Pont de Nemours and Company 2012
114. E.I. du Pont de Nemours and Company 2013
115. EMC Corporation 2011

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116. EMC Corporation 2012
117. EMC Corporation 2013

118. Eaton Corporation 2013
119. Ecolab Inc. 2012
120. Ecolab Inc. 2013

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121. Eli Lilly & Co. 2011
122. Eli Lilly & Co. 2012
123. Eli Lilly & Co. 2013
124. Exelon Corporation 2011
125. Exelon Corporation 2012

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126. Exelon Corporation 2013
127. Express Scripts Holding Company 2011
128. Express Scripts Holding Company 2012
129. Exxon Mobil Corporation 2011
130. Exxon Mobil Corporation 2012

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131. Exxon Mobil Corporation 2013
132. FedEx Corporation 2011
133. FedEx Corporation 2012
134. FedEx Corporation 2013
135. Ford Motor Company 2012

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136. Ford Motor Company 2013
137. Franklin Resources, Inc. 2011
138. Franklin Resources, Inc. 2012
139. Franklin Resources, Inc. 2013
140. Freeport-McMoRan Copper & Gold Inc. 2011

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141. Freeport-McMoRan Copper & Gold Inc. 2012
142. Freeport-McMoRan Copper & Gold Inc. 2013
143. General Electric Company 2011
144. General Electric Company 2012
145. General Electric Company 2013

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146. General Mills Inc. 2011
147. General Mills Inc. 2012
148. General Mills Inc. 2013
149. General Motors Company 2012
150. General Motors Company 2013

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151. Gilead Sciences, Inc. 2011
152. Gilead Sciences, Inc. 2012
153. Goldman Sachs Group Inc. 2011
154. Goldman Sachs Group Inc. 2012
155. Goldman Sachs Group Inc. 2013

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156. Google Inc. 2011
157. Google Inc. 2012

158. Google Inc. 2013
159. H.J. Heinz Company 2012
160. HCP Inc. 2012

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161. HCP Inc. 2013
162. Halliburton Company 2012
163. Halliburton Company 2013
164. Hess Corporation 2011
165. Hess Corporation 2012

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166. Hess Corporation 2013
167. Hewlett-Packard 2011
168. Hewlett-Packard 2012
169. Hewlett-Packard 2013
170. Honeywell International Inc. 2012

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171. Honeywell International Inc. 2013
172. Intel Corporation 2011
173. Intel Corporation 2012
174. Intel Corporation 2013
175. International Business Machines (IBM) 2011

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176. International Business Machines (IBM) 2012
177. International Business Machines (IBM) 2013
178. Intuit Inc. 2012
179. JPMorgan Chase & Co. 2011
180. JPMorgan Chase & Co. 2012

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181. JPMorgan Chase & Co. 2013
182. Johnson & Johnson 2011
183. Johnson & Johnson 2012
184. Johnson & Johnson 2013
185. Johnson Controls 2011

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186. Johnson Controls 2012
187. Johnson Controls 2013
188. Kellogg Company 2011
189. Kellogg Company 2012
190. Kellogg Company 2013

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191. Kimberly-Clark Corporation 2011
192. Kimberly-Clark Corporation 2012
193. Kimberly-Clark Corporation 2013
194. Kohl's Corporation 2011
195. Lockheed Martin Corporation 2011

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196. Lowe's Companies, Inc. 2012
197. Lowe's Companies, Inc. 2013

198. Marathon Oil Corporation 2011
199. Marathon Oil Corporation 2012
200. Marsh & McLennan Companies, Inc. 2012

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201. Marsh & McLennan Companies, Inc. 2013
202. MasterCard Incorporated 2013
203. Medtronic, Inc. 2011
204. Medtronic, Inc. 2012
205. Medtronic, Inc. 2013

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206. Merck & Co., Inc. 2011
207. Merck & Co., Inc. 2012
208. Merck & Co., Inc. 2013
209. MetLife, Inc. 2012
210. Microsoft Corporation 2011

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211. Microsoft Corporation 2012
212. Microsoft Corporation 2013
213. Monsanto Company 2011
214. Monsanto Company 2012
215. Monsanto Company 2013

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216. Morgan Stanley 2011
217. Morgan Stanley 2012
218. Morgan Stanley 2013
219. Motorola Solutions 2011
220. NIKE Inc. 2011

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221. NIKE Inc. 2012
222. NetApp Inc. 2011
223. Newmont Mining Corporation 2011
224. Newmont Mining Corporation 2012
225. Newmont Mining Corporation 2013

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226. Noble Energy, Inc. 2012
227. Noble Energy, Inc. 2013
228. Norfolk Southern Corp. 2011
229. Norfolk Southern Corp. 2012
230. Norfolk Southern Corp. 2013

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231. Northrop Grumman Corp 2011
232. Occidental Petroleum Corporation 2011
233. Occidental Petroleum Corporation 2012
234. Occidental Petroleum Corporation 2013
235. Oracle Corporation 2011

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236. Oracle Corporation 2013
237. PG&E Corporation 2011

238. PG&E Corporation 2012
239. PNC Financial Services Group, Inc. 2011
240. PNC Financial Services Group, Inc. 2012
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241. PNC Financial Services Group, Inc. 2013
242. PPG Industries, Inc. 2013
243. PepsiCo, Inc. 2011
244. PepsiCo, Inc. 2012
245. PepsiCo, Inc. 2013
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246. Pfizer Inc. 2011
247. Pfizer Inc. 2012
248. Pfizer Inc. 2013
249. Praxair, Inc. 2011
250. Praxair, Inc. 2012
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251. Praxair, Inc. 2013
252. Procter & Gamble Company 2011
253. Procter & Gamble Company 2012
254. Procter & Gamble Company 2013
255. Prudential Financial, Inc. 2011
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256. Prudential Financial, Inc. 2012
257. Prudential Financial, Inc. 2013
258. Public Service Enterprise Group Inc. 2011
259. QUALCOMM Inc. 2011
260. QUALCOMM Inc. 2012
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261. QUALCOMM Inc. 2013
262. Raytheon Company 2011
263. Raytheon Company 2012
264. Raytheon Company 2013
265. Reynolds American Inc. 2011
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266. Reynolds American Inc. 2012
267. Reynolds American Inc. 2013
268. Schlumberger Limited 2011
269. Schlumberger Limited 2012
270. Schlumberger Limited 2013
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271. Simon Property Group 2011
272. Simon Property Group 2012
273. Simon Property Group 2013
274. Spectra Energy Corp 2012
275. Spectra Energy Corp 2013
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276. Starbucks Corporation 2011
277. Starbucks Corporation 2012

278. Starbucks Corporation 2013
279. State Street Corporation 2011
280. State Street Corporation 2012

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281. State Street Corporation 2013
282. Sysco Corporation 2013
283. TJX Companies, Inc. 2011
284. TJX Companies, Inc. 2012
285. TJX Companies, Inc. 2013

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286. Target Corporation 2011
287. Target Corporation 2012
288. Target Corporation 2013
289. Texas Instruments Incorporated 2011
290. Texas Instruments Incorporated 2012

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291. Texas Instruments Incorporated 2013
292. The Chubb Corporation 2012
293. The Chubb Corporation 2013
294. The Coca-Cola Company 2012
295. The Coca-Cola Company 2013

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296. The Home Depot, Inc. 2011
297. The Home Depot, Inc. 2012
298. The Home Depot, Inc. 2013
299. The Travelers Companies, Inc. 2011
300. The Travelers Companies, Inc. 2012

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301. The Travelers Companies, Inc. 2013
302. Thermo Fisher Scientific Inc. 2012
303. Thermo Fisher Scientific Inc. 2013
304. Time Warner Inc. 2011
305. Time Warner Inc. 2012

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306. Time Warner Inc. 2013
307. U.S. Bancorp 2011
308. U.S. Bancorp 2012
309. U.S. Bancorp 2013
310. UPS 2011

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311. UPS 2012
312. UPS 2013
313. Union Pacific Corporation 2011
314. Union Pacific Corporation 2012
315. Union Pacific Corporation 2013

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316. United Technologies Corporation 2011
317. United Technologies Corporation 2012

318. United Technologies Corporation 2013
319. UnitedHealth Group Inc 2012
320. UnitedHealth Group Inc 2013
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321. Ventas Inc 2013
322. Verizon Communications Inc. 2011
323. Verizon Communications Inc. 2012
324. Verizon Communications Inc. 2013
325. Visa 2013
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326. Wal-Mart Stores, Inc. 2011
327. Wal-Mart Stores, Inc. 2012
328. Wal-Mart Stores, Inc. 2013
329. Walgreen Company 2011
330. Walt Disney Company 2011
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331. Walt Disney Company 2012
332. Walt Disney Company 2013
333. Waste Management, Inc. 2011
334. Wells Fargo & Company 2011
335. Wells Fargo & Company 2012
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336. Wells Fargo & Company 2013
337. Yahoo! Inc. 2012
338. Yahoo! Inc. 2013
339. Yum! Brands, Inc. 2012
340. Yum! Brands, Inc. 2013
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341. eBay Inc. 2011
342. eBay Inc. 2012
343. eBay Inc. 2013
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