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Systems enabling low-carbon operations: The salience of accuracy

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ABSTRACT

This article focuses on systems that enable low-carbon operations within organizations. The thesis that system accuracy matters to achieving low-carbon operations is explored using two approaches. First, a generic system model is developed and three alternative technical architectures are described, thereby illustrating that accuracy varies across architectures but can also be attended to outside system boundaries. Second, empirical analysis of 220 global organizations assesses the association between accuracy, managerial incentives, emission targets, and low-carbon impacts. Overall, empirical findings demonstrate that firms attending to accuracy tend to have managerial incentives to reduce emissions and emission reductions targets in place. They also tend to exhibit reduced carbon emissions for the same level of economic output.

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1. Introduction

Successful environmental initiatives such as lifecycle analysis, waste treatment, integrated assessment, and eco-design rely on accurate systems and data, including correctness and completeness (Binder et al., 2008; Moore, 2002; Zhang and Zwolinski, 2017). A sustainable business model archetype particularly reliant on accurate data is maximizing material and energy efficiency, including decarbonization (Bocken et al., 2014). Low-carbon operations require new data inputs, new parameters, new data calculations, and the generation of new informational outputs (Catulli and Fryer, 2012; Verdantix, 2009).[1] Accuracy is critical to attaining related organizational objectives such as reducing transport costs, meeting emissions targets, enabling remote work, and facilitating project decision making (Watson et al., 2010). As the World Resources Institute emphasizes in its Greenhouse Gas Protocol accuracy principle, organizations must: "Achieve sufficient accuracy to enable users to make decisions with reasonable assurance as to the integrity of the reported information" (WRI, 2012, p. 7).

Accuracy is a critical aspect of information systems in general and has been a focus of empirical research in other business contexts such as healthcare (Ward, 2004) and inventory management (Bertolini et al., 2015). Attention to accuracy has been demonstrated to enhance organizational objectives, such as improving immunization rates (Samuels et al., 2002). However, accuracy has not been a focus of prior environmental management research generally, and low-carbon operations in particular, despite concerns about the quality and reliability of corporate sustainability disclosures (Joshi and Li, 2016). As a result, it is unclear which organizations focus on accuracy, i.e., what other managerial practices may correlate with attention to accuracy, and how a focus on accuracy may correlate with low-carbon operations.

Spreadsheet systems are widely used to support low-carbon operations by enabling management of related data such as energy use and greenhouse gas scopes (Erlandsson and Tillman, 2009). This raises concerns about data accuracy given empirical studies demonstrating significant and widespread errors in spreadsheets, with negative economic and organizational consequences (Chadwick, 2007; LeBlanc et al., 2016; Panko and Aurigemma, 2010). Additional (and costly) efforts are required to ensure accuracy of emissions inventory calculation methods and data processes and reported emissions figures to support organizational decision making.

This article focuses on systems that enable organizations to adopt low-carbon operations by providing requisite informational and decision-making support, with a particular focus on accuracy

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[1] We use the term "low-carbon" to refer to reduced greenhouse gas emissions of any type (CO_2, CH_4, N_2O, etc.).

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(WRI, 2012). The main thesis is that system accuracy matters in the context of low-carbon operations, though it is unclear how and under what circumstances. To explore the thesis, two approaches are employed. First, a generic system model and use-case diagram are developed. Three alternative technical architectures – spreadsheet, specialized system, and software network – illustrate variation in accuracy, efficiency, and effectiveness. Regardless of adopted architecture, some firms add a system component to ensure accuracy of related data processes, while others do not, consistent with the notion that firms vary in terms of being proactive or reactive when it comes to data and systems accuracy (Gartner, 2015). Second, data collected by Carbon Disclosure Project (CDP) from 220 global firms is used to analyze hypotheses examining whether attention to data accuracy is correlated with other organizational practices such as carbon reduction targets and yields benefits related to low-carbon operations.

2. System modeling

In the computer age, organizational technology architectures encompassed complex enterprise systems for back-office activities (such as transaction processing), specialized systems for unit-specific functionality (such as customer relationship management), as well as stand-alone systems (such as tracking project activities in a spreadsheet). In the realm of environmental data management, both local systems and stand-alone systems have been employed, though stand-alone spreadsheets appear to be most widely used (Erlandsson and Tillman, 2009).

In the emerging fourth industrial age (Schwab, 2016), a new technology architecture is emerging with the potential to enhance efficiency, increase speed, and decrease errors. Software networks – interacting and autonomous software applications and data repositories that transcend devices, people, and machinery – bring new functionality, agility, and validity to data management. Organizations such as GE, Amazon, and Amtrak employ software networks to treat data and related functionality in a “publish and subscribe” model. Software networks encompassing machine learning nodes are emerging in a variety of contexts such as education, marketing, elections, finance, and medical diagnosis (Ronamai, 2016). Software networks also offer new possibilities for supporting and accelerating low-carbon operations, though few organizations have applied software networks to environmental management so there is much uncertainty regarding how firms might apply fourth industrial age organizing principles to reduce emissions, lower costs, and combat climate change (cf. Braun et al., 2017). To understand basic system features as well as compare and contrast the implications of adopting alternative technical architectures, a generic system model and use-case diagram are now developed.

2.1. Generic system model

Systems analysis is a robust conceptual approach for examining a system for enabling low-carbon operations as it focuses on a standard set of generic features and activities without the need for technical specificity (Wand et al., 1995). In this way, a single version of truth is afforded to different organizational stakeholders independent of architectural choices. Involving both systems analysts and business stakeholders, systems analysis is used as input to custom software development, as part of a software selection process, or as a component of failure analysis (Piccoli, 2012). Based on interviews with key informants inside three large organizations implementing and employing systems for low carbon operations (Melville and Whisnant, 2014), the system diagram in Fig. 1 was constructed.[2]

The system comprises essential elements of purpose, components, boundary, environment, inputs, outputs, interfaces, and constraints. The purpose of the system is to enable a firm to compute emissions, support decision-making, and enable low-carbon operations. Without such a system, a firm may enact a few sustainability initiatives, such as providing incentives for virtual meetings rather than plane flights, but no *ex ante* information would guide the choice of this option versus others, and no *ex post* information would support determination of whether related key performance indicators were indeed achieved. Over time, sub-optimal decision-making would undermine a firm's low-carbon operations efforts.

Beyond purpose, the components of the decarbonization system include data storage, data validation, analytics, and reporting. For example, a spreadsheet architecture would use a personal computer's storage, formulae, or visual basic macros for converting raw data into required information, and perhaps automated graph generation for tracking emissions over time. The system boundary delineates the system itself from its environment, the latter including other systems, users, system auditors, and so forth. For example, the system takes as input electricity use provided by other systems in the environment, e.g., accounting information systems or third-party billing aggregators. Other inputs might include gallons of fuel used by a corporate trucking fleet, coal burned onsite, and employee business travel.

Outputs include information required by the environment, such as carbon emissions by scopes, emissions per capita, emissions per building square foot, cost savings, and so forth. Interfaces represent connections between the system and its environment, which may involve humans (e.g., query about emissions per capita for past five years) or machines (call by the system to an external application programming interface (API) to obtain an emissions factor to convert energy use to Scope 2 emissions). Finally, constraints place limits on system use and operation, such as speed, storage, uptime, accessibility, flexibility, and so forth.

Another important element of systems analysis is a use-case diagram, which illustrates scenarios for which the system will be utilized (Irwin and Turk, 2005). Whether intended to be comprehensive or illustrative, a use-case diagram encapsulates how agents (humans and other systems) will interact with the system using a narrative form and depicted in a graphical format. In this way, use-case diagrams complement system models by adding story to features (Bustard et al., 2000). An illustrative use-case diagram was developed based on interviews with key stakeholders in three organizations that have implemented or are implementing systems for low carbon operations (Fig. 2). [2] We now describe varying affordances, features, and functionality across three technical architectures using the lens of the three use cases.

2.2. Technical architectures

2.2.1. Spreadsheet system

The spreadsheet system is widely employed in organizations due to its low cost and ease of use. An example use case concerning data collection is now described. A data request is emailed annually to each business unit in the form of an attached spreadsheet. Upon completion, the spreadsheet is emailed back to the environmental

[2] Two of the organizations were studied by the lead author in another research study: a large educational institution employing an in-house energy and carbon management system based on spreadsheets and macros and a global software and technology services company implementing a third-party system (Melville and Whisnant, 2014). A key informant in the third organization, a large government agency employing a contractor-developed system, was interviewed separately by the lead author for an in-process research study.

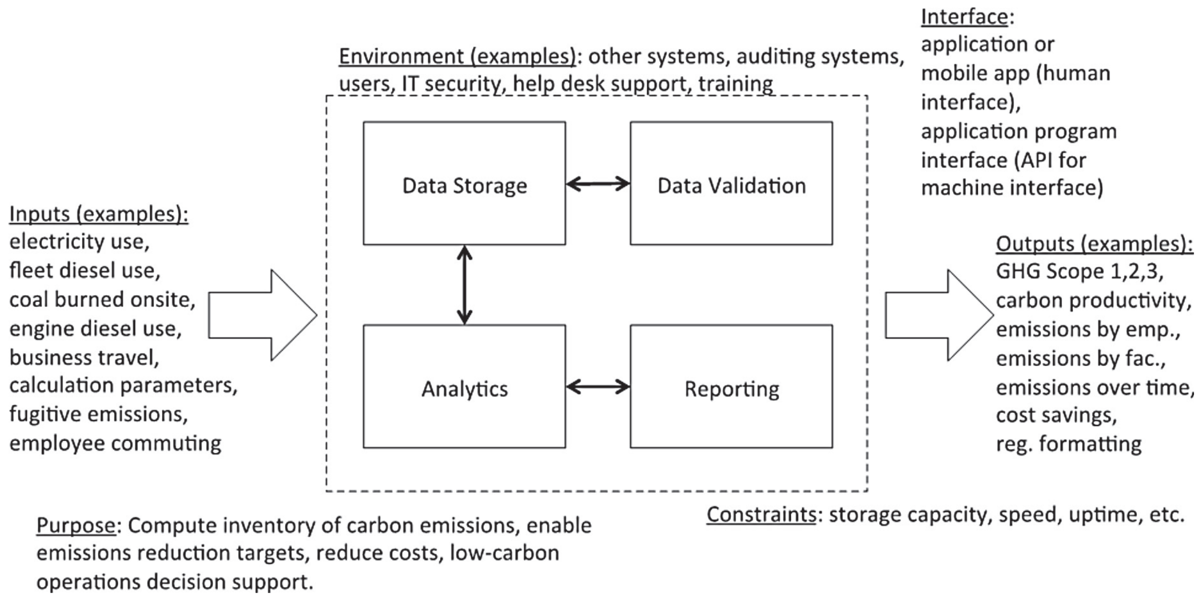

Fig. 1. Generic system model for enabling low-carbon operations.

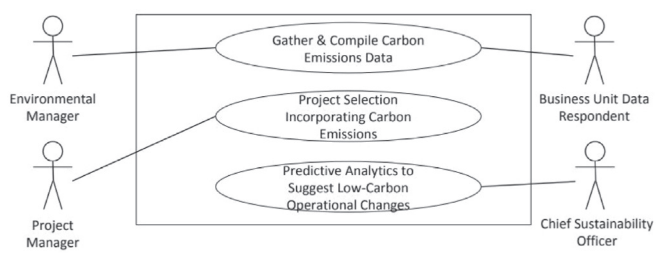

Fig. 2. System use-case diagram.

manager, who uses a pre-written macro to automatically transfer the data to a master data sheet. The master sheet, in turn, contains various macros to convert the compiled business unit data into emissions and other useful output information. The environmental manager owns and operates the system, including debugging the underlying macros, upgrading its features, and producing much of the data used within the organization's annual environmental report. For example, when new guidelines for calculating emissions are released, the manager must rewrite some of the calculation formulae, update relevant parameters, confirm their accuracy, and use them in subsequent calculations. Regarding accuracy, the stand-alone approach varies widely, though manual macro coding errors, human input errors, and the lack of automated data validation are three of several systemic challenges that threaten high degrees of accuracy (LeBlanc et al., 2016). Of the three GHG scopes, Scope 3 is most significantly affected by accuracy, given that it encompasses the upstream and downstream supply chain of the organization as well as evolving materiality guidelines (Blanco et al., 2016). Regarding efficiency, the system is not costly technically, but it is costly in terms of labor and related process costs. Moreover, the emailing of spreadsheets can cause reporting delays. Finally, though the system may be effective at a baseline objective of developing an annual inventory of carbon emissions, it is less effective for achieving other objectives such as aiding decision support, combining environmental data with financial data, or providing monthly updates (Table 1).

2.2.2. Specialized system

The specialized system architecture differs in many ways from the spreadsheet approach. Specialized systems are either adopted by organizations or developed in-house and enable better accuracy, higher efficiency, and enhanced effectiveness. First, specialized systems often include workflow management to validate and expedite each process as data are collected and processed. For example, an environmental manager can set a timeline of tasks to be completed and when due dates are passed an automated message is sent as an alert status. Moreover, cloud-based systems are updated frequently by the vendor and require no coding by users, reducing the likelihood that an environmental manager with little computing expertise may inadvertently introduce coding errors with unknown ramifications. Accuracy is also enhanced via use of industry standard data validation procedures such as field maxima and minima conformance, trend-based predictive validation, and data input confirmation checks. Efficiency is also improved as all stakeholders have a secure account for the system and can log in anytime and use the system based on a preconfigured user type (environmental manager, financial analyst, tech support, etc.). Combined with workflows, user account access also raises effectiveness by enabling the firm to not only develop emissions inventories but also to enable economic and environmental dimensions to be assessed across projects, more frequent data collection and reporting thereby improving accuracy, and up-to-date calculation procedures and parameters according to regulatory and voluntary emissions schemes (Fig. 2). For example, the system might enable production of a chart comparing traditional financial return metrics such as net present value with emissions reductions across various project alternatives (solar power, fleet change, waste heat recovery, etc.).

2.2.3. Software network

The third technical architecture is software networks. In this fourth industrial age approach — used by such pioneers as Amazon, Uber, Siemens, Spotify, and Netflix to manage operational data — business units are responsible for publishing their own data sets and associated metadata and functionality. These services are accessed via APIs and listed in catalogs so that other units can re-use their data and functionality for new purposes. For example,

Table 1
Technical architectures.

Feature	Spreadsheet	Specialized System	Software Network
Accurate (correct and complete)	Threats include macro coding errors, human input errors, and lack of automated data validation	Workflow mgmt. used to validate and expedite processes. Cloud-based systems updated frequently by vendor; require no coding by users. Industry-standard data validation procedures. Up-to-date calculation procedures and parameters according to published schemes.	Machine-to-machine interfaces reduce chances of human error. Re-use of application programming interfaces (APIs) reduces coding errors. Modularization of coding can result in enhanced accuracy relative to long, monolithic programs.
Efficient (no waste of time or effort)	Costly in terms of labor and related process costs. Emailing of spreadsheets and input delays can cause reporting delays.	All stakeholders have secure account and can login anytime and use system based on a preconfigured user type.	Lower cost and increased functionality. Faster development, testing, and enhancement.
Effective (achieves objectives)	May be effective at baseline objective of developing inventory of carbon emissions. Not effective in other important objectives such as aiding decision support, combining environmental data with financial data, and providing monthly updates.	User account access enables firm to not only develop emissions inventories but also to enable economic and environmental dimensions to be assessed across projects and more frequent data collection and reporting.	Broaden new app identification and coding to business unit IT personnel rather than centralized personnel. Innovation enhanced. Better transparency into environmental data sources and functionality to all employees.

Amtrak rail published data from its core operations platform via an API, and thereby enabled its schedules to be quickly and accurately integrated with Google maps (Buchholz et al., 2016). This opens a new marketing and sales channel for Amtrak as Google maps customers can easily determine whether going by rail might align with their route, schedule, and emissions preferences. Another example is Siemens' use of APIs to more efficiently and effectively incorporate smart meter functionality and value-added services for electric power customers (Goddard, 2016). This enables compliance and new apps via re-use rather than reinvention. In the realm of low-carbon operations, the re-use of already-tested APIs, reduced amount of human coding, ability to develop and test quickly, and direct machine-to-machine interfaces provide the potential to dominate specialized systems and spreadsheets across all three performance dimensions of accuracy, efficiency, and effectiveness. Future possibilities include the use of voice interaction and deep learning to enhance interactivity and leverage predictive analytics to suggest effective low-carbon operational tactics (Fig. 2).

In summary, tradeoffs exist among the three technical architectures. Though accuracy varies widely, at the dawn of the fourth industrial age firms often address accuracy outside the system boundary given widespread use of spreadsheets. For example, an auditor may review key processes, technologies, data inputs, and information outputs to assure accuracy and to ensure compliance with emissions standards (WRI, 2012). Given the importance of system and data accuracy – which can be a life or death matter in some contexts (Dillon and Lending, 2010) – the current study focuses on which firms attend to accuracy and what benefits might result. As emphasized in prior research: “A major concern about corporate CSR disclosure is its quality and reliability relative to conventional financial reporting” (Joshi and Li, 2016, p. 5). A key thesis of this article is that systems for enabling low-carbon operations require accuracy to support effective decision making and ultimately lead to reduced emissions for a given level of output. As a corollary, it is likely that complementary organizational practices are required to achieve accurate systems, as we now describe.

3. Hypotheses

Complex organizational initiatives such as adoption of low-carbon operations involve significant planning to develop clear objectives, determine focus areas, develop an implementation strategy, and identify key performance indicators (Bocken et al., 2014). Management control mechanisms are an important component of such initiatives (Crutzen et al., 2017), and prior research has focused on the importance of two specific control mechanisms in the context of low-carbon operations: managerial incentives to reduce carbon emissions (Eccles et al., 2012; Henri and Journeault, 2009; Seidel et al., 2014) and the presence of specific emission reductions targets (Biswas and O'Grady, 2016; Ioannou et al., 2016; Joshi and Li, 2016). Given the salience of these two mechanisms as well as the lack of prior research examining the role of accuracy in low-carbon operations, we develop two hypotheses concerning the complementarity of attention to accuracy, managerial incentives, and emission reductions targets.

3.1. Attention to system accuracy, managerial incentives, and reduction targets

Agency theory addresses situations in which owners and managers of firms have conflicting goals and the attendant mechanisms that may mitigate goal misalignment (Eisenhardt, 1989). One such mechanism is outcome-based contracts. In the low-carbon operations context, this might mean that senior executives (principals) provide explicit incentives to reduce greenhouse gasses that are tied to performance targets. In this way, goal misalignment may be mitigated as the manager now has clear incentives to achieve the sustainability objectives of the principal. Overall, this reasoning is consistent with the proposition of Eisenhardt (1989, p. 60) that “when the contract between the principal and agent is outcome based, the agent is more likely to behave in the interests of the principal.”

Empirical evidence supports the link between outcome-based contracts and managerial behavior in the context of strategic and individual choices (Devers et al., 2007), suggesting that this link may exist in the environmental context. If the manager holds the prior belief that accuracy is salient in the context of systems enabling low-carbon operations, it follows that managerial incentives to reduce greenhouse gas emissions would lead to greater attention to system accuracy. Moreover, clearly specified emissions reduction targets complement managerial incentives by providing a goal against which progress can be measured. In the absence of targets and incentives, even though managers may hold such prior beliefs, they may not attend to accuracy, as carbon emission reduction is not part of their performance evaluation. Managerial incentives tied to greenhouse gas reduction are thus hypothesized to be associated with a higher firm propensity to attend to accuracy in systems enabling low-carbon operations. Likewise, greenhouse gas reduction targets are also hypothesized to be associated with a higher firm propensity to attend to accuracy in systems enabling low-carbon operations. Based on these arguments, the first two hypotheses are stated as follows:

Hypothesis 1. *Managerial incentives tied to greenhouse gas reduction are positively associated with firm propensity to attend to accuracy in systems enabling low-carbon operations.*

Hypothesis 2. *Greenhouse gas reduction targets are positively associated with firm propensity to attend to accuracy in systems enabling low-carbon operations.*

3.2. Association of system accuracy and low-carbon operational outcomes

Accurate systems and data are necessary for enabling low-carbon operations. As emphasized by a recent report on corporate carbon reporting: "Assurance of carbon data can also assist companies in embedding good reporting practices and driving internal performance improvements." (King and Bartels, 2015, p. 20). However, the lack of prior research means that this assertion remains an open empirical question. For example, it is possible that firms are more interested in signaling pro-environmental behavior (branding) rather than actually achieving low-carbon operations. In this case, attending to the accuracy of data, for example by hiring a consultant to audit the resulting numbers, may be solely for signaling reasons. Media announcements associated with such actions may send a positive short-term signal to investors, consumers, employees, and other important stakeholders. Greenwashing has been shown to be an important and widespread phenomenon with a range of underlying mechanisms (Delmas and Burbano, 2011). In the case of systems enabling low-carbon operations, if greenwashing is in place, there may be no association between attending to accuracy and achievement of low-carbon operations. Despite this potential countervailing mechanism, in the absence of prior research it is hypothesized that firm attendance to system accuracy is associated with low-carbon operational outcomes. The third hypothesis is thus stated as follows:

Hypothesis 3. *Firm attendance to accuracy in systems enabling low-carbon operations is positively associated with low-carbon operational outcomes.*

4. Materials and methods

4.1. Data and sample

Primary data come from the CDP, which conducts an annual survey of large publicly traded global corporations. The CDP provides data on most of the variables of interest and is one of the most widely employed voluntary reporting agencies globally. Data from the annual CDP surveys has been used in prior research (Blanco et al., 2016; Reid and Toffel, 2009) and provides the only source of which we are aware concerning the accuracy of systems enabling low-carbon operations. Data were drawn primarily from CDP 2009, whose sample frame comprises lists of publicly traded firms such as the *Global 500* totaling 3741 firms. The main reason for our choice of using CDP 2009 was that the question on accuracy was only asked during a single year. Of the total 3741 firms that were surveyed by CDP, 1849 firms responded, with 1246 choosing to allow their data to be publicly available (Matisoff et al., 2013). We used the Risk Metrics database for additional environmental variables for global firms, and the Bureau van Dijk's (BVD) database for economic data of global firms. After matching firms that provided valid carbon emissions data and other organizational variables included in our analysis, the final sample comprises 220 firms.

Of the 220 firms in our final sample, 46.8% (103 firms) were present in the *Financial Times (FT) Global 500* list of 2009, suggesting that our sample is reasonably well represented in the *FT Global 500 list* of the same year. [3] To assess how representative our final sample (from CDP 2009) is of firms in more recent years, we checked for the overlap of our final sample with the *FT Global 500* list of 2016, and with the CDP 2016 respondent list. We found that 43.2% (95 firms) of firms in our sample are present in the 2016 *FT Global 500* list, and 84.09% (185 firms) of our sample responded to CDP 2016.[4,5] Taken together, these numbers suggest that the firms in our final sample in 2009 are reasonably well represented both in the *FT Global 500* list in that same year, and in more recent *FT Global 500* and CDP respondent lists.

Table 2 shows the breakdown of our sample across the ten Global Industry Classification Standard (GICS) list of industries, as well as the industry-wise breakdown of firms in the *FT Global 500* list of 2009. The breakdown of our sample across the GICS list of industries mirrors that of the *FT Global 500* list reasonably well.

Table 3 shows the country-wise breakdown of our sample, and the country-wise breakdown of the 2009 *FT Global 500* list.

Further, to assess how our final sample compares in terms of firm characteristics with the *FT Global 500* of that timeframe, we compared our sample firms with the *FT Global 500* list of 2009 on two metrics of firm size: *Total Assets* and *Number of Employees*. Specifically, we performed two-tailed T-tests of difference of means of *Total Assets* (shown in Appendix Table A.1) and *Number of Employees* (shown in Appendix Table A.2) on the overall lists and on the industry-wise splits. On *Total Assets*, we find that our sample, taken as a group, does not differ statistically ($p = 0.59$) from the *FT Global 500* list of 2009. When considered industry-wise, for eight of the ten GICS industries, our sample does not differ statistically ($p > 0.10$) from the mean *Total Assets* of the *FT Global 500*. For two industries (Health Care and Industrials), our sample differs statistically ($p < 0.10$) from the *FT Global 500* list. On *Number of Employees*, our sample taken as a group does not differ statistically ($p = 0.53$) from the *FT Global 500* list of 2009. When taken industry-wise, we find that for seven of the ten GICS industries, our sample does not differ statistically ($p > 0.30$) from the mean *Number of Employees* of the *FT Global 500*. For three industries (Health Care, Industrials, and Materials), our sample differs ($p < 0.10$ or $p < 0.05$) from the *FT Global 500* list.

Overall, these numbers suggest that: a) in terms of firm size (*Total Assets* and *Number of Employees*), our sample firms as a group do not differ statistically from the *FT Global 500* list of the same year; and b) when broken down by GICS industries, the sample means of *Total Assets* and *Number of Employees* of firms in each industry group do not differ statistically from most of the GICS industries in the 2009 *FT Global 500* list (barring two or three industries). These comparisons also give us some idea of the contribution of the 220 firms in our sample, suggesting that the firms in

[3] The overall overlap of CDP 2009 with the *FT Global 500* list in 2009 was 409 firms CDP_Report, 2009. Carbon Disclosure Project 2009: Global 500 Report.

[4] The full lists of firms in *FT Global 500* of the years 2009 and 2016 were obtained from the annual FT 500 rankings website (https://www.ft.com/ft500). Information regarding whether firms responded to CDP 2016 were obtained by running queries on the CDP open data portal (https://www.cdp.net/en/responses?utf8=%E2%9C%93&queries%5Bname%5D=).

[5] We note that 37.73% (83 firms) of firms in our sample were present in the *FT Global 500* lists in both 2009 and 2016. Also, 9.09% (20 firms) of firms in our sample were present in the 2009 *FT Global 500* list but dropped out of the 2016 list, whereas 5.45% (12 firms) of firms in our sample were present in the 2016 *FT Global 500* list but not the 2009 list.

Table 2
Industry Breakdown of Sample, and Comparison with *FT Global 500* breakdown.

Industry	Our Sample (CDP 2009)		Financial Times Global 500 (year 2009)	
	Number of firms	Percentage	Number of firms	Percentage
Consumer Discretionary	14	6.36%	55	11.00%
Consumer Staples	15	6.82%	50	10.00%
Energy	23	10.45%	51	10.20%
Financials	43	19.55%	104	20.80%
Health Care	12	5.45%	41	8.20%
Industrials	35	15.91%	24	4.80%
Information Technology	25	11.36%	36	7.20%
Materials	29	13.18%	61	12.20%
Telecommunications	9	4.09%	33	6.60%
Utilities	15	6.82%	45	9.00%
Total	220	100%	500	100%

Note: GICS (Global Industry Classification Standard) is used for industry classification.

Table 3
Country Breakdown of Sample, and Comparison with *FT Global 500* breakdown.

Country	Our Sample (CDP 2009)		Financial Times Global 500 (year 2009)	
	Number of firms	Percentage	Number of firms	Percentage
Australia	23	10.45%	14	2.80%
Canada	20	9.09%	27	5.40%
Denmark	1	0.45%	2	0.40%
Finland	2	0.91%	2	0.40%
France	11	5.00%	23	4.60%
Germany	8	3.64%	20	4.00%
Italy	2	0.91%	7	1.40%
Japan	14	6.36%%	49	9.80%
Netherlands	2	0.91%	8	1.60%
Norway	3	1.36%	1	0.20%
South Africa	7	3.18%	6	1.20%
South Korea	1	0.45%	5	1.00%
Spain	3	1.36%	13	2.60%
Sweden	2	0.91%	5	1.00%
Switzerland	7	3.18%	10	2.00%
USA	72	32.73%	181	36.20%
United Kingdom	42	19.09%	32	6.40%
Others	0	0%	95	19.00%
Total	220	100%	500	100%

our sample are substantially important to the world economy to the extent that a significant proportion of them were in the *FT Global 500* list of the same year, as well as in more recent *FT Global 500* and CDP respondent lists, and the sample, when taken as a group and when broken down by industry, is reasonably similar in terms of size (*Total Assets* and *Number of Employees*) to firms in the *FT Global 500* list of the same year.

4.2. Variables

A description of key variables follows, with a full listing provided in Table 4. The analysis employs a unique CDP survey question regarding system accuracy: "Does your company have a system in place to assess the accuracy of GHG emissions inventory calculation methods, data processes and other systems relating to GHG measurement?" Regarding low-carbon operational outcomes, both Scope 1 (emissions due to stationary and mobile combustion) and Scope 2 (emissions due to purchased electricity and energy) emissions are employed, consistent with prior research (Eccles et al., 2012). Scope 3 emissions exhibit variable accuracy given their purview extending beyond firm boundaries (upstream and downstream supply chain) (Blanco et al., 2016) and are thus excluded from the current analysis. The ratio of output to the sum of both scopes is computed and normalized by industry to develop a carbon productivity metric that is comparable across firms within industries (CP). Incentives (INCENT) and targets (TARGET) are measured by items in the CDP database. The former asks "do you provide incentives for individual management of climate change issues including attainment of GHG targets?" while the latter asks "Do you have an emissions and/or energy reduction target(s)?" (Table 4).

Control variables include climate agreements (UNFCCC and KYOTO) and measures of environmental strategy (STRAT). The latter is used by institutional investors, including investment managers, mutual funds, hedge funds and pension funds.[6] Other controls include environmental risk (RISK) and the number of years for which a firm has disclosed its emissions in the CDP (DISC) weighted to account for learning curve effects, which might serve as a proxy for its environmental capabilities.

4.3. Empirical modeling

Ordinary least squares regression was employed to estimate the following model: $CP_i = \alpha_o + \alpha_1 ACC_i + \alpha_2 HIEMIT_i + \alpha_3 SIZE_i + \alpha_4 TRADE_i + \alpha_5 UNFCCC_i + \alpha_6 KYOTO_i + \alpha_7 INCENT_i + \alpha_8 TARGET_i + \alpha_9 DISC_i + \alpha_{10} STRAT_i + \alpha_{11} RISK_i + \varepsilon_i$. However, in this model it is possible that self-selection bias is present, given that firms decide whether to attend to accuracy based on factors that may be unobserved. This is especially possible given the newness of the context and lack of prior research providing guidance on important phenomena and variables (unobserved heterogeneity). In this case, ordinary least squares estimation may result in biased estimation.

To correct for bias that may be present, a self-selection model is employed (Greene, 1997). The endogenous switching regression model assumes that firms decide which of two regimes to join based on unobserved characteristics (Heckman, 1979; Maddala, 1983). A simple analogy is students choosing whether to study ecology or graphic design based on their own private knowledge of their capabilities. Mackenzie chooses ecology as she expects to do better in that field given that she started a solar panel consultancy in high school. In contrast, Vinod chooses graphic design as he expects to do better in that field given his extensive art and drawing background and fascination with graphic novels. We would expect Mackenzie to do worse in college if a central planner decided to place her into the graphic design major, and likewise with Vinod into the ecology major. The self-selection model provides a test for such selections by examining the counterfactual that Mackenzie was indeed placed into graphic design. Moreover, if we ran a simple regression, biased estimates would result due to unobserved heterogeneity of the major choice antecedents.

The self-selection model is appropriate to address self-selection in new and emerging contexts where correlates with the decision process have yet to be identified and observed – precisely the current context. The model splits the sample into those that attend to accuracy and those that do not. It uses a first-stage adoption model to generate the Inverse Mills Ratio (IMR), then uses the IMR in the second stage as an additional term in the regression. If the

[6] For details, see RiskMetrics Group, "Global Compact Plus Assessment Service (GC+): A Concise Explanation of our Company Rating Model," June 2009.

Table 4
Variables.

Variable	Definition	Survey Item or Constructed Measure
ACC	Accuracy	Does your company have a system in place to assess the accuracy of GHG emissions inventory calculation methods, data processes and other systems relating to GHG measurement?
CP	Carbon productivity	Output/(Scope 1 + Scope 2), normalized to GICS 10 industry, where Revenue and Net Income are measures of output.
INCENT	Managerial incentives	Item "Do you provide incentives for individual management of climate change issues including attainment of GHG targets?"
TARGET	Carbon performance target	Item "Do you have an emissions and/or energy reduction target(s)?"
UNFCCC	Institutional pressure (not legally binding & no targets)	Number of years that country in which firm is domiciled has been a signatory to the non-legally binding United Nations Framework Convention on Climate Change (UNFCCC).
KYOTO	Institutional pressure (legally binding and targets)	Number of years that the country in which the firm is domiciled has been signatory to Kyoto Protocol.
STRAT	Environmental strategy	Independent rating of environmental strategy.
RISK	Monetary risk	Item "Do you consider your company to be exposed to [monetary] risks?"
DISC	Number of years that firm has voluntarily disclosed.	Years that firm has provided data to Carbon Disclosure Project (weighted by base 2 to account for learning curve effects).
SIZE	Firm size	Industry normalized revenue.
TRADE	Environmental trading	Item "Have you purchased any project-based carbon credits? Have you been involved in the origination of project-based carbon credits?"
HIEMIT	High emitting industry	Dummy for three industries with highest median raw carbon emissions.

Notes: CP numerator (operating revenue and net income) and SIZE are from Bureau van Dijk's (BVD) ORBIS database. UNFCCC and KYOTO are from the United Nations Statistics Division. STRAT is from MSCI Environmental, Social, and Governance (ESG) Research, Global Compact Assessment Environmental Strategy Score (used with permission of Innovest Strategic Value Advisors.) ACC is used from CDP 2008 as it did not appear in CDP 2009 (also referred to as CDP7) for which sufficient data exist for sample matching and estimation.

IMR is positive and significant, self-selection is present, the self-selection model is appropriate, ordinary least squares is biased, and firms are better off from a carbon productivity standpoint having attended to data accuracy. To estimate the self-selection model, three additional variables are employed to identify the first-stage adoption model that are not included in the performance regressions in the self-selection model (Greene, 1997). Firm size (SIZE) is proxied by revenue. Whether a firm engages in environmental trading of carbon credits (TRADE), which might affect its need for accurate data but which does not affect carbon productivity given that our GHG measure is gross of any adjustments due to purchase or sales of carbon credits, is also included. Finally, a control for whether a firm is in a high-emitting industry (HIEMIT), which are more regulated and may necessitate accuracy, and which is accounted for in the dependent variable in Stage 2, is also included in the first stage.

5. Results

5.1. Descriptive statistics

Descriptive statistics and correlations are provided in Table 5. Both INCENT and TARGET are positively and significantly correlated with ACC (0.37 and 0.31, respectively). Furthermore, when splitting the sample by adoption, we observe that incentives and targets are statistically significantly higher in firms attending to accuracy than others. These bivariate results provide initial support for our first two exploratory hypotheses that managerial incentives related to carbon emissions reductions and carbon emissions reduction targets are associated with a higher firm propensity to attend to accuracy in systems enabling low-carbon operations.

5.2. Association of system accuracy with managerial incentives & emission reduction targets

The first stage of the self-selection model estimation represents a Probit adoption model for the case of revenue used in the performance metric (Table 6, Column 2) and net income used in the performance metric (Table 6, Column 5). In both cases, the estimates of INCENT and TARGET are positive and significant, supporting the first two hypotheses in alignment with correlations presented in Table 5. Both types of climate agreements (UNFCCC and KYOTO) are weakly and positively associated with firm propensity to attend to accuracy in systems enabling low-carbon operations, as expected. Moreover, the positive and significant estimate for RISK also confirms *ex ante* beliefs that firms facing greater risk are more likely to attend to accuracy.

5.3. Association of system accuracy and low-carbon operational outcomes

Ordinary least squares regression estimation (Column 1) reveals that the ACC coefficient is negative (−0.321) and weakly statistically significant ($p < 0.1$), which appears to provides weak rejection of our third hypothesis (the pattern is the same for performance based on net income). However, as discussed in the methods section, these results are likely to be biased, as unobserved variables are likely to be present but not included.

The self-selection model estimation is presented in Columns 2–7. Columns 4 and 7 contain estimates of the two performance equations for firms attending to accuracy ($ACC = 1$). In the case of CP based on revenue (column 4), the self-selection coefficient (IMR) is positive (0.367) but only weakly significant (based on bootstrapped standard errors whose 95% confidence interval is heavily weighted above zero but does include a few instances below zero). In the case of CP based on net income, the IMR is positive and significant (0.940, $p < 0.01$). These findings are consistent with the presence of self-selection bias, as hypothesized, rendering OLS estimates biased.

Regarding the developed hypothesis of the association between system accuracy and low-carbon operational outcomes, the positive signs of Sigma and IMR in columns 4 and 7 are both consistent with the generated hypothesis (H3). Intuitively, if firms adopt a system to assess the accuracy of GHG emissions inventory calculation methods, data processes and other systems relating to GHG measurement based on unobserved adoption factors, an additional factor in the performance regression would be present (the IMR) (Greene, 1997; Maddala, 1983). Contrary to results presented in Table 6, if the IMR had not been statistically significantly, the OLS model would obtain as no self-selection bias would have been present. For further insight, we examined our results when we disaggregate our summed measure of carbon productivity. Scope 1 and Scope 2 emissions are very different to one another, though such differences are masked by our summation of the two in the denominator of carbon performance. Results of the selection equation estimation reveal the same sign and significance pattern and the same inferences for targets and incentives (for both variations of CP). For Scope 1, which is stationary and mobile

Table 5
Descriptive statistics.

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11
1. ACC	0.81	0.39	1										
2. CP	−0.04	0.96	*−0.17*	1									
3. HIEMIT	0.30	0.46	0.09	0.03	1								
4. SIZE	0.06	0.99	*0.13*	−0.03	−0.02	1							
5. TRADING	0.50	0.69	*0.20*	−0.09	*0.29*	*0.33*	1						
6. UNFCCC	15.33	1.00	*0.20*	0.01	0.11	−0.01	−0.05	1					
7 KYOTO	3.48	2.85	0.00	0.11	0.04	−0.01	*0.18*	*−0.59*	1				
8. INCENT	0.57	0.50	*0.37*	−0.06	−0.07	*0.28*	*0.22*	0.13	0.05	1			
9. TARGET	0.85	0.36	*0.31*	−0.12	−0.04	*0.18*	*0.17*	*−0.15*	*0.25*	*0.32*	1		
10. DISC	12.02	4.59	*0.20*	−0.01	0.09	*0.25*	*0.18*	*0.17*	0.02	*0.14*	0.08	1	
11. STRAT	7.88	1.31	*0.16*	−0.09	*−0.36*	*0.21*	0.10	−0.06	*0.14*	*0.22*	*0.23*	0.13	1
12. RISK	0.85	0.35	*0.13*	*−0.18*	−0.09	0.13	0.10	−0.08	0.01	0.11	0.11	0.07	*0.20*

Note: Italics indicates significant at $p \leq 0.05$.

Table 6
Estimation results for ordinary least squares and self-selection models.

DEP VAR	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Ordinary least squares	Self-sel adoption	Self-sel outcome (ACC = 0)	Self-sel outcome (ACC = 1)	Self-sel adoption	Self-sel outcome (ACC = 0)	Self-sel outcome (ACC = 1)
	CP_{rev}	ACC	CP_{rev}	CP_{rev}	ACC	CP_{NetInc}	CP_{NetInc}
ACC	**−0.321* (0.183)**						
HIEMIT		0.265 (0.248)			0.091 (0.220)		
SIZE		−0.006 (0.121)			−0.159 (0.101)		
TRADE		0.047 (0.175)			0.347* (0.180)		
UNFCCC	0.133 (0.084)	0.232* (0.121)	0.298 (0.238)	0.160 (0.140)	0.251** (0.122)	0 0.246 (0.243)	0.175 (0.116)
KYOTO	0.069** (0.028)	0.093* (0.050)	0.221* (0.124)	0.105*** (0.036)	0.024* (0.049)	0.078 (0.111)	0.050 (0.033)
INCENT	−0.023 (0.139)	**0.861*** (0.252)**	2.345*** (0.737)	0.054 (0.155)	**0.578** (0.236)**	1.754*** (0.670)	0.192 (0.155)
TARGET	−0.191 (0.196)	**0.747*** (0.276)**	0.467 (0.678)	0.043 (0.244)	**0.681** (0.271)**	0.495 (0.616)	0.143 (0.231)
DISC	0.002 (0.014)	0.021 (0.021)	0.067 (0.057)	−0.043** (0.017)	0.009 (0.023)	0.062 (0.052)	0.002 (0.016)
STRAT	−0.028 (0.051)	0.129 (0.093)	0.195 (0.197)	−0.201*** (0.062)	0.013 (0.091)	−0.236 (0.175)	0.009 (0.057)
RISK	−0.311* (0.179)	0.550** (0.280)	−0.389 (0.634)	−0.004 (0.223)	0.469* (0.258)	−0.378 (0.581)	0.059 (0.211)
Sigma (σ_i)			1.988*** (0.374)	**0.965*** (0.073)**		1.772*** (0.411)	**0.980*** (0.057)**
IMR ($\rho_{i\varepsilon}$)			0.868*** (0.073)	**0.367 [-0.19, 0.83]**		0.860*** (0.138)	**0.940*** (0.033)**
N		220	41	179	220	41	179

Notes: Bolded quantities refer to hypothesis tests. An intercept is included in all models; standard errors are in parentheses with ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. For self-selection models (columns 2–7), full-information maximum-likelihood (FIML) estimation is employed with SANN maximization. For operating revenue specification (columns 2–4), log-likelihood is −399.5062; significance of rho for ACC = 1 based on bootstrapped standard error, with 95% confidence interval in square brackets. For net income specification (columns 5–7), log-likelihood is −363.4744.

combustion, there is no significant self-selection for adopters, but for Scope 2 (purchased energy) the pattern for the aggregate measure is preserved. Performance results based on the aggregated metric would thus appear to be driven more by Scope 2 than Scope 1 emissions. This is an interesting finding that suggests a focus on both aggregated and disaggregate carbon performance metrics for maximal insights given the potential for differing drivers and outcomes.

To assess robustness of results, re-estimation of the self-selection model was undertaken using a two-step limited-information maximum likelihood (LIML) procedure using bootstrapped standard errors, with no change in the pattern of results. Also, a variance inflation factor (VIF) test of multicollinearity for LIML stage 1 was conducted, with all VIFs less than 2, which is well below the rule of thumb of 10 (Greene, 1997) and thereby mitigates concerns of multicollinearity. Though these results provide some support for the validity of inferences, the exploratory nature of the findings is emphasized given the newness of the domain, lack of prior research on which to build, and dearth of existing measures for key variables.

6. Discussion

6.1. Findings and implications

As a primary institution for organizing the production and distribution of goods and services, global organizations play a significant role in mitigating the causes and effects of climate change. Migration to low-carbon operations is thus critical. Much research has examined new business models, systems, and associated technologies for doing so (Bocken et al., 2014; Catulli and Fryer, 2012; El-Gayar and Fritz, 2006; Moore, 2002).

At the same time, the ability of organizations to produce sufficiently accurate information and associated processes to support low-carbon operational objectives is not well understood. While emissions standards specify that data must be accurate and of high quality and reliability, it is unknown whether firms are indeed meeting these aspirational guidelines. Moreover, it is unclear which firms are attending to accuracy and why.

To ensure accuracy, two approaches are possible. The first is at the system level, involving the use of an appropriate system to enable low-carbon operations. The second lies outside the system, and involves such measures as auditing and external validation to assess and ensure accuracy of data and processes. In this study, the fundamental thesis is that accuracy matters, though it is unclear how and under what circumstances. Using systems approaches and CDP data, this question was examined in two ways.

First, a systems model, use case diagram, and three technical architectures were introduced. Manifestation of features present in the generic systems across different architectures enabled comparison and contrast of spreadsheets, specialized systems, and software networks. While spreadsheets are widely used, and specialized systems increasingly being adopted, software networks are at the frontier of systems architecture. In this way, the systems analysis enabled both an assessment of existing approaches as well as an examination of next practices in low-carbon operations. This answers a call in academic research to pursue future-oriented studies in addition to focusing on the past (Teece, 2011).

A key result of the systems modeling exercise was identification of strengths and limitations of each technical architecture according to three key features: accuracy, efficiency, and effectiveness. For firms wishing to secure low-carbon operations through attention to accuracy, our results suggest that their approach should vary based on their existing system and capabilities. We find that accuracy is lacking with the widely used spreadsheet system, so firms with such a system can upgrade to either a specialized system and/or a software network for a long-term increase in accuracy. Alternatively, firms unwilling or unable to upgrade can follow the example of their peers and augment their spreadsheet systems with external audits and other extra-system approaches. To explore these further and provide a second perspective on the key thesis of the study, CDP data on 220 global organizations were analyzed.

Regression results were consistent with all three of the developed hypotheses. First, consistent with agency arguments and intuition, a positive association between attention to system accuracy and both managerial incentives and emission reduction targets was identified. This suggests that firms are enacting low-carbon operations by including both managerial programs as well as technical considerations. Second, consistent with the third hypothesis, a positive association was found between attention to system accuracy and low-carbon operational outcomes. Together with the first two hypotheses, this suggests that appropriate systems for low-carbon operations that include attention to data accuracy may enable firms to achieve more output without attendant increases in carbon emissions – one indicator of low-carbon operations.

6.2. Limitations and future research

It is acknowledged that this study suffers from some limitations, which can serve as a springboard for future research. First, the use of CDP data may limit generalizability to a wider population of firms. More specifically, firms in the CDP are generally large global firms. How the findings of this study may extend to firms of smaller size is an area for future research. Future research can extend this study to other contexts and firms of smaller size (e.g., small and medium enterprises) using other datasets. Second, although care in modeling was employed to account for the potential for self-selection, future research can use methods such as longitudinal analyses and case studies to build on these findings. Such an analysis may shed more light on underlying mechanisms that may explain more nuances of our findings. Third, future research can examine how other dimensions of the contextual environment may play a role in explaining how firms attend to accuracy in their sustainability initiatives. Some promising avenues for research may include the cultural and economic factors prevalent in specific countries. While our results do not indicate whether setting emissions goals and providing incentives to meet those goals lead to attention to accuracy or are a consequence of such attention, we do find that they are related and future research could investigate which companies aspiring to low-carbon operations should attempt first. Overall, notwithstanding the limitations, this study provides support to enable future researchers to extend the current research in several directions.

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Appendix A

Table A.1
Comparison of Sample with *Financial Times (FT) Global 500* (2009) on Total Assets.

Industry	Our Sample (CDP 2009)			FT Global 500 (2009)			Two-tailed *t*-test (*p*-value)
	Mean	SD	N	Mean	SD	N	
Consumer Discretionary	$23,201.96	$9245.54	9	$55,367.55	$8343.35	55	$p = 0.13$
Consumer Staples	$35,005.95	$8633.93	11	$34,942.75	$6583.94	50	$p = 0.99$
Energy	$48,384.08	$14,184.57	17	$62,559.31	$9494.79	51	$p = 0.44$
Financials	$607,016.80	$144,887.40	28	$585,038.27	$75,127.17	104	$p = 0.89$
Health Care	$48,778.18	$9576.37	11	$30,446.46	$4179.97	41	$p = 0.058^*$
Industrials	$19,022.82	$3576.10	24	$84,027.33	$33,895.54	24	$p = 0.063^*$
Information Technology	$29,496.27	$7773.63	18	$30,204.24	$4544.91	36	$p = 0.93$
Materials	$23,733.31	$5776.21	18	$32,299.79	$3350.24	61	$p = 0.22$
Telecommunications	$83,853.93	$24,733.06	9	$63,168.04	$12,345.52	32	$p = 0.44$
Utilities	$45,751.16	$10,028.01	10	$55,982.15	$8679.03	45	$p = 0.59$
All industries	$139,202.10	$31,413.37	155	$159,699.50	$18,592.69	499	$p = 0.59$

Notes:
(1) Significant at * $p < 0.10$. Means and SDs are in millions of US dollars. N is number of firms. *p*-values are of two-tailed *t*-tests for difference of means of our sample and the FT Global 500 2009 sample.
(2) Data on Total Asset values of firms in our sample are obtained from the Bureau van Dijk's (BVD) database for economic data of global firms. Data on Total Assets of *FT Global 500* firms are obtained from FT databases.
(3) For this comparison, we drop firms that have missing Total Assets values.

Table A.2
Comparison of Sample with *Financial Times (FT) Global 500* (2009) on Number of Employees.

Industry	Our Sample (CDP 2009)			FT Global 500 (2009)			Two-tailed *t*-test (*p*-value)
	Mean	SD	N	Mean	SD	N	
Consumer Discretionary	97.98	39.69	8	160.85	160.85	55	$p = 0.55$
Consumer Staples	132.30	56.59	8	91.77	15.50	49	$p = 0.36$
Energy	27.86	7.55	13	55.92	14.25	51	$p = 0.33$
Financials	84.70	16.13	21	73.61	73.61	101	$p = 0.57$
Health Care	69.31	10.83	9	39.52	39.52	41	$p = 0.011^{**}$
Industrials	84.72	22.03	20	157.92	29.93	23	$p = 0.062^{*}$
Information Technology	74.78	24.39	17	84.17	17.98	36	$p = 0.76$
Materials	29.40	5.27	13	65.15	8.10	60	$p = 0.047^{**}$
Telecommunications	110.55	29.10	7	81.46	16.15	30	$p = 0.43$
Utilities	47.17	28.00	10	29.72	6.31	44	$p = 0.35$
All industries	73.02	7.80	126	80.76	5.92	490	$p = 0.53$

Notes:
(1) Significant at $^{*}p < 0.10$, $^{**}p < 0.05$. Means and SDs are in thousands of employees. N is number of firms. *p*-values are of two-tailed *t*-tests for difference of means of our sample and the FT Global 500 2009 sample.
(2) Data on Number of Employees of firms in our sample are obtained from the Bureau van Dijk's (BVD) database for economic data of global firms. Data on Number of Employees of *FT Global 500* firms are obtained from FT databases.
(3) For this comparison, we drop firms that have missing values on Number of Employees.

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