Carbon Interactivity on Twitter/X and firm value: Does it matter?

Abstract

Social media is a useful channel of corporate communication with the potential to reduce information asymmetry and increase firm value. This study applies agenda-setting theory to examine whether capital markets price two-way communication on climate change matters, with an emphasis on carbon, over Twitter in their firm valuations. We introduce a unique measure of carbon interactivity (CITX), which captures the total volume of climate-related discourse involving a firm, disseminated by both the firm and the public about the firm, including tweets, retweets, likes and replies. Using a sample of 9,865 firm year observations from non-financial firms in the S&P 1500 composite index over the period 2011 and 2020, we find a significant positive association between CITX and firm market value. For every standard deviation increase in CITX, the firm market value increases by 7.18%. Additionally, our findings reveal that CITX significantly mitigate the market penalty typically applied to high emitting firms, suggesting that the interactive discourse on carbon issues influences investor perceptions and valuation. The findings are robust to alternative measures of market value and CITX. Further we observe differential effects depending on the source of the carbon-related tweet. While firm-initiated discourse affects firm value, the impact is significantly stronger whether the tweets originate from external market participants (i.e. stakeholders). This signifies the market's preference for third-party discourse as potentially a more credible signal of carbon engagement.

1. INTRODUCTION

Climate change has been described "the defining crisis of our time," and it has been met with serious concern from various stakeholder groups, including consumers and workers (United Nations, 2022). Recognising the urgency of climate action, the Intergovernmental Panel on Climate Change (IPCC) emphasised the need for "*deep, rapid and sustained mitigation and accelerated implementation of adaptation activities*" (IPCC, 2023: 7), whilst the sustainable development goal, SDG 13 calls for urgent action *"to combat climate change and its impacts*" (United Nations, n.d.). Investors also are paying more attention to climate risk, with US$30.3 trillion reported to have been invested in sustainable investing assets at the end of 2022 (Global Sustainable Investment Alliance, 2022) and individual investors increasingly seeking to increase their allocations to sustainable investments (Morgan Stanley, 2024). In response, firms are adopting an array of responses, including communication strategies particularly in the context of their transition toward a lower carbon future. Social media, particularly Twitter (now X) is widely used as a communication platform for firms seeking to engage with stakeholders on climate issues. Unlike traditional disclosure channels, Twitter is characterised by two-way interactivity involving both from and about firms.[1] As such, Twitter can be used by firms to engage in conversation with other twitter users, allowing them to both disseminate information regarding their climate responses and to maintain shareholder value during periods of disruption or heavy investor concerns. Such discourse introduces new dynamics in how climate related information is received and valued by investors.

This study examines the extent to which carbon interactivity – that is, interactivity on climate change through carbon communications on Twitter – affects firm value and moreover

[1] On the 23 July 2023 the social media platform, formerly known as Twitter, was rebranded as 'X'. This entailed a change in the logo from a blue bird to a white X on a black background, change in domain name and change in the app icon in App stores. We continue to refer to this platform as Twitter because the data was collected under the old name and logo. However, we acknowledge the new brand name in our variable CITX.

whether it is considered by investors when assessing a firm's carbon liability.[2] We specifically address the following two related research questions within the US context: 1) Do investors consider the carbon interactivity of firms via Twitter in their valuation decisions? And (2) Does carbon interactivity of firms via Twitter mitigate the valuation penalties documented on carbon emission?

Extant literature suggests that corporate use of Twitter enhances accountability and transparency, which in turn leads to better corporate social responsibility (CSR) outcomes, consistent with agenda setting theory (Balasubramanian, Fang, & Yang, 2021). Agenda setting theory posits that public consensus and prominence of key issues is established through mass media (Lippmann, 1922; McCombs, 2005), with studies pointing to social media as being highly influential in shaping public discourse (Meraz, 2011; Valenzuela, Puente, & Flores, 2017). Consequently, firms must be extremely cognisant of and responsive to social media influences in formulating their corporate policies and strategies (Balasubramanian et al., 2021; Guo & Vargo, 2015; Neuman et al., 2014). In fact, De Luca et al. (2022) find that climate action is one of six SDGs that result in greater stakeholder engagement on Twitter noting that "*This evidence suggests that stakeholders are more concerned about these issues, and firms need to pay more attention to such concerns for sustainable development and meet stakeholders' expectations*" (De Luca et al., 2022, p. 13). Further, the literature has presented evidence that firms that utilise Twitter to disseminate financial information are able to reduce information asymmetry (Blankespoor, Miller, & White, 2014; Prokofieva, 2015), lower cost of equity (Albarrak, Elnahass, & Salama, 2019) be used to predict stock returns (Bartov, Faurel, & Mohanram, 2018; Deng et al., 2018; Sul, Dennis, & Yuan, 2017) and can influence investor

[2] Whilst we include broader terms such as climate change and global warming in our search terms, our primary focus in this paper is on energy use, rather than all aspects of climate change such as physical effects of climate change. Thus, we adopt the term 'carbon interactivity' to capture the twitter activity around such climate-carbon matters.

perceptions (Cade, 2018). These studies focus on firm-generated tweets. However, Twitter is an interactive platform where firms cannot control externally generated tweets about the firm, and yet these tweets become part of the broader social media conversation.

Additionally, existing research documents a valuation penalty on high carbon emitters reflecting market concerns over the perceived presence of off-balance sheet liabilities and long-term carbon risk exposure (Bose, Saha, & Abeysekera, 2020; Choi & Luo, 2021; Clarkson et al., 2015; Jung, Herbohn, & Clarkson, 2018; Lemma et al., 2019; Matsumura, Prakash, & Vera-Munoz, 2014). What remains unclear is the role that carbon interactivity via Twitter plays in such valuation decisions. In the US setting, firms are permitted to release financial information via social media and such information flows can reduce information asymmetry (Blankespoor et al., 2014; Prokofieva, 2015) and lower cost of equity (Albarrak et al., 2019). Thus, it is plausible that the dissemination of carbon related information through Twitter serves as an alternative information channel, thereby reducing information asymmetry and influencing investors' assessment of climate risk, which could explain cross-sectional differences in the valuation penalties imposed on high carbon emitters. Additionally, it remains unclear whether investor valuations respond more strongly to firm-initiated carbon disclosures or to public-driven carbon discourse. This distinction is critical, as agenda-setting theory suggests that public-driven narratives may hold greater credibility and influence compared to firm-controlled messaging (McCombs and Shaw, 1972). Nevertheless, the relationship between carbon related information disseminated via an interactive social media platform and firm market value remains largely unexplored to date.

Our study adds to the extant literature by investigating the effects of carbon interactivity via Twitter on firm value after correcting for self-selection bias and endogeneity issues. We measure this communication, CITX, as the total volume of carbon-related issues on Twitter involving a firm, encompassing both tweets disseminated *to the public from a firm* and disseminated *by the public about the firm* (including tweets, retweets, likes and replies). We use Twitter's Application Programming Interface (API) to perform a search of tweets relevant to climate change, including keywords,[3] for all non-financial S&P1500 firms for the period 2011-2020. Using a final sample of 9,865 firm-year observations we find that carbon interactivity is significantly and positively associated with firm market value and that for every standard deviation increase of CITX, the sample firm's average market capitalisation increases by 7.18%. Further, we document that CITX has a moderating effect on the market penalty imposed on high emitting firms. Broadly our findings hold when using alternative measures of market value and CITX.

Our additional analyses show that the valuation impact of carbon interactivity on Twitter is significant for firms with high analyst following and for S&P 500 firms, suggesting firms having larger market visibility and stronger information intermediation, amplify the relevance of social media-based climate discourse. These results are consistent with social media increasing the information environment and thus reducing information asymmetry for capital market participants.

This study makes three key contributions to the literature. First, we extend the literature on value relevance of disclosures of non-financial information (Amir & Lev, 1996; Clarkson et al., 2008; Dye, 1985; Healy & Palepu, 2001; Luo & Tang, 2014; Verrecchia, 1983) by incorporating both firm-generated and public-generated tweets. Our carbon interactivity measure captures the overall effect of the social media 'carbon conversation' on firm value. The positive association between carbon interactivity and firm market value indicates that two-way communication is value enhancing.

[3] See footnote 8 for a full list of search terms.

Second, we provide novel insights into agenda setting theory by disaggregating the firm-generated and public-generated tweets, to draw comparisons between the market responses to each side of the conversation. Here, the positive association between tweets about the firm and market value is interesting as it points to markets placing greater value on public-generated tweets rather than firm-generated, which can be perceived as greenwash. Thus, extending the work of Balasubramanian et al. (2021) that argues that CSR communication via social media leads to better CSR outcomes, it is possible that markets are interpreting the tweets about firms as outside parties placing greater pressure and accountability on firms that will lead to better outcomes in the future.

Our third contribution adds to the literature examining the effect of carbon risk on firm valuations. Prior literature in this field documents a valuation decrement on high emitting firms (Bolton & Kacperczyk, 2021; Chapple, Clarkson, & Gold, 2013; Clarkson et al., 2015; Griffin, Lont, & Sun, 2017; Matsumura et al., 2014; Wang, 2023) and establishes that there are several factors that can explain cross-sectional differences in the magnitude of the penalty (Clarkson et al., 2015; Clarkson, Li, & Richardson, 2004; He et al., 2021; Johnston, Sefcik, & Soderstrom, 2008; Luo & Tang, 2014; Millar, Clarkson & Herbohn, 2024). Our findings suggest that carbon interactivity can partially mitigate the penalty on high-emitting firms. Consistent with agenda setting theory, we interpret these findings as capital markets perceiving that twitter conversations are highly influential in shaping public discourse, raising the accountability of entities by keeping climate change on the corporate agenda.

Collectively, these results are of particular relevance to management as it increases our understanding of the importance of ongoing conversations beyond the basic communication of financial disclosures. It is therefore interesting for managers to consider the value of establishing and maintaining interactive social media accounts that can both reveal corporate initiatives and values and attenuate negative concerns. Likewise for investors, increased usage of media conversations around carbon provides additional insights on a firm's position on climate change, but with the advantage of having lower acquisition costs.

The remainder of this paper is organised as follows: Section 2 describes the institutional setting and provides a brief review of relevant literature. Section 3 presents the research design and empirical models used, and Section 4 presents the main results and discussion thereof. Section 5 presents cross-sectional, additional analysis, sensitivity tests are discussed in Section 6, and Section 7 details how we address endogeneity concerns. Section 8 concludes.

2. INSTITUTIONAL SETTING AND LITERATURE REVIEW

2.1. Institutional setting

Investor scrutiny on climate risk continues to rise, with an estimated investment of US$30.3 trillion annually in sustainability in 2022, and forecasts of increased investment to surpass US$40 trillion by 2030 (Bloomberg, 2024). Additionally, many stakeholders such as consumers and employees have significant concerns about climate change (United Nations, 2022). From a regulatory perspective, the US EPA's 2009 Greenhouse Gas Reporting Program (GHGRP) requires all US facilities with emissions exceeding 25 000 tons of GHG per annum to report these directly to the EPA. Facilities caught by this regulation were required to begin reporting their emissions for the 2010 reporting year, with emissions data from 2010 onwards publicly available. Within this context, the US policy on climate change has swung back and forth over time, from initially rejecting the Kyoto Protocol, to embracing the later Paris Agreement, with commitments seesawing between being rescinded and being renewed at various junctures. The US setting is also of interest as the SEC expressly permits entities to publish earnings and other material information on social media. This contrasts with other jurisdictions such as Australia where the ASX prohibits the release of new information via social media platforms.

2.2. Literature Review

The literature examining the role of social media in the capital markets over the last decade has grown, with a greater concentration of studies around Twitter in recent years. Twitter has become a dominant choice for corporate social media use (Lee, Hutton, & Shu, 2015) and is used more predominantly by users in the United States (Statista, 2024). Moreover, evidence suggests that markets respond favourably to firms launching a Twitter account (Chahine & Malhotra, 2018). In fact, prior research shows how firms utilise this communication channel to reduce information asymmetry (Blankespoor et al., 2014; Prokofieva, 2015), predict stock returns (Bartov et al., 2018; Deng et al., 2018; Sul et al., 2017) and influence investor perceptions (Cade, 2018). The earlier study by Blankespoor et al. (2014) on the ability of tweets to reduce information asymmetry shows that these firm-generated tweets improve the information environment, particularly for smaller firms that are less known, i.e. less visible firms. Interestingly, even in the Australian setting, where social media is not permitted as the primary channel for news dissemination, Prokofieva (2015) found a negative association between bid-ask spread and twitter variables, indicating that twitter dissemination reduces information asymmetry. Consistent with Blankespoor et al. (2014), their results were more noticeable for less visible firms.

Another strand of this research investigates whether and how management strategically disseminates financial information. Jung et al., (2018) find that firms are less likely to utilise Twitter to disseminate quarterly earnings announcements when news is bad and when the magnitude of the bad news is worse. They concluded that incentives for strategic tweeting are higher for higher litigation firms, with lower investor sophistication and larger social media audiences. Mazboudi and Khalil (2017) show that the use of firm-generated tweets to reduce information asymmetry around acquisition announcements can enhance stability in the markets. Likewise, Lee et al. (2015) show that firms can strategically use social media to attenuate negative market reactions to consumer product recall announcements. Interestingly however, they observed that the extent of the attenuation depended on the amount of control that the firm held over the social media content. With the two-way nature of twitter activity, they documented that the market reaction to product recall announcements was attenuated by firm-generated tweets but exacerbated by the frequency of tweets generated by other parties. Additionally, Srinivasan, Jha, and Verma (2022) show that Twitter provided a beneficial platform to maintain shareholder value during the massive disruption caused by COVID-19 lockdowns, noting that "*firms tweeted about 57 times per week, and each additional tweet could preserve about $5.85 million of a firm's market valuation, on average*." (2022: 1).

Linking carbon issues to Twitter, Balasubramanian et al. (2021) investigate whether having a Twitter account is associated with CSR outcomes. Finding that having a twitter account is positively associated with higher CSR rankings, they conclude that social media imposes greater accountability, which in turn leads to better CSR outcomes. Importantly, testing for causality they observe that the social media presence drives CSR outcomes, consistent with intermedia agenda setting theory. Jha and Verma (2022) investigate how firms use social media for sustainability-related communication and its corresponding impact on customer responses. Using firm-generated tweets they find that social media communication has a significantly positive impact on firm value through an increase in sales, with disproportionately more usage of social media by industries where sustainability investment is costly. They conclude that consumers appreciate firm's sustainability efforts, but they are not savvy enough to distinguish between the sustainability requirements of different industries and instead appear to trust firm's communications as an indicator of sustainability efforts. These results are consistent with Servaes and Tamayo (2013) who show that CSR activities are more value enhancing if they are conducted by firms with greater consumer awareness. From an investor perspective, Albarrak et al. (2019) show that firms can lower their cost of equity by broadly disseminating carbon information over Twitter. Again, using firm-generated carbon tweets, their documented negative relation between tweets and cost of equity suggest that carbon tweets improve the information environment and transparency, enabling investors to better evaluate firm risk at lower acquisition costs.

In the main, these studies have focused on the valuation effect of firm-generated tweets, however the effect of carbon interactivity of firms through social media, using both firm-generated and public-generated carbon-specific tweets, on firm market value is left unexplored. Moreover, these prior studies ignore the context of carbon risk exposure presented through emissions. These prior studies point to the role that firm-generated tweets play in improving the information environment, thereby lowering information asymmetry and being positively valued by the capital markets. Further, agenda setting theory posits that public opinion on important issues is established through mass media (Lippmann, 1922; McCombs, 2005). Specifically, research based on intermedia agenda setting theory, which considers the relative roles of social media and traditional media in setting agendas, indicates that social media has significant impact on shaping public discussions (Meraz, 2011; Valenzuela et al., 2017). An important implication of studies that test intermedia agenda setting theory is that firms must be highly aware of and adaptable to social media influences when developing their corporate policies and strategies (Balasubramanian et al., 2021; Guo & Vargo, 2015; Neuman et al., 2014). Using a mixed methods approach, Balasubramanian et al. (2021) show that social media platforms like Twitter serve as a valuable conduit for public engagement and "*is an effective way to improve transparency and accountability of corporations. Social media may strengthen corporate awareness of CSR and redefine corporate thinking on CSR communications using social media*." (Balasubramanian et al., 2021, p. 753)

Moreover, social media may be used to foster relationships with customers, resulting in long-term relationships and repeat business (Chahine & Malhotra, 2018; Jha & Verma, 2022) and can be an important mechanism to convey social values, ideas, attitudes, beliefs and practices (Voelklein & Howarth, 2005). According to social exchange theory, Human relationships are formed after evaluating alternatives to inform a cost benefit analysis. Where the benefits of social exchange outweigh the costs, value is derived, resulting in positive relationships. On this basis, Chahine and Malhotra (2018) posit that interactive (two-way) communication is likely to be more rewarding than firm initiated one-way communications. In their study on the impact of launching a Twitter profile on stock price, they find that smaller firms that are less known benefit from an interactive social media strategy in comparison to larger firms. They argue that such firms have less resources available and that social media provides a low-cost alternative to strengthen relationships with external parties and increase information flows that signal market value (Chahine & Malhotra, 2018). We therefore argue that firms with greater interactivity in the carbon arena via Twitter, demonstrated through the extent of both firm-generated and public-generated carbon-specific tweets, are more cognisant of stakeholder pressures to meet carbon norms and are thus rewarded by capital markets through higher valuations.

Studies in accounting that investigate the carbon risk-firm value relation indicate that capital markets impose valuation penalties on high carbon emitting entities due to associated carbon risk exposure (Choi & Luo, 2021; Clarkson et al., 2015; Griffin et al., 2017; Matsumura et al., 2014). Further investigations in this body of literature address cross-sectional differences in valuation penalties assigned to high emitters, pointing to markets using other information when assessing the magnitude of the penalty on high emitters, such as holding sufficient emissions allowances (Clarkson et al., 2015; Johnston et al., 2008), the existence and quality of carbon management systems (Choi & Luo, 2021), voluntary carbon disclosures (Berkman, Jona & Soderstrom, 2021; Plumlee et al., 2015), proactive carbon responses (Millar et al., 2024) and other environmental performance information (Clarkson et al., 2004). For example, Plumlee et al. (2015) finds evidence consistent with signalling theory to suggest that firms that are better environmental performers are more forthcoming in their voluntary carbon disclosures, and that capital markets respond well to these disclosures by reducing the penalties on high emitters. Of some relevance to our study, Jung, Herbohn et al. (2018) show that greater carbon awareness moderates the positive relation between cost of debt and carbon risk. Zhou et al. (2018) examine this cost of debt-carbon risk relation further and the moderating effect of media attention within the Chinese context. Using news articles around carbon issues they find that carbon risk exerts an interval effect on cost of debt, which exists mainly for private firms rather than state-owned firms, and that positive media attention can moderate this relationship. Similarly, Byun and Oh (2018) show that media coverage of CSR activities moderates the relationship between carbon risk and share value. On the basis that greater carbon interactivity, as demonstrated through both firm-generated and public-generated carbon-specific tweets, may strengthen corporate awareness of carbon-related issues and force entities to be more cognisant of stakeholder pressures around carbon-related issues we argue that capital markets may impound this carbon interactivity in their valuation decisions. Thus, we posit that greater carbon interactivity may play a mitigating role in the penalties imposed on high emitting firms.

3. RESEARCH DESIGN

3.1. Sample and data

Our sample comprises all S&P Composite 1500 non-financial firms for the period from 2011 to 2020.[4] Our sample starts from year 2011, a period following the SEC's issuance of extended interpretive guidance on climate-related disclosures in 2010. This guidance specifically encompassed climate risk-related material information that should be included in SEC regulatory filings. The 2020 year represents the latest available data at the time of data

[4] This index accounts for 90% of the US market capitalisation, comprises the S&P500, the S&P MidCap 400 and the S&P SmallCap 600 indices.

collection. We exclude financial firms as many of these sell insurance products to hedge against climate-related risk (Li et al., 2020).

Key to our paper is constructing the variable carbon twitter interactivity. We do this by extracting firm level (and public-firm level) carbon related tweets from Twitter.[5] In doing so we carefully compiled a dataset of Twitter activity, encompassing complete historical records of non-financial S&P 1500 firms and public carbon tweets from 2011 - 2020. Since there is no centralised database of firms' official Twitter account/ usernames, we had to undertake a thorough manual search via corporate websites, including their investor relations page and contact page. If a Twitter account is not identified on the corporate webpage, we match their names on Twitter via the user's search engine. Additionally, we use the Google search engine to search for a firm's presence on Twitter, ensuring that we only use the official corporate pages if they exist. For the tweets from companies, only the certified Twitter accounts, evidenced by the blue Twitter badges, are utilised to ensure the firm as the main source of information. For the tweets from public about the company, both the verified Twitter username as well as their ticker code preceded by the '$' sign was utilised to identify relevant tweets.[6]

We use Twitter's Application Programming Interface (API) to perform a search of tweets that contain any of a set of fixed search terms around carbon related issues for the sample companies over the 10-year period (2011 to 2020).[7, 8] We also use Twitter's advanced search

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[5] See footnote 8 for a list of carbon related terms.

[6] Some firms have just one letter as the ticker code, such as Ford Motor (F) and Visa Inc (V) and using the hashtag "#" followed by the ticker code would result in the retrieval of much irrelevant data. Therefore, following Bartov et al. (2018) we utilise the cashtag convention of Finance stakeholders on Twitter, i.e. the "$" to precede ticker codes.

[7] We performed the search in 2021 before the acquisition of Twitter by Elon Musk in 2022. Twitter was rebranded as X in July 2023 and remains as a platform for companies to disclose information, facilitate real-time communication, engage with broad audience and stakeholders,

[8] Our search terms include the following from Albarrak et al., (2019) : "Greenhouse gas*", "GHG", "Pollution", "CO2 reduction", "CO2 emission*", "Global warming", "Net zero", " TCFD", "Fossil fuels", "Green initiative", "Renewable energy", "Carbon emissions", "carbon neutral", "Carbon footprint", "Climate change", "Climate adaptation", "Carbon offset*", "Clean energy", " Planet-warming", "Carbon pricing", "Carbon credits", "Carbon sequestration", "@CDP", "RGGI", "#global warming", "#globalwarming", "#global_warming", "#climate-change", "#climate change", "#climate_change", "#ClimateChange", "#net zero", "#net_zero", "#netzero", " #TCFD".

option using keywords to further refine the retrieval of relevant tweets. Once downloaded, we analysed the number of tweets that are relevant for each company per year. Specifically, we counted the annual number of tweets (from and about) that match our sample firms or zero otherwise. Firms that don't tweet or do not have a twitter account are coded 0.

The data for firm value and control variables are obtained from Compustat North America and IBES. The sample initially consists of 10,734 firm-year observations, excluding financial firms (SIC 6000-6900). After excluding 868 firm-years with missing market value of equity, and one firm-year with missing operating income (OPINC), our final sample includes 9,865 firm-year observations (as shown in Panel A of Table 1). Panel B of Table 1 shows the breakdown of firms by industry that use Twitter to interact carbon related matters as of 2020. This industry-specific analysis reveals significant disparities in the use of Twitter for carbon and non-carbon related issues across sectors. Industries like Real estate and Insurance are more active on the platform, while those in steel works and mining are comparatively less engaged in carbon tweeting. Figure 1 illustrates the annual percentage of firms within our sample that have used Twitter for communication. Over the years, there has been a notable increase in Twitter usage for both carbon and non-carbon related issues among firms, eventually stabilising at just below 80% towards the latter part of the observed period.

[Insert Table 1 here]

[Insert Figure 1 here]

3.2. Model Specification and Variable Definitions

Our research question of whether carbon-related interactivity via Twitter affect firm value, is subject to self-selection bias as firms voluntarily choose to engage in carbon-related issues on Twitter. This means that the firms participating in such discussions may inherently differ from those that do not, possibly in their environmental commitment, public relations strategies, or stakeholder engagement practices. In other words, this self-selected group likely represents a specific subset of the business community with distinct characteristics, such as a higher commitment to sustainability or a more proactive public relations approach. Consequently, any analysis of Twitter's impact on firm value might be skewed by these underlying differences, rather than solely by the Twitter activity itself.

Thus, firm value and the decision to use Twitter to engage in carbon-related matters may be jointly determined as reported in prior established studies (e.g. Matsumura et al. 2014; Choi and Luo 2021; Han et al. 2023). We address the self-selection bias issue by using a two-stage Heckman model (Heckman, 1979).[9] The first-stage probit model is employed to estimate the firm's decision to engage on Twitter regarding carbon-related issues and is shown in the following logit estimation model:

$$CITX\_FChoice = \beta_0 + \beta_1 INDCTWEETS_{it} + \beta_2 SIZE_{it} + \beta_3 BM_{it} + \beta_4 LEV_{it} + \beta_5 INSTOWN_{it} + \beta_6 FRNSALES_{it} + +\beta_7 EPA_{it} + Industry\ fixed\ effects + Year\ fixed\ effects + \varepsilon_{it} \quad \text{Eq (1)}$$

The dependent variable is an indicator variable (*CITX_FChoice*) where a firm having tweeted carbon-related issues on Twitter equals 1, and 0 otherwise. Like prior studies (e.g. Choi & Luo, 2021; Matsumura et al., 2014), the independent variables selected represent the firm characteristics of those that are more likely to disclose carbon information on Twitter. Firms' engagement performance on environmental issues is influenced by peer firms' performance in the same industry and year (Albarrak et al., 2019). The proportion of firms in an industry that have carbon tweets (INDCTWEETS), captures the industry pressure and is

[9] Matsumura et al. (2014) employed the FIML approach to address the selection bias on the choice of disclosure of carbon emission. The FIML method produces consistent and more efficient parameter estimates than two-step procedure, in that it uses all information at once and therefore reducing potential biases and errors arising from when Inverse Mills Ratio is calculated in first stage for second stage estimation (Tucker, 2010; Greene, 2008).

calculated as the ratio of firms having carbon tweets to the total firms in the industry in our sample. Prior evidence (e.g. Clarkson et al, 2008) suggests that firms with higher environmental score, are considered more environmentally proactive and have incentives to voluntarily disclose more carbon related information given this is less observable by investors and other stakeholders. Firm size (SIZE) is included and is calculated as the natural logarithm of total assets. Book-to-market ratio (BM) controls for the firm growth, is measured by book value divided by the market value of equity. Firm leverage (LEV) is calculated as total debt divided by the sum of total debt and the book value of equity. Prior research has indicated that firms with higher institutional ownership may be more likely to provide carbon disclosures (Plumlee et al., 2010), whilst Matsumura et al. (2014) argue that firms with fewer institutional owners may be more likely to use voluntary channels such as the CDP to attract more institutional owners. Thus, we control for institutional ownership by including INSTOWN, which is the proportion of total shares held by institutional investors to the total number of shares outstanding.[10] Prior studies show firms with higher proportion of international sales tend to disclose carbon emission (Matsumura et al., 2014; Stanny and Ely, 2008) and therefore we control the proportion of international sales to total sales by including FRNSALES. We also include EPA, an indicator variable for firms that are subject to EPA's GHG mandatory reporting rule. Industry- and year- fixed effects are included. All variables are defined in Appendix A.

Next, for the firm-value model, our model of interest which tests our research questions, we adapt the Matsumura et al. (2014) model by including Carbon twitter interactivity (CITX) as shown below in Eq 2:

[10] Similar to on the methodology of Akbas (2016) and Al Guindy (2021), firms not listed with institutional ownership in the 13F database are presumed to have no institutional holdings.

$$MV_{it} = \beta_0 + \beta_1 CITX_{it} + \beta_2 ASSET_{it} + \beta_3 LIAB_{it} + \beta_4 OPINC_{it} + \beta_5 \mathrm{TCO2}it + Industry\ \ effects + \ Year\ effects + \varepsilon_{it} \qquad \text{Eq (2)}$$

where the dependent variable, market value (MV), is measured using two ways: 1) the firm's market value of common equity (in millions of dollars) calculated as the price per share multiplied by the number of shares outstanding at the end of the fiscal year (MV); and 2) Price per share (MV_CSHO). The key variable, CITX, and control variables used in the model are discussed below. Description and measurement of the variables used in the model are summarised in Appendix 1.

Carbon Twitter Interactivity Variable

Prior literature has used twitter use in various contexts (Srinivasan et al., 2022; Balasubramanian et al., 2021; Lee et al., 2015; Blankespoor et al., 2014). Likewise, in this paper the variable CITX is used to measure a firm's social media interactivity on carbon matters. It is intuitive that it is not only when a company initiates social media conversations around carbon that demonstrates their carbon social media presence status, but also when outside parties talk about companies within that context. Hence, the total number of carbon issues on Twitter is disseminated to the public *from* a firm (firm-generated tweets) and disseminated by the public *about* the firm (public-generated tweets) on carbon matters. Further, if a tweet has been retweeted, liked, or replied to, this would increase the level of interactivity on Twitter. Thus, we use several alternative variants of Twitter interactivity to obtain the variable of interest, CITX. To begin, we distinguish between the total amount of twitter interactivity on carbon issues (including initial tweets, retweets, likes and replies) arising from firm-generated tweets (CITX_from) from the total amount of twitter interactivity on carbon issues (including initial tweets, retweets, likes and replies) arising from public-generated tweets (CITX_about). Next, we aggregate these two 'sides' of the carbon interactivity to capture the total carbon-related twitter interactivity for a firm (CITXT). We also follow emerging literature

(Srinivasan et al., 2022) by using narrower measures of carbon interactivity to include the sum of initial tweets (CITX_Tweets), and the associated retweets (CITX_Retweets), likes (CITX_Likes), and replies (CITX_Replies) to test whether capital markets respond to these respective elements of the Twitter interactivity differently, or at all.

<u>Control variables</u>

Consistent with prior studies, we utilise a number of standard control variables for the balance sheet valuation model such as total assets (ASSET), liabilities (LIAB) and operating income (OPINC) at the end of the fiscal year. The results are expected with a positive coefficient for ASSET, a negative coefficient for LIAB, and a positive coefficient for OPINC (Barth & McNichols, 1994; Campbell, Sefcik, & Soderstrom, 2003; Matsumura et al., 2014). Additionally, we control for emissions (TCO2) and similar to prior studies (Choi & Luo, 2021; Clarkson et al., 2015; Griffin et al., 2017; Matsumura et al., 2014) we expect a negative coefficient.[11]

We report results using both unscaled and scaled variables. Some researchers favour the use of unscaled variables (e.g. Clarkson et al., 2015; Matsumura et al., 2014) arguing that unscaled variables are considered to generally perform better than scaled market value models (Barth & McNichols, 1994; Campbell et al., 2003; Barth and Clinch, 2009) and the coefficients from an unscaled model are intuitive and economically meaningful (Ziliak & McCloskey, 2004). Nevertheless, we also re-estimated the model with scaled variables. In addition, the industry (2-digit SIC code) and year fixed effects are included to control for potential industry-level and time-invariant omitted variables. All the continuous variables are winsorized at the

[11] We obtain emissions data through a process of triangulation from two sources, viz. CDP submissions and Refinitiv (reported and estimated) emissions data. We begin by downloading available emissions data from the Refinitiv database. Next, we extract emissions data from the CDP database. While the two sources largely converge, there are observations that only appear in one database, increasing the sample size. We complement the observations using emissions data downloaded from Refinitiv. The advantage of this database is that Refinitiv uses an estimation methodology for missing data and thus partially alleviates the need to correct for self-selection bias. For firms with missing TCO2, we report as 0 indicating non-disclosure. We also perform sensitivity test for firms with TCO2 values.

1st and 99th percentiles. The reported t-statistics are based on robust standard errors clustered at firm-level.

4. EMPIRICAL RESULTS

4.1. Descriptive statistics

Table 2 Panel A shows the summary statistics for the variables included in Eq 1 and Eq 2 for our full sample of S&P 1500 firms from 2011 to 2020. The mean and median value of market value (MV) is $16.00 billion and $3.24 billion, respectively. The average number of total carbon related tweets, retweets, replies and likes including those that are firm-generated and public-generated (CITXT) per year is 3,710. The mean book values of total assets (ASSET), total liability (LIAB), and operation income (OPINC) are $12.929, $8.17, and $1.134 billion, respectively.[12] The mean TCO2 emissions (scope 1 and 2) is 1,824 million tonnes.

The full sample summary statistics for the variables used in the main analysis and carbon choice model are shown in Panel B of Table 2. Firms having disclosed carbon tweets (CITX_FChoice) have significantly larger means and medians than those firms with no carbon tweets for market value (MV), total assets (ASSET), total liability (LIAB), earnings (OPINC) and emissions (TCO2) at 1%.

[Insert Table 2 here]

Table 3 reports the Spearman ranked (Pearson) correlation coefficients above (below) the diagonal. MV and CITXT are significantly positively correlated (0.453, p=0.01), indicating that firms with higher carbon interactivity have greater market value. High-carbon-interactivity firms on Twitter (CITXT) are significantly positively correlated with total assets (ASSET), liability (LIAB), and operating income (OPINC) at 1%. Regarding the choice of carbon tweets model, CITX_FChoice is positively correlated with the ratio of the number of firms with

[12] The sample includes S&P 400, S&P 500, and S&P 600, which potentially has a smaller value of total assets, total liability, and earnings than the studies based on S&P 500 (e.g. Matsumura et al., 2014).

available carbon information on Twitter to the total number of firms in the same industry (INDCTWEETS), firm size (SIZE), and leverage (LEV), while it is negatively associated with book-to-market ratio (BM) and institutional ownership (INSTOWN).

[Insert Table 3 here]

4.2. Firm Value Effects of Climate-carbon twitter activity

We test our key question – Does the market value carbon interactions on Twitter? – and report the results in Table 4. To address self-selection bias, we adopt the two-step approach to estimate the Heckman regression model and report the second stage results in Table 4 after controlling for the inverse Mills ratio (IMR) estimated based on the first stage.[13] Panel A reports the estimations using unscaled market value model variables, while Panel B reports the estimations using scaled and transformed variables. Column (1 and 4) shows that CITXT is significantly positive (coefficient = 19.497, t = 2.50) associated with firm value. It implies that every standard deviation increase in carbon interactivity on Twitter results in a $1.149 billion dollar increase in market capitalisation (19.497 * 58.97) which translates into a 7.18% increase in the sample firms' average market capitalisation. Moreover, from column (1), the coefficients of ASSET, LIAB and OPINC are 0.942 (t = 2.50), -0.743 (t = -7.62) and 7.216 (t = 27.64), respectively. Following prior literature (Matsumura et al., 2014; Hassan, 2018, Millar et al., 2024) the coefficient on emissions (TCO2) is negative and significant in all models, suggesting a market penalty applied to high emitters. The sign and significance of coefficients on other variables are consistent with Matsumura et al. (2014). When we disaggregate carbon interactivity based on the two sides of the carbon conversation, we find an insignificant

[13] There are two common approaches to applying the Heckman model to address selection bias. Some authors, such as Matsumura et al., 2014, follow the full information maximum likelihood (FIML) approach, which is argued to be more efficient as it uses all the information simultaneously and avoids possible misuse of formulae when calculating the IMR (Tucker, 2010). Alternatively, we follow Han et al., 2023 and Goncharov and Peter, 2019, by applying a two-step approach which is argued to have fewer limitations than the FIML's simultaneous approach and is more robust (Puhani, 2000). For robustness, however, we report results based on the FIML method in our additional analyses.

coefficient on CITX_from of 33,899.271 (t = 1.48) in column (2), and Column (3) reports that the coefficient of CITX_about is 304.497 (t = 4.47) which is significantly positive to the firm value. Our initial results hold when using scaled variables (see Panel B) and suggest that whilst markets consider a firm's level of carbon-related twitter interactivity in valuation decisions, it is the interactivity around carbon tweets generated by external parties (CITX_about) regarding the firm that drive these valuation decisions.

Table 4 presents the results from the choice of carbon tweets model as per Eq 2. Since this is not the main model, we shall highlight some of the interesting insights. The coefficient on INDCTWEETS is positive and significant for the full sample ($p < 0.01$) consistent with our expectation that the proportion of firms with carbon tweets to the total number of tweets posted by firms in the same industry are more likely to disclose carbon information on Twitter. The positive and significant coefficients on SIZE (0.261, $p < 0.01$) and FRNSALES (0.534, $p < 0.01$), and the negative and significant coefficients of BM (-0.176, $p < 0.01$), and INSTOWN (-0.113, $p < 0.01$) are consistent with prior voluntary disclosure literature. However, the negative coefficient on LEV, which is in the same direction as that found by Matsumura et al. (2014), is not significant.

[Insert Table 4 here]

4.3. Carbon interactivity, emissions, and firm value

Studies have shown that capital markets penalise firms with higher carbon emissions (Matsumura et. al., 2014; Clarkson et al., 2015; He et al., 2021). Building on this foundational research, we test the potential mitigating effect of heightened carbon interactivity through Twitter on the market penalties typically associated with high carbon emissions. From our baseline results in Table 4, we show that the market indeed penalises firms with high emissions (negative and significant TCO2). Thus, if the market values carbon related information via Twitter as shown in our earlier results, we should observe carbon interactivity moderating the negative effect on the firm value for high carbon-related firms. To an extent, firms having large carbon emissions or in higher carbon-emitting industries are more likely to engage in conversation around carbon to reduce information asymmetry and mitigate the negative impact on firm value. We conjecture the positive association between carbon interactivity and market value would be more pronounced for firms with higher carbon concern. To test this, we modify our model in Eq 2 to include an interaction between interactivity and high emitting firms as follows:

$$MV_t = \beta_0 + \beta_1 CITX_t + \beta_2 TCO2 + \beta_3 CITX * TCO2 + \beta_4 ASSET_t + \beta_5 LIAB_t + \beta_6 OPINC_t + Industry, Year\ Fixed\ effects + \varepsilon_t \quad \text{Eq 3}$$

Where, as before, we utilise the alternate measures of carbon interactivity, CITXT and its disaggregated components *CITX_from* and *CITX_about.*

Table 5, Panel A shows the results using unscaled variables for the full sample in columns (1) to (4), and for the sub-sample of firms with emissions data available in columns (5) to (8). For transparency, we report the results using variables scaled by number of shares in Panel B, and using log transformations for our main variable in Panel C.[14] The coefficient on TCO2 is, as expected, negative and significant throughout, except when scaling the emissions in the tweets from firms' specifications (columns (2) and (5) in Panels B and C) indicating that the market penalises firms that emit high carbon and those in high-emitting industries. Now, moving to the variable of interest, CITX*CTO2 which tests whether carbon interactivity mitigates the negative effect of carbon emission on market value. From Panel A, we find a positive and significant coefficient of 0.016 on the interaction term with total carbon interactivity for the full sample in column (1) of Panel A ($t = 9.67$, $p < 0.01$) and 0.017 ($t = 8.45$, $p < 0.01$) for the carbon disclosing firms in column (5), suggesting that carbon

[14] For brevity, we only discuss the unscaled results, except where there are notable differences using scaled variables.

interactivity on Twitter attenuates the negative relation between firm value and emissions. These results hold when using log transformations (see columns (1) and (4) in Panel C) and for the carbon disclosing firms reflected in Panel B, column (5).

Regarding the carbon interactivity on the public-initiated tweets (CITX_about), we find a positive and significant coefficient of 169.637 ($t = 2.55$, $p < 0.05$) for the full sample in column (3) in Panel A, providing support to suggest that markets regard the conversation that others are having around a firm in their valuation decisions, consistent with agenda setting theory. Moreover, and of great interest, the positive and significant coefficients on the interaction terms (CITX_about*TCO2) in all specifications of the model suggests that this interactivity around externally generated Tweets on a firm's carbon issues are beneficial to firms when markets assess the magnitude of the penalties on emissions.

Our results regarding interactivity on the firm-initiated tweets (CITX_from) in column (2) show a negative and significant coefficient of -40,908.972 ($t = -1.66$, $p < 0.1$) suggesting that such interactivity on firm generated carbon-related tweets are harmful to firm value. A possible explanation for this is that markets may have some scepticism when interpreting firm-generated tweets and may view them as greenwashing. These results, however, do not hold when using scaled versions of the model, and thus we interpret these results with caution and explore further through our cross-sectional analysis.

[Insert Table 5 here]

5. CROSS-SECTIONAL ANALYSES

5.1. Carbon Intensive industry

We investigate whether there are cross-sectional differences between firms based on their industry affiliation and separate the sample into high and low carbon intensity industries.[15] From Table 6, column (1) we find that CITXT is more value relevant for the firms in the higher carbon intensity industries. Consistent with our earlier findings, CITX_about is significantly positively associated with market value for firms in the higher carbon intensity industries (coefficient = 5401.898, $t = 13.98$, $p < 0.01$). The positive coefficient on CITX_about of 186.3704 ($t = 2.13$, $p < 0.05$) for firms in the low carbon intensity industries is still significant, but the strength and magnitude of the relation is less pronounced. As before we do not find a significant relationship for CITX_from.

We also apply model (3) to this cross-sectional analysis and find that CITXT*TCO2 is significantly positively related to market value ($t = 13.04$, $p< 0.01$) in the high carbon intensity industry firms (see panel B, column (1)). We also find, in column (5), a significantly positive coefficient on the interaction CITXT*TCO2 for firms in the low carbon intensity industries ($t = 2.49$, $p<0.05$), however the magnitude and strength of this relation is less pronounced for these firms. Consistent with our earlier findings, we also observe in Panel B column (3) a significantly positive coefficient of 0.099 on CITX_about*TCO2 ($t = 9.22$, $p< 0.01$) for firms in the high carbon intensity industries that is more pronounced than the significantly positive association on the interaction term for firms in the low carbon intensity industries in column (7) ($t = 2.23$, $p< 0.05$).

[Insert Table 6 here]

[15] We use Carbon Intensive Industry Sectors as defined by TCFD (TCFD, 2017). Takes a value of 1 if the firm operates in energy, materials, industrials, utilities, real estate, financials and consumer staples, and 0 otherwise using 2-digit GICS codes.

5.2. Paris Agreement of December 2015

The Paris Agreement of December 2015 is considered as an exogenous shock to firms' exposure to the financial market's attention to firms' exposure to climate risk or carbon risk (Bolton and Kacperczyk, 2021). We expect that the carbon interactivity effect is more pronounced in the post-Paris Agreement period when the market may have become more aware of climate risk. Model (2) is estimated with the sub-samples of firms with disclosed emissions in the pre-Paris Agreement and post-Paris Agreement periods in Table 7. Using unscaled values in Panel A, we find that CITX_about (column 6) is positively significantly associated with market value ($t = 3.08$, $p<0.01$) in the post-Paris Agreement period, and not so in the previous years. Whilst the coefficient on CITX_from in column (4) is positive and significant ($t = 1.88$, $p <0.01$) in the post-Paris agreement period, total interactivity, CITXT (column 2) is not. Instead, CITXT is only positive and significantly associated with MV in the post-Paris agreement period when scaled (see Panels B and C, column (2)). Our takeaway from these results is that on balance, the results on CITX_about is stable in all specifications in the post-Paris agreement period, pointing to markets taking greater cognisance of carbon interactivity arising from public-generated tweets, consistent with agenda setting theory.

Likewise, when we estimate Eq (3) with the sub-sample of firms with disclosed emissions in the pre-Paris Agreement and post-Paris Agreement periods in Panels D to F, we find that total CITXT*TCO2 in column (2) of Panel D, having a positive and significant effect on firm market value ($t = 6.78$, $p <0.01$) in the post-Paris agreement period. Whilst we also find that this interaction is significantly positive in the pre-Paris agreement period, the t-statistic ($t = 3.05$, $p <0.01$) points to a weaker effect. Considering CITX_from*TCO2 in column (3), we find a significantly positive coefficient of 9.156 ($t= 3.91$, $p <0.01$) in the pre-Paris agreement period and a significantly positive coefficient of 9.787 ($t = 6.00$, $p <0.01$) in column (4) for the post-Paris Agreement period. We find similar results, with significantly positive coefficients on the CITX_about*TCO2 interaction in both the pre- and post-Paris agreement periods, but with marginally larger coefficients and t-statistics in the post period (see columns (5) and (6)). We infer form this, that based on the larger coefficients in the post period, that carbon interactivity arising from both firm-generated and public-generated tweets has become only marginally more value relevant since the Paris Agreement for high carbon emitting firms.

5.3. S&P index (S&P 500, S&P400, S&P600)

To test whether the results hold across the different levels of market capitalisation, we partition the sample into S&P 500, S&P400 and S&P 600 index and apply model (2) to these sub samples. Table 8 Panel A shows that the coefficients of CITXT, and its disaggregated CITX_from and CITX_about components are positive and significant for the S&P500 firms. This would suggest that capital markets appear to consider twitter conversations when making valuation decisions, consistent with agenda setting theory, and are holding them to account. The findings complement prior studies that focus only on a single index (e.g., S&P 500).

Noteworthy is that interactivity on firm generated tweets (CITX_from) do not appear to be significantly associated with market value for the mid-cap (S&P400) firms, however they are significantly positive for small cap firms (S&P600) (coefficient =12,420.359, t = 2.02). We conjecture that this is because of the richer information environment for the large and mid-cap firms, and the concern that firm generated tweets may be perceived as greenwashing. For the small cap firms however, with lower information flows, it is likely that capital markets perceive interactivity on firm-generated tweets as being indicative of their awareness of carbon issues, as opposed to their silent index counterparts. Given that carbon awareness is considered to be the starting point for climate risk responses (Jung et al., 2018), capital markets may be interpreting this as a positive indicator of their responsiveness to carbon risks. Further, the interactivity on firm generated tweets in small-cap firms may be perceived by capital markets as reducing information asymmetry, consistent with Blankespoor et al. (2014) and Prokofieva (2015).

[Insert Table 7 here]

We also apply model (3) to our S&P500 sub-sample.[16] From Table 8, Panel B, our results show that the interaction term on all alternate proxies for carbon interactivity (CITXT, CITX_from, CITX_about) are effective in partially mitigating the valuation penalties imposed on high emissions for the S&P500 firms.

[Insert Table 8 here]

5.4. Nature of Tweets

We delve deeper into the Twitter interactivity in our analysis by disaggregating interactivity further into the initial tweets (CITX_Tweets), retweets (CITX_Retweets), likes (CITX_Likes) and replies (CITX_Replies), to investigate whether these dimensions add further value to Twitter conversations from a valuation perspective. From Table 9, we find that tweets about carbon for the full sample of firms, excluding other interactivity elements, are positive and significant using both scaled and unscaled variants (column 1). Moreover, we find positive and significant coefficients on the interaction between emissions and Tweets, CITX_TCO2 (column (2), confirming our earlier results that carbon-related tweets can partially mitigate the valuation penalties assigned to emissions.[17] These results are consistent for the restricted sample of firms disclosing emissions (Table 9, Panel B, columns (1) and (2)).

[16] Since we do not find any significance for the mid-cap sample and very little for the small cap, we do not test whether carbon interactivity has a mitigating effect on emissions penalties for these sub-samples.

[17] Untabulated results show that these findings remain unchanged when we include all components – tweets, retweets, likes and replies – in one model.

Similarly, we find that each component of carbon interactivity on Twitter, aside from the initial tweets, are individually value relevant. The results for the full sample are reported in Table 9, which indicates that retweets, likes and replies to initial carbon-related tweets are positive and significantly associated with firm value. As before, from Table 9, Panel B, the interactions between the sub-components of interactivity and emission indicate that they too may partially mitigate the valuation penalties on emissions. In the main, these results hold for the restricted sample of firms disclosing emissions. In untabulated results, we re-estimate our models using a restricted sample of TCO2 disclosing firms and our results are quantitively the same.

[Insert Table 9 here]

6. SENSITIVITY ANALYSES

We conduct several sensitivity tests to determine the robustness of our findings that include using alternate measures of carbon interactivity, scaled variables, incorporating additional control variables and the use of an alternate model. First, prior studies shows that overall organisational visibility (firm visibility) plays a mediating role on environmental disclosures (e.g., Hassan, 2018). Given that an official presence on social media platforms increase firm visibility (Balasubramanian et al., 2020) we control for firm visibility. Commonly used proxies in prior studies include firm size (Henriques and Sadorsky, 1999; Bowen, 2000), number of analysts following a firm (Baker, Powell & Weaver, 1999, Hassan, 2018; Millar et al., 2024), advertising expense (Servaes & Tamayo, 2013) as a measure of organisational visibility and, emissions as a proxy for environmental visibility (Choi & Luo, 2021; Brammer & Pavelin, 2006). Since we have already controlled for the size and emissions, we additionally control firm visibility in the main model, using number of analysts following (ANFWG) and advertising expenses (XAD). Panel A of Table 10 presents the results of main model with additional ANFWG and XAD, the results remain unchanged.

Since the number of firm-year observations with advertising expenses are few, we perform cross-sectional analysis using analyst following to test whether, consistent with Prokofieva (2015) and Blankespoor et al. (2014), the results are more noticeable for less visible firms, indicative of reducing information asymmetry. Interestingly, we do not find this to be the case. Instead, from Panel B, we find that CITXT is positively significant for firms with greater visibility among sophisticated investors, indicated by above median number of analysts following, and that this carbon interactivity remains positively associated with market value for both firm-generated and public-generated twitter interactivity. These results support our earlier findings that suggest that investors do consider carbon interactivity in their valuation decisions, particularly in rich information environments where investors are utilising all available information in decision making. We propose that small firms are still less engaged in carbon communications, and thus our results are not entirely surprising.

There were fewer tweets about carbon in 2020, which is the COVID year, and therefore we also run our tests omitting the 2020 year. The results, presented in Panel C of Table 10, are consistent with our earlier findings that carbon interactivity is significantly positively related to firm market value. Interestingly, however, is that the exclusion of 2020 results in a significantly positive coefficient of 45,992.305 ($t=2.00$, $p < 0.05$) on CITX_from, suggesting that prior to the COVID year, capital markets were impounding carbon interactivity arising from firm-generated tweets into firm valuations. We suggest that the Covid-19 crisis may have diverted attention for investors away from carbon matters toward more fundamental and immediate short-term risks of going concern, inventory shortages, supply chain challenges, despite the ongoing carbon interactivity occurring on the Twitter platform.

We also estimate the effect of carbon visibility on firm-value using a modified Ohlson (1995) valuation model, jointly with the choice of carbon tweets model (Equation (1)).

$$MV_t = \beta_0 + \beta_1 CITX_t + \beta_2 BVEQ_t + \beta_3 EARN_t + Industry, Year\ Fixed\ effects + \varepsilon_t$$

Eq (4)

where BVEQ is the book value of common equity and EARN is income before extraordinary items. As with our main results, using this model we find that CITXT is consistently significantly positively associated with firm value, shown in Panel D of Table 10. For the reduced sample of firms with reported emissions, as before, we find that it is the carbon interactivity from public-generated tweets that is of interest to investors, rather than the firm-generated carbon interactivity, consistent with agenda setting theory.

Our final sensitivity test is to apply a full maximum likelihood (FIML) approach to estimate the Heckman model by jointly estimating the firm-value model with the firms' choice to engage in twitter activity. Our results, reported in Panel E of Table 10 do not change, suggesting that the association between carbon interactivity and market value is not sensitive to the use of the two-stage Heckman model or the FIML model.

[Insert Table 10 here]

7. ENDOGENEITY ISSUE

7.1. Propensity score matching (PSM)

We employ propensity score matching (PSM) to reduce the treatment assignment bias and mimic randomization. The propensity score is estimated using the MV model variables (ASSET, LIAB OPINC TCO2), following equation (2). The control firms are identified by the closest propensity score with 0.0001 caliper from the same index, industry, and year. This procedure results in 2,606 firm-year observations (1,303 pairs). The verifying covariates are presented in Appendix B. By using a propensity score matched (PSM) sample, Panel A of Table 11 shows the consistent results that market value significantly increases for firms with greater carbon-interactivity on Twitter. For robustness, we repeat the process using a reduced sample of firms with carbon emissions, shown in Panel A and find consistent results for the reduced sample.

7.2. Entropy balancing

Furthermore, we use the entropy balancing method (EBM) as an alternative approach to address possible endogeneity arising from observable missing variables. EBM is a multivariate reweighting method that reweights data to ensure that the covariate distributions meet specified moment conditions (Hainmueller, 2012). We run our models using EBM for both the full sample and the carbon emissions sub-sample, and our results in Table 11, Panel B, remain quantitively the same. See Appendix B for details of means for the treatment and control groups before and after reweighting.

8. CONCLUDING REMARKS

This study examines whether investors consider carbon interactivity of firms via twitter in their valuation decisions for a sample of S&P 1500 firms for the years 2011 to 2020. The results establish a significant positive relationship between carbon interactivity via twitter and firm market value. In particular, a significantly positive relationship between tweets generated by outside parties about a firm and firm market value is documented. According to intermedia agenda-setting theory and prior literature, social media usage serves as an instrumental step that triggers improvements in CSR outcomes. Our results support this notion and reveal that investors recognise this and thus impound carbon interactivity via Twitter in their valuation decisions. Moreover, the results show limited evidence that carbon interactivity around tweets released by smallcap firms that are arguably smaller, less known firms are value relevant. It is likely that such firm-generated tweets are viewed favourably by investors due to the low information environment for such firms, thereby reducing information asymmetry.

We further examine whether carbon interactivity via twitter is more meaningful for high -emitting firms. Our results show that carbon interactivity via twitter attenuates the negative relation between carbon emissions and firm market value for firms with disclosed emissions, even when controlling for organisational visibility. Interestingly, we find that carbon interactivity stimulated by public-generated tweets is effective in partially mitigating the valuation penalties, consistent with agenda setting theory. However, and somewhat surprisingly, we find some evidence pointing to carbon interactivity stimulated by firm-generated tweets to be potentially harmful to firm market value for high emitting firms, that is that carbon interactivity can have a magnifying effect on the penalty imposed on high emitters. We conjecture that this may be because markets may be more sceptical regarding firm communications on social media, regarding them as potential greenwash. We do not explore the content of these tweets to differentiate between substantive comments or marketing ploys, which is a limitation of our study, and provides an avenue for future research.

Addressing the potential endogeneity issues, we employ propensity score matching, and the entropy balancing model. Both yield consistent results that market value significantly increases for firms with higher carbon interactivity on Twitter, particularly in relation to public-generated tweets. Our sensitivity tests include additional controls for the number of analysts following and advertising expenses for firm visibility, excluding the COVID year and use of the Ohlson and FIML models. These sensitive analyses affirm the consistent results.

A potential limitation of the study is that we have not considered either the content of the tweets, such as whether the statements are substantive (e.g. call for action/ commendation on action) or not (e.g. personal axe to grand/ sarcasm and so on). Our motivation for this study is to build on the carbon valuation literature by investigating whether carbon interactivity, on average, affects market value and could explain cross-sectional variations in the valuation penalties imposed on high emitters. Thus, we do not consider the sentiment of the tweets, which operate on a different time scale, and are more likely to result in daily price reactions.

Nonetheless the results of this study are of interest to managers and investors as they provide a better understanding of the factors that affect market perceptions of carbon risks. High carbon emissions represent future challenges for firms to transition to net zero, and as such pose future climate change risks. Carbon interactivity places greater pressure on firms and increases the likelihood of climate change being a priority on corporate agendas. Therefore, these results suggest that greater carbon interactivity via twitter may increase the likelihood of firms addressing climate change concerns and thereby may be better positioning themselves for net zero transitions.

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Appendix A: Variable Definitions

Variable	Expected	Definition	Source
Carbon Interactivity			
CITX		Carbon Interactivity on Twitter/X measured by the following proxies:	
CITXT	?	Sum of the number of firm-generated and public-generated carbon-related twitter activity, including tweets, retweets, likes and replies	
CITX_from	?	Sum of the number of carbon-related issues on Twitter generated by its own firm, including tweets, retweets, likes and replies	
CITX_about	?	Sum of the number of carbon-related issues on Twitter generated by public, including tweets, retweets, likes and replies	Twitter API; extracted and constructed by Author
CITX_tweets	?	Sum of number of firm-generated and public-generated carbon-related tweets.	
CITX_retweets	?	Sum of number of firm-generated and public-generated carbon-related retweets	
CITX_likes	?	Sum of number of firm-generated and public-generated carbon-related likes	
CITX_replies	?	Sum of number of firm-generated and public-generated carbon-related replies	
Firm-value model			
MV		Market value of common equity (in millions of dollars), calculated as the number of shares outstanding multiplied by the price per share of the firm's common stock at the end of fiscal year t.	Compustat
MV_CSHO		Market value (MV) scaled by total number of common shares outstanding	Compustat
ASSET	+	Book value of total assets in $ millions (TA)	Compustat
ASSET_CSHO	+	Book value of total assets in $ millions scaled by total number of common shares outstanding	
LIAB	-	Book value of total liabilities in $ millions (LT)	Compustat
LIAB_CSHO	_	Book value of total liabilities in $ millions scaled by total number of common shares outstanding	
OPINC	+	Operating income after depreciation in $ millions	Compustat
OPINC _CSHO	+	Operating income after depreciation in $ millions scaled by total number of common shares outstanding	
TCO2	-	Total Scope 1 and Scope 2 carbon emissions in metric tons (in thousands)	Compustat/ Refinitiv/ CDP
TCO2_CSHO	-	Total Scope 1 and Scope 2 carbon emissions in metric tons (in thousands) scaled by total number of common shares outstanding	

Carbon tweets choice model			
Variable	**Expected**	**Definition**	**Source**
CITX_FChoice		An indicator variable equals 1 if firm has carbon issues on Twitter, 0 otherwise	
INDCTWEETS	+	The ratio of the number of firms with carbon-related tweets to the total number of firms in the industry in our sample.	
SIZE	+	The natural logarithm of total assets at the end of fiscal year (LN(AT))	Compustat
BM	-/?	Book-to-market ratio, measured as the book value of equity divided by market value of equity (CEQ/PRCC_F*CSHO)	Compustat
LEV	+	Firm's leverage, measured as total debt divided by sum of total debt and book value of equity (DLTT+DLC)/(DLTT+DLC+CEQ)	Compustat
INSTOWN	-/?	Institutional ownership, measured as total shares held by institutional investors divided by total number of shares outstanding	Compustat
FRNSALES		Foreign sales divided by total sales	Refinitiv
EPA		An indicator variable equal to 1 if the firm operates in an industry that will be required by the EPA's GHG Mandatory Reporting Rule to report its GHG emissions, and 0 otherwise.	
Additional controls			
ANFWG		The number of financial analysts following the firms	IBES Refinitiv
XAD		Total advertising expenses	Compustat
Controls in Ohlson model			
BVEQ		Book value of common equity	Compustat
EARN		Income before extraordinary items	Compustat

Appendix B: Verifying covariates balance

Appendix B reports the mean, difference and the T-test of the mean of variables used in the PSM and entropy balancing methos between firms having carbon-related tweets or not. The propensity score is estimated on the market model variables and the results show that all variables are significantly different before matching and the matched sample show that they are no longer different indicating that the groups are similar.

Panel A: PSM mean differences (N=2,606)

Variable	Treated	Control	Difference	t-value
ASSET	11802.640	12438.760	-636.114	-0.651
LIAB	6996.410	7746.195	-749.785	-1.266
OPINC	1089.147	1138.907	-49.760	-0.463
TCO2	999.328	1335.790	-336.462	-1.571

Panel B: Entropy balancing - differences in covariates (N=9,865)

	Treatment Group	Control Group	
Variable	mean	mean before weighting	mean after weighting
ASSET	29447.00	9065.00	29444.00
LIAB	19415.00	5536.00	19413.00
OPINC	2447.00	827.10	2447.00
TCO2	5766.00	901.40	5766.00

Figure 1: Tweeting and Carbon Tweeting Firms

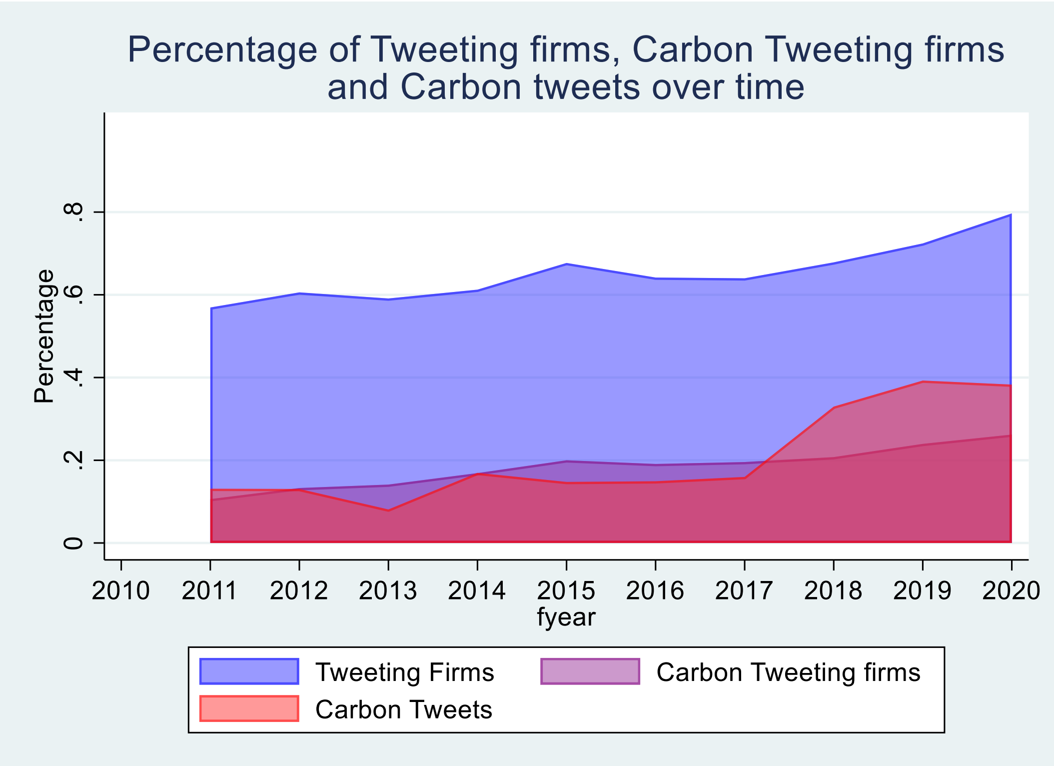

Figure 1 shows the percentage of firms with twitter account, percentage firms have posted carbon tweets, percentage of carbon tweets over the total number of tweets.

Table 1: Sample selection and distribution

Panel A: Sample selection

		Number of firm-years
S&P 1500 constituent firms (non-financial) for 2011-2020[18] from Compustat		10,734
Less:		
Missing market value of equity (MV)	(868)	
Missing earnings (OPINC)	(1)	
Number of firm-years in the sample used in baseline regression		9,865

Panel B: Distribution of observations across industries

	Industry	Number of Firms	Twitter Account		Carbon Tweet	
		N	N	%	N	%
1	Agriculture	20	14	0.70	1	0.05
2	Food Products	247	148	0.60	51	0.21
3	Candy & Soda	39	33	0.85	9	0.23
4	Beer & Liquor	60	43	0.72	17	0.28
5	Tobacco Products	20	19	0.95	7	0.35
6	Recreation	35	22	0.63	1	0.03
7	Entertainment	79	61	0.77	17	0.22
8	Printing and Publishing	74	59	0.80	22	0.30
9	Consumer Goods	206	142	0.69	46	0.22
10	Apparel	183	148	0.81	21	0.11
11	Healthcare	162	65	0.40	8	0.05
12	Medical Equipment	325	143	0.44	20	0.06
13	Pharmaceutical Products	441	204	0.46	64	0.15
14	Chemicals	307	217	0.71	77	0.25
15	Rubber and Plastic Products	76	30	0.39	9	0.12
16	Textiles	38	21	0.55	12	0.32
17	Construction Materials	233	96	0.41	24	0.10
18	Construction	208	106	0.51	21	0.10
19	Steel Works Etc	183	74	0.40	10	0.05
20	Fabricated Products	10	10	1.00	7	0.70
21	Machinery	447	247	0.55	72	0.16
22	Electrical Equipment	107	53	0.50	24	0.22
23	Automobiles and Trucks	229	122	0.53	27	0.12
24	Aircraft	97	68	0.70	11	0.11
25	Shipbuilding, Railroad Equipment	38	22	0.58	4	0.11
26	Defense	47	27	0.57	11	0.23
27	Precious Metals	10	9	0.90	7	0.70

[18] We utilise SP 1500 Indices as at 8 March 2021. Financial firms (GICS codes 4010, 4020 and 4030) were excluded.

28	Non-Metallic and Industrial Metal Mining	56	16	0.29	0	0.00
29	Coal	12	10	0.83	2	0.17
30	Petroleum and Natural Gas	313	210	0.67	86	0.27
31	Utilities	450	378	0.84	243	0.54
32	Communication	178	121	0.68	24	0.13
33	Personal Services	105	69	0.66	16	0.15
34	Business Services	922	590	0.64	199	0.22
35	Computers	276	185	0.67	73	0.26
36	Electronic Equipment	538	325	0.60	121	0.22
37	Measuring and Control Equipment	244	117	0.48	59	0.24
38	Business Supplies	112	70	0.63	38	0.34
39	Shipping Containers	65	43	0.66	18	0.28
40	Transportation	347	213	0.61	99	0.29
41	Wholesale	380	199	0.52	48	0.13
42	Retail	593	495	0.83	54	0.09
43	Restaraunts, Hotels, Motels	225	154	0.68	20	0.09
44	Banking	31	30	0.97	8	0.26
45	Insurance	76	76	1.00	22	0.29
46	Real Estate	65	65	1.00	30	0.46
47	Trading	853	853	1.00	76	0.09
48	Other	103	92	0.89	34	0.33
	Total	9865	6514		1870	

Table 1 describes the sample used in baseline regressions. Panel A reports the sample development process. The sample consists of 9,865 firm-year observations from 2011-2020. Panel B presents the distribution of the number of firm-years by industry, using the Fama French 48 industry classification, and Twitter use between 2011-2020. The number of companies, companies that use Twitter, and companies that use Twitter to communicate carbon information in the given industry are reported.

Table 2: Descriptive statistics
Panel A: Full Sample (N=9865)

Variable	Mean	StdDev	Min	Median	Max
Firm-value model					
MV ($million)	16007.00	40559.00	55.27	3241.00	424736.00
MV_CSHO	0.07	0.12	0.00	0.04	3.51
CITXT ('000)	3.71	58.97	0.00	0.00	2474.00
CITXT _CSHO	0.00	0.00	0.00	0.00	0.04
CITX_from (‘000)	0.00	0.01	0.00	0.00	0.55
CITX_from_CSHO	0.00	0.00	0.00	0.00	0.00
CITX_about ('000)	0.52	6.57	0.00	0.00	219.00
CITX_about_CSHO	0.00	0.00	0.00	0.00	0.00
CITX_tweets (‘000)	0.52	6.58	0.00	0.00	219.40
CITX_tweets S_CSHO	0.00	0.00	0.00	0.00	0.00
CITX_retweets (‘000)	0.90	15.05	0.00	0.00	732.50
CITX_retweets _CSHO	0.00	0.00	0.00	0.00	0.01
CITX_replies (‘000)	0.20	3.31	0.00	0.00	150.40
CITX_replies_CSHO	0.00	0.00	0.00	0.00	0.00
CITX_likes ('000)	2.10	36.17	0.00	0.00	1576.00
CITX_likes_CSHO	0.00	0.00	0.00	0.00	0.02
ASSET ($'million)	12928.64	30678.31	51.48	2953.84	316481.00
ASSET_CSHO	0.05	0.06	0.00	0.04	1.29
LIAB ($'million)	8166.50	19661.80	7.60	1739.06	185517.00
LIAB_CSHO	0.03	0.04	0.00	0.02	0.66
OPINC ($'million)	1134.09	2984.21	-7160.00	232.89	28986.00
OPINC_CSHO	0.01	0.01	-0.07	0.00	0.28
TCO2 ('000 tons)	1823.53	8117.34	0.00	0.00	106726.00
TCO2_CSHO	0.01	0.03	0.00	0.00	0.65
Carbon Disclosure Model					
CITX_FChoice	0.19	0.39	0.00	0.00	1.00
INDCTWEETS	0.01	0.01	0.00	0.00	0.12
SIZE	8.13	1.61	3.96	7.99	12.67
BM	0.43	0.34	-0.88	0.37	2.51
LEV	0.40	0.31	0.00	0.39	2.77
INSTOWN	0.65	0.37	0.00	0.79	1.22
FRNSALES	0.21	0.26	0.00	0.04	1.00
EPA	0.18	0.39	0.00	0.00	1.00

Table 2: Descriptive statistics
Panel B: Univariate analysis

Variable	*CITX_FChoice* = 0 (N=7995) Mean	Median	*CITX_FChoice* = 1 (N=1870) Mean	Median	T-tests for means	Wilcoxon tests for median
Firm-value model						
MV	12000.00	2586.91	34000.00	11000.00	-21.73***	28.99***
MV_CSHO	0.07	0.04	0.08	0.05	-4.85***	-13.3***
ASSET	9065.09	2349.83	29000.00	10000.00	-26.79***	-31.38***
ASSET_CSHO	0.05	0.04	0.07	0.05	-11.88***	-18.36***
LIAB	5535.61	1330.31	19000.00	6622.23	-28.6***	-31.55***
LIAB_CSHO	0.03	0.02	0.05	0.03	-14.5***	-20.94***
OPINC	827.06	186.00	2446.78	796.46	-21.62***	-26.74***
OPINC_CSHO	0.00	0.00	0.01	0.00	-4.86***	-13.59***
TCO2	913.89	0.00	6504.19	188.83	-23.17***	-34.21***
TCO2_CSHO	0.00	0.00	0.02	0.00	-14.78***	-32.69***
Carbon Choice Model						
INDCTWEETS	0.00	0.00	0.01	0.00	-20.32***	-21.21***
SIZE	7.87	7.76	9.22	9.23	-34.6***	-31.376***
BM	0.44	0.38	0.41	0.35	3.44***	3.613***
LEV	0.39	0.38	0.46	0.47	-9.89***	-13.469***
INSTOWN	0.65	0.80	0.63	0.76	1.93*	5.21***
FTSALES	0.19	0.00	0.28	0.23	-13.87***	-13.685***
EPA	0.14	0.00	0.35	0.00	-21.49***	-21***

Table 2 Panel A reports full sample summary statistics for the variables used in the main analysis. Panel B presents the tests for mean and Wilcoxon tests for median of the related variable comparing firms disclosing carbon information via Twitter/X (CITX_FChoice=1) and those that don't (CITX_FChoice=0). *, ** or *** indicates a significance level at 10%, 5% and 1%, respectively.

Table 3: Correlation Matrix

		1	2	3	4	5	6	7	8	9	10
1	*MV*	1	0.292***	0.453***	0.299***	0.464***	0.453***	0.436***	0.430***	0.393***	0.869***
2	*CITX_Fchoice*	0.214***	1	0.589***	0.993***	0.417***	0.572***	0.590***	0.577***	0.441***	0.316***
3	*CITXT*	0.144***	0.038***	1	0.598***	0.896***	0.994***	0.885***	0.890***	0.774***	0.463***
4	*CITX_from*	0.059***	0.262***	0.450***	1	0.433***	0.583***	0.605***	0.590***	0.464***	0.326***
5	*CITX_about*	0.190***	0.051***	0.839***	0.449***	1	0.908***	0.793***	0.786***	0.734***	0.473***
6	*CITX_tweets*	0.190***	0.051***	0.839***	0.450***	1.000***	1	0.861***	0.859***	0.760***	0.464***
7	*CITX_retweet*	0.141***	0.041***	0.961***	0.499***	0.790***	0.790***	1	0.891***	0.795***	0.448***
8	*CITX_like*	0.133***	0.032***	0.991***	0.407***	0.780***	0.780***	0.930***	1	0.791***	0.435***
9	*CITX_reply*	0.099***	0.031***	0.949***	0.399***	0.841***	0.841***	0.844***	0.952***	1	0.402***
10	*ASSET*	0.811***	0.260***	0.122***	0.100***	0.127***	0.127***	0.118***	0.118***	0.092***	1
11	*LIAB*	0.756***	0.277***	0.119***	0.110***	0.111***	0.111***	0.118***	0.117***	0.088***	0.968***
12	*OPINC*	0.876***	0.213***	0.098***	0.041***	0.130***	0.130***	0.094***	0.090***	0.072***	0.838***
13	*TCO2*	0.199***	0.235***	0.011	0.128***	0.011	0.011	0.014	0.01	0.006	0.377***
14	*INDCTWEETS*	0.009	0.200***	-0.006	0.145***	-0.011	-0.01	-0.011	-0.004	-0.003	0.083***
15	*SIZE*	0.584***	0.329***	0.059***	0.102***	0.070***	0.070***	0.059***	0.054***	0.044***	0.670***
16	*BM*	-0.101***	-0.018*	-0.003	0	-0.007	-0.007	-0.008	-0.001	0.003	-0.014
17	*LEV*	0.026***	0.035***	-0.001	0.009	-0.005	-0.005	-0.001	0	0	0.043***
18	*INSTOWN*	-0.072***	-0.020**	-0.014	-0.001	-0.014	-0.014	-0.016	-0.013	-0.01	-0.061***
19	*FTSALES*	0.178***	0.138***	-0.01	-0.01	0.002	0.002	-0.013	-0.01	-0.011	0.114***
20	*EPA*	0.153***	0.211***	-0.016	0.086***	-0.023**	-0.023**	-0.015	-0.015	-0.016	0.277***

		11	12	13	14	15	16	17	18	19	20
1	*MV*	0.818***	0.866***	0.606***	0.099***	0.869***	-0.372***	0.255***	-0.055***	0.277***	0.255***
2	*CITX_Fchoice*	0.318***	0.269***	0.344***	0.214***	0.316***	-0.036***	0.136***	-0.052***	0.138***	0.211***
3	*CITXT*	0.465***	0.411***	0.439***	0.135***	0.463***	-0.120***	0.185***	-0.114***	0.157***	0.214***
4	*CITX_from*	0.328***	0.275***	0.355***	0.224***	0.326***	-0.034***	0.142***	-0.055***	0.136***	0.225***
5	*CITX_about*	0.476***	0.416***	0.449***	0.125***	0.473***	-0.126***	0.192***	-0.104***	0.145***	0.234***
6	*CITX_tweets*	0.466***	0.413***	0.439***	0.128***	0.464***	-0.116***	0.180***	-0.116***	0.155***	0.219***
7	*CITX_retweet*	0.450***	0.390***	0.439***	0.144***	0.448***	-0.111***	0.181***	-0.121***	0.159***	0.222***
8	*CITX_like*	0.439***	0.375***	0.429***	0.147***	0.435***	-0.130***	0.195***	-0.109***	0.146***	0.194***

9	*CITX_reply*	0.407***	0.350***	0.384***	0.092***	0.402***	-0.112***	0.171***	-0.132***	0.111***	0.178***
10	*ASSET*	0.976***	0.840***	0.662***	0.138***	1.000***	-0.034***	0.451***	-0.042***	0.207***	0.352***
11	*LIAB*	1	0.816***	0.658***	0.130***	0.976***	-0.082***	0.585***	-0.038***	0.171***	0.351***
12	*OPINC*	0.795***	1	0.580***	0.044***	0.840***	-0.265***	0.311***	-0.078***	0.242***	0.264***
13	*TCO2*	0.380***	0.235***	1	0.203***	0.662***	-0.062***	0.270***	-0.093***	0.213***	0.426***
14	*INDCTWEETS*	0.086***	0.001	0.241***	1	0.138***	0.095***	0.083***	0.046***	0.070***	0.259***
15	*SIZE*	0.665***	0.590***	0.349***	0.150***	1	-0.034***	0.451***	-0.042***	0.207***	0.352***
16	*BM*	-0.033***	-0.071***	0.040***	0.050***	-0.007	1	-0.171***	0.01	-0.128***	0.123***
17	*LEV*	0.080***	0.035***	0.034***	0.014	0.137***	-0.267***	1	0.057***	-0.078***	0.174***
18	*INSTOWN*	-0.058***	-0.074***	-0.001	0.057***	-0.014	0.005	0.026***	1	-0.01	-0.022**
19	*FTSALES*	0.091***	0.151***	0.007	-0.015	0.188***	-0.044***	-0.041***	-0.005	1	0.054***
20	*EPA*	0.288***	0.185***	0.369***	0.275***	0.366***	0.053***	0.040***	0.047***	0.062***	1

Table 3 presents the Spearman (Pearson) correlation for the unscaled MV model and the coefficients are below (above) the diagonal. *, ** or *** indicates a significance level at 10%, 5% and 1%, respectively. All variables are defined in Appendix A.

Table 4: Carbon interactivity on Twitter/X and firm value

	Panel A Unscaled Market value of equity (MV)					Panel B Scaled Market value of equity (MV_CSHO)			
Carbon Interactivity	*CITXT*	*CITX_from*	*CITX_about*	*CITX*		*CITXT*	*CITX_from*	*CITX_about*	CITX
	1	*2*	*3*	*4*		*5*	*6*	*7*	8
CITX	**19.497****	33,899.271	**304.497*****		*CITX_CSHO*	**12.034*****	3,746.748	**108.693*****	
	(2.50)	(1.48)	(4.47)			(2.80)	(0.36)	(2.94)	
CITX_from				-38,024.118	*CITX_from_CSHO*				-14,295.416
				(-1.35)					(-1.20)
CITX_about				**370.802*****	*CITX_about_CSHO*				**132.951*****
				(4.41)					(3.15)
ASSET	0.942***	0.956***	0.932***	0.942***	*ASSET_CSHO*	1.271***	1.271***	1.274***	1.274***
	(14.05)	(14.29)	(13.94)	(14.05)		(8.70)	(8.70)	(8.72)	(8.73)
LIAB	-0.743***	-0.763***	-0.732***	-0.744***	*LIAB_CSHO*	-0.886***	-0.886***	-0.889***	-0.887***
	(-7.62)	(-7.82)	(-7.52)	(-7.62)		(-4.65)	(-4.65)	(-4.67)	(-4.66)
OPINC	7.216***	7.266***	7.158***	7.216***	*OPINC_CSHO*	10.427***	10.427***	10.435***	10.421***
	(27.64)	(27.76)	(27.46)	(27.64)		(21.08)	(21.08)	(21.09)	(21.07)
TCO2	-0.185***	-0.188***	-0.181***	-0.185***	*TCO2_SALE*	-0.109*	-0.109*	-0.108*	-0.111**
	(-3.45)	(-3.51)	(-3.40)	(-3.45)		(-1.93)	(-1.93)	(-1.92)	(-1.97)
Choice of carbon tweets									
INDCTWEETS	27.721***	27.721***	27.721***	27.721***	*INDCTWEETS*	27.721***	27.721***	27.721***	27.721***
	(12.34)	(12.34)	(12.34)	(12.34)		(12.34)	(12.34)	(12.34)	(12.34)
SIZE	0.261***	0.261***	0.261***	0.261***	*SIZE*	0.261***	0.261***	0.261***	0.261***
	(22.54)	(22.54)	(22.54)	(22.54)		(22.54)	(22.54)	(22.54)	(22.54)
BM	-0.176***	-0.176***	-0.176***	-0.176***	*BM*	-0.176***	-0.176***	-0.176***	-0.176***
	(-3.41)	(-3.41)	(-3.41)	(-3.41)		(-3.41)	(-3.41)	(-3.41)	(-3.41)
LEV	-0.061	-0.0613	-0.061	-0.061	*LEV*	-0.061	-0.061	-0.061	-0.061
	(-1.00)	(-1.00)	(-1.00)	(-1.00)		(-1.00)	(-1.00)	(-1.00)	(-1.00)
INSTOWN	-0.113**	-0.113**	-0.113**	-0.113**	*INSTOWN*	-0.113**	-0.113**	-0.113**	-0.113**

	(-2.54)	(-2.54)	(-2.54)	(-2.54)		(-2.54)	(-2.54)	(-2.54)	(-2.54)
FRNSALES	0.534***	0.534***	0.534***	0.534***	*FRNSALES*	0.534***	0.534***	0.534***	0.534***
	(8.99)	(8.99)	(8.99)	(8.99)		(8.99)	(8.99)	(8.99)	(8.99)
EPA	0.237***	0.237***	0.237***	0.237***	*EPA*	0.237***	0.237***	0.237***	0.237***
	(5.71)	(5.71)	(5.71)	(5.71)		(5.71)	(5.71)	(5.71)	(5.71)
/mills lambda	-8197.22***	-7820.35***	-8434.53***	-8653.592***		.0128**	.0127**	.0128**	.01368**
Constant	included	included	included	included	Constant	included	included	included	included
Industry and year	included	included	included	included	Industry and year	included	included	included	included
Observations	9865	9865	9865	9865	Observations	9865	9,865	9,865	9,865
Chisq	6451	6444	6504	6505	Chisq	145.8	4.337	244.3	1970.5
Uncensored	1870	1870	1870	1870	Uncensored	1870	1870	1870	1870

Using twostep method, we estimate the Heckman (1979) model to correct for selection bias; that is, first the choice of carbon disclosure via twitter is estimated and the market value is estimated in the next step. Panel A uses the unscaled MV model as per Matsumura et al (2014), while Panel B uses scaled MV model (natural log CITX). T-statistics are included in parentheses. *, ** or *** indicates a significance level at 10%, 5%, and 1%, respectively, using a two-tailed test. All variables are defined in Appendix A.

Table 5: Carbon Interactivity, Carbon emission and firm value
Panel A: Unscaled Market Value (MV)

	Full Sample				Firms disclosing TCO2			
Carbon Interactivity	*CITXT*	*CITX_from*	*CITX_about*	*CITX*	*CITXT*	*CITX_from*	*CITX_about*	*CITX*
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
CITXT	4.059				-29.937			
	(0.52)				(-1.09)			
TCO2	-0.233***	-0.312***	-0.289***	-.325	-0.200***	-0.296***	-0.250***	-0.283***
	(-4.43)	(-5.62)	(-5.51)	(-6.01)	(-3.28)	(-4.61)	(-4.14)	(-4.49)
*CITXT*TCO2*	**0.016*** **				**0.017*** **			
	(9.67)				(8.45)			
CITX_from		**-40,908.97***		**-106867.6*** **		**-109714.210** **		-64585.130
		(-1.66)		(-3.43)		(-2.41)		(-1.45)
*CITX_from*TCO2*		**8.795*** **		**3.982*** **		**10.107*** **		2.854***
		(7.41)		(2.75)		(7.00)		(1.74)
CITX_about			**169.637** **	**361.837*** **			181.936	208.645
			(2.55)	(4.19)			(1.05)	(1.19)
*CITX_about*TCO2*			**0.117*** **	**.010*** **			**0.119*** **	**.109*** **
			(11.64)	(8.26)			(10.37)	(8.07)
Market value model controls	included	included	included	included	included	included	included	included
Carbon tweets choice model	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	included	included	included	included	included	included	included	included
Industry and year	included	included	included	included	Industry and year	included	included	included
Observations	9865	9865	9865	9865	3,748	3,748	3,748	3,748
Chisq	6451	6444	6504	7057	6084	6047	6321	6337
Uncensored	1870	1870	1870	1870	1312	1312	1312	1312

Using twostep method, we estimate the Heckman (1979) model to correct for selection bias; that is, first the choice of carbon disclosure via twitter is estimated and the market value is estimated in the next step. For simplicity, the results from the choice model and control variables are not reported. Estimations 1-3 reports the results using

full sample, while estimations 4 – 6 reports results using observations with reported TCO2 (i.e. TCO2>0). Panel A uses the unscaled MV model as per Matsumura et al (2014), while Panel B uses scaled MV model (Panel C uses natural log CITX). T-statistics are included in parentheses. *, ** or *** indicates a significance level at 10%, 5%, and 1%, respectively, using a two-tailed test. All variables are defined in Appendix A.

Table 5: Carbon Interactivity, Carbon emission and firm value
Panel B: Scaled Market Value (MV_CSHO)

	Full Sample				Firms disclosing TCO2			
Carbon Interactivity	*CITXT*	*CITX_from*	*CITX_about*	*CITX*	*CITXT*	*CITX_from*	*CITX_about*	*CITX*
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
CITXT_CSHO	**10.730****				**71.151*****			
	(2.45)				(4.48)			
TCO2_CSHO	-0.112**	-0.096	-0.115**	-0.121**	-0.108	-0.096	-0.117*	-0.1111
	(-1.99)	(-1.61)	(-2.04)	(-2.02)	(-1.64)	(-1.33)	(-1.78)	(-1.56)
*CITXT_CSO*TCO2_CSHO*	428.975				**1,008.240****			
	(1.60)				(2.39)			
CITX_from_CSHO		5,730.154		-13222.81		-2,827.909		-1043.844
		(0.50)		(-0.99)		(-0.12)		(-0.04)
*CITX_from_CSHO*TCO2_CSHO*		-186770.612		87906.02		-112793.197		-144582.3 (-0.27)
		(-0.45)		(0.21)		(-0.21)		
CITX_about_CSHO			**96.631*****	**119.632*****			**296.592*****	**296.270*****
			(2.59)	(2.72)			(2.73)	(2.73)
*CITX_about_CSHO*TCO2_CSHO*			**6,524.692****	**6223.916****			**19,367.448*****	**19380.64*****
			(2.17)	(2.06)			(4.33)	(4.33)
Market value model controls	included	included	included	included	included	included	included	included
Carbon tweets choice model	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	included	included	included	included	included	included	included	included
Industry and year	included	included	included	included	Industry and year	included	included	included
Observations	9865	9865	9865	9865	3,748	3,748	3,748	3,748
Chisq	1972	11951	1978	1980	1503	1412	1489	1489
Uncensored	1870	1870	1870	1870	1312	1312	1312	1312

Using twostep method, we estimate the Heckman (1979) model to correct for selection bias; that is, first the choice of carbon disclosure via twitter is estimated and the market value is estimated in the next step. For simplicity, the results from the choice model and control variables are not reported. Estimations 1-3 reports the results using

full sample, while estimations 4 – 6 reports results using observations with reported TCO2 (i.e. TCO2>0). Panel A uses the unscaled MV model as per Matsumura et al (2014), while Panel B uses scaled MV model (Panel C utilises natural log CITX). T-statistics are included in parentheses. *, ** or *** indicates a significance level at 10%, 5%, and 1%, respectively, using a two-tailed test. All variables are defined in Appendix A.

Panel C: Scaled Market Value (MV_CSHO) (note: but Log CITX instead of scale)

	Full Sample				Firms disclosing TCO2			
Carbon Interactivity	*CITXT*	*CITX_from*	*CITX_about*	*CITX*	*CITXT*	*CITX_from*	*CITX_about*	*CITX*
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
LCITXT	**0.023*****				**0.023*****			
	(8.63)				(6.48)			
TCO2_CSHO	-0.137**	-0.085	-0.162***	-0.148**	-0.169**	-0.067	-0.203***	-0.152
	(-2.23)	(-1.38)	(-2.74)	(-2.41)	(-2.35)	(-0.91)	(-2.91)	(-2.06)
*LCITXT*TCO2_CSHO*	**0.023*****				**0.211****			
	(8.63)				(1.99)			
LCITX_from		0.139		**-.2132****		0.198		0.1090
		(1.46)		(-2.09)		(1.15)		(0.64)
*LCITX_from*TCO2_CSHO*		-1.939		-2.010		-2.706		**-7.784*****
		(-0.87)		(-0.85)		(-0.97)		(4.89)
LCITX_about			**0.036*****	**0.039*****			**0.036*****	**.0328*****
			(8.23)	(8.19)			(5.38)	(4.89)
*LCITX_about*TCO2_CSHO*			**0.502****	**0.570*****			**0.940*****	**1.253*****
			(2.57)	(2.70)			(3.81)	(4.68)
Market value model controls	included	included	included	included	included	included	included	included
First step Carbon tweets choice model	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	included	included	included	included	included	included	included	included
Industry and year	included	included	included	included	Industry and year	included	included	included
Observations	9865	9865	9865	9865	3,748	3,748	3,748	3,748
Chisq	6451	6444	6504	2169	6084	6047	6321	1570
Uncensored	1870	1870	1870	1870	1312	1312	1312	1312

Using twostep method, we estimate the Heckman (1979) model to correct for selection bias; that is, first the choice of carbon disclosure via twitter is estimated and the market value is estimated in the next step. For simplicity, the results from the choice model and control variables are not reported. Estimations 1-3 reports the results using

full sample, while estimations 4 – 6 reports results using observations with reported TCO2 (i.e. TCO2>0). Panel A uses the unscaled MV model as per Matsumura et al (2014), while Panel B uses scaled MV model (Panel C utilises natural log CITX). T-statistics are included in parentheses. *, ** or *** indicates a significance level at 10%, 5%, and 1%, respectively, using a two-tailed test. All variables are defined in Appendix A.

Table 6: Cross Sectional Analysis – Carbon Emissions Intensity Industry TCFD
Panel A: Carbon interactivity on Twitter/X and firm value

	Unscaled MV model (MV)							
	High Carbon Intensity Industry				**Low Carbon Intensity Industry**			
	CITXT	CITX_from	CITX_about	CITX	CITXT	CITX_from	CITX_about	CITX
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
CITXT	**301.366*** **				11.705			
	(6.51)				(1.18)			
TCO2	-0.202***	-0.216***	-0.206***	-0.209***	-0.601*	-0.593*	-0.596*	-0.592*
	(-5.07)	(-5.34)	(-5.52)	(-5.58)	(-1.69)	(-1.66)	(-1.68)	(-1.67)
CITX_from		33,870.79		-25,102.08		-4,968.660		**-169076.861*** **
		(1.44)		(-1.13)		(-0.13)		(-2.79)
CITX_about			**5,401.898*** **	**5,486.436*** **			**186.369** **	**481.358*** **
			(13.98)	(13.95)			(2.13)	(3.5)
	Scaled MV model (MV_CSHO)							
CITXT	-0.928				15.596***			
	(-0.08)				(2.7)			
TCO2	-0.053*	-0.054*	-0.054*	-0.055*	0.132	0.133	0.132	0.130
	(-1.83)	(-1.85)	(-1.85)	(-1.88)	(0.91)	(0.92)	(0.92)	(0.9)
CITX_from		-2,176.450		-2,262.420		15,082.500		**-56,331.124***
		(-0.36)		(-0.37)		-0.72		(-1.86)
CITX_about			113.610	114.667			**136.309*** **	**232.921*** **
			(0.74)	(0.75)			(2.76)	(3.25)
	Scaled MV model (MV_CSHO) and Log CITX							
CITXT	0.004**				0.029***			
	(2.32)				(7.38)			
TCO2	-0.055*	-0.054*	-0.056*	-0.059**	0.128	0.133	0.128	0.128
	(-1.91)	(-1.86)	(-1.96)	(-2.04)	(0.91)	(0.91)	(0.91)	(0.91)
CITX_from		-0.042		-0.090		0.198		**-0.536*** **
		(-0.78)		(-1.64)		(1.22)		(-2.96)
CITX_about			**0.012*** **	**0.013*** **			**0.045*** **	**0.055*** **
			(3.19)	(3.51)			(7.31)	(7.78)

Market value model controls	Included	Included	Included	Included	Included	Included	Included	Included
Carbon tweets choice model	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Included	Included	Included	Included	Included	Included	Included	Included
Industry and year	Included	Included	Included	Included	Included	Included	Included	Included
Observations	5052	5052	5052	5052	4813	4813	4813	4813
Uncensored	1126	1126	1126	1126	744	744	744	744

Table 6: Cross Sectional Analysis – Carbon Emissions Intensity Industry TCFD

Panel B: Carbon Interactivity, Carbon emission and firm value

	Unscaled MV model (MV)							
	High Carbon Intensity Industry				**Low Carbon Intensity Industry**			
	CITXT	CITX_from	CITX_about	CITX	CITXT	CITX_from	CITX_about	CITX
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
CITXT	-41.877				6.118			
	(-0.83)				(0.6)			
TCO2	-0.238***	-0.313***	-0.260***	-0.261	-0.703**	-0.637	-0.694*	-0.224
	(-6.40)	(-7.60)	(-7.11)	(-6.86)	(-1.97)	(-1.08)	(-1.95)	(-0.36)
*CITXT*TCO2*	**0.021*****				**0.008****			
	(13.04)				(2.49)			
CITX_from		**-105219.353*****		-45772.050		-5,210.150		**-133087.100****
		(-3.65)		(-1.71)		(-0.13)		(-2.09)
*CITX_from*TCO2*		**7.304*****		-0.642		12.571		-132.745
		(7.99)		(-0.64)		(0.09)		(-0.86)
CITX_about			**1,238.061****	**1215.472****			145.152	**384.681*****
			(2.12)	(2.08)			(1.63)	(2.61)
*CITX_about*TCO2*			**0.099*****	**0.107*****			**0.068****	**0.065****
			(9.22)	(8.79)			(2.23)	(1.79)
	Scaled MV model (MV_CSHO)							
CITXT	-3.106				1.485			
	(-0.12)				(0.35)			
TCO2	-0.053*	-0.059*	-0.049*	-0.057	-0.028	0.466	-0.121	-0.077
	(-1.83)	(-1.87)	(-1.68)	(-1.83)	(-0.27)	(1.16)	(-1.12)	(-0.26)
*CITXT*TCO2*	31.008				**52,442.738*****			
	(0.10)				-26.03			
CITX_from		-3,725.68		-5,656.34		16,887.490		14452.870
		(-0.52)		(-0.78)		(0.8)		(0.63)
*CITX_from*TCO2*		78,807.85		119921.8		-12673000		-1675496
		(0.41)		(0.62)		(-0.89)		(-0.16)

CITX_about			**1,130.402****	**1182.702*****			6.394	-18.788
			(2.21)	(2.29)			(0.17)	(-0.34)
*CITX_about*TCO2*			**-11,955.182****	**-12530.400*****			**501,073.479*****	**502579.400*****
			(-2.08)	(-2.17)			(24.62)	(24.5)
Scaled MV model (MV_CSHO) and Log CITX								
CITXT	**0.006*****				**0.008****			
	(2.66)				-2.53			
TCO2	-0.031	-0.052	-0.015	-0.028	-0.564***	-1.074**	-0.492***	0.080
	(-0.92)	(-1.57)	(-0.45)	(-0.82)	(-5.05)	(-2.53)	(-4.34)	(0.25)
*CITXT*TCO2*	-0.063				11.313***			
	(-1.32)				(22.73)			
CITX_from		-0.037		**-0.123***		0.156		-0.130
		(-0.54)		(-1.75)		(0.96)		(-0.90)
*CITX_from*TCO2*		-0.143		1.172		**363.018*****		**-175.410***
		(-0.13)		(0.97)		(3.02)		(-1.86)
CITX_about			**0.021*****	**0.024*****			**0.014*****	**0.016*****
			(4.07)	(4.32)			(2.80)	(2.80)
*CITX_about*TCO2*			**-0.319****	**-0.364*****			**16.542*****	**16.835*****
			(-2.54)	(-2.61)			(21.59)	(21.07)
Market value model controls	Included	Included	Included	Included	Included	Included	Included	Included
Carbon tweets choice model	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Included	Included	Included	Included	Included	Included	Included	Included
Industry and year	Included	Included	Included	Included	Included	Included	Included	Included
Observations	5052	5052	5052	5052	4813	4813	4813	4813
Uncensored	1126	1126	1126	1126	744	744	744	744

Using the twostep method, we estimate the Heckman (1979) model to correct for selection bias; that is, we estimate the firm-value model jointly with the disclosure choice model by S&P index. t-statistics are included in parentheses *, ** or *** indicates a significance level at 10%, 5%, and 1%, respectively, using a two-tailed test. All variables are defined in Appendix A..

Table 7: Cross-sectional analyses: Paris Agreement effects of value relevance of CITX

Panels A to C: Paris Agreement effects - Carbon Interactivity and Firm Value

	CITXT		CITX_from		CITX_about	
	Year <2016	Year>= 2016	Year <2016	Year >= 2016	Year <2016	Year >= 2016
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Market value of equity (MV)						
CITX	26.548	14.620	-5,669.398	**51,015.518***	82.382	**260.076*****
	(0.88)	(1.59)	(-0.12)	(1.88)	(0.93)	(3.08)
TCO2	-0.045	-0.127	-0.045	-0.131	-0.045	-0.125
	(-1.00)	(-1.41)	(-0.98)	(-1.46)	(-0.99)	(-1.39)
Panel B: Scaled Market value of equity (MV_CSHO)						
CITX_CSHO	-1.040	**14.676*****	-10,042.529	11,256.272	4.650	**135.130*****
	(-0.10)	(2.70)	(-0.96)	(0.80)	(0.16)	(2.69)
TCO2_CSHO	-0.021	-0.117	-0.023	-0.112	-0.022	-0.116
	(-0.59)	(-1.36)	(-0.64)	(-1.31)	(-0.60)	(-1.35)
Panel C: Scaled Market value of equity (MV_CSHO)						
LCITX	**0.009****	**0.028*****	-0.055	0.120	**0.013****	**0.052*****
	(2.20)	(6.78)	(-0.31)	(0.72)	(2.27)	(7.20)
TCO2_CSHO	-0.017	-0.126	-0.009	-0.122	-0.013	-0.120
	(-0.37)	(-1.34)	(-0.19)	(-1.27)	(-0.29)	(-1.28)
Market model Controls	included	included	included	included	included	included
Carbon tweets Choice	Yes	Yes	Yes	Yes	Yes	Yes
Industry, year FE	included	included	included	included	included	included
Observations	1384	2364	1384	2364	1384	2364
Uncensored	671	885	671	885	671	885

Table 7: Cross-sectional analyses

Panels D to F: Paris Agreement effects – Carbon Interactivity, Emissions and Firm Value

	CITXT		CITX_from		CITX_about	
	Year <2016	Year>= 2016	Year <2016	Year >= 2016	Year <2016	Year >= 2016
	(1)	(2)	(3)	(4)	(5)	(6)
Panel D: Market value of equity (MV)						
CITX	**1,866.321*****	**-92.238*****	**-203905.540****	-70,490.427	**4,704.632*****	**-482.814****
	(3.67)	(-3.09)	(-1.97)	(-1.42)	(3.74)	(-2.50)
TCO2	-0.084	**-0.167***	**-0.158****	**-0.237****	**-0.090***	**-0.208****
	(-1.54)	(-1.76)	(-2.40)	(-2.43)	(-1.66)	(-2.24)
*CITX*TCO2*	**0.020*****	**0.015*****	**9.156*****	**9.787*****	**0.077*****	**0.131*****
	(3.05)	(6.78)	(3.91)	(6.00)	(4.46)	(9.09)
Panel E: Scaled Market value of equity (MV_CSHO)						
CITX_CSHO	1,556.074	**68.414*****	-42,573.016	18,381.661	**7,209.513*****	**285.525****
	(1.62)	(3.72)	(-1.56)	(0.60)	(2.72)	(2.27)
TCO2_CSHO	-0.040	-0.138	-0.028	-0.099	-0.008	-0.147
	(-0.78)	(-1.45)	(-0.54)	(-0.96)	(-0.16)	(-1.55)
*CITX_CSHO*TCO2_CSHO*	13,292.710	**970.541****	300,896.870	-493709.429	-16,181.984	**18,788.236*****
	(0.89)	(1.99)	(0.65)	(-0.71)	(-0.33)	(3.63)
Panel F: Scaled Market value of equity (MV_CSHO)						
LCITX	**0.007***	**0.024*****	-0.139	**0.366***	**0.012***	**0.036*****
	(1.77)	(5.51)	(-0.68)	(1.69)	(1.95)	(4.37)
TCO2_CSHO	-0.036	**-0.207****	-0.030	-0.055	-0.019	**-0.244****
	(-0.70)	(-1.99)	(-0.56)	(-0.53)	(-0.35)	(-2.50)
*LCITX*TCO2_CSHO*	0.059	**0.257***	1.311	**-7.058***	0.038	**1.301*****
	(0.71)	(1.78)	(0.71)	(-1.77)	(0.19)	(3.98)
Market model Controls	included	included	included	included	included	included
Carbon tweets Choice	Yes	Yes	Yes	Yes	Yes	Yes
Industry, year FE	included	included	included	included	included	included
Observations	1384	2364	1384	2364	1384	2364
Uncensored	427	885	427	885	427	885

Using the twostep method, we estimate the Heckman (1979) model to correct for selection bias; that is, we estimate the firm-value model jointly with the disclosure choice model by S&P index. t-statistics are included in parentheses *, ** or *** indicates a significance level at 10%, 5%, and 1%, respectively, using a two-tailed test. All variables are defined in Appendix A.

Table 8: Cross-sectional analyses

Panel A: S&P 500, S&P 400, S&P 600

	Market value of equity (MV or MV_CSHO)								
	SP500			**SP400**			**SP600**		
	CITXT	CITX_from	CITX_about	CITXT	CITX_from	CITX_about	CITXT	CITX_from	CITX_about
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CITX	**149.378*** **	**118,575.364** **	**1,523.819*** **	0.964	2,248.789	1.776	-1.720	1,066.196	-11.415
	(5.35)	(2.24)	(7.84)	(1.40)	(0.98)	(0.27)	(-0.82)	(0.28)	(-0.86)
TCO2	-0.117	**-0.150** **	-0.109	-0.018	-0.018	-0.018	**-0.279* **	**-0.281* **	**-0.279* **
	(-1.58)	(-2.01)	(-1.51)	(-0.83)	(-0.84)	(-0.81)	(-1.75)	(-1.76)	(-1.74)
CITX_CSHO	**763.651*** **	47,637.329	**12,724.224*** **	0.197	6,650.624	1.033	-1.088	**12,420.359** **	-0.573
	(18.93)	(0.91)	(29.97)	(0.12)	(1.30)	(0.07)	(-0.24)	(2.02)	(-0.02)
TCO2_CSHO	-0.122	**-0.163* **	-0.087	-0.021	-0.022	-0.021	-0.410	-0.371	-0.410
	(-1.52)	(-1.77)	(-1.26)	(-0.56)	(-0.59)	(-0.56)	(-1.15)	(-1.05)	(-1.16)
LCITX	**0.033*** **	0.2014	**0.064*** **	0.001	0.038	0.001	0.002	0.077	0.001
	(8.59)	(1.07)	(9.60)	(0.77)	(0.93)	(0.29)	(0.44)	(0.58)	(0.22)
TCO2_CSHO	**-0.154* **	**-0.156* **	-0.144	-0.022	-0.021	-0.021	-0.415	-0.407	-0.413
	(-1.70)	(-1.69)	(-1.60)	(-0.60)	(-0.58)	(-0.57)	(-1.17)	(-1.15)	(-1.16)
Market model controls	included	included	included	included	included	included	included	included	included
Industry, year FE	included	included	included	included	included	included	included	included	included
Observations	3,299	3,299	3,299	2576	2576	2576	3990	3990	3990
Uncensored	1115	1115	1115	430	430	430	325	325	325

Using the twostep method, we estimate the Heckman (1979) model to correct for selection bias; that is, we estimate the firm-value model jointly with the disclosure choice model by S&P index. t-statistics are included in parentheses *, ** or *** indicates a significance level at 10%, 5%, and 1%, respectively, using a two-tailed test. All variables are defined in Appendix A.

Table 8: Cross-sectional analyses

Panel B: S&P 500 – Carbon Interactivity, Carbon Emissions and Market Value

	S&P 500											
	MV				**MV_CSHO**				**MV_CSHO (Log CITX)**			
	CITXT	CITX_from	CITX_about	CITX	CITXT	CITX_from	CITX_about	CITX	CITXT	CITX_from	CITX_about	CITX
	1	2	3	4	5	6	7	8	9	10	11	12
CITX	50.173				-31.536				-31.536			
	(1.47)				(-0.61)				(-0.61)			
TCO2	-0.178**	-0.295***	-0.216***	-0.259	-0.210***	-0.104	-0.175**	-0.101	-0.209***	-0.104	-0.175**	-0.206**
	(-2.41)	(-3.80)	(-2.96)	(-3.41)	(-3.06)	(-1.03)	(-2.52)	(-1.36)	(-3.06)	(-1.03)	(-2.52)	(-1.94)
*CITX*TCO2*	**0.012*** **				**54,662.400*** **				**54,662.400*** **			
	(5.01)				-20.68				(20.68)			
CITX_from		**- 194497.38** **		**-124475.90* **		95,007.480		**86028.350* **		95,007.470		0.041
		(-2.53)		**(-1.65)**		(1.56)		(1.93)		(1.56)		(0.18)
*CITX_from*TCO2*		**10.707*** **		**4.252** **		-1050200		**-1513639*** **		-1050200		**-9.718*** **
		(5.55)		**(1.98)**		(-1.49)				(-1.49)		(-2.76)
CITX_about			**955.230*** **	**992.096*** **			**9,654.245*** **	9322.151			**9,654.250*** **	**0.049*** **
			(4.57)	**(4.79)**			(13.87)	(13.21)			(13.87)	(6.52)
*CITX_about*TCO2*			**0.088*** **	**0.075*** **			**146,210.260*** **	**161272.9*** **			**146,210.260*** **	**1.464*** **
			(6.7)	(4.79)			(5.5)	(5.93)			(5.5)	(4.01)
Market model controls	included	included	included	included	included	included	included	included	included	included	included	included
Carbon Tweets Choice	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry, year FE	included	included	included	included	included	included	included	included	included	included	included	included
Observations	3,299	3,299	3,299	3,299	3,299	3,299	3,299	3,299	3,299	3,299	3,299	3,299
Chi	4522	4511	4751	4772	3184	1247	3234	3271	3184	1247	3234	4471
Uncensored	1115	1115	1115	1115	1115	1115	1115	1115	1115	1115	1115	1115

Using the twostep method, we estimate the Heckman (1979) model to correct for selection bias; that is, we estimate the firm-value model jointly with the disclosure choice model by S&P index. t-statistics are included in parentheses *, ** or *** indicates a significance level at 10%, 5%, and 1%, respectively, using a two-tailed test. All variables are defined in Appendix A.

Table 9 Additional Analysis by Nature of Tweets – Full Sample

	Panel A: Unscaled Market value of equity (MV)							
Carbon interactivity =	*CITX_Tweets*		*CITX_Retweets*		*CITX_Likes*		*CITX_Replies*	
	1	2	3	4	5	6	7	8
CITX	**303.740*** **	**169.120** **	**63.786** **	18.047	**28.704** **	4.537	237.220	-58.553
	(4.47)	(2.55)	(2.24)	(0.65)	(2.18)	(0.34)	(1.57)	(-0.38)
TCO2	**-0.181*** **	**-0.291*** **	**-0.186*** **	**-0.258*** **	**-0.185*** **	**-0.206*** **	**-0.186*** **	**-0.234*** **
	(-3.40)	(-5.54)	(-3.47)	(-4.91)	(-3.45)	(-3.89)	(-3.46)	(-4.14)
*CITX*TCO2*		**0.116*** **		**0.064*** **		**0.023*** **		**0.276*** **
		(11.65)		(10.85)		(7.84)		(8.21)
	Panel B: Scaled Market value of equity (MV_CSHO)							
CITX_CSHO	**108.370*** **	**96.356*** **	**37.246** **	**33.040** **	**20.222*** **	**17.901** **	**216.574*** **	**207.725** **
	(2.93)	(2.58)	(2.35)	(2.06)	(2.8)	(2.43)	(2.76)	(2.56)
TCO2_CSHO	**-0.108***	**-0.115** **	**-0.108***	**-0.112** **	**-0.109***	**-0.112** **	**-0.109***	**-0.110***
	(-1.92)	(-2.04)	(-1.92)	(-1.99)	(-1.93)	(-1.98)	(-1.93)	(-1.95)
CITX*TCO2_CSHO		**6,522.382** **		**2,412.661***		673.352		1,680.478
		(2.17)		(1.86)		(1.59)		(0.45)
	Panel C: Scaled Market value of equity (MV_CSHO)							
LCITX	**0.040*** **	**0.036*** **	**0.034*** **	**0.030*** **	**0.028*** **	**0.026*** **	**0.060*** **	**0.049*** **
	(9.95)	(8.3)	(9.62)	(7.95)	(9.95)	(8.57)	(10.25)	(7.78)
TCO2_CSHO	**-0.106***	**-0.162*** **	**-0.107***	**-0.155*** **	**-0.106***	**-0.146** **	**-0.104***	**-0.138** **
	(-1.91)	(-2.72)	(-1.93)	(-2.68)	(-1.92)	(-2.54)	(-1.89)	(-2.50)
LCITX*TCO2_CSHO		**0.468** **		**0.411*** **		**0.279** **		**1.449*** **
		(2.44)		(2.67)		(2.39)		95.13)
Market model controls	included	included	included	included	included	included	included	included
Industry, year FE	included	included	included	included	included	included	included	included
Observations	9,865	9,865	9,865	9,865	9,865	9,865	9,865	9,865
Uncensored	1870	1870	1870	1870	1870	1870	1870	1870

Using the twostep method, we estimate the Heckman (1979) model to correct for selection bias; that is, we estimate the firm-value model jointly with the disclosure choice model by S&P index. t-statistics are included in parentheses *, ** or *** indicates a significance level at 10%, 5%, and 1%, respectively, using a two-tailed test. All variables are defined in Appendix A.

Table 10: Sensitivity Analysis

Panel A: Additional Visibility Control Variables

Dependent variable: Market Value (MV)	*CITXT* *1*	*CITX_from* *2*	*CITX_about* *3*	*CITX* *4*
CITX	**16.313****			
	(2.12)			
CITX_from		**37,296.969***		-23,831.004
		(1.66)		(-0.87)
CITX_about			**272.782*****	**314.516*****
			(4.07)	(3.81)
ASSET	0.926***	0.937***	0.916***	0.913***
	(14.19)	(14.40)	(14.09)	(14.00)
LIAB	-0.708***	-0.726***	-0.698***	-0.690***
	(-7.41)	(-7.60)	(-7.33)	(-7.22)
OPINC	6.944***	6.988***	6.894***	6.864***
	(26.99)	(27.08)	(26.84)	(26.50)
TCO2	-0.165***	-0.167***	-0.161***	-0.160***
	(-3.13)	(-3.17)	(-3.08)	(-3.06)
ANFWG	827.636***	838.476***	815.253***	810.745***
	(8.66)	(8.77)	(8.55)	(8.49)
ADV	347.677	373.040	362.436	354.514
	(1.03)	(1.11)	(1.08)	(1.06)
Choice of carbon tweets model	Yes	Yes	Yes	Yes
Constant	Included	Included	Included	Included
Industry and Year	Included	Included	Included	Included

Observations	9865	9865	9865	9865
Chisq	6915	6904	6973	6978
Uncensored	1870	1870	1870	1870

Panel B: Cross sectional analysis High and Low Analyst Following

Dependent Market Value (MV)	Number of Analyst following (ANFWG) (N = 9,865)							
	CITXT		*CITX_from*		*CITX_about*		CITX	
	High	Low	High	Low	High	Low	High	Low
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
CITXT	**156.643*** **	1.016						
	(5.97)	(0.76)						
CITX_from			**121,904.276** **	3,625.816			**89,094.136* **	6,216.0001
			(2.47)	(0.83)			(1.84)	(0.94)
CITX_about					**1,594.543*** **	3.344	**1,567.981*** **	-9.565
					(8.76)	(0.28)	(8.60)	(-0.52)
TCO2	-0.175**	-0.029	-0.219***	-0.028	-0.165**	-0.029	-0.168**	-0.0279
	(-2.50)	(-1.30)	(-3.11)	(-1.27)	(-2.39)	(-1.30)	(-2.44)	(-1.25)
Choice of carbon tweets model	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Included	Included	Included	Included	Included	Included	Included	Included
Industry and Year	Included	Included	Included	Included	Included	Included	Included	Included

Panel C: Excluding Covid-19 2020

Dependent: Market Value (MV)	Total Sample (N=8713)			
	CITXT	*CITX_from*	*CITX_about*	CITX
	1	*2*	*3*	*4*
CITX	**18.452****			
	(2.26)			
CITX_from		**45,992.305****		-28,999.746
		(2.00)		(-1.00)
CITX_about			**304.279*****	**355.848*****
			(4.59)	(4.23)
TCO2	-0.181***	-0.183***	-0.178***	-0.177***
	(-3.46)	(-3.49)	(-3.41)	(-3.39)
	CO2 sample (N=3,201)			
	CITXT	*CITX_from*	*CITX_about*	CITX
	1	*2*	*3*	*4*
CITX	**145.480*****			
	(5.22)			
CITX_from		**121,600.906*****		**99,207.750*****
		(3.42)		(2.84)
CITX_about			**1,240.387*****	**1,194.208*****
			(7.10)	(6.84)
TCO2	-0.133**	-0.144**	-0.128**	-0.124**
	(-2.27)	(-2.45)	(-2.21)	(-2.15)
Choice of carbon tweets model	Yes	Yes	Yes	Yes
Constant	Included	Included	Included	Included
Industry and Year	Included	Included	Included	Included

Panel D: Ohlson model

Dependent: Market Value (MV)	Total Sample (N=9,865)			
	CITXT	*CITX_from*	*CITX_about*	CITX
	1	*2*	*3*	*4*
CITX	**18.197****			
	(2.30)			
CITX_from		9,710.788		**-64,703.179****
		(0.41)		(-2.24)
CITX_about			**277.158*****	**389.484*****
			(3.99)	(4.53)
TCO2	-0.226***	-0.229***	-0.222***	-0.217***
	(-4.11)	(-4.16)	(-4.04)	(-3.94)
BVEQ	1.802***	1.814***	1.789***	1.781***
	(27.84)	(28.12)	(27.64)	(27.48)
EARN	7.127***	7.154***	7.080***	7.039***
	(25.70)	(25.81)	(25.54)	(25.34)

Dependent: Market Value (MV)	CO2 sample (N=3,748)			
	CITXT	*CITX_from*	*CITX_about*	CITX
	1	*2*	*3*	*4*
CITX	**98.621*****			
	(4.04)			
CITX_from			24,741.158	15,990.859
			(0.63)	(0.41)
CITX_about		**840.479*****		**836.972*****
		(4.72)		(4.70)
TCO2	-0.155**	-0.150**	-0.172***	-0.150**
	(-2.39)	(-2.31)	(-2.64)	(-2.31)
CEQ	1.681***	1.665***	1.743***	1.665***
	(20.81)	(20.61)	(21.95)	(20.61)
IB	7.209***	7.136***	7.381***	7.141***
	(21.53)	(21.28)	(22.13)	(21.29)
Choice of carbon tweets model	Yes	Yes	Yes	Yes
Constant	Included	Included	Included	Included
Industry and Year	Included	Included	Included	Included

Panel E: MV FIML model

Dependent: Market Value (MV)	Total Sample (N=9,865)			
	CITXT	*CITX_from*	*CITX_about*	CITX
	1	*2*	*3*	*4*
CITX	**19.364****			
	(1.97)			
CITX_from		33,923.499		-38,546.954
		(0.75)		(-0.57)
CITX_about			**301.409****	**368.763****
			(2.56)	(2.19)
TCO2	-0.190***	-0.194***	-0.187***	-0.184***
	(-2.75)	(-2.82)	(-2.74)	(-2.77)
ASSET	0.935***	0.948***	0.925***	0.919***
	(7.06)	(7.10)	(7.02)	(6.93)
LIAB	-0.753***	-0.773***	-0.740***	-0.727***
	(-3.66)	(-3.75)	(-3.64)	(-3.57)
OPINC	7.201***	7.247***	7.148***	7.099***
	(10.17)	(10.49)	(10.12)	(10.21)
Dependent: Market Value (MV)	CO2 sample (N=3,748)			
	CITXT	*CITX_from*	*CITX_about*	CITX
	1	*2*	*3*	*4*
CITX	**102.409*****			
	(2.78)			
CITX_from		97,671.7263		82,917.352
		(0.93)		(0.89)
CITX_about			**908.276*****	**881.902*****
			(3.09)	(3.28)
TCO2	-0.134**	-0.150**	-0.133**	-0.130**
	(-2.01)	(-2.17)	(-2.02)	(-1.96)
ASSET	0.985***	1.055***	0.978***	0.981***
	(6.99)	(7.54)	(6.96)	(6.95)
LIAB	-0.835***	-0.933***	-0.818***	-0.839***
	(-4.26)	(-4.98)	(-4.15)	(-4.42)
OPINC	7.358***	7.562***	7.216***	7.313***
	(9.65)	(11.01)	(9.35)	(10.29)
Choice of carbon tweets model	Yes	Yes	Yes	Yes
Constant	Included	Included	Included	Included
Industry and Year	Included	Included	Included	Included

Using the Full Information Maximum Likelihood (FIML) method, we estimate the Heckman (1979) model to correct for selection bias; that is, we estimate the firm-value model jointly with the twitter carbon disclosure choice model for both full sample and those with carbon emissions. Note: in full sample model, observations without carbon emissions values are replaced with 0. t-statistics are included in parentheses and are based on Huber-White robust standard errors. *, ** or *** indicates a significance level at 10%, 5%, and 1%, respectively, using a two-tailed test. All variables are defined in Appendix.

Table 11: Endogeneity Issue – Other techniques

Panel A: Propensity score matching (PSM) – OLS Regression

Dependent: Market Value (MV)	Total Sample (N=2,606)			
	CITXT *1*	*CITX_from* *2*	*CITX_about* *3*	CITX *4*
CITX	**11.279****			
	(1.98)			
CITX_from		**14,886.621***		**-93,214.101***
		(1.81)		(-1.88)
CITX_about			**227.217****	**385.440****
			(2.21)	(2.23)
TCO2	-0.211	-0.214	-0.202	-0.184
	(-1.04)	(-1.05)	(-1.01)	(-0.94)
ASSET	1.080***	1.082***	1.076***	1.066***
	(6.27)	(6.25)	(6.29)	(6.23)
LIAB	-0.706**	-0.708**	-0.702**	-0.690**
	(-2.23)	(-2.22)	(-2.27)	(-2.26)
OPINC	6.508***	6.531***	6.453***	6.407***
	(6.94)	(6.91)	(7.02)	(7.05)
Dependent: Market Value (MV)	CO2 sample (N=1,307)			
	CITXT *1*	*CITX_from* *2*	*CITX_about* *3*	CITX *4*
CITX	**154.421****			
	(2.10)			
CITX_from		50,181.576		48,436.256
		(1.30)		(1.26)
CITX_about			**952.613*****	**951.683*****
			(2.85)	(2.84)
TCO2	0.027	0.033	0.005	0.036
	(0.13)	(0.16)	(0.02)	(0.17)
ASSET	1.087***	1.074***	1.099***	1.072***
	(6.03)	(5.95)	(5.75)	(5.94)
LIAB	-0.870***	-0.843***	-0.885***	-0.841***
	(-2.99)	(-2.86)	(-2.67)	(-2.85)
OPINC	6.475***	6.372***	6.842***	6.365***
	(7.20)	(7.08)	(7.30)	(7.06)
Choice of carbon tweets model	Yes	Yes	Yes	Yes
Constant	Included	Included	Included	Included
Industry and Year	Included	Included	Included	Included

(note: adjusted R-squared for each estimation range between 0.70 and 0.863 and F test are all significant at p<0.01)

Table 11: Endogeneity Issue – Other techniques

Panel B: Entropy Balancing (EBM) – OLS Regression

	Total Sample (N=9,865)			
Dependent: Market Value (MV)	*CITXT* *1*	*CITX_from* *2*	*CITX_about* *3*	CITX *4*
CITX	**21.775***			
	(1.93)			
CITX_from		14,890.709		-34,616.908
		(0.59)		(-0.77)
CITX_about			**214.325***	**251.017***
			(1.75)	(1.68)
TCO2	-0.174***	-0.182***	-0.175***	-0.174***
	(-4.65)	(-4.79)	(-4.69)	(-4.68)
ASSET	0.559***	0.565***	0.556***	0.555***
	(3.95)	(4.06)	(3.94)	(3.94)
LIAB	-0.277	-0.255	-0.257	-0.255
	(-1.52)	(-1.39)	(-1.40)	(-1.40)
OPINC	6.163***	6.098***	6.080***	6.065***
	(10.67)	(10.72)	(10.64)	(10.57)
	CO2 sample (N=3,748)			
Dependent: Market Value (MV)	*CITXT* *1*	*CITX_from* *2*	*CITX_about* *3*	CITX *4*
CITX	**27.282****			
	(2.27)			
CITX_from		29,153.709		28,535.715
		(0.50)		(0.51)
CITX_about			**393.351***	**393.064***
			(1.94)	(1.93)
TCO2	-0.116***	-0.125***	-0.114***	-0.113***
	(-3.19)	(-3.35)	(-3.14)	(-3.11)
ASSET		0.576***	0.555***	0.554***
		(4.38)	(4.11)	(4.09)
LIAB		-0.310*	-0.303*	-0.305*
		(-1.84)	(-1.80)	(-1.80)
OPINC		6.353***	6.296***	6.310***
		(11.04)	(10.81)	(10.82)
Choice of carbon tweets model	Yes	Yes	Yes	Yes
Constant	Included	Included	Included	Included
Industry and Year	Included	Included	Included	Included

(note: adjusted R-squared for each estimation range between 0.845 and 0.863 and F test are all significant at p<0.01)