Forthcoming in *Manufacturing & Service Operations Management*
manuscript MSOM-21-179.R2

Online Companion
A classification of carbon abatement opportunities of global firms

Christian Blanco
Ohio State University, blanco.58@osu.edu

Online Companion

We present additional material described but not included in the main manuscript here.

Appendix A: Implications of the Existence of a Dominant Opportunity

We present a short proof that shows that firms will adopt the dominant type of opportunity (if it exists) regardless of their preferences on a weighing scheme. We consider a type to dominate if $Z_k > Z_l$, that is, $z_{kj} > z_{lj}$ for each $j = 1, \ldots, n$ and $k \neq l$; each metric is, on average, more attractive. We will assume that $Z_k, Z_l > 0$.

Proposition. If $Z_k > Z_l$, then for any $w_j > 0$, such that $\sum_{j=1}^{n} w_j = 1$, $P(Z_k/Z_l) > 1$.

Proof. It is sufficient to show that $\log(P(Z_k/Z_l)) = \sum_{j=1}^{n} w_j \log(z_{kj}/z_{lj}) > 0$ for any $w_j > 0$ because $z_{kj} > z_{lj}$ for each $j = 1, \ldots, n$ and $k \neq l$. $\square$

This establishes that if a dominant type exists, then even if firms have different weighting schemes they will choose the dominant type of opportunity.

Appendix B: Survey Question on Carbon Abatement Opportunities

We present screenshots of the survey questions from 2011-2016 that we use in this study. The CDP survey did evolve from 2011-2016, so the questions are not identical. Some information was only collected in later years, but the three most important data (text description, costs, and savings) were available from 2011-2016. The CDP question in 2015 is identical to the one in 2016, so we do not include a screenshot for that year. Prior to 2015, CDP did not collect the scope of emissions covered. Prior to 2014, CDP did not collect data on the lifetime of the project. When the lifetime of the project is not available we use the average lifetime by activity type as estimated by the CDP. Prior to 2012, CDP did not collect data on emissions reduction.

Figure 1 **Screenshot of the question in the CDP 2016 survey. (The question is identical to the 2015 survey.)**

CC3.3b For those initiatives implemented in the reporting year, please provide details in the table below

Activity type	Description of activity	Estimated annual CO_2e savings (metric tonnes CO_2e)	Scope	Voluntary/ Mandatory	Annual monetary savings (unit currency – as specified in CC0.4)	Investment required (unit currency – as specified in CC0.4)	Payback period	Estimated lifetime of the initiative	Comment

Figure 2 **Screenshot of the question in the CDP 2014 survey, p. 5.**

CC3.3b For those initiatives implemented in the reporting year, please provide details in the table below **(CDP 2013 Q 3.3b, amended)**

Activity type	Description of activity	Estimated annual CO_2e savings (metric tonnes CO_2e)	Annual monetary savings (unit currency – as specified in CC0.4)	Investment required (unit currency – as specified in CC0.4)	Payback period	Estimated lifetime of the initiative, years	Comment

Figure 3 **Screenshot of the question in the CDP 2013 survey, p. 4.**

3.3b For those initiatives implemented in the reporting year, please provide details in the table below

Activity type	Description of activity	Estimated annual CO2e savings (metric tonnes CO2e)	Annual monetary savings (unit currency – as specified in Q0.4)	Investment required (unit currency – as specified in Q0.4)	Payback period

Figure 4 **Screenshot of the question in the CDP 2012 survey, p. 4.**

3.3b For those initiatives implemented in the reporting year, please provide details in the table below (CDP 2011 Q3.3a, amended)

Activity type	Description of activity	Estimated annual CO2e savings	Annual monetary savings (unit currency)	Investment required (unit currency)	Payback period

Figure 5 Screenshot of the question in the CDP 2011 survey, p. 3.

3.3 Did you have emissions reduction initiatives that were active within the reporting year (this can include those in the planning and/or implementation phases)

If yes, complete questions 3.3a and 3.3b:

3.3a Please provide details in the table below

Activity type	Description of activity	Annual monetary savings (unit currency)	Investment required (unit currency)	Payback period

Appendix C: Constructing the Document-Word Matrix with a New Metric

We code the text in a document-word matrix. In this matrix, a row represents a single document and each column corresponds to a word. The document-word matrix describes the frequency of words that appear in the corpus, a collection of text. There are other ways to code the matrix apart from using *word frequencies*. We describe the difference between one of the most commonly used weights and the one we develop to code the document-word matrix.

The *word frequency inverse document frequency* (TFIDF) is one of the most commonly used weights in text processing (Lan et al. 2008). The *document frequency* is the number of documents that include a specific word. The TFIDF is the product of the *word frequency* and the inverse of the *document frequency*. A typical metric for the *inverse document frequency* (IDF) is $log(D/d_t)$, where D is the total number of documents, and d_t is the number of documents that include the word t. The TFIDF is designed to favor words concentrated in a few documents within a collection (Salton and Buckley 1988, p. 516). This metric works well in identifying keywords that appear only in a few documents. This is an effective strategy in classifying text with very different topics, but it may not successfully classify the projects if the reports are standardized. Using only the *word frequency* weights may favor words that appear across the entire collection, and therefore may not work well in our setting. We develop a new metric that is more suitable for analyzing a collection of text that uses common parlance or jargon.

The ideal metric balances the weight based on the *document frequency distribution* of the words. We want to assign the most weight on the most "average" word, and put less weight on words that occur in too many documents. Similarly, we want to put very little weight on words that appear in a small number of documents.

We develop weights that take the *document-frequency distribution* into account. We start with calculating the average document frequency across all words, $\overline{d} = \frac{\sum_{t=1}^{T} d_t}{T}$, where T is the total unique words in the collection[1] and d_t is the number of documents that include word t. We weight each word by measuring how much it departs from the average document frequency and squaring that number. We then normalize this value between 0 and 1 by dividing it by the variance of the document-frequency distribution, denoted σ_d^2, and taking the exponent of its negative value. The weight for each word is

$$W_t = exp(-\frac{(d_t - \overline{d})^2}{\sigma_d^2}). \tag{1}$$

[1] This is after we remove stop words and words that only appear in less than 0.1% of the documents. We remove these extremely infrequently used words because they could be unique abbreviations or misspelled words.

The intent of equation (1) is to assign the highest weight of 1 to words that appear in $\overline{d}$ documents (the average count of documents each word appears). The weight approaches zero for very common words. The same is true for very uncommon words.

Appendix D: Calculating the Agreement Metric

Cohen's kappa is one of the most commonly used measure to assess the agreement between two raters, however, this measure cannot be used for calculating the agreement across many raters against an algorithm. We modify Cohen's kappa to compare the agreement rate of raters against an algorithm. The test statistic uses the overall agreement p_0 and the probability that the raters match the classification by pure chance p_e. The test statistic is $\kappa = (p_0 - p_e)/(1 - p_e)$. Next, we describe how we calculate p_0 and p_e.

Let n be the number of documents to be rated, m is the number of survey takers (or judges), and k is the number of types. It is not necessary that each judge classify each document, but we do require that each document be classified by the same number of judges. We recap the numbers in the study to make it more concrete. In our study, we have $n = 24$ documents (or investments), $m = 60$ survey takers and $k = 6$ types, but each document is only classified by exactly 30 participants. Let I_{rd} be an indicator variable that takes value 1 if the rater's choice agrees with the classification of the algorithm and 0 otherwise. The overall agreement rate is then

$$p_0 = (\sum_{r=1}^{30} \sum_{d=1}^{24} I_{rd})/(30 \times 24). \tag{2}$$

Next we calculate the probability that the rater and the algorithm agree by pure chance. Let $x_{rd}^{(i)}$ take value 1 if rater r classifies document d into type i. We define $p_i = (\sum_{r=1}^{60} \sum_{d=1}^{12} x_{rd}^{(i)})/(60 * 12)$. This represents that propensity of a rater to select type i. Next we define q_i as the probability that algorithm will classify the investment as type i. The overall probability of matching by chance is then $p_e = \sum_{i=1}^{6} p_i q_i$. In this study, the chance the algorithm will classify an investment as *transportation* is roughly 0.11 and the probability it will classify an investment as *renewable energy* is about 0.07.

Appendix E: Correlation Table of Payback Periods, Costs, Savings, and Carbon Emissions Reduction

Appendix F: Alternative Metrics to Describe Carbon Abatement Opportunities

Table A1 Summary of alternative metrics across all 16,525 projects by type.

Type	Median Savings per CO2e	Median Cost per CO2e	Total Cost	Total CO2e
Transportation	13.51	12.76	544,927,614	5,072,435
Materials	9.40	7.52	636,565,991	5,734,328
Behavioral changes	10.19	8.70	412,287,002	3,583,451
Industrial processes	11.22	18.20	2,513,033,733	15,864,340
Buildings	15.47	33.48	500,192,139	2,795,500
Renewable energy	8.29	8.41	653,207,984	5,740,128

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Paybak period	1.00													
(2) Ln(Cost)	0.40	1.00												
(3) Ln(Savings)	−0.08	0.40	1.00											
(4) Ln(CO2e)	−0.05	0.20	0.55	1.00										
(5) *Transportation*	−0.07	−0.09	0.08	0.04	1.00									
(6) *Materials*	−0.06	−0.03	0.05	0.09	−0.13	1.00								
(7) *Behavioral*	−0.06	−0.04	0.04	0.04	−0.10	−0.10	1.00							
(8) *Buildings*	0.04	0.09	−0.08	−0.13	−0.35	−0.35	−0.28	1.00						
(9) *Industrials*	0.05	−0.03	−0.15	−0.14	−0.14	−0.14	−0.11	−0.38	1.00					
(10) *Renewable*	0.09	0.06	0.14	0.22	−0.10	−0.10	−0.08	−0.28	−0.11	1.00				
(11) Cash/Asset	−0.02	−0.05	−0.07	−0.09	0.01	−0.02	0.02	−0.03	0.05	−0.02	1.00			
(12) Current Ratio	−0.01	0.01	−0.05	−0.07	−0.03	0.01	−0.02	0.06	−0.04	−0.02	0.27	1.00		
(13) PPEGT/Asset	−0.01	0.06	0.17	0.21	0.07	0.05	−0.04	−0.04	−0.07	0.06	−0.11	0.01	1.00	
(14) EBIT/Sales	−0.00	−0.04	−0.12	−0.02	0.00	−0.01	−0.00	0.01	−0.01	−0.01	−0.01	−0.02	−0.03	1.00
(15) COGS/Sales	−0.06	−0.04	0.03	0.05	0.06	0.00	0.01	−0.04	−0.02	0.02	0.02	0.01	0.14	−0.06
(16) SLTD Ratio	−0.02	−0.04	−0.03	−0.00	−0.01	0.08	−0.02	−0.02	−0.02	−0.00	−0.03	−0.04	−0.00	0.05

The values for cost and savings are in 2020 USD. SLTD stands for Short-to-Long-Term Debt. The correlation between COGS/Sales and SLTD ratio is 0.07.

Appendix G: Wilcoxon rank-sum tests of marginal abatement costs by type

Table A2 Summary of $p-$values of the Wilcoxon rank-sum tests of marginal abatement costs compared by type.

	Materials	Behavioral change	Industrial process	Buildings	Renewable energy
Transportation	0.00	0.00	0.00	0.00	0.00
Materials	–	0.57	0.17	0.05	0.00
Behavioral change	–	–	0.07	0.13	0.00
Industrial process	–	–	–	0.00	0.00
Buildings	–	–	–	–	0.00

Appendix H: Summary Statistics of Costs and Carbon Emissions Reduction by Type and Sector

We provide the summary statistics of the median costs and median carbon emissions reduction by type and sector in Tables A3 and A4.

Table A3 **Median Investment cost (in $1,000 2020 USD values) by type and sector.**

Type	Consumer Discre-tionary	Consumer Staples	Energy	Financials	Health Care
Transportation	27.05	52.47	36.51	10.76	31.88
Materials	74.48	76.27	877.99	32.69	92.87
Behavioral changes	40.58	202.23	229.03	9.94	113.84
Industrial process	188.76	148.50	275.68	228.27	225.12
Buildings	61.28	137.30	80.88	46.47	70.98
Renewable energy	321.33	586.52	1091.95	112.60	1091.95
	Industrial	Info. Technology	Materials	Telecom. Services	Utilities
Transportation	72.44	20.27	67.56	332.26	157.67
Materials	51.72	54.25	252.36	1078.35	600.71
Behavioral changes	53.13	24.80	194.96	540.86	553.83
Industrial process	65.41	76.09	67.78	657.43	289.77
Buildings	26.08	58.19	37.45	339.95	59.82
Renewable energy	313.48	134.68	1078.35	721.70	1091.95

Table A4 **Median emissions reduction by type and sector.**

Type	Consumer Discre-tionary	Consumer Staples	Energy	Financials	Health Care
Transportation	379	470	1400	276	540
Materials	1000	887	10000	400	500
Behavioral changes	474	1124	1028	734	1000
Industrial process	410	398	3476	355	530
Buildings	176	219	405	76	133
Renewable energy	2204	8230	10000	400	3000
	Industrial	Info. Technology	Materials	Telecom. Services	Utilities
Transportation	1885	581	893	800	258
Materials	559	490	2386	600	9663
Behavioral changes	413	1035	2700	925	3000
Industrial process	207	287	626	592	2280
Buildings	98	142	134	614	868
Renewable energy	2555	7175	10000	1136	10000

References

Lan M, Tan CL, Su J, Lu Y (2008) Supervised and traditional term weighting methods for automatic text categorization. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 31(4):721–735.

Salton G, Buckley C (1988) Term-weighting approaches in automatic text retrieval. *Information Processing & Management* 24(5):513–523.