The Relevance to Investors of Greenhouse Gas Emission Disclosures

PAUL A. GRIFFIN, *University of California, Davis*

DAVID H. LONT, *University of Otago*

ESTELLE Y. SUN, *Boston University*

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Corresponding author: David H. Lont, Department of Accountancy and Finance, University of Otago, Dunedin, New Zealand 9054. 64-3-479-8119 (tel.), 64-3-479-8171 (fax), david.lont@otago.ac.nz (e-mail).

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Abstract

This study finds that investors price firms' greenhouse gas (GHG) emissions as a negative component of equity value, and this valuation discount does not differ between firms that voluntarily disclose to the Carbon Disclosure Project (CDP) and non-disclosing firms. We derive the GHG emissions for non-disclosers from an estimation model that incorporates firm characteristics and industry. The finding that investors view CDP amounts and estimates of emissions as equally value-relevant suggests that equity values reflect GHG information from channels other than the CDP. An event study of investors' response to emission-related information in firms' 8-K filings further supports this finding. Economically, our results suggest that, for the median S&P 500 firm, GHG emissions impose a market-implied equity discount of $79 per ton, representing about one-half of 1 percent of market capitalization.

JEL Classification: G14, M41, M48, K22, Q51, Q56.

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1. Introduction

Companies today face a daunting task of determining what and how much to disclose publicly about the risks and costs of their greenhouse gas emissions. On the one hand, investors and public interest groups worldwide call for more disclosure, greater uniformity, and more transparency (e.g., Black 2013; Coburn, Donahue, and Jayanti 2011). Companies and insurers, on the other hand, worry about the costs of disclosure, particularly from competitive disadvantage and liability exposure (e.g., Allen, Seaman, and DeLascio 2009; Weigand 2010); and others press for a more balanced consideration of the costs and benefits (e.g., Li, Richardson, and Thornton 1997). This study examines and extends the literature on this important disclosure issue, namely, whether investors view greenhouse gas (GHG) emission disclosures as relevant for valuation purposes.

While some raise doubts about the relevance of GHG disclosures for investors (e.g., Kolk, Levy, and Pinsky 2008), several studies show that investors act as if equity values vary negatively with GHG emissions (e.g., Chapple, Clarkson, and Gold 2013, for Australian firms; Clarkson, Li, Pinnuck, and Richardson 2015, for European firms; and Matusmura, Prakash, and Vera-Muñoz 2014, for U.S. firms). These results support the view that GHG emissions affect equity values negatively through firms' exposure to future regulatory and compliance costs. The preceding studies, however, differ widely in their assessment of the impact of GHG emissions on equity value. Matsumura et al. (2014) assess an overall valuation discount for U.S. firms of $US212 per ton of GHG, whereas Chapple et al. (2013) and Clarkson et al. (2015) assess much lower amounts, of $AUS17 to $AUS26 for Australian firms and €75 for the uncovered GHG emissions of European firms, respectively.

To shed light on this disparity, this study reexamines the valuation impact of GHG emissions (hereafter, GHGE) on U.S. firms. We investigate two related issues. First, we extend the prior work showing that investors act as if equity values vary negatively with GHGE by introducing a design innovation that analyzes the valuation impact of GHGE on equity value for both GHGE disclosing firms and non-disclosing firms. We investigate this by introducing a model to estimate GHGE for firms that do not report emissions to the Carbon Disclosure Project (hereafter, CDP)[1], which we term as non-CDP disclosing firms. This approach offers an alternative way to understand how GHGE might relate to firm value in the absence of CDP disclosure. We find results more in line with Chapple et al. (2013) and Clarkson et al. (2015) than with Matsumura et al. (2014). We also use an estimation model to represent investors' assessments of GHGE in the absence of CDP disclosure because much prior research indicates that investors in efficient capital markets such as in the United States price securities based on multiple channels of information. Because Matsumura et al. (2014) examine the same set of firms as we do and use the same source of data (CDP), we reconcile our results with theirs by examining whether model and variable choice might explain their more negative valuation discount. Our estimation model also circumvents the need to control for bias from self-selection that can occur in studies such as Matsumura et al. (2014) that analyze only firms reporting GHGE through a single channel, in this case, the CDP. In addition, our alternative design does not impose assumptions about why firms do not report to the CDP. Those reasons could vary widely and in ways not consistent with the Heckman (1979) approach used by Matsumura et al. (2014) to correct for self-selection. We further investigate whether the valuation discount in Matsumura et al. (2014) might reflect a selection bias by forward-testing for a market valuation impact of GHGE in later years. Since the CDP survey response rates increased in the later years, this testing helps address whether selection bias might affect their results.

[1] The Carbon Disclosure Project (online at www.cdp.net) (last retrieved March 11, 2016), founded in 2000 and supported in 2015 (2010) by 822 (475) signatory institutional investors representing $US95 trillion ($US55 trillion) in assets, offers the largest collection of self-reported environmental information in the world. By working with the endorsement of signatory investment firms that require strict data protocols, CDP offers standardized data of the highest quality for use by investors and academics. According to the CDP, the data have been used in 70 peer-reviewed studies published in 2005–2015, arguably making it the foremost source of environmental data for academic research. Originally named the Carbon Disclosure Project, the organization now operates as CDP Worldwide (a registered charity in the United Kingdom) and offers a wide array of services to investors, companies, cities, governments, and financial reporting regulators.

Second, we examine the contention in Matsumura et al. (2014) that firms paid an additional penalty by choosing not to disclose GHGE to the CDP, which the authors estimate as $5.7 ($2.3) billion for the average (median) non-CDP disclosing firm in their sample, representing 40 (28) percent of average (median) firm value according to their data. We do this by comparing the valuation penalty for reported GHGE for CDP disclosers and estimated GHGE for CDP non-disclosers. If investors impound the effects of GHGE on equity value using disclosures and estimates from multiple channels (e.g., sustainability reports, news services, regulatory filings, and estimates from proprietary models), then factors other than the non-reporting of GHGE to the CDP, such as firm characteristics unrelated to GHGE and/or model specification, could account for the additional discount in that study. In addition, given voluntary disclosure theory, one would predict that, with the passage of time, long-term value-maximizing managers would not voluntarily withhold GHGE information from investors knowing that such decisions would inflict a significant dollar penalty on firm value (Kumar, Langberg, and Sivaramakrishnan 2012). Rational investors, moreover, would understand that firms could have multiple reasons for non-disclosure to the CDP, such as disclosure through another channel, immaterial amount, failure to complete the CDP survey, and lack of tools to measure GHGE; and not all of these reasons would impose a significant penalty on firm value from non-disclosure.

We examine these issues using an extension of the Ohlson (1995) valuation model, which relates the market value of a firm's common equity to the book value of common equity and residual income. We extend the model by adding an equity valuation factor related to GHGE. This factor captures investors' expectations that higher GHGE will drain more cash flow from the firm in the form of higher future compliance, abatement, regulatory, and operating costs not already reflected in the market's assessments of residual income or book value (and other control variables in our model). We apply our specification of the Ohlson model to the S&P 500 using actual GHGE if reported voluntarily to the CDP and, if not, estimated GHGE from our estimation model.

Based on a sample of 3,276 firm-year observations over the 2006 to 2012 period[2], we report four main results. First, we find that investors price GHGE as a reduction in equity value, and such reduction increases in the level of GHGE. For the median S&P 500 firm in the sample period, our results indicate a market-implied equity discount of $79 per GHGE ton. This equates to a market-implied equity discount of less than one-half of 1 percent of median market capitalization. Second, while we are able to confirm the results in Matsumura et al. (2014), we are unable to substantiate that their coefficient for the market-implied price of 1 ton of GHGE of $US212 (and average impact on common equity) is robust to changes in model and variable specification or generalizes to more recent years (in our case, through 2012), which have higher CDP participation rates.

Third, while we are also able to confirm the finding in Matsumura et al. (2014) that CDP disclosers have higher market value than CDP non-disclosers, we find no significant difference in the coefficient for the valuation impact of GHGE for disclosers (based on emissions reported to the CDP) versus non-disclosers (based on emissions from an estimation model). This result implies that firms' equity values reflect similar GHGE attributes irrespective of whether the firm makes a formal disclosure to the CDP. It also suggests that the discount for non-disclosure reported in Matsumura et al. (2014) might relate to factors other than GHGE, for example, the residual effects of firm size not removed by their propensity score matching procedure. In this regard, we note that the Matsumura et al. (2014) propensity score model does not account for how the level of GHGE might affect firm value. Instead, they examine only whether the propensity to disclose affects firm value. This distinction seems important given that the level of GHGE is associated with a market-implied equity discount, which is our first result (and the result of the prior research).

Fourth, we analyze a sample of 1,964 Securities and Exchange Commission (SEC) 8-K filings that refer to GHG or carbon emissions (8-K emission filings) and find a distinct increase in stock price volatility around the day of an 8-K

[2] The initial sample size of 3,460 GHGE observations drops to 3,276 GHGE observations for the analyses due to missing data for certain variables in the valuation model.

emission filing, consistent with investors' use of 8-K emission information. We do not, however, find that investors' response around the 8-K filing date differs significantly for CDP disclosers versus CDP non-disclosers. This is further circumstantial evidence that disclosure to the CDP makes no difference to the way investors view the impact of GHGE on firm value (also consistent with our third result).

Our study adds to the literature in several unique ways. First, we introduce a model to estimate GHGE for CDP non-disclosers and validate the accuracy of this model. This model innovates by offering a way for future studies to use less restrictive samples. It also obviates the need to use statistical procedures that may not be sufficiently effective to test and control for sample selection bias when analyzing firms that report GHGE to a single organization such as the CDP. Second, we extend earlier findings on investors' pricing of environmental obligations by showing a similar equity valuation impact of GHGE for CDP disclosers and non-disclosers. This occurs because investors in non-CDP disclosing firms are able to value GHGE information from channels other than the CDP, such as sustainability reports, regulatory filings, and estimates from proprietary models. We further support this argument by showing a significant investor response to GHGE-related disclosures in 8-K filings. Third, our results have an economic interpretation, showing that for each ton of GHGE emitted by the median firm in our sample, U.S. investors recognize approximately $79 per ton as a market-implied off-balance sheet valuation discount.

Our paper proceeds as follows. Section 2 discusses the institutional environment and relevant prior research and states the empirical tests. Section 3 summarizes the data, sample, and research design. Section 4 presents the results, section 5 describes additional tests, and section 6 concludes and suggests topics for future research.

2. Institutional features, prior research and empirical tests

Institutional features

Many large U.S. firms disclose their GHG emissions voluntarily through the CDP. The CDP works with firms worldwide to measure and manage their emissions and climate change strategies and collects and publishes emissions data based on consistent guidelines as part of its annual surveys (see, also, note 1). The CDP also tracks non-participation, so that each survey covers a well-defined population, in our case the S&P 500. This makes the CDP data attractive from a research design standpoint. The proportion of the S&P 500 reporting GHG emissions to the CDP has also grown over the years studied, from 29 percent in 2006 (the first reporting year) to 58 percent in 2012 (Table 1, panel A). The institutional landscape of GHG emission reporting by U.S. firms also involves compliance with federal regulations. For example, mandatory GHG reporting is required for U.S. firms under EPA Rule 40 CFR Part 98 (EPA 2009, 2011). However, the rules for EPA emissions reporting apply mainly to direct (scope 1) emissions by domestic facilities, which means that they only partially cover the direct emissions of firms with international operations, as would apply to most S&P 500 firms; and they pay little attention to indirect (scope 2) emissions), namely those emitted indirectly as a consequence of the use of energy produced by others, which for some firms (e.g., electricity, fuel, and water users) can be substantial. Both direct and indirect emissions can impose future and uncertain compliance, abatement, regulatory, and production costs not already recognized in the accounting statements.[3]

Reporting and disclosure of carbon emissions and climate change information may also result from federal regulations promulgated by the SEC, although so far it has only issued guidance releases to supplement existing disclosure frameworks. For example, SEC Release 33-9106 (also 17 CFR Parts 211, 231 and 241) (SEC 2010) outlines the SEC's interpretation on what constitutes compliance with existing disclosure laws, such as Regulation S-K Item 101

[3] The nature and uncertainty of these future costs may differ, however, for firms with direct and indirect GHGE. For direct emissions, future costs may relate more to the costs associated with the regulation of facilities that produce emissions, such as a cap-and-trade program. But the specifics and timing of future GHGE regulation would seem quite uncertain in the United States given the prior failures at the federal level, for instance, the American Clean Energy And Security Act Of 2009 (H.R. 2454,111th). Indirect emissions, on the other hand, would more likely encompass additional future costs of production, such as the purchase of carbon offsets and other GHGE abatement efforts, investment in capital to reduce GHGE consumed by the use of energy and other resources, and higher tax and compliance costs for some inputs in the form of GHGE costs passed on by others. Section 5 addresses the potential for the valuation impact of GHGE to differ for direct and indirect emissions.

on environmental laws and Item 103 on environmental litigation. Regulation S-K further requires disclosure of material risks and trends as either a separate section or as part of management's discussion and analysis. Such risks and trends could include climate change factors such as GHG emissions, but there is no requirement to disclose such.

Existing SEC regulations, however, also require U.S. firms to disclose material information about firm events and activities in an 8-K filing, and the SEC lists several categories of such that might trigger an emission-related disclosure, for example, disclosure under Regulation FD (Item 7.01), Other Events (Item 8.01), and Financial Statements and Exhibits (Item 9.01). We exploit this feature of the institutional environment by extracting all GHG emission-related information in the 8-K reports of the S&P 500 firms we study. This provides us with a sample of publicly available emission-related disclosures independent of whether or not a firm discloses GHGE to the CDP and, hence, another way to test for differences in equity investors' response to an alternative channel of emission-related information conditional on disclosure to the CDP.

Prior research and empirical tests

Much prior literature has studied the valuation effects of environmental disclosures.[4] The categories studied include examinations of the relation between environmental liabilities and equity value (Shane and Spicer 1983; Barth and McNichols 1994; Cormier and Magnan 1997; Li and McConomy 1999; D'Souza, Jacob, and Soderstrom 2000; Campbell, Sefcik, and Soderstrom 2003), how equity or debt markets relate to environmental and social responsibility disclosures (Spicer 1978; Blacconiere and Patten 1994; Campbell, Sefcik, and Soderstrom 1998; Konar and Cohen 2001; Stanny and Ely 2008; Clarkson, Fang, Li, and Richardson 2013; Dhaliwal, Li, Tsang, and Yang 2011; Schneider 2011; Griffin and Sun 2013; Plumlee, Brown, Hayes, and Marshall 2015); and whether the market pays attention to pollution indicators such as SO_2 emissions (Hughes 2000; Johnston, Sefcik, and Soderstrom 2008), toxic waste (Al-

[4] This review is intended to highlight the relevant studies rather than comprehensively summarize the empirical literature.

Tuwaijri, Christensen, and Hughes 2004), and toxic chemicals (Clarkson, Li, and Richardson 2004).

However, a majority focuses only on one or a few industries (e.g., chemicals firms, electric utilities, pulp and paper companies) and/or firms whose emissions (mainly scope 1) relate to domestic production or manufacturing (e.g., the EPA's Toxic Release Inventory (TRI) data, which measure the release and transfer of toxic chemicals from U.S. manufacturing facilities only). Thus, it is unclear from the above that we should observe a similar negative relation if based on an inclusive measure of GHG emissions (scope 1 and 2) relating to a broad set of firms not subject to comprehensive emission regulation (e.g., cap-and-trade), in our case, the S&P 500.

Three studies relate most closely to the present analysis and base their results on a version of the Ohlson (1995) valuation model. First, Chapple et al. (2013) study 58 disclosures by Australian firms and report an equity valuation discount of $AUS17 to $AUS26 per ton of GHGE for high emission intensity relative to low intensity Australian firms (Chapple et al. 2013, 27). Second, Clarkson et al. (2015) investigate a sample of 843 firm-year observations from the European Carbon Emissions Trading Scheme (EU ETS) over the period of 2006–2009 and find an equity valuation discount of €75 (or $US97.5 at €1.00=$US1.30) per ton of uncovered GHGE (namely, GHGE uncovered by allowances or offsets granted by the regulator under a cap-and-trade or similar regulatory system) and a smaller equity valuation discount of €39 per ton during phase 1 of the EU ETS, when significant free allowances were granted to firms by the regulator. Third, Matsumura et al. (2014) examine 549 CDP disclosures by S&P 500 disclosers over the 2006–2008 period. Similar to the above, they find a significantly negative relation between GHGE and equity value and report an average valuation discount of $212 per ton of GHGE, which they suggest results from "uncertainty surrounding new regulatory compliance, and uncertainty surrounding physical climate parameters" (Matsumura et al. 701), future compliance costs and litigation (Matsumura et al. 703), and the cost of "measuring, monitoring, and reducing carbon emissions" (Matsumura et al. 720). They comment that their results differ from Chapple et al. (2013), who analyze smaller firms and do not account for the effects of disclosure on the data sets (Citigroup and VicSuper),[5] which could introduce bias because their sample may not be representative of the population (selection bias) and some firms in the sample may have preferred to report only good news (disclosure bias). This divergence of results between Matsumura et al. (2014) and Chapple et al. (2013) (and Clarkson et al. 2015) adds further motivation for this present research, as it is a testable proposition that selection and disclosure bias might explain the divergence versus other explanations, for example, the application of the procedure in Matsumura et al. (2014) to model and control for selection bias.

3. Data, sample, and research design

Data and sample

We extract the GHG emission data disclosed to the CDP for the S&P 500 for reporting years 2006 (the first year of S&P 500 data collection) to 2012 (the most recent year for analysis) from the annual S&P 500 reports published by the CDP.[6] As a set of large and widely-held firms, the S&P 500 should be of high interest regarding the valuation effects of GHG emission disclosure. S&P 500 firms should also share similar disclosure incentives, in that their stocks trade frequently (mostly by institutional investors) in efficient markets. We extract two fields of emission data from the 2006–2012 CDP surveys, namely, direct (scope 1) and indirect (scope 2) emissions, and combine these data into a single GHG emission measure.[7] We also extract the Carbon Disclosure Leadership Index (CDLI) score as a proxy for the

[5] These two data sources rely primarily on data collected by the CDP on Australian firms. VicSuper also uses a proprietary model to estimate GHGE (Chapple et al. 2013, footnote 23).

[6] The CDP sets the reporting year to coincide with a firm's fiscal year and publishes a summary of the survey data usually in the succeeding September or October of the reporting year. The CDP requests submission of the data by the end of May. We allow for membership changes in the S&P 500 sample.

[7] We combine the two GHGE measures as a single amount because not all firms provide a breakdown of scope 1 (direct) and scope 2 (indirect) emissions. However, where possible, our GHGE estimation model (model 1) estimates direct and indirect emissions for non-CDP disclosers separately and then combines them into a single amount. In a later section, we investigate whether the equity valuation effect might differ for firms with more direct versus indirect emissions.

comprehensiveness of emission disclosure.[8] We combine these data with information from CRSP, Compustat, and KLD STATS to provide a basis for the descriptive sample statistics (this section) and the valuation and event studies (section 4).

Table 1 summarizes the sample of 3,460 firm-year emission observations, comprising 1,677 from the CDP and 1,783 from the estimation model (details below). Panel A reports the CDP response rate and shows that it approximately doubles from 29.23 percent in 2006 to 58.03 percent in 2012. We exploit this increase in response rates in our empirical tests on sample selection bias. Panel B reports the data by 10 GICS (Global Industry Classification Standard) industry sectors and shows that utilities have the overall highest GHGE response rate and that consumer discretionary, financials, and energy have the lowest. We use the GICS sector to represent industry as the CDP survey uses this classification in the same way. Untabulated analysis indicates that the CDP response rate correlates positively with the level of GHGE and CDLI (disclosure comprehensiveness). For example, the product-moment correlations between the combined response rate (across all sectors and all years) and mean GHGE and between the combined response rate and mean CDLI are 0.68 and 0.75, respectively. We control for industry and disclosure comprehensiveness in the research design.

[Insert Table 1 about here.]

Research design

Our research design comprises three stages: (1) a model to estimate emission production for firms not reporting emissions to the CDP (CDP non-disclosers), (2) a model of the relation between equity value and actual or estimated GHGE, and (3) a model of the relation between SEC 8-K emission disclosures and daily unsigned excess stock return around the 8-K filing date.

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[8] A high CDLI indicates a comprehensive response to the CDP survey, including "clear consideration of business-specific risks and potential opportunities related to climate change and good internal data management practices for understanding GHG emissions" (online at www.cdp.net) (last retrieved March 11, 2016).

GHG emission estimation model

The first stage estimates GHGE for firms not reporting emissions to the CDP. Since a substantial number of S&P 500 firms do not report to the CDP (Table 1), this approach increases the sample size considerably and potentially removes a key source of selection bias from the results. We generate an estimate of GHGE for a non-disclosing firm by regressing GHGE for a disclosing firm on a linear combination of scale of operations, investment, asset composition, sector, and other key financial data (emission production variables). We then use the coefficients from this regression to estimate GHGE for a non-disclosing firm. As one way to motivate our GHGE estimation model, we link it to a production function of a firm's periodic emissions, specified as GHGE = $A.\prod (x_1^{\alpha}, x_2^{\beta}, x_3^{\gamma}, \ldots)$, where A is a constant and the $x_i>0$ are the assumed inputs producing the emissions.[9] We then convert the GHGE production function to a log-linear form (using natural log), so it becomes $logGHGE = \log A + \alpha \log x_1 + \beta \log x_2 + \gamma \log x_3 \ldots$ etc., paralleling our empirical estimation model. In other words, our estimation model of *logGHGE* includes a fixed effect ($\log A = \alpha_0$) and varies linearly with emission production variables x_i such as those in model 1 below; for example, firm output (*REVT*), investment (*CAPX*), and asset age (*PPEDP*). We also include additional variables in the *GHGE* estimation model that potentially vary systematically with the level of firm emissions, namely, the sector in which the firm operates (*SECT*), the extent of intangible assets (*INTAN*), gross margin (*GMAR*), and outside borrowing (*LEVG*).[10] Our empirical model without subscripts *i* and *t* for firm and year is:

$$logGHGE = \alpha_0 + \Sigma_{1j}\alpha_{1j}SECT_j + \alpha_2 logREVT + \alpha_3 logCAPX + \alpha_4 logPPEDP + \alpha_5 logINTAN + \alpha_6 GMAR + \alpha_7 LEVG + \varepsilon, \qquad (1)$$

where *GHGE*=greenhouse gas emissions per CDP reporting year in metric tons; *SECT*=one for each of the *j* GICS industry sectors (the 10th is in the intercept), otherwise zero; *REVT*=total revenue (Compustat variable code=*revt*);

[9] In its most primitive form, the view economists tend to have of emissions is that they are a firm output in the form of a cost-inducing joint product produced by the firm's emission production function. The firm is assumed to trade off emission output (possibly subject to self-imposed or regulatory constraints) against other cost-inducing or revenue producing joint products to maximize firm-wide profits or minimize costs (e.g., Ebert and Welsch 2007; Siebert and Nixdorf 2008).

[10] These variables are also listed and defined in the appendix.

CAPX=capital expenditures (*capx*); *PPEDP*=gross property, plant and equipment to depreciation expense (*ppegt/dp*); *INTAN*=intangibles (*intan*); *GMAR*=gross margin (1-*cogs*/*revt*); *LEVG*=long-term debt divided by total assets (*dltt/at*); *log*=log to base *e*; and ε=random error.[11] In addition to its resemblance to a production function, our log-linear estimation model helps reduce skewness in the distributions of certain variables (e.g., *GHGE*, *REVT*, *CAPX*, *INTAN,* and *PPEDP*) that could, otherwise, generate improper parameter estimates. Empirically, we expect α_1 to reflect differences across the sectors, $\alpha_2>0$, $\alpha_3>0$, and $\alpha_4>0$, to reflect positive relations between GHGE and the input variables, and $\alpha_5<0$, as firms with more intangible assets should emit fewer emissions. We are uncertain about the signs of α_6 and α_7 and include them as control variables only. For instance, if firms with higher gross margin can afford to pay for the cost of higher emissions, we might expect $\alpha_6>0$; and if higher-debt firms were to emit fewer emissions because of creditors' monitoring activities, we might expect $\alpha_7<0$, although α_7 might also be positive if highly levered firms were to make riskier investments that increased GHGE. Our estimation approach increases the sample size from 1,657 actual disclosures to a maximum of 3,276 actual and estimated GHGE observations with available data for the other variables in model 1 (Table 2).

Where available, we estimate model 1 for direct and indirect emissions separately (otherwise as a combined amount) as a pooled, cross-sectional regression, where the observations are pooled for the *i* firms that reported emission data to the CDP for years up to and including the estimation year *t*. Thus, the later years use more emission observations to estimate the parameters. We then combine the separate estimations of direct and indirect emissions (based on the regression coefficients and the non-discloser regressor variables) to estimate total emissions. For example, we estimate $logGHGE_{2009}$ for non-discloser S&P 500 firms in 2009 based on S&P 500 firms with CDP emission data for the 2006–

[11] For financial companies, we arbitrarily set revenue equal to net interest income (if available) and gross margin to zero. These assumptions do not affect the overall results.

2009 period.[12] We combine the separate estimations of direct and indirect GHGE, as different industries generate different levels of direct and indirect emissions, and both kinds can potentially affect investors' assessments of future cash outlays for compliance and regulation. For example, utilities and energy firms tend to produce more direct emissions, which are more likely to be subject to future compliance costs, especially given the EPA's 40 CFR Part 98 reporting program, which points clearly in the direction of future controls and limits on GHGE production. On the other hand, consumer- and manufacturing-based sectors tend to produce more indirect emissions (through energy use), which can be costly to a firm not only because of future production costs and the threat of future controls and limits on GHGE (e.g., the requirement to produce of low-carbon transportation, such as electric or hydrogen-powered cars) but, also, because of efforts by stakeholders and self-regulatory bodies to constrain and abate firm activities that produce emissions.

Equity valuation model

The second stage uses a variant of the Ohlson (1995) valuation model to assess valuation relevance by regressing stock price three months after fiscal year-end t ($PRCC_t$) on the carrying value of common equity per share at t ($CVCE_t$); residual income per share for t ($RESI_t$); actual or estimated GHG emissions per share for t ($GHGPS_t$); and other information variables (labeled as *CNTL*), such as disclosure comprehensiveness (*CDLI*) and whether we use actual *GHGPS* from the CDP or estimated *GHGPS* from model 1 (*DSCL*).[13] Our equity valuation model without subscripts i and t for firm and year is:

$$PRCC = \beta_0 + \beta_1 CVCE + \beta_2 RESI + \beta_3 GHGPS + \Sigma\beta_k CNTL_k + \varepsilon. \quad (2)$$

Barth and Clinch (2009) show that a per-share specification of model 2 works well under several model

[12] Our results are unchanged if we derive the coefficients using data for all years prior to the year of the firm characteristics to calculate *logGHGE*. We lose one year of data (2006), however, under this approach.

[13] We deflate actual or estimated GHG emissions for year t by *csho* x 1,000, and hereafter refer to this variable as GHGE per share or *GHGPS* in model 2. All variables are listed and defined in the appendix.

performance metrics. Following prior research (Dechow, Hutton, and Sloan 1998; Begley and Feltham 2002; Callen and Segal 2005; Barth and Clinch 2009), we predict positive coefficients for *CVCE* (β_1>0) and *RESI* (β_2>0). As per the prior research, we predict a negative coefficient for *GHGPS* (β_3<0). This negative coefficient reflects investors' assessments of the additional expenditures or uncertainties regarding GHG emissions in the form of increased future compliance, abatement, regulatory, and production costs not already recognized in the accounting statements. We also confirm and forward-test using more recent years the Ohlson (1995) equity valuation model used by Matsumura et al. (2014) and conduct tests of the sensitivity of their findings on selection and disclosure bias.

Event study

Rather than study legislative events as per some earlier work (Blacconiere and Northcut 1997; Chapple et al. 2013), we focus on investors' response to firm disclosures about GHG emissions or related factors in 8-K filings. We select 8-K emission filings because these represent an alternative channel through which investors might learn about the effects of GHGE on equity valuation and because firms through the act of a filing deem these news events as ex ante material.[14] Specifically, our event study examines the significance of investor response at time *t*, where *t*=0 is the 8-K filing day. We measure the response at *t* as the unsigned daily stock return for trading day *t* (RET_t) in excess of the day *t* return on the CRSP value-weighted market index (MKT_t), that is, $XRET_t$ = absolute value of (RET_t – MKT_t).[15] We then test whether $XRET_t$ at *t*=0 is positive and/or exceeds $XRET_t$ on the other days within the interval *t*=-10 to 10. We view this approach as a test of investor response to a given disclosure (Beaver 1968; Bamber 1986; Cready and Mynatt 1991). Later studies suggest we can also interpret such a response as an indication of how a given disclosure might change investor uncertainty about future stock returns (Veronesi 1999; Ozoguz 2009).

[14] We use the term "ex ante material" to indicate that companies base their decisions to release news in an 8-K filing on the predicted importance of such news, which is unknown at the time, and not what might have happened ex post.

[15] We use a market-adjusted measure of excess return, instead of a more complicated estimate based on multiple risk factors, as our sample comprises the S&P 500, which represents a broad cross-section of industries, firm size, and other financial characteristics (Table 2), whose beta risk factor approximates one by construction.

To implement this test, we access directEDGAR to identify all 8-Ks during the period from January 1, 2005 to January 1, 2010 containing the following key terms: carbon and emission, carbon and climate, emission and climate, greenhouse gas, and climate change. This search produces 6,543 8-K filings. We then eliminate 8-Ks with the same SEC identifier (Central Index Key or CIK) and filing date and, after matching the CIKs with each firm's CRSP permanent issue identifier (PERMNO), we obtain a final sample of 1,966 8-K emission filings of which 1,728 contain a firm press release. These 8-K emission filings are well suited for an event study, in that they distribute broadly over the study period (33.1 per month on average for the 60 months from January 2005 to December 2009 and a standard deviation of 21.5 per month), relate to one or more 8-K items that we can pinpoint to a day with precision, and do not cluster unduly on the same day (40 percent have no similar release by a different firm, 67 percent have 0 or 1, 75 percent have 0 to 2, and 94 percent have no more than four other releases on the same day). Inspection of these 8-Ks, however, reveals mentions of key terms that do not indicate specific emissions or similar information but relate more to climate change risk generally.[16] We, therefore, split the 1,966 observations into two groups, 1,059 8-Ks with specific emission information and 907 with non-specific emission information, with the expectation that the results should be more conservative for the full sample versus the emission-specific group.[17] For each of the 1,966 filings, we also use

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[16] The extent of GHG emission disclosure and climate change information varies in these 1,966 8-K climate change filings. The most common types of disclosure include (1) mention of GHG-related environmental and regulatory concerns as a risk factor (e.g., Dow Chemical Company, filed 9/25/2009); (2) discussion of the operational and financial impact of potential GHG-related legislation (e.g., Vectren Utility Holdings, Inc., filed 3/6/2009; Enterprise Products Partners L.P., filed 12/4/2009; PNM Resources, Inc., filed 5/19/2009); (3) discussion of activities to reduce GHG emissions and improve energy efficiency in operations (e.g., Exxon Mobil Corporation, filed 3/30/2009); (4) summary of achievements in GHG emission reduction (e.g., FirstEnergy, filed 12/1/2005; Alcoa Inc. sustainability report, filed 3/23/2005); (5) disclosure of an environmental strategic plan (e.g., Exelon Corporation, filed 7/17/2008; Westar Energy, Inc., filed 2/20/2008; Public Service Enterprise Group, Inc., filed 9/26/2007); and (6) other disclosures with a GHG or climate change focus (e.g., appointment of a director with extensive experience on climate change issues, such as Boeing Company, filed 6/27/2007, and Energy Recovery, Inc., filed 2/26/2009).

[17] We code "non-specific emission information" if *directEDGAR* identifies the search terms as part of a firm disclaimer, forward-looking statement, or synopsis about the firm. We acknowledge the arbitrary nature of this coding. In the event study, we define the variable as *SPEC* = 1, if the 8-K emission disclosure contains firm-specific emission or climate change information, otherwise 0. We report the results of an even more restrictive sample of 8-K disclosures in Section 5 on robustness tests.

directEDGAR to identify the 8-K item numbers, which enables us to separate emission 8-Ks with earnings information (item 2 and item 9 disclosures) from emission 8-Ks without earnings information.

4. Results

Descriptive statistics

First, panel A of Table 2 summarizes the variables used to describe the samples, primarily the variables in model 1. CDP disclosing firms differ from non-disclosers in terms of size (*logREVT* and *logAT*) and investment (*logCAPX*), and these differences occur regardless of sector. As such, we expect disclosing firms to reflect higher average *GHGE*, which panel A also indicates occurs for every sector. On the other hand, panel A also shows that disclosing and non-disclosing firms are mostly equally profitable (*GMAR*), and the two groups share similar amounts of outside financing (*LEVG*). Panel A further shows that, apart from scale, the sectors rank almost identically on *GHGE* regardless of whether a firm discloses or not. As expected, utilities, energy, and materials lead in emission output, whereas financials, healthcare, and information technology rank at the bottom.

[Insert Table 2 about here.]

Second, panel B of Table 2 shows descriptive statistics for the variables in model 2 (and *GHGE* in relation to revenues, i.e., greenhouse gas intensity). We scale several variables by shares outstanding, as this has the general effect of reducing the differences between disclosers and non-disclosers and within each discloser sector and across the sectors. This reduction in heterogeneity should improve the reliability of our regression estimates (Barth and Clinch 2009). For example, *CVCE* and *RESI* are not statistically different for disclosers versus non-disclosers, and for one-half of the sectors price per share (*PRCC*) is higher for the non-discloser group. Consistent with panel A, though, *GHGPS* and *GHGI* are higher for disclosers than non-disclosers, which mostly reflects higher emissions for CDP disclosers in general (panel A).

GHGE estimation model

Because we use estimates of firms' emissions based on model 1 to test for the effects of *GHGE* on firm value, we conduct tests of the reasonableness of this model. Table 3 summarizes the results. We first report the explanatory power (adjusted R^2) of the model, which regresses *logGHGE* (reported to the CDP) each year on the assumed emission production variables in model 1. We then use the parameters from these regressions to predict *logGHGE* for non-CDP disclosing firms. Panel A of Table 3 shows the adjusted R^2 percentages from the regressions and the total observations used in the estimation (cumulative from 2006). For 2006 and 2007, when only total reported GHGE are available, the explanatory power of model 1 exceeds 80 percent, and in the subsequent years, the combined explanatory power of the model continues to exceed 70 percent. However, when we require separate estimations of direct and indirect emissions for each firm, we lose observations, and the explanatory power drops to 60–70 percent for direct emissions and 30–38 percent for indirect emissions. The most significant emission production variables in these regressions are sales revenue and sector membership. The F-statistics for the yearly regressions are all highly significant at $p<.001$, although model 1 performs better in explaining direct emissions versus indirect emissions.

[Insert Table 3 about here.]

Our second test assigns *logGHGE* (the measure reported to the CDP) into deciles (the expected deciles) and then determines the percentage of the estimated *logGHGE* amounts from the model that remain in the same or adjacent deciles based on reported *logGHGE*. Panel B of Table 3 shows the percentages, which range from 69.34 to 92.55. On average, 81.3 percent of the estimated *logGHGE* amounts remain in the same or an adjacent decile (the one above or the one below the expected decile) as the reported CDP amounts. Third, we compare estimated *logGHGE* with *logGHGE* for CDP disclosers and test whether the means of the distributions differ for each year based on a two-tailed test of the difference. The *p* values in panel C of Table 3 show that the means of estimated *logGHGE* and actual *logGHGE* do not differ significantly in any of the years. This is consistent with an absence of positive or negative bias in the *GHGE* estimates.

Equity valuation model regressions

Panel A of Table 4 reports the univariate correlations among the variables used in model 2, with significant correlations at $p<.05$ shown in bold. As expected, the strongest correlation occurs between the primary valuation variables, that is, common equity (*CVCE*) and residual earnings (*RESI*). In addition, we observe positive correlations between *GHGPS* and *CDLI* (and *DSCL*), which suggests higher *GHGPS* for disclosers and firms with more comprehensive emission information, although this could relate to a common size effect (e.g., from *CVCE* or *RESI*). Note, also, in keeping with our primary hypothesis, the correlation between *GHGPS* and *PRCC* is negative (insignificant, however), and this occurs even though the *GHGPS*/*CVCE* and *GHGPS*/*RESI* correlations are positive, suggesting that the negative valuation effects of *GHGPS* relate to off-balance-sheet items rather than recognized accounting numbers such as *CVCE* and *RESI*. We use regression analysis to control for these correlations in testing for a negative relation between *GHGPS* and *PRCC.* We discuss this next.

Panel B of Table 4 summarizes three versions of model 2 for each year separately and for 2006–2012 combined as follows: the main model (panel B(1)); model 2 with a control for the CDP disclosure leadership index (*CDLI*) (panel B(2)); and model 2 with an interaction for whether the firm disclosed GHG emissions to the CDP (*DSCL*) (panel B(3)).

[Insert Table 4 about here.]

Panel B(1) shows the results for the main model, which regresses stock price (*PRCC*) three months after fiscal year-end *t* on the carrying value of common equity per share (*CVCE*), residual earnings per share *(RESI)*, and GHG emissions per share (*GHGPS*). For our estimations of the coefficients for the combined years, we exclude 2008 due to the effects of the global financial crisis on market capitalization and, thus, potentially the other variables as well. First, the coefficients for *CVCE* and *RESI* are positive and significant across all the years in the table. However, the coefficient for *RESI* drops significantly in 2008. We conjecture this reflects the possible effects of the global financial crisis of 2008. After excluding 2008, the β_1 and β_2 coefficients for *CVCE* and *RESI* average 0.78 and 10.80, respectively, broadly consistent with prior studies (e.g., Callen and Segal 2005, Tables 3 and 7, based on 1990–2001 data). Second, in the main regression model, we report significantly negative β_3 coefficients for *GHGPS* for all years (excluding 2008) and all but two of the individual years (panel B(1)). Also, we observe no pronounced trend in the β_3 coefficients over the years examined.[18] Third, we add controls to the main model. Panel B(2) shows that we continue to observe negative coefficients for *GHGPS* when we add *CDLI* as an additional explanatory variable. *CDLI* is not significant overall, however, and varies in sign across the individual years. Panel B(3) analyzes the valuation relevance of *GHGE* for firms that disclose to the CDP survey versus those that do not by interacting *GHGPS* with *DSCL*. The key insight from panel B(3) is that while we observe positive coefficients for the interaction variable (*GHGPS* x *DSCL*), consistent with a numerically more negative effect for non-disclosers, such coefficients are insignificant for all firm-years combined and all but one of the individual years.[19] This is evidence that the *GHGPS* coefficients are similar for CDP disclosers and CDP non-disclosers. This implies that the equity market acts as if CDP survey data are not the only source of information about GHG emissions. Untabulated results further support this implication, in that when we estimate the *GHGPS* coefficients in the regressions in panels B(1) to B(3) separately for CDP disclosers and CDP non-disclosers, we continue to find significantly negative *GHGPS* coefficients for both groups for all years combined and for all but one of

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[18] While not tabulated, the *GHGPS* coefficients for the pooled regressions based on the full study period (without exclusion of 2008) are as follows: -0.1035, Panel B(1); -0.1038, Panel B(2); and -0.1485 for *GHGPS* and 0.0668 for *GHGPS* x *DSLC*, Panel B(3).

[19] Our results show that the β_3 coefficients for *GHGPS* for disclosers and non-disclosers are not significantly different (panel B(3) of Table 4) and are not confined to the first few years of GHG reporting to the CDP, when participation rates were lower (panel A of Table 1). They also support the view that selection bias has a limited effect on the results. See, also, the next section, which confirms and replicates key aspects of Matsumura et al. (2014).

the individual years over the 2006–2012 period.[20]

Economic interpretation of the GHGPS coefficients

Table 5 offers an economic interpretation of the *GHGPS* coefficients documented in Table 4. First, we calculate the dollar per share effect by multiplying the *GHGPS* coefficient in panel B of Table 4 (-8.3 percent) calculated over all firm-years 2006–2012 except for financial crisis year 2008 by the sample median value of *GHGPS* (1.278), so that the median stock price (our dependent variable) drops by $0.106 per ton of GHGE (calculation 3). Given that the median sample firm has 301.38 million shares outstanding, this translates into a median dollar valuation effect of $32.07 million ($0.106 dollars per share times 301.38 million shares). This represents 0.275 percent of average market capitalization (calculation 7), and for the individual years, this percentage ranges from 0.196 percent (2007) to 0.485 percent (financial crisis year 2008). Because the median firm in the sample emits 407,110 tons of GHGE per year, this equates to a market-implied penalty of $78.8 per GHGE ton (calculation 9). Table 5 also shows that this overall market-implied penalty varies across the years, especially in 2008 (and possibly in 2009) when it increased, primarily because of a drop in market capitalization in those years (due to the financial crisis).[21] Table 5 also shows an inter-quartile range around those estimates of $43.6 to $126.0 dollars per GHGE ton, with the highest variation in 2009–2010. Finally, Table 5 shows market-implied penalties of less than one-half of 1 percent of median firm value and approximately 1 to 1.3

[20] The *GHGPS* coefficients estimated separately for CDP and non-CDP disclosers also continue to be negative and significant at least at p<0.1. However, they are not significantly different from each other in the individual years, other than in 2012, and all years combined as per panel B(3) of Table 4. Nonetheless, the non-discloser *GHGPS* coefficients are numerically more negative for most of the years. Specifically, the sub-sample *GHGPS* coefficients listed by Year, Discloser coefficient (Non-discloser coefficient) are as follows: 2006: -0.0203 (-0.1642); 2007: 0.0109 (-0.2163); 2008: -0.0485 (-0.2124); 2009: -0.0310 (-0.1215); 2010: -0.0287 (-0.0873); 2011: -0.0626 (-0.0684); 2012: -0.0206 (-0.3287), all years ex 2008: -0.0367 (-0.1818).

[21] In untabulated analysis, we also find (i) that the equivalent market-implied penalties per GHGE ton based on all sample years (without exclusion of 2008) are $97.6 (median), $55.5 (first quartile), and $157.0 (third quartile); and (ii) that the median impact of GHGE on market capitalization for CDP disclosers is qualitatively the same as the average impact for CDP non-disclosers.

percent when based on firms at the third quartile of the sample distribution.[22]

[Insert Table 5 about here.]

Replication of Matsumura et al. (2014)

The *GHGPS* valuation coefficients in panel B of Table 4 and the economic interpretation of such in Table 5 suggest a lower emission valuation penalty from that implied by the *TCO2* coefficient of -0.212 reported in Matsumura et al. (2014, Table 4). To potentially understand why their valuation penalty for U.S. firms differs from ours, we replicate the main results in Matsumura et al. (2014, Tables 4 and 5) for the same CDP years they examine (2006–2008) and then forward-test their analysis using the remaining years in our sample (2009–2012).[23] Table 6 summarizes our analysis of their valuation model (Equation 1). As expected, for the same CDP years, we confirm the β coefficients for *TCO2*, *ASSET*, *LIAB*, and *OPINC*, which we estimate (with their coefficients in parentheses) for the full sample as -0.204 (-0.212), 1.218 (1.129), -1.292 (-1.186), and 3.036 (4.421), respectively.[24] We also confirm the coefficients for their Heckman model (Equation 2); for example, we show a coefficient for their *SIZE* variable of 0.354 (0.394). We then replicate their Equations 1 and 2 for CDP disclosers for each year separately from 2006 to 2012. We find four results of interest from this replication. First, the *TCO2* coefficient for individual year 2008 differs insignificantly from zero. After dropping the 2008 observations from their 2006–2008 sample, the *TCO2* coefficient then increases negatively to -0.348. Second, in five of the seven years, the *TCO2* coefficient exceeds the 2006–2008 average of -0.204 (their estimate, -0.212). Thus, when applied year by year, the replicated *TCO2* coefficients continue to suggest an emission valuation penalty that well exceeds the results reported in this study (and in the prior literature). Third, the

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[22] We use the first and third quartiles of the relevant distributions because of extreme skewness in the data, which makes the mean values much less representative of the overall sample and population.

[23] Brown (2013) and Dyckman and Zeff (2014) call for increased publication of replications in the accounting literature, for "without replications, researchers are likely to accept, simplistically and without question, the results of the previous studies on which the current study depends." (Dyckman and Zeff 2014, p. 698).

[24] We were also able to confirm the results for the EPA=1 and EPA=0 partitions in Matsumura et al. (2014, Tables 4 and 5).

replicated *TCO2* coefficients reflect high variation over the seven-year period, ranging from -0.368 (2006) and -0.379 (2012) to -0.015 (2008) and -0.147 (2009).[25] This places a wide band of uncertainty around the average estimate of -0.204 (their estimate, -0.212) based on 2006–2008 data, thereby raising a concern about generalizability.[26]

[Insert Table 6 about here.]

Fourth, we confirm the finding in Matsumura et al. (2014, Table 5) that the average (and median) market value of CDP disclosers exceeds the average (and median) market value of CDP non-disclosers.[27] However, whereas Matsumura et al. (2014) state that this difference supports the view that non-CDP disclosure penalizes the average (median) non-CDP disclosing firm by $5.2 ($2.3) billion, our analysis supports an alternative explanation, premised on the following evidence. First, our Table 4, panel B, results show that the valuation penalty (*GHGPS*) does not differ significantly for CDP disclosers and CDP non-disclosers, consistent with investors using multiple channels of information to assess the firm valuation effects of GHGE. Second, we find that the putative non-CDP disclosure penalty does not decline over time when we replicate their Table 5, panel A, results for each of years 2006 to 2012. We would expect such penalty to decline because CDP participation rates and GHGE disclosure to the CDP increased in the later years (Table 1). The putative non-CDP disclosure penalty should also decline over time because a rational, value-maximizing manager would not intentionally inflict a significant non-disclosure cost on shareholders for an extended period (Kumar et al. 2012). One interpretation is that the propensity matching procedure used by Matsumura et al. (2014) may not have established a sample matched in all characteristics other than the firm's choice to disclose GHGE to the CDP, for

[25] The *TCO2* coefficients also reflect higher time-series variation over the 2006–2012 period than the *GHGPS* coefficients in Table 4, panel B.

[26] We also considered whether model or variable specification might explain the divergent results. First, to reduce variable skewness and heterogeneity, we reweighted the individual observations using a common share transformation. With this specification, the *TCO2* coefficient under a per common share approach dropped substantially in absolute magnitude, to -0.0178. Second, our replication suggests that the use of a Heckman model (Equation 2) may have made little difference to the overall results. For example, when we replicated their valuation model without a Heckman model (based on unscaled variables), the *TCO2* coefficient was -0.1863, compared with -0.204 with a Heckman model, Table 6, col. 1.

[27] We also show in Table 2 that this result holds for all years in the study period (2006–2012).

example, by not completely removing the effects of firm size.[28] A final consideration is that Matsumura et al. (2014) do not demonstrate that their estimated capital market penalty relates to GHGE, as they simply compare the market value of CDP disclosers with the market value of propensity matched CDP non-disclosers and ascribe the difference to an emission penalty. Conducting a test of whether a possible non-CDP disclosure penalty relates to GHGE would require an estimate of GHGE for the non-CDP disclosing firms, such as one generated by our GHGE estimation model. But the use of a GHGE estimation model is not part of their study.[29]

In sum, while we are able to confirm the results in Matsumura et al. (2014, Tables 4 and 5), we also show that the emission valuation penalty under their approach reflects higher cross-sectional and temporal variability and does not generalize to out-of-sample data, that is, future years for the same firms. This higher cross-sectional and temporal variability may help explain why the estimated emission valuation penalty in this study (and other similar studies) diverges from theirs.

Event study

Table 7 summarizes our tests for an increase in unsigned excess stock return around the 8-K emission filing date, where excess return equals daily stock return inclusive of dividends for day *t* in excess of the day *t* return on the *CRSP* value-weighted market index. We also test whether the filing date response associates with a proxy for firm-related

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[28] This view of the matching procedure is also suggested by the unusually large size of the penalty for non-disclosure in relation to firms' market capitalization: of 36 percent based on averages – \$5.16 billion (Matsumura et al. 2014, Table 5, panel C) in relation to non-disclosing firms' market capitalization of \$14.32 billion (Matsumura et al. 2014, Table 2, panel B) and 27 percent based on medians – \$2.27 billion in relation to \$8.29 billion. Another comment relates to the number of non-disclosers the procedure actually matches. For example, before matching, their sample has 550 disclosers and 815 non-disclosers (their Table 4). After matching, their sample has 538 disclosers and 696 non-disclosers, which is still 85 percent of their non-discloser sample (their Table 5).

[29] We also test for a possible *increase* in firm value when an S&P 500 firm in their sample switches from non-CDP disclosure status (year *t*-1) to CDP disclosure status (year *t*), purportedly to avoid the non-disclosure penalty. For the 118 S&P 500 firms in their sample that switched during the 2006–2008 period, however, the mean (median) market value decreases. This is inconsistent with an implication of their contention that non-disclosure of GHGE to the CDP imposes an additional valuation penalty.

emissions information and whether the response of firms that disclose emissions to the CDP (CDP disclosers) differs from the response of firms that do not (CDP non-disclosers).

[Insert Table 7 about here.]

Panel A of Table 7 shows evidence of an investor response on day 0. First, for all partitions of the sample, mean unsigned excess return on day 0 significantly exceeds mean unsigned excess return calculated over days -10 to 10 excluding day 0. Thus, we can reject the hypothesis that mean unsigned excess return on day 0 equals the mean for the other days versus the alternative hypothesis of a higher amount. Second, we observe a differential investor response around day 0 for high and low classifications within the various partitions. Mean unsigned excess return varies negatively with firm size, as S&P 500 firms (and larger market capitalization firms) have lower unsigned excess returns than non-S&P 500 firms (and smaller market capitalization firms). In addition, for the S&P 500 sample only (i.e., all potential CDP reporting firms), firms with higher (lower) GHGE intensity (estimated or actual *GHGE* per dollar of total revenues in thousands) exhibit lower (higher) unsigned excess returns around the 8-K filing date. Third, we observe higher unsigned excess returns for S&P 500 firms that do not disclose to the CDP relative to CDP disclosers. These results are prima facie evidence that investors respond at the 8-K filing date to emissions-related information disclosed through a channel other than the CDP, in this case, a regulatory 8-K filing. In addition, the response is more pronounced when the GHG emission disclosure is more news-worthy (i.e., for non-S&P 500 firms, low GHGE intensity firms, S&P 500 non-disclosers, and small market capitalization firms). The differential response between CDP disclosers and non-disclosers in panel A, however, derives from a univariate comparison and could, for example, relate to the fact that CDP non-disclosers are smaller and have lower GHGE intensity. We, therefore, conduct a multivariate test by regressing unsigned excess return over days -1 to 1 (and day 0) on variables that might condition that response.

Panel B of Table 7 summarizes the results of estimating the following cross-sectional regression model, without subscripts for firm and year (prior fiscal year):

$$XRET_t = \eta_0 + \eta_1 DSCL_t + \eta_2 SIZE_t + \eta_3 GHGI_{t-1} + \eta_4 EARN_t + \eta_5 PRES_t + \eta_6 SPEC_t + \varepsilon_t, \tag{3}$$

where $XRET_t$ = unsigned excess stock return on days t = -1 to 1 or day 0 relative to the 8-K filing date; $DSCL_t$ = 1 if GHGE disclosed to the CDP, otherwise 0; $SIZE_t$ = log of market value of common equity at end of fiscal year; $GHGI_{t-1}$ = 1 if GHGE intensity in prior year is greater than the sector median, otherwise 0, where GHGE intensity = *GHGE* per dollar of total revenues in thousands; $EARN_t$ = 1 if the 8-K reports earnings information, otherwise 0; $PRES_t$ = 1 if a press release accompanies the 8-K, otherwise 0; and $SPEC_t$ = 1 if the 8-K report contains relatively more emission-specific information, otherwise 0 (see footnote 16 for more details regarding the specification of *SPEC*).

The regressions in panels B(1) and B(2) of Table 7 introduce the explanatory variables successively. Focusing first on panel B(1), regression 1 shows that *XRET* relates negatively with *DSCL*. However, *SIZE* subsumes this relation, as the η_1 coefficient for *DSCL* becomes insignificant in regressions 2 to 4. Regressions 3 and 4 show the η_3 coefficient for *GHGI* as significant (p<.001); and regression 4 shows the coefficients for *SIZE* (p<.001), *GHGI* (p<.001), and *EARN* (p<.001) as significant but not the coefficients for *DSCL*, *PRES*, or *SPEC*. This suggests that disclosure of GHGE to the CDP and dummy variables for press release and the specificity of 8-K emission information add no additional explanatory power to the regression. In all the regressions, the intercept is significant (p<.001), but this reflects the higher filing day response around t=0 (panel A). The results in panel B(2), for returns on day 0, are substantially similar for all the regressions.

Overall, Table 7 shows that investors respond to 8-K filings and the response varies with an emissions attribute of the firm (*GHGI*) after controlling for firm size and whether the 8-K contains a press release or an earnings announcement. We reasoned earlier why we should see a significantly negative η_3 coefficient for *GHGI* around t=0, namely, because investors respond to information relative to expectations, which depend on the quality, mix, and totality of all news regarding emissions and related factors. Since investors naturally demand more (less) information about emission effects for GHGE intensive (non-GHGE intensive) firms, those expectations are better (less well) developed, regardless of the information channel – from the firm, CDP, or elsewhere. Relative to expectations, we expect news releases for non-GHGE intensive firms to elicit more response, as the news is more of a surprise. Our evidence of a negative GHGE intensity response coefficient is consistent with this explanation. Table 7 also shows that disclosure of GHGE to the CDP makes no difference to investors' response to an 8-K filing. This result is consistent with our earlier evidence suggesting that investors use multiple channels of information to assess the impact of GHGE on firm value.[30]

5. Additional analysis

Sample selection bias

Because firms disclose to the CDP survey, the GHGE amounts for CDP disclosers could also reflect other firm attributes that explain equity value, the omission of which could produce an unreliable estimate of the β_3 coefficient for *GHGPS* in model 2. GHGE estimates for non-disclosing firms could also be affected because model 1 estimates GHGE for non-disclosers based on disclosing firm data only. We address this issue further by applying the two-stage Heckman approach to our own model to derive an alternative estimator of the GHGE valuation coefficient.

The first stage estimates the likelihood of disclosure based on a selection model, and the second stage includes a transformation of that likelihood (the inverse Mills ratio or *IMR*) as an additional variable in the valuation regression, estimated for disclosers only (model 2). We test the null hypothesis that the *IMR* coefficient equals zero, in other words, that firms' decision to disclose to the CDP does not significantly affect the model 2 coefficients, versus the alternative that CDP disclosure makes a difference. We model the disclosure decision as a function of firm size (*logAT*), book-to-

[30] We also find that similar results hold when we conduct an event study on a smaller sample of 8-K filings, with more restrictions on whether the 8-K might contain information relevant to firms' GHG emissions (section 5).

market ratio (*BTM*), leverage (*LEVG*), the number of KLD environmental strengths less the number of concerns (*KLD*), and dummy variables (one for the condition, zero otherwise) for previous CDP disclosure (*DSCL_PREV*), other (non-mandated) channel of emission disclosure (*OTHER_CHANNEL*), and industry sector (*SECT*). We include *OTHER_CHANNEL* to indicate whether a non-CDP disclosing firm in our sample uses other channels for emission disclosure. This could attenuate the effects of selection bias, as a non-CDP discloser that discloses elsewhere could have the same characteristics as a CDP discloser. We define our proxy for another channel as a dummy variable equal to one if the firm was covered by the California Climate Action Registry, CSRwire, Verisk Maplecroft,[31] the EPA, or filed a carbon-related 8-K, otherwise zero.[32]

We posit the following expectations regarding the signs of the Heckman model coefficients: positive for *logAT* and *DSCL_PREV* (Stanny and Ely 2008); positive for *OTHER_CHANNEL* (Beyer, Cohen, Lys, and Walther 2010); positive or negative for *LEVG*, depending on the role of credit (Armstrong, Guay, and Weber 2010); positive or negative for *SECT*, depending on industry characteristics (Hou and Robinson 2006); and positive or negative for *BTM*, depending on how growth prospects might encourage or discourage disclosure.

Table 8 summarizes the results of applying the Heckman approach to the first two versions of model 2 (Table 4, panel B). First, the selection equation shows significantly positive coefficients for *logAT*, *KLD, DSCL_PREV*, and *OTHER_CHANNEL (*e.g., larger firms and previous disclosers are more likely to disclose); the sector variables (not reported) vary by sector; and negative coefficients for *BTM* and *LEVG*, suggesting that higher growth option and higher leverage firms are less inclined to disclose to the CDP. Second, the *IMR* coefficients in the second-stage price regressions applied to the discloser sample are insignificant, suggesting that self-selection is not a concern. Third, we

[31] Online at www.climateregistry.org, www.csrwire.com, www.maplecroft.com (all last retrieved on March 11, 2016).

[32] Our limited list of other channels adds noise to this variable, since with additional channels we would more likely find that an S&P 500 firm made a decision to disclose emission information other than through the CDP. Of our sample of 1,083 actual CDP emission amounts, in an untabulated analysis we identified 53.3% as relating to at least one other channel.

calculate a low variance inflation factor (VIF) when we regress *IMR* on the remaining explanatory variables in model 2, and so we meet a recommended criterion for appropriate use of the Heckman approach (Belsley 1991). Thus, after controlling for self-selection by CDP disclosers, we cannot reject the hypothesis that the *GHGPS* coefficients in Table 8 do not differ qualitatively from the *GHGPS* coefficients in panel B of Table 4. In both instances, we show uniformly negative *GHGPS* coefficients across the same models. Table 8 thus buttresses the results in panel B(3) of Table 4 that show qualitatively similar *GHGPS* coefficients for CDP disclosers and CDP non-disclosers.

[Insert Table 8 about here.]

Robustness tests

We subject our tests to alternative specifications, methods, definitions, and partitions of the data. First, we examine different versions of model 1, including a more complex model, with additional controls, including log of cash, standard deviation of IBES analysts' forecasts, number of IBES analysts' forecasts, log of foreign sales, number of segments, and a dummy variable for finance sector. While the complex model suggests some improvement from the additional regressors, we find no qualitative impact on the results in panel B of Table 4 when we use a more complex model. Second, we examine additional versions of model 2 with alternative calculations of residual income, namely, *RESI*=change in *epspx*, *RESI*=*epspx* – *r*.*CVCE*/*csho*, where *r*=12 percent, and *RESI*=*epspx* – (r_e x *CVCE*/*csho*), where r_e is calculated as β x (R_m - R_f) and where R_m=return on market portfolio for year *t* and R_f=risk-free rate for year t, and β=CRSP beta, or as r_e=cost of capital from a simple valuation model.[33] These alternative calculations do not appreciably change the results in panel B of Table 4. Third, we repeat the analysis in panels A and B of Table 7 for adjusted trading volume, defined as reported trading volume divided by common shares outstanding at day *t* (times 50 percent for a NASDAQ firm) (Anderson and Dyl 2005). The same variables that Table 7 shows as significant

[33] r_e=((*epspx* ÷ *p*) + *g*), where *p*=market price at fiscal year-end plus three months, *g*=five-year expected earnings growth from IBES, and *epspx*=earnings per share. Also, *csho*=common shares outstanding.

(insignificant) are significant (insignificant) for adjusted trading volume.

Fourth, we adopt a more restrictive definition of an 8-K emission filing by selecting only those within the sample of 1,966 filings that referenced the word “carbon” in relation to the terms “carbon emissions”, “carbon regulation”, or “carbon credits”, or in descriptions of how the firm reduced or planned to reduce its carbon footprint (718 filings for 343 CDP disclosers and 375 non-disclosers). We use this more restrictive definition as a robustness test because of the potential of the larger sample to reflect bias in favor of a response, in that all 8-K disclosures, including those misclassified in the larger sample, could potentially elicit an investor response. Untabulated results for this restrictive sample show that the intercept term in model 3 remains positive and significant ($p<.001$) for unsigned excess returns over day 0 and days -1 to 1. In addition, similar to panel B of Table 7, the response is significantly more positive for smaller firms (*SIZE)* ($p<.001$) and firms with earnings information (*EARN*) ($p<.05$) and does not differ for CDP disclosers versus non-disclosers (*DSCL*). However, the investor response on day 0 or days -1 to 1 does not vary significantly with an emission attribute of the firm (*GHGI*), although the signs of the *GHGI* coefficients are negative, consistent with those in panel B of Table 7.

Lastly, we re-estimate model 2 including a variable (*SCOPE*) to test whether the *GHGPS* valuation penalty might differ for firms with mostly direct (scope 1) emissions versus indirect (scope 2) emissions. To implement this test, we define *SCOPE* as equal to 1 if the ratio of actual or estimated direct emissions to actual or estimated total emissions is greater than 0.5, otherwise zero, and estimate model 2 such that $\Sigma\beta_k CNTL_k = \beta_4 SCOPE + \beta_5 SCOPE \text{ x } GHGPS$. Untabulated results show a negative but insignificant β_5 coefficient for the interaction of *SCOPE* and *GHGPS* for the full study period 2008–2012 (with regression standard errors clustered by firm and year) and for 2008 and 2009 estimated separately for each year (standard errors clustered by firm).[34] The β_5 coefficients are significantly negative,

[34] The CDP did not provide separate disclosure of direct and indirect GHGE in 2006 and 2007.

however, for each year from 2010 to 2012. Thus, while our overall results in panel B of Table 4 do not change qualitatively investors' GHGE penalty for direct versus indirect emissions, we find some evidence to suggest that such penalty potentially strengthens for the former, consistent with the notion that firms with direct emissions incur greater future regulatory and compliance costs and/or that indirect emissions contains additional measurement error.

6. Conclusions and implications

This paper increases our knowledge of the relation between the greenhouse gas emission disclosures and equity value in several ways. First, we document that GHG emissions reported to the Carbon Disclosure Project (CDP) associate negatively with equity values. Second, we estimate GHG emissions using an emissions estimation model based on industry and firms' operating characteristics for non-CDP disclosing firms and document the same finding; so that equity values vary equally negatively with actual and estimated GHG emissions. Third, for the median S&P 500 firm in our sample, we find a market-implied GHG emission penalty of $79 per ton of GHGE, which represents about one-half of 1 percent of median market capitalization. Because this amount diverges from the penalty of $212 per ton estimated by Matsumura et al. (2014) for the same population (the S&P 500), we forward-test their results using out-of-sample data. These tests rule out selection bias as a possible explanation for their divergent result. We also find no evidence of an equity valuation discount that Matsumura et al. (2014) suggest relates to firms' absence of reporting their emissions to the CDP. In addition, we find much higher cross-sectional and temporal variation in their emission estimates, which we contend relates to model and variable choice, such as their use of unscaled variables in the valuation equation and, possibly, their use of a relatively short sample period.

We also contribute to knowledge of the relation between greenhouse gas emission disclosures and equity value by documenting an increase in mean unsigned excess stock return around the day of an 8-K emission filing. This short-term market response is not subsumed by controls for other features of the filings. This result reinforces our finding of a negative relation between equity value and greenhouse gas emissions because it shows that a significant market response occurs when investors receive fresh emission-related information. This result also shows a significant stock market response to an emission information channel other than the CDP, in this case, an 8-K filing.

Our study raises interesting issues for future research. In addition to CDP emissions data and 8-K emission filings, investors have available numerous other channels of emission information, including mandated emission information under the U.S. EPA's 40 CFR Part 98 reporting program. Yet, much is unknown about how these alternative channels might influence investors' returns, especially, mandated disclosures whose incremental market effects could be limited given what we know about emission disclosures from the CDP and estimates from an emission estimation model. Future research could also analyze the components of the equity valuation discount for GHG emissions. Much is also unknown about managers' incentives to disclose emission information voluntarily or to pre-disclose emission amounts conditional on possible later requirements for mandatory disclosure.

Appendix

Variable definitions*

GHGE Estimation Model			Source
GHGE	=	GHG emissions per CDP reporting year in metric tons;	CDP
SECT	=	One of 10 industry sectors based on the Global Industry Classification Standard (GICS) taxonomy developed by Standard & Poor's and others for use by investors globally;	COMP
REVT	=	Total revenue (*revt*);	COMP
CAPX	=	Capital expenditures (*capx*);	COMP
PPEDP	=	Gross PP&E divided by depreciation (*ppegt/dp*);	COMP
INTAN	=	Total intangibles (*intan*);	COMP
GMAR	=	Gross margin calculated as sales minus cost of goods sold, scaled by sales ((*sale-cogs*)/*sale*);	COMP
LEVG	=	Long-term debt divided by total assets (*dltt/at*).	COMP
Valuation Model			
PRCC	=	Stock price at the end of the first quarter after fiscal year *t* (*prcc_f*);	CRSP
CVCE	=	Common equity divided by common shares outstanding (*ceq*/*csho*);	COMP
RESI	=	Residual earnings per share (*epspx* and alternative definitions);	COMP
GHGPS	=	*GHGE* divided by common shares outstanding (*csho*) in thousands;	CDP
CDLI	=	Actual or estimated CDP Disclosure Leadership Index (estimated as the median *CDLI* for the industry sector);	CDP
DSCL	=	Indicator variable equal to 1 if *GHGE* is disclosed to the CDP, 0 otherwise;	CDP
Event Study Model			
XRET	=	Unsigned excess stock return on days *t* = -1 to 1 or day 0 relative to the 8-K filing date (equals the difference between the day *t* raw return and the day *t* CRSP value-weighted market index);	CRSP
SIZE	=	Log of market capitalization of common equity (*MCAP*) (*prcc_f* x *csho*);	COMP
GHGI	=	Indicator variable equal to 1 if GHGE intensity in CDP year is greater than the sector median, 0 otherwise; where GHGE intensity = *GHGE* per dollar of total revenues (*revt*) in thousands;	CDP
EARN	=	Indicator variable equal to 1 if the 8-K reports earnings information in 8-K, 0 otherwise;	DE
PRES	=	Indicator variable equal to 1 if a press release accompanies the 8-K, 0 otherwise;	DE
SPEC	=	Indicator variable equal to 1 if 8-K contains emission-specific information, 0 otherwise. See, also, footnote 16.	DE
Heckman Model and Other			
logAT	=	Log of total assets (*at*);	COMP
BTM	=	Book value of common equity divided by market value of common equity (*ceq*/(*prcc_f* x *csho*));	COMP
KLD	=	Number of KLD environmental strengthens minus number of KLD environmental concerns;	KLD
DSCL_PREV	=	Indicator variable equal to 1 if *GHGE* disclosed to the CDP in a prior year, 0 otherwise;	CDP
OTHER_CHANNEL	=	Indicator variable equal to 1 if the firm was covered by California Climate Action Registry, CSRwire, Maplecroft, the EPA, or filed an emission related 8-K, 0 otherwise;	OTHER
SCOPE	=	Indicator variable equal to 1 if the ratio of actual or estimated direct *GHGE* to actual or estimated total *GHGE* is greater than 0.5, 0 otherwise.	CDP

*Compustat identifier codes in parentheses (in lower case italics); Data sources are: Carbon Disclosure Report (CDP), Compustat (COMP), the Center for Research in Security Prices (CRSP), KLD Research and Analytics, Inc (KLD), Direct Edger (DE), and hand collected data (OTHER).

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TABLE 1

Sample composition and response rates for GHG emission data for S&P 500 firms by year and sector

	CDP Discloser	CDP Non-discloser	Total	Response rate
Panel A: Sample composition and responses rates by year				
2006	140	339	479	29.23%
2007	198	296	494	40.08%
2008	222	271	493	45.03%
2009	264	234	498	53.01%
2010	276	223	499	55.31%
2011	288	211	499	57.72%
2012	289	209	498	58.03%
All observations	1,677	1,783	3,460	
Panel B: Sample composition and responses rates by sector				
Utilities	158	60	218	72.48%
Consumer Discretionary	183	372	555	32.97%
Consumer Staples	203	79	282	71.99%
Energy	106	162	268	39.55%
Financials	240	354	594	40.40%
Health Care	175	193	368	47.55%
Industrials	180	213	393	45.80%
Information Technology	267	249	516	51.74%
Materials	137	77	214	64.02%
Telecommunications	28	24	52	53.85%
All observations	1,677	1,783	3,460	

This table provides a summary of the GHG emission data for S&P 500 firms, extracted from the Carbon Disclosure Project (CDP), available online at www.cdp.net/reports (last retrieved March 11, 2016). The column CDP discloser indicates that a firm disclosed total, direct, or indirect GHGE in that reporting year. The column CDP non-discloser indicates no GHGE data were reported. The CDP makes public this information in survey results, usually published in September-October of the following year. Sector is based on the same 10 Global Industry Classification Standard (GICS) sector categories used in the CDP surveys. Membership of the S&P 500 may change each year.

TABLE 2

Descriptive statistics for variables in models by sector

Panel A: Model 1 and other variables		Utilities	Cons. Discr.	Cons. Stap.	Energy	Financials	Health Care	Industrials	Info. Tech.	Materials	Telecom.	All S&P 500
GHGE	Discloser	32,500,000	1,616,927	2,295,960	18,800,000	417,935	546,548	3,462,844	504,563	12,000,000	3,741,093	6,320,279
	Non-Discloser	21,200,000	542,143	1,773,328	6,597,191	463,769	245,559	677,850	133,536	2,903,482	1,767,260	1,960,292
	Signif.	***	***	ns	***	ns	***	***	***	***	**	***
logGHGE	Discloser	16.77	13.48	13.78	15.93	11.81	12.43	13.84	12.11	15.22	14.66	13.61
	Non-Discloser	16.51	12.60	13.89	14.67	11.11	11.71	12.60	11.16	14.59	13.33	12.58
	Signif.	ns	***	ns	***	***	***	***	***	***	***	***
logCAPX	Discloser	21.27	19.94	20.01	22.23	12.08	19.70	20.18	19.59	20.12	22.32	19.10
	Non-Discloser	20.96	19.10	19.99	20.93	17.08	18.78	19.31	18.47	19.26	20.44	19.03
	Signif.	***	***	ns	***	***	***	***	***	***	***	ns
logREVT	Discloser	22.96	23.50	23.45	23.80	23.25	23.32	23.48	22.77	23.04	24.32	23.26
	Non-Discloser	22.77	22.74	23.61	22.64	22.31	22.58	22.86	21.82	22.28	22.40	22.55
	Signif.	**	***	ns	***	***	***	***	***	***	**	***
logAT	Discloser	23.98	23.36	23.41	24.41	25.25	23.67	23.63	23.15	23.24	25.07	23.80
	Non-Discloser	23.74	22.71	23.10	23.16	24.45	22.73	22.93	22.28	22.43	23.34	23.01
	Signif.	**	***	**	***	***	***	***	***	***	***	***
logINTAN	Discloser	17.71	19.54	22.12	17.06	19.64	22.27	20.25	20.77	20.96	21.61	20.25
	Non-Discloser	14.53	19.26	19.98	12.32	20.20	21.25	19.89	20.01	19.73	21.00	19.05
	Signif.	***	ns	***	***	ns	***	ns	**	***	ns	***
GMAR	Discloser	0.27	0.33	0.45	0.41	0.38	0.60	0.32	0.57	0.34	0.59	0.42
	Non-Discloser	0.25	0.41	0.33	0.37	0.39	0.49	0.34	0.56	0.30	0.56	0.41
	Signif.	*	***	***	ns	ns	***	ns	ns	*	ns	ns
LEVG	Discloser	0.30	0.22	0.28	0.19	0.17	0.19	0.21	0.10	0.22	0.34	0.20
	Non-Discloser	0.32	0.23	0.26	0.22	0.12	0.19	0.20	0.14	0.24	0.54	0.20
	Signif.	ns	ns	ns	**	***	ns	ns	***	ns	***	ns
logPPEDP	Discloser	3.38	2.57	2.74	2.81	2.00	2.03	2.69	1.95	2.88	2.45	2.50
	Non-Discloser	3.38	2.37	2.75	2.93	1.97	2.04	2.45	1.96	2.98	2.62	2.36
	Signif.	ns	ns	ns	**	ns	ns	***	ns	**	ns	***
logMCAP	Discloser	23.08	23.22	23.68	24.29	23.67	23.89	23.52	23.46	23.14	24.36	23.55
	Non-Discloser	22.85	22.80	23.23	22.98	23.07	22.99	23.05	22.80	22.42	22.75	22.91
	Signif.	**	***	***	***	***	***	***	***	***	***	***
No. obs.	Discloser	155	177	198	106	235	175	180	267	136	28	1,657
	Non-Discloser	57	359	77	159	226	186	212	245	74	24	1,619
	All	212	536	275	265	461	361	392	512	210	52	3,276

Table 2, contd.

Panel B: Model 2 and other variables		Utilities	Cons. Discr.	Cons. Stap.	Energy	Financials	Health Care	Industrials	Info. Tech.	Materials	Telecom.	All S&P 500
PRCC	Discloser	39.48	41.09	48.30	61.25	42.46	51.14	58.62	40.66	51.12	25.80	46.74
	Non-Discloser	36.84	59.67	38.98	48.27	50.71	58.81	57.97	49.57	56.13	17.62	52.88
	Signif.	ns	***	***	***	*	ns	ns	ns	ns	*	***
CVCE	Discloser	25.81	16.01	11.87	31.99	29.63	18.26	19.54	10.80	18.09	12.56	19.28
	Non-Discloser	21.63	14.88	12.91	22.08	28.54	18.09	20.83	12.68	20.51	5.36	18.57
	Signif.	*	ns	ns	***	ns	ns	ns	*	*	***	ns
RESI	Discloser	2.61	2.06	2.56	4.28	2.51	2.88	3.60	1.59	2.58	0.70	2.57
	Non-Discloser	2.28	2.30	2.03	2.64	2.66	2.66	3.49	1.84	3.31	1.07	2.53
	Signif.	ns	ns	**	***	ns	ns	ns	ns	ns	ns	ns
GHGPS	Discloser	118.73	4.31	3.48	19.22	0.85	0.70	7.41	0.62	41.95	1.56	17.78
	Non-Discloser	71.31	2.39	4.18	22.07	0.51	0.96	2.27	0.46	23.76	3.44	7.09
	Signif.	***	***	ns	ns	ns	**	***	**	*	ns	***
GHGI	Discloser	3.40	0.09	0.08	0.69	0.03	0.03	0.18	0.04	0.76	0.08	0.48
	Non-Discloser	2.36	0.05	0.07	0.53	0.04	0.03	0.05	0.04	0.50	0.21	0.20
	Signif.	***	ns	**	*	ns	***	***	ns	***	**	***
No. obs.	Discloser	155	177	198	106	235	175	180	267	136	28	1,657
	Non-Discloser	57	359	77	159	226	186	212	245	74	24	1,619
	All	212	536	275	265	461	361	392	512	210	52	3,276

This table reports the mean values of the key variables used in models 1 and 2 and whether the mean values differ between CDP disclosers and CDP non-disclosers by sector. Sector is based on the same 10 Global Industry Classification Standard (GICS) sector categories used in the CDP surveys. Disclosers are firms that reported GHGE data to CDP. *, **, ***, indicate significance at the 0.10, 0.05, and 0.01 levels, respectively using two-tailed tests. ns indicates not significant. The appendix defines the variables.

TABLE 3

Tests of the GHG emission estimation model

Panel A: Explanatory power of model 1

Model 1 Adjusted R^2	2006	2007	2008	2009	2010	2011	2012
logGHGE (total)	81.20%	80.44%	72.72%	71.04%	73.43%	74.58%	75.03%
No. obs. (total)	135	323	537	793	1,059	1,335	1,612
logGHGE (direct)	na	na	60.50%	63.85%	67.68%	69.95%	70.83%
logGHGE (indirect)	na	na	38.40%	37.42%	35.57%	33.54%	33.10%
No. obs. (direct)	135	323	214	470	736	1,012	1,289

Panel B: Predictive ability of model 1

Expected decile based on actual *logGHGE*	Percentage in same or adjacent deciles based on estimated *logGHGE*
Lowest=1	92.55%
2	81.44%
3	77.07%
4	77.36%
5	79.33%
6	86.60%
7	75.35%
8	69.34%
9	82.78%
Highest=10	91.16%

Panel C: Test of bias of model 1

Significance of actual less estimated *logGHGE* for CDP disclosers

	Actual *logGHGE*			Estimated *logGHGE*			Diff.	*p*-value
	mean	std. dev.	no. obs.	mean	std. dev.	no. obs.	Act.-Est.	
2006	14.070	2.26	135	14.121	2.02	135	-0.051	0.8446
2007	13.955	2.20	188	14.064	1.94	188	-0.109	0.6143
2008	13.754	2.23	214	13.672	1.80	214	0.082	0.6765
2009	13.587	2.25	256	13.485	1.84	256	0.102	0.5732
2010	13.471	2.25	266	13.388	1.90	266	0.083	0.6458
2011	13.428	2.14	276	13.425	1.87	276	0.003	0.9863
2012	13.404	2.09	277	13.394	1.83	277	0.010	0.9524
All	13.613	2.20	1,612	13.587	1.89	1,612	0.026	0.7116

This table provides three tests of the reasonableness of the GHG emission estimation model. Panel A shows the adjusted R^2 from the total GHGE estimation and separate direct and indirect GHGE estimations, respectively. Separate GHGE disclosure is not available (na) in 2006 and 2007. Panel B shows the percentage of the estimated *logGHGE* that remain in the same or adjacent deciles of actual *logGHGE* using the discloser sample. Panel C compares the estimated *logGHGE* with actual *logGHGE* by year using the CDP discloser sample.

TABLE 4
Regression analysis

Panel A: Product moment correlations among the regression variables in Panel B

	PRCC	*CVCE*	*RESI*	*GHGPS*	*CDLI*	*DSCL*
PRCC	1.0000					
CVCE	**0.4978**	1.0000				
RESI	**0.6172**	**0.5179**	1.0000			
GHGPS	-0.0044	**0.1652**	**0.0547**	1.0000		
CDLI	**0.0715**	**0.0990**	**0.0762**	**0.0347**	1.0000	
DSCL	**-0.0566**	0.0240	0.0081	**0.1386**	**0.3757**	1.0000

Panel B: Regression of stock price on common equity per share, residual earnings per share, and GHG emissions per share

	2006-2012 ex 2008		2006		2007		2008		2009		2010		2011		2012	
	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
1: Main regression																
Intercept	9.835	**	18.08	***	10.37	ns	9.71	**	7.89	ns	10.25	*	6.82	ns	5.32	ns
CVCE	0.779	***	0.569	***	0.951	***	1.045	***	1.279	***	0.427	**	0.464	*	0.765	***
RESI	10.803	***	8.548	***	7.936	***	3.042	***	7.427	***	12.839	***	13.779	***	14.080	***
GHGPS	-0.083	***	-0.064	*	-0.058	*	-0.105	***	-0.100	*	-0.046	ns	-0.083	*	-0.075	ns
No. obs.	2,813		441		458		463		471		480		483		480	
Adj R^2	0.452		0.447		0.439		0.389		0.472		0.490		0.463		0.467	
2. Add control for *CDLI*																
Intercept	8.416	ns	18.50	***	18.43	***	9.11	**	16.11	***	12.37	ns	-5.49	ns	4.90	ns
CVCE	0.776	***	0.569	***	0.960	***	1.045	***	1.273	***	0.431	**	0.457	*	0.765	***
RESI	10.802	***	8.552	***	7.948	***	3.035	***	7.496	***	12.830	***	13.775	***	14.079	***
GHGPS	-0.083	***	-0.062	**	-0.061	*	-0.106	***	-0.096	*	-0.046	ns	-0.085	*	-0.075	ns
CDLI	0.025	ns	-0.013	ns	-0.155	**	0.011	ns	-0.142	*	-0.034	ns	0.174	*	0.006	ns
No. obs.	2,813		441		458		463		471		480		483		480	
Adj R^2	0.452		0.447		0.443		0.389		0.475		0.491		0.466		0.467	
3. Add interactions for *DSCL*																
Intercept	8.895	*	18.60	***	18.87	***	8.88	**	15.16	***	12.82	ns	-2.69	ns	6.12	ns
CVCE	0.934	***	0.560	***	0.942	***	1.045	***	1.283	***	0.424	**	0.458	*	0.757	***
RESI	8.942	***	8.595	***	8.057	***	3.027	***	7.468	***	12.833	***	13.632	***	14.078	***
GHGPS	-0.148	***	-0.120	ns	-0.168	**	-0.153	***	-0.074	ns	-0.097	ns	-0.084	ns	-0.264	**
DSCL	-8.442	***	-1.025	ns	-3.822	ns	-2.428	ns	-8.530	**	-11.857	***	-13.797	***	-9.696	*
DSCL x *GHGPS*	0.067	ns	0.069	ns	0.128	ns	0.057	ns	-0.004	ns	0.076	ns	0.011	ns	0.237	*
CDLI	0.100	*	0.001	ns	-0.127	ns	0.038	ns	-0.051	ns	0.067	ns	0.253	**	0.070	ns
No. obs.	2,813		441		458		463		471		480		483		480	
Adj R^2	0.434		0.448		0.443		0.391		0.482		0.500		0.475		0.471	

This table presents the analysis of the relation between stock price and GHG emissions per share. Panel A reports the Pearson correlation coefficients among the variables in Panel B. Significant coefficients in Panel A at $p<.05$ are shown in bold. Panel B reports the results from the regression of stock price on common equity per share, residual earnings per share, and GHG emissions per share by year. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. *t*-statistics (not tabulated) and *p*-values are calculated using clustered standard errors by firm and year. The appendix defines the variables.

TABLE 5

Economic significance of the GHGE regression coefficients in Table 4

	Calculation	2006-12 ex 2008	2006	2007	2008	2009	2010	2011	2012
GHGE/(csho*1000) regression coefficient	1	-0.083	-0.064	-0.058	-0.105	-0.100	-0.046	-0.083	-0.075
GHGE/(csho*1000), median	2	1.278	1.399	1.485	1.102	1.121	1.178	1.337	1.217
GHGE valuation effect, per share	3 = 1 x 2	$0.106	$0.089	$0.087	$0.116	$0.112	$0.055	$0.111	$0.091
Shares outstanding, millions, median	4	301.38	310.29	308.19	301.62	296.60	302.92	297.14	295.62
GHGE valuation effect on market cap., millions	5 = 3 x 4	$32.07	$27.62	$26.77	$34.97	$33.28	$16.57	$33.09	$26.93
Market cap., millions, median	6	$11,682	$13,506	$13,646	$7,215	$8,937	$11,243	$11,149	$12,502
Impact on market cap., percent	7 = 5 / 6	0.275%	0.204%	0.196%	0.485%	0.372%	0.147%	0.297%	0.215%
GHGE in tons, median	8	407,110	461,000	462,239	350,024	366,513	384,015	384,197	393,264
Market-implied penalty per ton, median	9 = 5 / 8	$78.8	$59.9	$57.9	$99.9	$90.8	$43.2	$86.1	$68.5
Market-implied penalty per ton, first quartile		$43.6	$32.9	$25.2	$58.1	$57.9	$23.9	$44.6	$42.7
Market-implied penalty per ton, third quartile		$126.0	$104.7	$88.0	$138.9	$147.8	$72.7	$112.7	$110.6
Impact on market cap., percent, first quartile		0.018%	0.013%	0.011%	0.033%	0.027%	0.010%	0.019%	0.016%
Impact on market cap., percent, third quartile		0.990%	0.866%	0.631%	1.334%	1.279%	0.577%	0.980%	0.797%

This table presents the estimates of the market-implied penalty per ton of GHGE using the regression coefficients for *GHGPS* in panel B of Table 4. We use these coefficients to calculate the market-implied penalty for the median firm in the sample based on median shares outstanding, market capitalization, and GHGE tons emitted per year. We also calculate the market-implied penalty for the firm at the first quartile and the third quartiles on the distribution of these variables.

TABLE 6

Replication of Matsumura et al. (2014)

Regression	All (2006-2008)		All (2006-2007)		2006		2007		2008		2009		2010		2011		2012	
Variables	Coef.	Z-stat.	Coef.	Z-stat.	Coef.	Z-stat.	Coef.	Z-stat.	Coef.	Z-stat.	Coef.	Z-stat.	Coef.	Z-stat.	Coef.	Z-stat.	Coef.	Z-stat.
TCO2	-0.204	-4.59	-0.348	-6.11	-0.368	-4.35	-0.313	-4.21	-0.015	-0.27	-0.147	-2.03	-0.224	-4.51	-0.266	-4.35	-0.379	-5.44
ASSET	1.218	16.15	1.415	13.29	1.702	9.16	1.252	9.68	0.722	6.27	0.355	4.63	0.271	2.58	0.447	3.80	0.547	4.78
LIAB	-1.292	-16.87	-1.501	-14.35	-1.764	-9.80	-1.345	-10.50	-0.756	-6.22	-0.393	-5.24	-0.391	-3.65	-0.594	-4.86	-0.665	-5.55
OPINC	3.036	13.4	2.904	8.25	1.885	3.12	3.413	7.69	3.527	9.74	6.872	20.70	7.641	19.17	6.342	15.48	6.202	15.14
Disclosure-Choice Model (*DISC_CDP*)																		
CNCRN	-0.117	-2.46	-0.075	-1.33	-0.070	-0.90	-0.120	-1.40	-0.266	-3.01	0.030	0.36	-0.162	-1.76	0.038	0.33	0.108	0.66
STRNG	0.380	6.04	0.364	5.04	0.369	3.72	0.237	2.06	0.339	2.56	0.052	0.46	0.367	4.38	0.064	0.71	0.114	0.95
PROPDISCL	0.028	10.82	0.029	8.88	0.034	6.01	0.032	6.90	0.027	5.75	0.021	5.05	0.018	3.37	0.024	3.68	0.022	3.31
SIZE	0.354	9.36	0.420	9.29	0.540	8.26	0.296	4.56	0.246	3.38	0.265	3.45	0.116	1.37	0.152	1.54	-0.020	-0.21
MF	0.013	1.39	0.018	1.68	0.022	1.55	-0.004	-0.21	0.004	0.21	0.024	1.26	0.006	0.32	0.001	0.05	-0.020	-0.06
BM	-0.668	-5.86	-0.931	-4.05	-1.468	-3.51	-0.636	-2.27	-0.535	-3.74	-0.252	-0.95	0.081	0.25	-0.068	-0.26	-0.072	-0.24
LEV	-0.512	-2.82	-0.422	-1.96	-0.767	-2.50	-0.207	-0.67	-0.824	-2.53	-0.722	-2.15	-0.783	-2.05	-0.159	-0.43	0.122	0.32
II	-0.301	-2.55	-0.264	-1.94	-0.112	-0.58	-0.421	-2.14	-0.242	-1.08	-0.019	-0.08	-0.379	-1.49	-0.165	-0.59	0.309	1.13
FRNSALE	0.289	1.66	0.369	1.93	0.699	2.43	-0.025	-0.08	0.114	0.37	0.371	1.18	0.068	0.20	0.729	2.17	0.195	0.61
DISC_CDP	1.562	12.11	1.237	6.89	0.000	0.00	1.722	8.29	2.058	9.60	1.998	10.21	1.990	11.44	2.589	12.08	2.697	13.42
EPA	0.111	1.05	0.087	0.71	0.077	0.43	-0.152	-0.81	0.057	0.29	-0.160	-0.86	-0.237	-1.21	-0.429	-1.95	-0.223	-1.03
Likelihood Ratio	21.1***		35.14***		21.25***		17.68***		9.59***		15.68***		0.370		0.920		0.030	
No. obs.	1,457		966		477		489		490		492		495		496		495	
Uncensored	560		337		140		197		222		263		275		286		286	

This table presents the results of replicating Matsumura et al. (2014, Table 4). *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. The variables in this table are defined in Matsumura et al. (2014, 724).

TABLE 7

Event study of investor response to emission-related information around 8-K filing date

Panel A: Investor response around event days -10 to 10: Unsigned excess returns (*XRET*)

Partition/ Event day	S&P 500	Non-S&P 500	High GHGE Intensity	Low GHGE Intensity	S&P 500 GHG Discloser	S&P 500 Non GHG Discloser	Small Market Cap.	Large Market Cap.
-10	0.0163	0.0215	0.0148	0.0178	0.0121	0.0197	0.0260	0.0139
-9	0.0164	0.0200	0.0153	0.0176	0.0124	0.0173	0.0238	0.0140
-8	0.0172	0.0220	0.0142	0.0202	0.0120	0.0188	0.0268	0.0143
-7	0.0179	0.0220	0.0149	0.0208	0.0129	0.0189	0.0267	0.0149
-6	0.0179	0.0241	0.0163	0.0194	0.0129	0.0175	0.0298	0.0145
-5	0.0160	0.0220	0.0146	0.0175	0.0126	0.0161	0.0262	0.0139
-4	0.0182	0.0225	0.0152	0.0212	0.0135	0.0197	0.0278	0.0147
-3	0.0168	0.0221	0.0146	0.0190	0.0131	0.0181	0.0260	0.0147
-2	0.0174	0.0245	0.0149	0.0198	0.0127	0.0184	0.0285	0.0157
-1	0.0192	0.0267	0.0154	0.0229	0.0130	0.0203	0.0323	0.0163
0	0.0277	0.0371	0.0219	0.0334	0.0200	0.0312	0.0452	0.0232
1	0.0211	0.0288	0.0182	0.0241	0.0150	0.0211	0.0356	0.0172
2	0.0179	0.0249	0.0150	0.0207	0.0130	0.0190	0.0301	0.0152
3	0.0161	0.0240	0.0141	0.0182	0.0120	0.0171	0.0277	0.0148
4	0.0171	0.0222	0.0150	0.0192	0.0125	0.0186	0.0268	0.0144
5	0.0157	0.0224	0.0150	0.0165	0.0120	0.0179	0.0261	0.0142
6	0.0160	0.0208	0.0140	0.0180	0.0115	0.0171	0.0252	0.0135
7	0.0166	0.0220	0.0140	0.0191	0.0120	0.0176	0.0264	0.0141
8	0.0161	0.0210	0.0135	0.0187	0.0121	0.0172	0.0247	0.0142
9	0.0163	0.0220	0.0140	0.0185	0.0125	0.0167	0.0264	0.0140
10	0.0170	0.0209	0.0144	0.0195	0.0122	0.0178	0.0254	0.0141
No. of filings	830	1,136	415	415	526	304	892	1,074
Sig. *t* statistic ($XRET_0$ differs from the other days)	***	***	***	***	***	***	***	***

Panel B: Regression tests of investor response to emission-related information around 8-K filing date

(1) Unsigned excess returns (*XRET*), days -1 to 1.

Regression no.	1			2			3			4		
Variable	Coeff.	t-stat	Sig.	Coeff.	t-stat	Sig.	Coeff.	t-stat	Sig.	Coeff.	t-stat	Sig.
Intercept	3.2745	11.84	***	11.5017	8.92	***	10.2317	13.36	***	9.9205	18.41	***
DSCL	-1.4779	-7.71	***	0.2418	0.94	ns	0.0942	0.57	ns	0.0907	0.67	ns
SIZE				-0.6062	-7.3	***	-0.4993	-9.23	***	-0.4950	-11.78	***
GHGI							-0.4597	-3.17	***	-0.4187	-2.67	***
EARN										0.6083	3.23	***
PRES										0.0047	0.02	ns
SPEC										0.1348	0.73	ns
Adj. R^2	3.26%			8.67%			8.32%			9.07%		
No. obs.	5,922			5,922			2,495			2,495		

(2) Unsigned excess returns (*XRET*), day 0.

Variable	Coeff.	t-stat	Sig.	Coeff.	t-stat	Sig.	Coeff.	t-stat	Sig.	Coeff.	t-stat	Sig.
Intercept	3.9129	11.07	***	13.2342	9.83	***	12.5912	4.61	***	11.8446	6.09	***
DSCL	-1.6482	-6.17	***	0.2967	0.95	ns	0.3682	0.67	ns	0.3318	0.71	ns
SIZE				-0.6866	-7.99	***	-0.6195	-3.24	***	-0.5996	-3.81	***
GHGI							-0.8001	-3.12	***	-0.7172	-2.88	***
EARN										0.9847	2.96	***
PRES										0.2023	0.3	ns
SPEC										-0.0060	-0.02	ns
Adj. R^2	2.96%			7.94%			8.66%			10.14%		
No. obs.	1,964			1,964			829			829		

This table presents the analysis of investor response to emission-related information around 8-K filing date. Panel A reports the unsigned excess return over days -10 to 10 days by various sample partitions. The *t* test for significance shows whether the mean unsigned excess return on day 0 $XRET_0$ differs significantly from the mean unsigned return over days -10 to 10 excluding day 0 ($XRET_{-10\ to\ 10}$). Panel B reports the regression results of investor response to emission-related information around 8-K filings date. Coefficients are times 100. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. ns indicates not significant. The *t*-statistics are calculated using standard errors clustered by firm and year. The appendix defines the variables.

TABLE 8

Regression of stock price on common equity, residual earnings, and GHG emissions per share with selection equation

Dependent variable=*PRCC*	Table 4 Panel B(1) valuation model		Table 4 Panel B(2) valuation model	
Second-stage valuation model	Coef.	Sig.	Coef	Sig.
Intercept	16.193	***	7.786	**
CVCE	0.605	***	0.594	***
RESI	7.177	***	7.152	***
GHGPS	-0.057	***	-0.052	***
CDLI			0.115	***
Inverse Mills ratio (*IMR*)	2.351	ns	3.823	ns
No. obs. in the valuation regression	1,657		1,657	
First-stage selection model	Coef.	Sig.	Coef	Sig.
Intercept	-8.748	***	-8.748	***
logAT	0.376	***	0.376	***
BTM	-0.223	***	-0.223	***
LEVG	-0.313	*	-0.313	*
KLD	0.295	***	0.295	***
DSCL_PREV	0.654	***	0.654	***
OTHER_CHANNEL	0.753	***	0.753	***
SECT	Yes		Yes	
No. of CDP disclosers in the selection equation	1,657		1,657	
Wald Chi Square	1,001.22		1,011.85	
Average VIF of regressing *IMR* on independent variables in the second-stage valuation model	1.27		1.20	

This table presents the analysis of the relation between stock price and GHG emissions per share using the Heckman selection model. The number of observations in the second-stage valuation model represents the number of S&P 500 with CDP emission disclosure over 2006–2012. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests, ns indicates not significant. *t*-statistics (not tabulated) and *p*-values are calculated using clustered standard errors by firm and year. VIF = variance inflation factor. The appendix defines the variables.