The extent and effectiveness of Corporate Voluntary Action in the context of liberalised market policies:

The influence and implications of Energy Attribute Certificate utilisation and The Carbon Disclosure Project

Abstract

Corporate voluntary action is increasingly relevant in our global climate crisis, with methods of Greenhouse Gas emissions disclosure and certification connecting the influence of markets, stakeholders and shareholders to drive appropriate corporate action. Yet, corporate mitigation action relies increasingly on novel market-based approaches, including the use of Energy Attribute Certificates (EACs), the effectiveness of which has been questioned. There is a need to unite the critical analysis of these instruments with perspectives of strategic certification and disclosure, to further enlighten effective patterns of corporate action, and the factors that motivate them.

This thesis conducts a statistical analysis of corporate reporting with the Carbon Disclosure Project's Climate Change dataset, exploring links between corporate energy efficiency action and the utilisation of EACs. The analysis considers industry groupings, reporting methodologies and market variables, such as price sensitivity and consumer exposure, to produce a holistic picture of strategic certification and disclosure.

The dual nature of EAC utilisation, for both accounting and the appropriation of beneficial attributes, is linked to a divergence in the outcomes of corporations who are, or are not, utilising the signalling benefits of EACs through market-based reporting. Strategic uses of EACs in combination with the market-based method (Signallers) and location-based method (Assurers) were identified, driven by trade-offs between the benefits of external signalling, and the benefits of internal abatement and accounting. These differences were linked to mitigation investment and outcomes with the latter group providing exceptional transparency and excellence, exhibiting a greater extent of efficiency-based action. EAC use overall correlated significantly with lower emissions mitigation outcomes, demonstrating reduced cost-effectiveness in efficiency-based and low-carbon initiatives alike.

The dual lens of EAC analysis underpins recommendations such as the use of Zero-One-Inflated Beta Distributions to improve the modelling of corporate action and the implementation of mandatory demand targets to realise additionality within EAC purchasing.

Introduction

Industrial contributions to Climate Change:

Modern economies are growing rapidly and becoming increasingly globalised, leading to increased Greenhouse Gas (GHG) emissions and supply chain complexity, whilst the efforts of international co-operation have proved insufficient in addressing the emerging climate crisis posed by global warming (Huwart and Verdier, 2013). Industry GHG emissions (defined by IPCC as relating to the creation of physical goods) have increased and are higher than other energy end-use sectors, with literature suggesting broad mitigation options beyond energy efficiency are required for an absolute emissions reduction, particularly to offset sector growth (Fischedick et al., 2014). For instance, energy consumption of both services and industry rose in the UK over 2017-2018, with the former increasing 1.1%, though the latter remained relatively stable at just +0.3% (Waters, 2019). However, significant opportunities for energy intensity reductions exist still, up to ~25%, with focus on developing global markets (Fischedick et al., 2014). Shifts from fossil fuels to electricity with low or negative emissions factors are highlighted for importance in long term scenarios, with the quality, completeness and certainty of publicly available data raised as a significant challenge (ibid.).

Corporate Short-Termism: The Danger of Target-Based Approaches

Troubling trends have emerged from recent reports, with FCLT Global reporting a rise in short-termism across “a full range of industries and functions”, with an ~8% increase in senior executive respondents reporting feeling “pressure to demonstrate strong financial performance within two years or less”, at 87% (Barton, et al., 2018). This short-termism was also found in Graham et al.’s paper, with 80% of participants allowing a theoretical decrease in Research and Development or Maintenance, and 55.3% proposing delaying a new project (even sacrificing value), just to meet an immediate earnings target (Graham, et al., 2005).

Projecting and producing change: The Role of Finance and Frameworks

These perverse executive incentives seem to have failed the wider public on issues such as climate change, but the financing of large scale and corporate emissions mitigation projects also presents obstacles. Looking at climate change projections, primarily the IPCC’s representative concentration pathway (RCP) framework, uncertainty also is raised as a significant issue. The Stern Review (Weitzman, 2007) concerned itself with these two strands: firstly stating that current discount rates are far too high to justify the “strong, early action on climate change” required to stabilise GHG levels; secondly proposing that large, difficult to quantify uncertainties should be avoided. The major shifts in investment patterns and expectations require the involvement of central banks, regulators and financial firms, alongside the frameworks and methodologies supporting both mandatory and voluntary corporate action (Bank of England, 2019).

Corporations engage with this action to identify and account for climate risks, whether reputational, market-based, physical or litigative, as well as the opportunities the climate crisis presents, for improving governance, profitability, and strategic advantage. The role of financial instruments shall be explored alongside concepts of corporate voluntary action (CVA) in the following section, showing how each may act as a catalyst or a barrier to effective action.

Energy Attribute Certificates (EACs) and Other Market-Based Instruments

One form of market-based or legislative risk comes from Carbon-pricing and Emissions Trading Schemes (ETS), designed to incentivise mitigation projects by internalising the cost of emissions within polluting institutions, in line with the "Polluter Pays" principle (European Commission, n.d.). The EU's ETS is a complex system, but attributable emissions savings range from 40 – 80 $MtCO_2$/year, or 2-4% of total capped emissions, averaged 2008-2013 (Laing et al., 2014). Analysis found there were no negative impacts to corporate competitiveness during the first two phases, rather small stimulating effects to innovation, however the former has been attributed to over-allocation of allowances, and the ability of firms to pass costs to consumers (Joltreau and Sommerfeld, 2018). The over-allocation of free permits is simply a transfer of tax payer's funds (at least €7 billion) to industry, with no additional social benefit. (Martin et al., 2010). One form of carbon-pricing is derived from the inherent difference in emissions intensity of differing fuels and renewable energy sources. This pricing is realised through a market for attribute certificates, which quantify the emissions associated with a specified quantity of energy (e.g. MWh). The trade in these attributes is separate from the physical electricity, occurring through Energy Attribute Certificates (EACs). These instruments are present in the EU's ETS, and may also be undermined by over-supply and the appropriation of tax-payer funds. Terms such as "EAC utilisation", and "extent" or "effectiveness" of corporate action are defined in Appendix A.

In Summary

Corporations have a role to play, but must be correctly incentivised, given that target-based approaches can lead to perverse short-termism. CVA links to risk management, which include government emissions "incentivisation" through carbon-pricing/ETS. The effects of some of these ETS have not negatively impacted corporations but rather may have transferred public funds to them.

One must question how societies can best incentivise and manage corporate action, in order to ensure action is completed to the extent and effectiveness expected?

Previous Literature and the Path Forward

CVA, CSR and other TLAs

Questioning the efficacy of Corporate Voluntary Action (CVA), requires not just consideration of the resultant actions of the corporation, and their effects upon society; but also the pathways that led the corporation to that action. Traditional perspectives include a top-down approach deemed “Corporate Social Responsibility”, for which Allen and Craig (2016) describe corporate action as discretionary, sporadic, short-term and idiosyncratic. This is exemplified by the corporate embodiment of self-selected, self-serving social values, with Bowers’ work (2010) finding a “concerted effort to define sustainability in terms of economic value”, where one-way communication and focus on stakeholders issues may underrepresent the publics’ perspectives on the efficacy and desirability of corporate action (Department for Business, Innovation & Skills, 2014)

Whilst these stakeholder issues could be presumed to be independent factors for each corporation, Uysal (2014) found that any engagement from activist shareholders can initiate reactive responses, leading to more proactive measures that may “meet or even exceed societal expectations of a broader set of stakeholders”. The stakeholder interface is emphasised within the concept of Corporate Social Responsiveness (CSR), described by William C Frederick as “the capacity of a corporation to respond to social pressures” (Frederick, 1994). This thesis shall capitalise on how CSR eschews the solely top-down approach, focusing instead on "how organizational processes and structures need to react to the social needs and values of a wide range of individuals and groups who have an interest in the organization … Responsiveness concerns the relative permeability of the organization’s boundaries and its willingness and ability to anticipate and adjust to society’s changing character, needs, and values. In this way responsive organizations are able to be more socially responsible by virtue of their willingness to hear and respond to social needs, standards, and values” (Seeger and Hipfel, 2007, p. 157).

Frederick’s CSR framework was epitomised by a few key questions and statements: “**Can a company respond? Will it? Does it? How does it? To what extent? And with what effect?** One searches the organization for mechanisms, procedures, arrangements and behavioural patterns that, taken collectively, would mark the organisation as more or less capable of responding to social pressures.” (Frederick, 1994, emphasis added).

Frederick's definition (1994) shift towards the pragmatic, managerial approach of CSR integrates wider driving forces behind CVA, which corporations pursue not primarily for the benefits of running an environmentally-sustainable, socially-just business, but principally for the benefits that occur from signalling that a business is capable of responding to changing societal expectations and pressures. This literature review shall harness this pragmatism, focusing on two aspects of Frederick's questioning of CSR:

To what extent does a corporation respond? With what effect?

Unsurprisingly, particularly for corporations concerned with brand value, investors and stakeholders are driving disclosure of corporate policy and action relating to CSR. For environmental policies affecting water quality, land use and climate change, the Carbon Disclosure Project (CDP) unites and codifies corporate disclosure. These CSR policy areas are often used as proxies for organisational effectiveness and brand reputation, as demonstrated by white papers espousing the benefits of CDP disclosure for "operational efficiency" and "financial performance" (ADEC Innovations, 2017). In fact the CDP is utilised in Environmental, Social and Governance (ESG) scores, which are used as the primary metric for CSR by investors, which have also been linked to corporate financial performance, and a high ESG score offers a corporation significant advantages: through higher valuations and lower costs of capital, higher profitability and lower tail risk exposure (Giese et al., 2019), and lower share price volatility (Jakobsson and Lundberg, 2018).

ESG scoring can consider some 400+ metrics (Refinitiv, 2019), but while these cannot fully communicate all the elements of organisational CVA, Siew et al (2016) correlated ESG disclosures to lower bid-ask spreads, indicating a lower liquidity cost, and therefore lower information asymmetry. However, opportunities for unrepresentative or ineffective signalling persist, with the effect attenuated by higher levels of institutional ownership, due to increased exploitation of private ESG information (Siew, Balatbat and Carmichael, 2016). Targeting green signals to a given audience, particularly institutional investors, may lead to the uptake of specialised instruments and certification, the representativeness and effectiveness of which varies. This shows that not only the quantity of information disclosed is important, but how and who it is disclosed to, an issue of contention for investor-led disclosure systems such as the CDP. The efficacy and legitimacy of signalling is a key issue to all corporations undertaking disclosure, and here comparable, verified disclosure becomes essential, provided through various systems of certification.

The CDP as certification.

Certification is the confirmation of specified characteristics of an organisation or its actions. Certification can occur at various levels, sometimes stacked within one another, as is the case with the CDP, where data is "prone to manipulation through the bundles of certification it employs" (Røpke, 2016).

Tang and Luo describe the CDP as constituting a "voluntary code developed by a non-government organization to encourage consideration of carbon emission issues in decision making" which can "flexibly bridge the gap between individual companies' sustainability initiatives and mandatory, legal regulation." (Tang and Luo, 2011). Tang and Luo's description of the CDP as a "code" is interpretable in two ways: either that disclosing corporations are following a set of principles within the CDP's sphere; or that the CDP codifies acceptable and excellent carbon disclosure. Considering the CDP as an investor-led "code" leads to the prioritisation of verification and assurance, and therefore the CDP can be viewed as a form of composite certification, where groups of finer attributes are bundled into a single overview of the quantity and quality of disclosure.

It should also be stated that despite the CDP maintaining a level of accessibility to the general public, the platform is primarily investor-led, therefore when considering carbon disclosure, this is within the context of shareholder activism. The CDP is in a unique position as a centralised platform for disclosure of not just emissions, but also environmental impacts related to water usage, forestry and a host of other anthropogenic impact areas, however this thesis shall concern itself solely with greenhouse gas emissions mitigation.

The case for certification

One could question why corporations certify and disclose in the first place, but corporations are motivated by many incentives, as disclosure provides not only a positive proxy signalling organisation effectiveness, but also aids in reducing exposure to emerging regulation, demonstrated by increased investment and involvement with renewable energy projects for affected industries (Southworth, 2009). The assessment and management of risk often motivates disclosure, for both investors and corporations, with the latter facing not only direct financial risks through stranded assets, but also reputational risks, as belied by increased climate change response for businesses with integrated climate change risk management and greater interaction with the end consumer (Damert and Baumgartner, 2017). The same analysis found these risk factors to be much more influential than both a corporation's native climate change policy, or its degree of internationalisation (ibid.). In terms of direct financial incentives, such as those linked to share price, two narratives are presented. The first, by Prakash et al. (2011), proposes that “markets penalize all firms for their carbon emissions, but a further penalty is imposed on firms that do not disclose emissions information.”, motivating disclosure and mitigation alike.

The second narrative states that the influence of climate change mitigation on share performance has been overestimated, with mainstream investors lacking a business case, and the actions of ethical investors being counteracted by arbitrage (Harmes, 2011). The latter focuses on the weakness of the carbon risk business case, that disclosure does not aid with the internalisation of externalities due to the lack of real costing of climate change mitigation, citing a 2008 study of fund managers: “[v]irtually without exception, the interviewees cited the EU ETS [Emission Trading System] as the critical—and, in many cases, the only—driver for them to explicitly consider climate change in their investment analysis.” (Pfeifer and Sullivan, 2008, p. 258). This mandated pricing approach alongside the analysis that mainstream investors are focused on “low-cost” and “soft” mitigation (ibid), for primarily reputational reasons, may explain the popularity of market-based approaches such as Energy Attribute Certificates.

From the investor’s perspective, disclosure allows for socially responsible investing, which integrates **“**social, environmental, and economic responsibilities into investment processes.”. This not only provides a more socially-just, responsive financial system, but also deals directly with reputational, physical and financial risk; particularly in the case of climate change where “by 2050 the economic impact of extreme events and climatic variability is projected to increase financial losses by factors up to 3.9 times those currently experienced (Preston 2013)” (Allen and Craig, 2016). Stakeholders’ carbon disclosure claims are often given priority, incentivising the stakeholder salience (Herold, 2018). From this perspective disclosure allows for stakeholders and investors to increase their salience, whilst also dealing with socially derived risk and attempting to address the increased financial losses posed by climate change. Whilst the benefits of these first two points would be provided by simply engaging in “socially responsible” practice, it should be noted that the level of information asymmetry between a corporation and its stakeholders may hamper accurate stakeholder analysis and valuation. This is particularly the case where information may be manipulated through strategic certification, before communication in a bundled format, such as in the ESG and CDP datasets that many institutional investors utilise.

From the public's perspective, carbon disclosure is useful for sensitising corporations to their expectations through improved stakeholder governance mechanisms. Influence over corporations still concentrates around stakeholders, rather than the public generally, but these stakeholders socially construct the norms and expectations the corporation will institutionalise through interaction**.** One could argue over whether this concentration of power is socially just, but with regards to incentivising action evidence shows "that shareholder activists withdraw their resolutions only when the corporate management shows 'sincerity and legitimate progress' toward meeting the goal or request posited in the resolution (Carleton et al., 1998; Graves et al., 2001, p. 296)" (Uysal and Tsetsura, 2014). Although Herold (2018) mapped the expansion of disclosure transparency within the logistics industry from 2010-2015 (Figure 1, below), corporate disclosure has been marred by the divergence of social benefit and private cost, with the lower social benefit to private cost ratios leading corporations to excessive secrecy (Haeberle and Henderson, 2016). This divergence is evident in the disparity between transparencies across sectors and institutions, with Tang and Luo (2011) reporting that "74% of 243 firms achieved 50% or higher on the [Carbon Disclosure Transparency Score] (sample average is 60%), so their reports are reasonably transparent, and the remaining were un-transparent (or opaque)." They attributed the disparity due to "a lack of managerial incentive" alongside relevant factors such as firm size, leverage, industry membership, emission trading scheme (ETS) and stringency of environmental regulation. Herold and Lee consider a similar dualism to Tang and Luo (2011), describing corporate approaches as either "transparent" or "symbolic"; with Herold building a framework to categorise the above factors as either internal or external pressures (Figure 1), with corporations responding with internal and external carbon management practices. The balance of, and engagement with, these practices determined a corporation's overall categorisation.

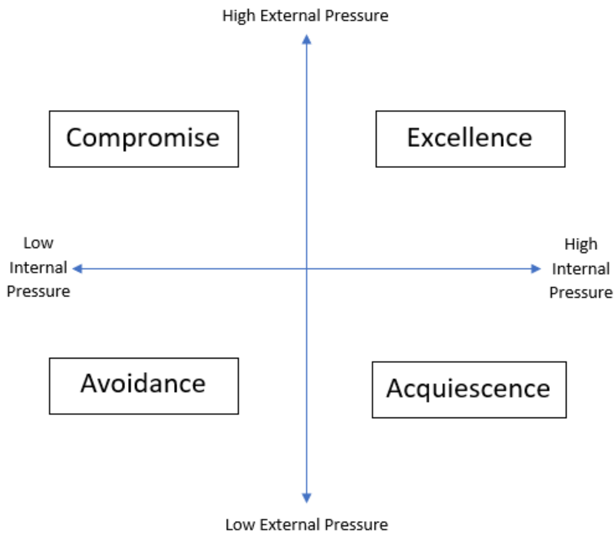


Figure 1: Herold's 2018 internal/external pressure quadrant framework for categorising strategic corporate disclosure.

Strategic Approaches: Factors affecting disclosure

Herold's full description of Figure 1's strategic categories is presented within Appendix B along with their connection to specific carbon management practices such as Verification and Assurance. This methodology analysed 26 specific internal and external carbon management practices, of a sample of 40 global logistic corporations, to form the framework. CDP and Bloomberg ESG data were used, with analysis conducted across the 2012-2014 timeseries, and consistent strategic approaches were reflected. Herold and Lee's 2018 work identified key drivers such as internal policies and procedures, or external engagement with policy makers and non-governmental organisations. Though some of these factors cannot be linked to specific CDP variables, the degree to which proxies may exist within the CDP data can be explored using timeseries overlapping with Herold's analysis, in the years 2014 and 2015. Similar analysis was repeated using the 2010-2015 timeseries in Herold's 2018 work.

Considering the factors affecting disclosure and certification generally, Genς (2013) found companies certify strategically in markets with low price sensitivity, providing the informed consumer market is sufficiently large and the certification costs are a sufficiently low proportion of production costs. Flowers et al.'s (2018) methodology revealed preferences within the building sector for corporate certification to "avoid high-cost resource use, appeal to key stakeholders, and communicate building and organization quality". Though the relevance of the study may be limited by its focus on building regulation, the paper notes the capacity for certification to mitigate market barriers associated with the energy-efficiency gap (ibid.), an issue that will be considered later when comparing corporate preferences for external market-based spending, and internal capital investment. The energy-efficiency gap case could be attributed in part to the current deployment of "soft" economic instruments (Pfeifer and Sullivan, 2008), with Røpke (2016) stating "For a long time, it has been possible to reap much larger profits through speculation in financial assets than by investing in the real economy (Kallis et al., 2009; Chang, 2011; Stiglitz, 2010)."

Introducing the Energy Attribute Certificate and Zero-Carbon emissions factors

Though many market-based instruments (MBIs) offer speculative financial returns, this thesis shall focus on Energy Attribute Certificates (EACs), and their effectiveness (or lack thereof) in incentivising additional renewable generation (see additionality, Appendix A) and mitigating carbon emissions. EACs provide a market-based accounting mechanism for Emissions Trading Schemes (ETS), allowing the "renewable" attribute of generated energy to be traded between corporations and markets. These include EU Guarantees of Origin (GOs), UK Renewable Energy GOs (REGOs), the US' Renewable Energy Certificates (RECs) and international systems such as the International Renewable Energy Certificates (I-RECs). These instruments originated from electricity or fuel mix disclosure and can provide both an emissions accounting system and, in theory, "a customer-driven demand for renewable energy" (Raadal et al., 2012). This allows organisations to modify their consumed fuel mix by "retaining ownership of the attributes for that specific production source" (Recs.org, 2020), however the cancelation (utilisation) of EACs increase the producer's grid's emissions factor, as the low-carbon attributes are cancelled for a private benefit, instead of becoming a "public commodity" (ibid.). Haeberle and Henderson's link (2016) between low public benefit-cost ratios and excessive secrecy may lower public visibility of EACs.

The efficacy of EACs can be questioned in two ways, firstly whether they genuinely deliver investment in renewable energy projects and create new generation in their current configuration. Parallel subsidisation frequently occurs for EAC markets, such as in the UK where Feed in Tariffs (FiTs), Renewable Obligation Certificates and Contracts for Difference provide financing for renewable energy generation, depending on the generator size (Maroulis, 2019). This subsidisation can reveal imperfections within markets: for example, Tamás et al. (2010) found insufficient competition between differing FiT and EAC markets, although also indicating EAC markets offered the UK higher social welfare. Despite EAC's origins as an accounting system, markets often suffer from incompatibility and inconsistencies where they meet. For example, the Norwegian-Swedish system has a deadline for projects to receive subsidies in Norway, but not Sweden, which increases reluctance to participate amongst Swedish investors (Finjord et al., 2018). This complexity produces information asymmetry and reduces market transparency, defined where "much is known by many about what products are available at what price and where", with the European Commission Intelligent Energy Programme recommending the enhancement of transparency and liquidity in EAC markets (Voogt et al., 2005). Multitude methodologies were offered to achieve this, but "providing certainty on demand" as a concept has some prominence in other papers, including Nielson and Jeppesen's 2003 analysis, stating that as supply is induced through national targets, the "demand must be induced by a politically determined demand obligation specifying the [renewable energy] part of the total energy consumption.". For example the UK's overall renewable energy target (as opposed to fuel mix legislation) was described as "purely illustrative" (Commons Select Committee on Energy and Climate Change, 2015), without the sanctions for non-compliance recommended by Nielsen and

Jeppesen. It is this mandated supply, with parallel subsidisation, that has kept the market awash with unclaimed EACS, hence prices remain far below other renewable electricity support mechanisms (Gowdy, 2018). These incredibly low prices have allowed some corporations to "green" their electricity consumption for fractions of the cost of producing new generation, claiming "100% renewable electricity", without significantly increasing the production of renewables (Raadal et al., 2012), a topic explored further in the next section.

The issue of Greenwashing

The second issue, of EAC additionality, has already been recognised at the national scale, with the Chinese approach separating the accounting and subsidisation of the electricity; where EACs are sold, they are not counted towards a province's demand compliance, and project owners cannot claim subsidies, "forcing the purchase of more capacity from other provinces, or causing additional capacity to be built" (Qiao et al., 2018). Energy supply companies have also struggled with opaque terms such as "Green Energy Tariffs", which could cover a range of programs, including EACs, calling for more transparent reporting methodologies (Gowdy, 2018). This makes it hard even for examples of corporate excellence to distinguish themselves: "the competition is so intense, and the means of marketing green products so opaque, that […] it is extremely hard for ethical companies to make a stand" (ibid.). This has already led to some corporations turning away from EACs, as illustrated by Tesco's acknowledgement in an interview with The Times newspaper, where the corporation stated that "its current policy of buying cheap "renewable certificates", which allow companies to claim they are sourcing green electricity, has "low credibility" among customers" (The Times, 2019)

It is this degree of transparency, and conversely, information asymmetry that can determine corporation's tendency for both greenwashing and certification, as was found by Genç (2013), where information asymmetry lead to greenwashing dominating in markets with low price sensitivity and proportions of informed consumers below 30%, regardless of certification costs. When the informed consumer proportion fell between 30% and 50%, the balance of certification becomes partially dependent on the certification/production cost ratio. This has two interesting implications: firstly that the utilisation and diversification of meaning for terms like "100% renewable" and "green tariff" has actually made these terms more opaque, and increased information asymmetry (Gowdy, 2018), which could constitute a positive feedback for greenwashing. Were the proportion of informed consumers to rise, the first certification to be adopted will be that with the lowest certification/production cost ratio, which at ~15p/MWh, is most likely EACs.

Secondly, one can consider the price sensitivity of markets, and consider factors that may influence this, notably level of consumption and the marginal utility of energy as found by (Nesbakken, 1999). This would lead us to find that sectors with high energy consumption and low marginal utility would be the most price sensitive (e.g. manufacturing where significant energy efficiency projects have not completed), and therefore least likely to adopt certification, or require a higher informed consumer proportion. This information can be used to predict areas where certification is less likely to emerge, such as mineral extraction or materials processing, and sectors where energy consumption is relatively low, but utility is high, such as retail, where most electricity is consumed through heating and lighting spaces, which many managers would argue provide significant utility to the retailer in meeting customer perceptions (Hetrick, Hoffman and Swartz, 2020) .

One implication for the secondary EAC market, where green attributes are purchased separately from the electricity they were associated with, is that they offer a convenient alternative to other methods of reducing Scope 2 emissions, such as Power Purchase Agreements (PPAs), or energy efficiency measures, and may be in a state of limited competition, as was found with parallel subsidisation schemes (Tamás et al., 2010). This is because EACs provide two services: theoretical abatement, and signals of "sustainability" or other organisational qualities; as seen in the building certification sector: "While building quality improvements often provide returns with or without signalling, organizational quality must be labelled to provide returns (Matisoff, Noonan, and Mazzolini 2014; Corbett and Muthulingam 2007)." (Flowers et al., 2018).

Though corporations value both aspects, one must question the balance offered by each instrument/initiative individually. For example, upgrading high power transformers may offer significant abatement, but communicating the increased efficiency to a wider audience is difficult, limiting the green signalling. EACs on the other hand offer only intangible abatement, through the theoretical motivation of new renewable capacity, but they allow easy communication of attributes, as this has been "certified" on the behalf of the corporation.

In Summary:

Corporations may embed societal expectations in a fixed or responsive manner, with varied levels of commitment, but "opportunities for unrepresentative or ineffective signalling persist" (Siew, Balatbat and Carmichael, 2016), particularly where EACs allow for the re-appropriation of another corporation's organisational quality. These negative effects may be "attenuated by higher levels of institutional ownership" (ibid.), and as certification is bundled via the CDP, opportunities for manipulation are present (Røpke, 2016). This is problematic regardless of whether the manipulation is part of "a set of principles within the CDP's sphere" or the CDP's codification of "acceptable and excellent carbon disclosure." (Tang and Luo, 2011). The pursuit of lower carbon emissions, if through insubstantial market-based instruments (not offering other benefits), may lead some to the conclusion that there is no significant difference between corporations with differing market-based emissions, leading to the arbitrage of ethical investors (Harmes, 2011).

This could undermine the sensitising and incentivising effects of ethical investors, whilst "mainstream investors are focused on "low-cost" and "soft" mitigation, for primarily reputational reasons" (Pfeifer and Sullivan, 2008). As such disclosure could undermine the attempts of ethical investors whilst corporate disclosure has been marred by the divergence of social benefit and private cost, leading corporations to excessive secrecy (Haeberle and Henderson, 2016).

Therefore, understanding corporate transparency/carbon management is very important: Herold (2018) proposes a dualism between "transparent" and "symbolic", with four categories of action based on internal and external pressure (see Figure 1). Genς (2013) provides alternative factors for strategic certification: price sensitivity, information asymmetry and certification costs within a market. From examination of EACs schemes their dual nature can be revealed, compounding issues such as parallel subsidisation, incompatibility across EAC market borders and market complexities increasing information asymmetry. As the public subsidises mandatory supply with no mandated demand, unclaimed EACs become "low-cost", "soft" mitigation, that allow corporations to "green" their electricity consumption at the fraction of the cost of producing new renewable generation.

It is important to question if EACs do play a role in "greenwashing", attempt to link EAC utilisation to the factors proposed by Herold and Genς, and investigate whether there are compound effects beyond their lack of additionality. This thesis shall explore what insight into CVA and signalling may be gained through uniting the dual lens of EAC utilisation with Frederick's questioning of CSR. The thesis' objectives, below, ask whether, and why EAC use may modify the extent and the effectiveness of corporate mitigation action.

The Objectives of this Thesis

1. To explore the relationship between EAC purchase and less theoretical forms of abatement, such as energy efficiency.
2. To explore links between other factors contributing to strategic certification, such as the price sensitivity of electricity across various industries, and the reputational or organisational qualities communicated by industry membership.

From these objectives Null and Alternative Hypotheses were finalised (referred to as the NH and AH respectively) for each of the objectives, as numbered above:

1. NH: There will be no statistically significant correlation between utilisation of EACs (NH1.1), the proportional certification of Scope 2 electricity (NH1.3), or their market-based outcomes (NH1.2); and corporate energy efficiency mitigation through "Process" and "Other" emissions reduction activities.
   AH: There will be a statistically significant correlation between corporate utilisation of EACs and other forms of abatement.
2. NH: There will be no statistically significant correlation or clustering relating a corporation's industry price sensitivity (NH2.2), or membership within industry groups (NH2.1); with the utilisation of EACs.
   AH: Statistically significant correlations will occur between EAC utilisation and industry price sensitivity, and there will be distinct clusters of EAC utilisation when comparing corporations with industry membership against those without.

The Methodology

Though this section provides a holistic overview of the methods used in this thesis, and the justification for their selection, this analysis consists of thousands of operations and more than 600 lines of code, and therefore cannot be documented fully in the main body of this thesis. For the sake of transparency, this methodology is documented and annotated entirely in the appendix, from the initial handling of the data in Excel (Appendix C) to the generation of statistical outputs in R Studio (Appendix D).

The data provided by the CDP, in the form of 4 CSV files, detailed the Supply Chain and Investor Public Climate Change data for 2018, and the 2014-2016 period, alongside the Public Investor Climate Scores for these years. All data provided was handled in accordance with the relevant confidentiality and data handling guidelines. The 2018 data was used in this thesis due to time constraints and data incompatibility. The data was examined by eye and secondary variables computed within the Microsoft Excel software package, due primarily to the software's familiarity to the author, alongside its ability to facilitate visual checks of the data. Excel's in-built error handling, along with "IfError()" statements, replaced blanks and zero length text strings with "#N/A" error codes. It should be noted that at this stage no distinction is made between cells for which a response was omitted and cells where the CDP's questionnaire determined the question was not relevant (marked with "Hidden Answer").

The consistency of Excel's error handling is maintained when the relevant data is transferred from the secondary worksheet into the R Studio software package, running the R 3.6.2 statistical package. The package allows handling where data was not available (NA) or where a calculation has led to an undefined value: Not a Number (or NaN, equivalent to Excel's #DIV/0!). All statistical analysis was performed within the R software, which allows the utilisation of pre-developed functions and classes, as well as supporting new routines integrating base and third-party packages, whilst providing transparency and documentation.

After handling errors and data-types, the data first is filtered by "Sense.Check", a variable introduced in the Excel handling to ensure all proportions lie in their allowable ranges (e.g. 0-1). Next, a function was defined to allow for exclusion of points that lie outside of the confidence interval for a given level of significance. Two versions of this function were defined, using the Z-score function within R (scale), to trim a singular column (*cleanDirty*), or a whole dataframe based upon a singular column (*cleanDF*). Histograms were assessed before and after the applying of these functions to ensure core distributions were not altered.

Once the core data was prepared, any non-CDP data was considered, namely the RE100 membership data, forming a categorical variable for each company listing whether they were present in the organisation in 2018, 2019, or were not found, as described below:

1. RE100 data was identified within Annex 1 of their progress report (RE100, 2019).
2. Data was scraped using PDF-excel webtool: (PDF to Excel Converter, 2020).
3. Predictably flawed excel data was reformatted properly such that each corporation's whole identifier occupies a single cell. This was done by consolidating the output for each PDF page into a single page, then using the text to column function to split the identifiers, separated by a line break (accessed via ctrl + J).
4. Corporate identifiers were matched with CDP identifiers, and checked visually, whilst ensuring all corporations had the correct year for joining the RE100, which would be categorised as "Pre-2019" (present in the CDP 2018 data), "2019", and "Not Found".

The only other set of non-CDP data used was the 2018 year-to-December (HM Revenue & Customs, 2020) exchange rates of global currencies to GBP, which was integrated for all currencies present in the initial CDP spreadsheet. This allowed comparison of corporate financial responses through the conversion of all relevant financial information into GBP (£).

In assessing comparability, one must also consider the reporting methodologies available through the CDP, with many reporting standards and national guidelines available, variance is expected. Most standards draw upon the Global Reporting Initiative (GRI), which modified its guidelines for Disclosure 305-2 in 2016, allowing corporations to "account and report energy indirect (Scope 2) GHG emissions based on both the location-based and market-based methods". The latter allows the reduction of private emissions factors through the trading of attribute certificates and contractual instruments, with no caveat for the realisation (or lack there-of) of the attributes traded. In contrast, a location-based method requires a corporation to use the emissions factor of the national grid of the relevant region of operation. Due to this, guideline corporations may currently choose which methodology they use to report as their "final" Scope 1 and 2 emissions within the CDP, though they must provide a location-based Scope 2 figure. This thesis uses the difference between the reported emissions figure and the location-based figure as a primary explanatory variable (abbreviated to EV1), as this proportion represents both the direction and magnitude of reductions "gained" through the use of market-based instruments and reporting. These market-based instruments include EACs, with the Proportion of Scope 2 electricity certified by EACs as the secondary explanatory variable of this thesis (EV2).

The first step in beginning this analysis is to select test sample for size and variation. Various methods exist, for example selecting by primary industry will give a more homogenous sample, whereas selecting by nationality will allow direct comparison within a single policy framework. For detailed analysis, a sample size between 50 and 100 is ideal, allowing some room to trim outliers. The UK was originally selected as a sample for all primary analysis, with a longstanding EAC scheme (the Renewable Electricity Guarantees of Origin, or REGO scheme, est. 2015), as directed by the EU Guarantees of Origin Scheme (GO). The UK also has faced issues of parallel subsidisation, understanding which can require detailed knowledge of the policy context, hence this author's focus. However, it was found that as the dataset will be segregated further based upon market-based instrument utilisation and disclosure; and will go on to lose further data where Z-scores are above the critical value. Hence a larger initial dataset was required, therefore a subset of EU nations utilising EACs was formed from the dataset using the “grepl” function and corporation’s listed nation. Though a corporation may have significant operations outside of their Listed Nation, access to EACs will be available within the nations selected.

Next, a set of statistical tests will be proposed and justified for each pair of hypotheses, based upon the quality and distribution of the data for each relevant variable (Table 1, below). For each of the statistical tests described, the following steps shall be applied:

1. Select a probability of error (alpha) level for initial testing.
2. Choose which variable form will be utilised for later analysis, some of which seem redundant but have subtle variations, e.g. the reported total Scope 1 and 2 emissions may not match the sum of Scope 1 and Scope 2 location emissions, where companies use a market method. Necessary secondary or proportional variables have been formed in Excel, and for these proportions, data that does not pass the “Sense Check” will be removed.
3. Using the *cleanDF* function defined earlier, data outliers will be identified and removed based upon their Z-score, using the probability of error level selected earlier to calculate the critical Z-score. A lower probability of error (higher significance) requires a higher Z-score, meaning that the “reject” regions of the distribution are smaller.
4. Test differences between groups (Kruskal Wallis Test) or begin regressions analysis, and review whether the probability of error level is appropriate. Data points where leverage may lead to over-biasing may be removed where appropriate and justifiable.

Table 1: A table of proposed statistical tests, with their associated level of significance, and a justification of their use.

Testing for	**Proposed Test**	**Output/Test Statistic (Level of Significance)**	**Justification**
NH1.1	Kruskal-Wallis Test of emissions reductions of Market- and location-method data respectively.	Chi-square value determines significance (0.05)	A one-way ANOVA is unsuitable due to the lack of normality present in the data.
NH1.2	Regression Analysis using linear modelling of efficiency mitigation vs Proportion Market-based	Fitted Model object alongside a F-statistic and p-value. (0.05)	The linear model was compared with other model types (glm, gamma etc) and found to have the best fit and lowest Akaike information criterion (AIC).

NH1.3	Regression Analysis using linear modelling of efficiency mitigation vs Proportion EAC	Fitted Model object alongside a F-statistic and p-value. (0.05)	The linear model was examined alongside the model derived from test NH1.2, but the co-variance of the market-based proportion may have introduced over-biasing.
NH2.1	Kruskal-Wallis Test comparing EAC utilisation by membership of RE100	Chi-square value determines significance (0.01)	A one-way ANOVA is unsuitable due to the lack of normality present in the data.
NH2.2	Kruskal-Wallis Test comparing EAC utilisation by Primary Industry	Chi-square & critical chi-square value determines significance (0.01)	A one-way ANOVA is unsuitable due to the lack of normality present in the data.
Exploring Causality	Kruskal-Wallis tests linking EAC use to risk assessment and financial measures (Adjusted investment, financial & emissions savings per pound spent) alongside mitigation outcomes (change in emissions factor, total mitigation) Linear models relating numerical risk variables (cost of management, frequency of assessment, value of opportunities) and mitigation initiatives	Chi-square value determines significance for Kruskal-Wallis tests. F-statistic and p-values will determine utility of linear models. (0.05)	The lack of normality requires Kruskal-Wallis tests, but also limits the utility of the linear modelling. Time constraints in the analysis meant that the lack of linearity in the causal variables/relationships could not be resolved. Consequently the linear models have been to explore the magnitude and direction of causality, rather than linking variables to provide conclusive predictions.

An aside: the datapoint for “Dixon’s Carphone” was removed for testing NH1, due to its high leverage and over-biasing, as it lists a 79% reduction in emissions due to “physical” and “other” emissions reduction activities, whilst only listing 540 tCO_2e mitigated through efficiency initiatives. It seems likely that the company has declared its total Scope 1 and 2 consumption incorrectly, firstly as the company declared location-method emissions values below their market-method emissions (~67,795 compared to 82,294 tCO_2e), implying the corporation is selling EAC instruments. Even if the company's market value was utilised, the figures do not quite add up, with the corporation listing global emissions reductions of 73,314.5 tCO_2e, as a 17% reduction from the 2016-17, which would yield emissions figures of approximately ~430,000 tCO_2e, far removed from the figure they reported of 106,830.7, given this was their only listed emissions reduction.

It should also be noted in order to maintain the dataset size, complete entries are required, however as "Proportion Scope 2 certified" (EV2) and "Proportion Market Based" (EV1) were listed as "NA" (Not Available) for corporations not utilising these instruments. One can only compare corporate utilisation across all groups by replacing these NA values with 0 or 1 respectively. Where no EACs are utilised, EV2 is zero, and EV1 is set to 1 where the market-location methodology yields no proportional change. This allows models to be compared within the same dataset but also leads to further distortion from the "Zero-inflation" effect. Models exist for zero- and one-inflated distributions between 0 and 1, but no relevant model was found for the inflation that occurs in EV1, which is bounded at 0, but not at 1.

Results and Initial Discussions of their Relevance

Due to the theoretical nature of this thesis, relating variables that are part of larger causal networks, this section will not only present the findings of the methodology above, but draw in the wider literature in order to assign meaning and importance to these findings. Significant outputs that are representative of a wider trend in the data and literature will be highlighted as such. Consider also that the description of concrete findings in this wide, sprawling causal environment is very difficult, particularly given the scope of this thesis. As such, relevant caveats for each significant finding will be introduced here, but in-depth discussions of this thesis' implications, limitations and proposals for further research will be conducted in the next section, by the same name. Important insights are revealed before any data manipulation occurs, by examining initial data quality, and comparing this to our "sense-checked" and "trimmed" datasets (Figures 2 & 3, right, overleaf).

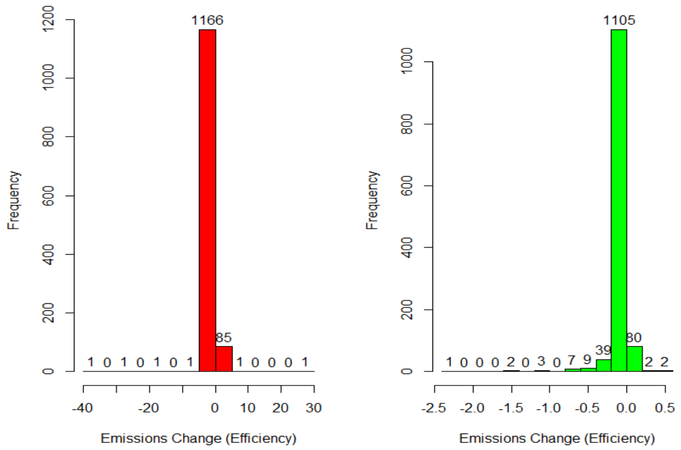


Figure 2: The difference in the distribution of the Response variable before (red) and after (green) "trimming", with an increase in normality, but clear inflation between 0 and -0.25 persisting.

One can also examine whether selecting EU ETS nations only affected the distribution of our independent variables (Figure 4, below). It can be seen that some of the outlying producers of market based instruments (MBI) (with market based (MB) emissions <300 times larger than their location emissions) have been excluded, but the overall utilisation of EACs is equivalent, though the zero-inflated curve is smoother for the global data, as one expects. Figures 2 & 3 reveal how the zero-and one-inflation effects (for market based emissions this one-inflation results from zero proportional change), add complexity to the analysis of both variables. This is the case before non-EAC/non-MB values are assigned a value of zero or one respectively, and is not a classical zero-inflated count model, being neither discrete, or in the case of MB change, bounded 0-1.

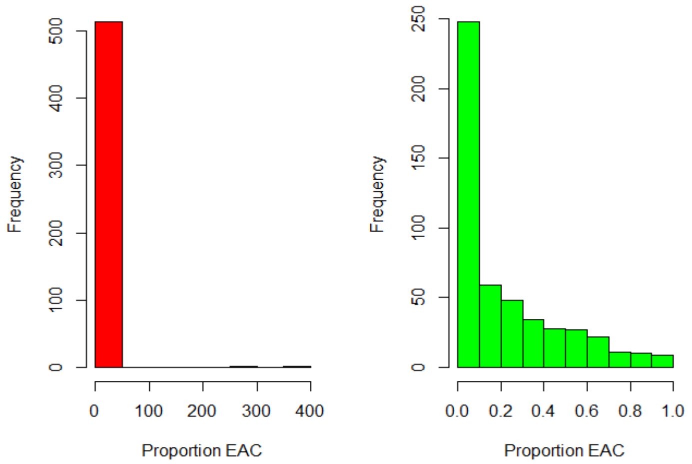


Figure 4: The difference in the distribution of EV2 before (red) and after (green) "trimming". Note that the axis shows data is correctly bounded (: 0-1 for proportions) after trimming.

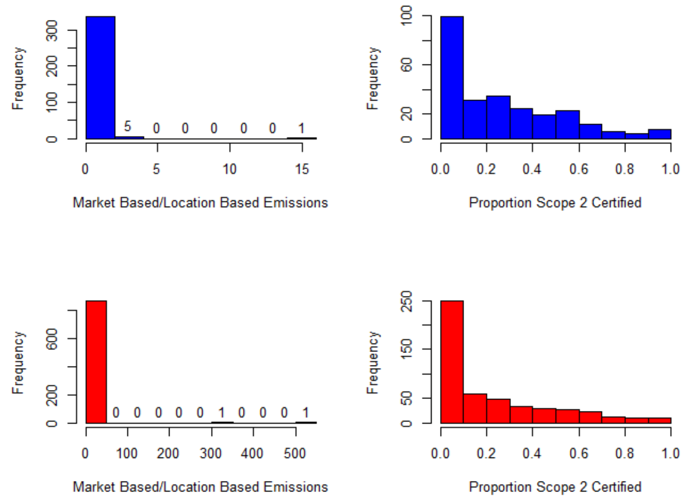


Figure 3: A comparison of the distribution of EV1 and EV2 over the EU ETS group (blue) and the global data (red), with the latter showing the presence of more extreme EV1 outliers, but a smoother EV2 distribution, to be expected given the larger sample size.

These factors led to difficulties in selecting an appropriate model for the data, as discussed later. For ease of reference, the dependent variable under investigation: Emissions changes derived from actions categorised as "Process" or "Other" (energy efficiency actions), or "Reported.Emissions.Change..Physical...Other.Efficiency."; will be refered to simply as "the response variable" or "the response". For ease of reference, groups of corporations shall be categorised and referred to via their reporting method (Signallers or Assurers), and their utilisation of EACs (Certified or Uncertified) as demonstrated in Table 2 (right).

Table 2: The summarised groups and their mean responses.

Group Name	Using EACs?	Market-Based?	Mean Response
Uncertified Assurer	No	No	-4.84%
Uncertified Signaller	No	Yes	-4.11%
Accounting Assurer	Yes	No	-12.0%
Certified Signaller	Yes	Yes	-4.07%

Null Hypothesis 1 (NH1.1-NH1.3)

All the data for NH1 was tested at the 0.05 significance level, with areas of exclusion removed for points with Z-scores outside of the -1.64 – 1.64 range, using the cleanDF function defined earlier. The EU dataset was used throughout, excluding the "Dixons Carphone" datapoint, as discussed earlier. The global data was used when verifying the findings of NH1.1 held at a global level, using the same Z score methodology.

NH1.1: Energy Efficiency across categories of Reporting Methodologies and EAC use.

Though evidence of an indirect rebound effect in the market-based group was expected due to access to "low-cost" EACs (Department for Business, Energy & Industrial Strategy, 2019), this test (**Table 1**) resulted in an insignificant Kruskal-Wallis chi-squared value of 0.192 for EU ETS corporations using a market method (Signallers); but gave a significant chi-squared value for EU ETS corporations using a location method (Assurers) (11.7). Further evidence of divergence between corporations is seen through the difference of means in Table 2.

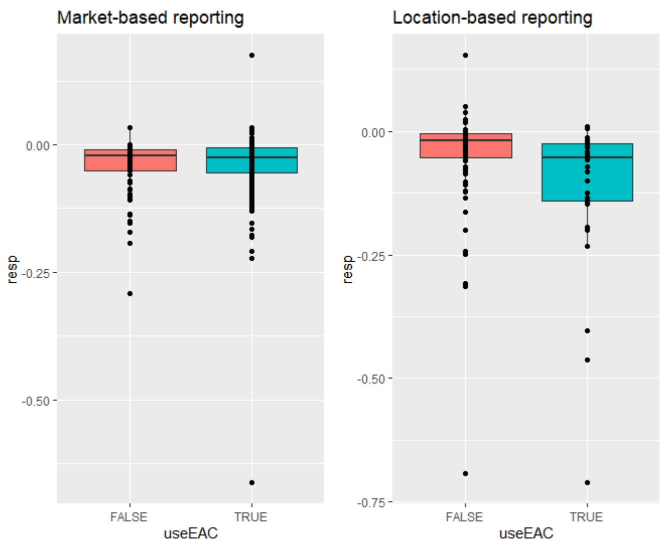


Figure 5: A significant difference in the response (resp) linked to the use of EACs alongside market-based

The same relationship was present in global market-based and location-based data, with chi-squared values of 0.00685 and 5.41 respectively. These tests show the significance of reporting methodologies within EAC use and signalling; for corporations in the EU ETS dataset and globally.

Figure 5 (above), shows that the use of EACs amongst Certified Assurers is linked with significantly greater emissions reductions from energy efficiency measures. The same cannot be said for corporations utilising a market-based methodology, attributed to the dual nature of EAC utilisation leading to a divergence in the outcomes of corporations using them. Recall that EACs can either provide an accounting structure for corporations, or a system for incentivising new generation.

The Certified Assurers group cannot lower their emissions factors (fixed by location) through EACs' lower market emissions factors, and so, for this group, the EACs cannot contribute directly to green signals such as a reduction in reported Scope 2 emissions. This leads to a focus on EAC utilisation as part of internalised best practices, the labelling of organisational qualities, or for use in improving the accountancy and transparency of Scope 2 electricity utilisation. Location-based reporting does not allow the direct appropriation of theoretical abatement that EACs provide, which some have considered a low-credibility action (The Times, 2019); but location-based EAC use still offers benefits. Flowers et al linked certification in the building sector to the positive environmental externalities, and signals of management and product quality, with higher quality employees attracted to firms with green certification, who in turn "feel more useful and equitably recognized, and are more likely to work uncompensated overtime." (2018).

Additionally, as RECS.org (2020) state that "Some larger electricity producers have gone so far as to issue GOs for all of their electricity production sources, non-renewable electricity included, as a means of proper accounting and responsible information disclosure.", one expects Verification and Assurance-focused corporations to also exploit the EAC's role in accounting and disclosure. This is particularly relevant where corporations have internal or external targets: "obligated market participants must hand over the requisite number of certificates to the monitoring authority (typically on an annual basis). In this context, green certificates act as an accounting instrument which verifies whether the obligation has been met (Linden et al, 2005)." (Brick and Visser, 2009). Where these obligations are internal, and a corporation wishes to make no change to market-based emissions figures, due to methodology or credibility concerns, a corporation may purchase but not use their EACs for reporting, maintaining ownership of renewable attributes whilst preserving them for accounting purposes and as a public good. This fits well with Herold's concepts of "Excellence", where "unity between organisational members fosters a sense of identity and commitment", whilst "making carbon information comparable by an active engagement to work on the standards and transparency of carbon-related activities", which "may include the adoption of technical international and industry procedures", such as utilising EACs for accounting regardless of their external signalling potential.

In contrast, the efficacy of EACs in incentivising new generation, and therefore its validity in direct signalling, have been questioned, with prices for EACs depressed by systems of mandatory supply across national schemes (Gowdy, 2018), the complexity of which can increase reluctance amongst international investors (Finjord et al., 2018). The current sale of EACs increases the grid emissions factors of energy producers generally (Recs.org, 2020), without significantly increasing the production of renewables (Raadal et al., 2012). This leads to appropriation rather than additionality, and impacts the credibility of both EACs and their use in signalling.

NH1.2: Energy Efficiency and Market-Based Emissions Signals.

The signalling effects of EAC use (through market-based emissions reductions) can be explored by analysing links between a corporation's reported market-based figure, expressed as a proportion of their location-based emissions figure (EV1) and their energy efficiency response. This continuous variable (EV1) will be 1 for corporations not utilising market-based reporting; less than 1 where corporations have reduced their reported emissions with MBIs; and greater than 1 where corporations have higher market-based emissions, due to the sale of MBIs. This allows comparisons across the whole dataset but will distort the distribution of the data further. That said, the proportion market-based data is already highly non-normal, and though the distribution was identified as continuous, asymmetric and bounded at 0, no suitable distribution was identified. It should be stated that all linear models seek to give an idea of the direction and magnitude of correlations, rather than accurately model interactions.

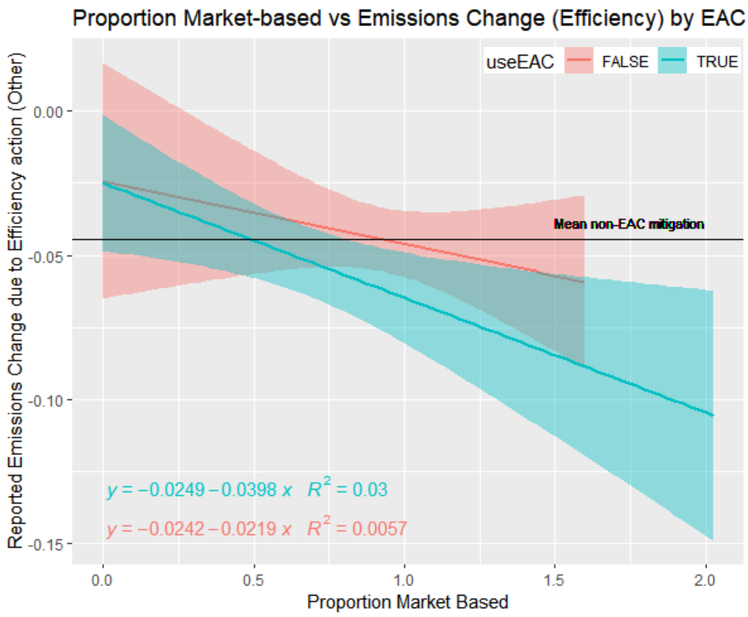


Figure 6: The interaction between a corporation's use of EACs, and the trade-off occuring between the signal of market-based emissions reductions (x-axis) and internal abatement (y-axis). The black line shows the average emissions change of a corporation using no EACs.

The test for NH1.2 (Table 1) produced a linear model describing two significant correlations for EU ETS corporations. These correlations are divided by use of EACs and link the response variable with signalling outcomes derived from the utilisation of a market method (the response). Both correlations are significant, with Pr(>|t|) values of 0.071 and 0.003 for the Uncertified and Certified groups, respectively. Both t-values are negative, showing a trade-off between the response and signalling outcomes, but this trade-off is greater where EACs are utilised, due to a lower t-value (-2.97 compared to -1.81). The model had an overall F-statistic of 4.50 on 2 and 398 degrees of freedom, with a p-value of 0.0116.

Figure 6 (previous page) shows that greater net reductions from MBIs correlate to lesser emissions reductions from corporate energy efficiency action. The steeper gradient for Certified corporations is evidence of EACs' involvement in strengthening the trade-off between signalling derived from external instruments, with possibly theoretical abatement, and internal efficiency abatement (the response). It should be noted that the model fit for these Certified corporations was much better than for Uncertified corporations, but both have low adjusted R^2 values (0.03 and 0.0057 respectively). The increase in the slope and fit of the EAC trendline, (Figure 6), shows that Certified corporations trade-off more strongly between internal efficiency and market-based abatement. This shall now be explored.

Although the difference in gradients is clear and significant, attributing the cause of the difference is less simple. Besides differences in strategy, the diminishing returns of a market-based approach would also explain the difference in gradient between trendlines, as EAC utilisation would allow for a low-cost "jump to the left" for many corporations, but with corporations already utilising EACs or other MBIs, this "jump" will be much shorter, leading to a "compression" of the trendline. This theory degrades where EAC certification is sold as well as purchased; there is uncertainty over whether these corporations are "utilising" EACs through their sale, or through cancellation & reporting of their lower emissions factor. Demographic differences between groups likely persist, despite the use of the proportional EV1 negating effects from differences in the size of corporations and their emissions.

A difference in the risks faced between the Certified and Uncertified groups could also motivate Certified corporations to take more efficiency action for a given market-based proportion. A difference in cost of mitigation may allow the Certified corporations to "green" large segments of their organisation with lower technical or transaction costs, leaving more time, effort and finance for energy efficiency measures. The overall outcome when a corporation switches to utilising EACs would seem to depend on their reporting methodology, though one would expect both groups' emissions reductions to increase, moving down from the red trendline to the blue; those using a market-based methodology also simultaneously move left as "EACs enable depression of the market-based proportion for relatively little cost. The latter effect clearly outweighs or negates the former, as Certified Signaller group has the lowest response in Table 2, and it is clear that Certified corporations with market-based proportions of 0.5 or less perform worse than the average Uncertified corporation. Another clear outcome supports the statement from Flowers et al (2018), that "[construction] upgrading to the highest tiers are more likely to deploy practices with private gains.". Here it is seen the greater the investment in MBIs, the lower the commitment to energy efficiency measures, with the presumption that corporations are favouring the most cost-beneficial projects. The trade-off between increased signalling and decreased cost-effectiveness with energy efficiency projects was also found by Flowers et al (2018), whose "Results suggest a willingness to extend short time horizons associated with energy-efficiency investments in exchange for marketing benefits.".

NH1.3: Correlating Energy Efficiency to the Continuous EAC variable (EV2)

Care must be taken when correlating the response to EV1 and EV2 together, as an inverse covariance between higher EAC utilisation and lower market-based proportions can be seen through their Pearson correlation coefficient of -0.563, with Kruskal-Wallis tests giving a Kruskal-Wallis chi-squared value of 49.6, correlating the proportion of Scope 2 electricity certified with market-based reporting utilisation (Appendix E). This relationship would accentuate the theorised trade-off of NH1.2, with increased EAC use pushing Market-Based corporations further left on the x-axis of Figure 6, where emissions reductions are lower. The linear correlation between the Proportion of Scope 2 electricity certified by EACs (EV2), and Emissions change due to efficiency (the response) was significant for the location-based group only however (Figure 7, right). The graphed model shows the location-based group having a synergistic rather than antagonistic relationship between utilisation of EACs and the response, with corporations using more EACs also reporting greater emissions reductions through energy efficiency, though the data fit is not very good.

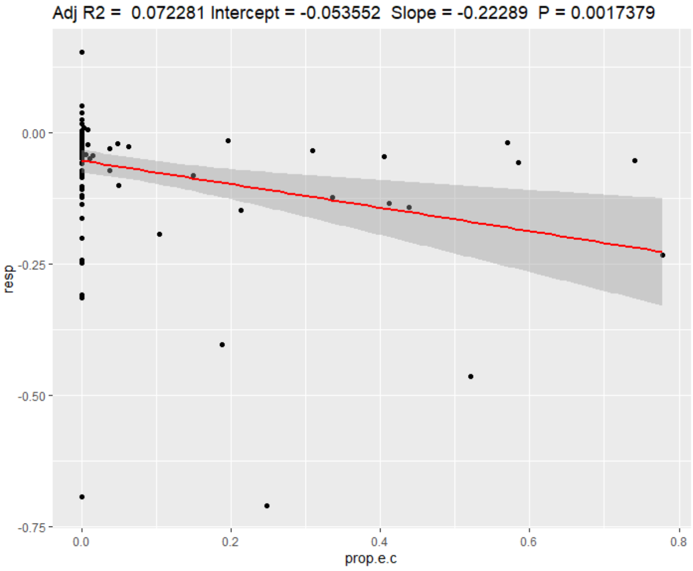


Figure 7: The response increases with the proportion of scope 2 electricity certified by EACs (EV2 or prop.e.c.) across the Location-based group.

This strengthens the link between the location-based group and transparency and accountancy, where EAC utilisation is part of internalised best practices, the labelling of organisational qualities, or efforts improving the accountancy and transparency of Scope 2 electricity utilisation (Flowers et al, 2018; RECS.org, 2020; Brick and Visser, 2009).

The statistical insignificance for the market-based group (Appendix E) should be noted however, supporting the conclusion that the strengthened trade-off in Figure 6 is almost entirely offset by market-based corporations moving left, increasing their reported emissions reductions instead of their response action. It could be theorised that the trade-off between the green signal of market-based emissions reductions and internal abatement through energy efficiency only occurs where EACs can reduce the proportion of a corporation's market-based emissions significantly (Figure 6). This would undermine the existence of a trade-off between green supply action (purchase of renewable energy), and green demand action (energy efficiency), in fact the location-based data correlates corporate investment in the two together. Instead, this analysis suggests that the trade-off occurring within the market-based group is between the resultant green signal available through market-based emissions reductions (which can be wholly underpinned by EACs for some corporations but not others) and the green signal and performance benefits available through internal abatement action.

Modelling outcomes of NH1

Several forms of Generalised Linear Model were also examined to address the non-normality of the data, with the Gamma distribution achieving the lowest AIC and residual deviance (-691.97 and 4.5679 respectively). These models however did not perform better than the linear model presented in Figure 6, and so these alternative modelling methods were not carried forward in the analysis but have been summarised in Appendix E. It should be stated that the linear modelling was by no means perfect, with zero distortion from zero-inflation, and over-dispersion at both extremes leading to an "S-shaped" Q-Q plot (Figure 8, below).

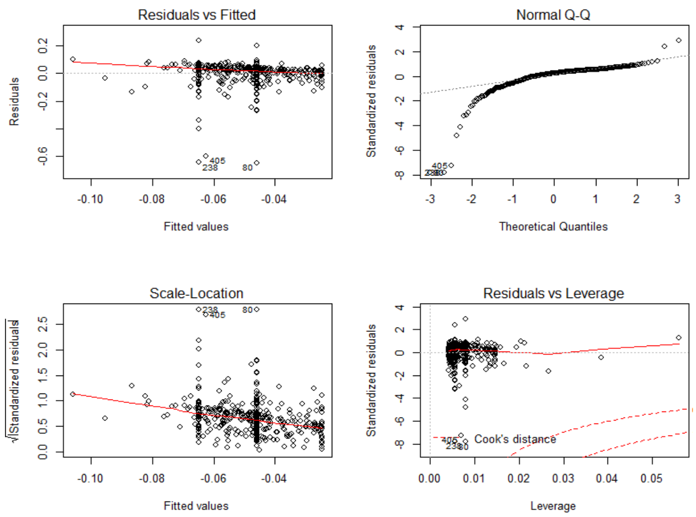
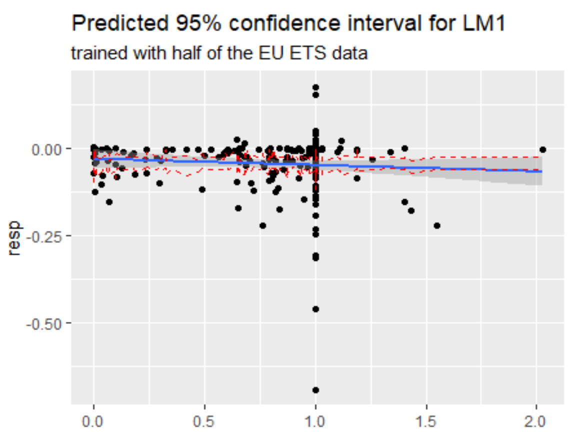
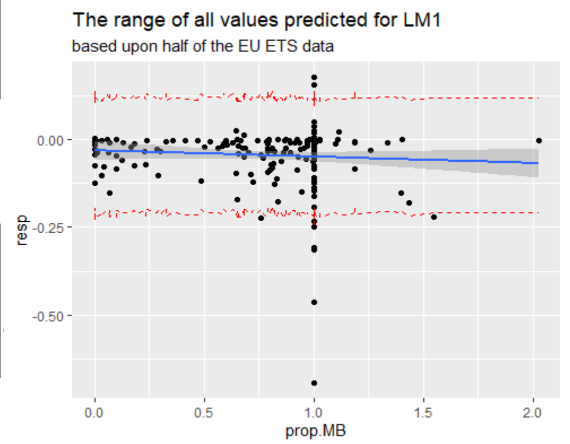


Figure 8: Diagnostic plots for the linear model connecting EAC use and a corporation's market-based proportion to changes in the response.





Figures 9 & 10: The range of predicted values graphed for the 95% and 100% confidence intervals respectively.

Outcomes and Significance of NH1:

The predictive abilities of the model are also very poor; however this is to be expected as EAC utilisation only forms a small part of variance between corporations (Figures 9 & 10, previous page). Despite this, there is sufficient significant evidence to reject Null Hypothesis 1, and state that an interaction exists between Emissions Changes due to efficiency action (the response) and the utilisation of EACs: inversely correlated with the proportion market-based for companies utilising this reporting methodology.

Null Hypothesis 2 (Tests NH2.1 and NH2.2)

In order to fully utilise the RE100 dataset, containing less than 200 corporations present in the 2018 data, the global CDP dataset was utilised. Using the EU ETS subset would have risked reducing the dataset to a statistically insignificant size when considering RE100 membership. The same Z-score methodology was utilised to remove points with Z-scores exceeding the critical Z-score (±2.32); corresponding to a 0.01 level of significance.

The Kruskal-Wallis chi-squared values for the difference in EAC utilisation between groups, divided by RE100 membership and Listed Primary Industry, were 16.4 and 57.4 respectively. These significant differences highlight the importance of external signalling and industry price sensitivity respectively; for the utilisation of EACs, supporting the theories of Genç (2013) and Herold (2018). The results were displayed in Figures 11 and 12.

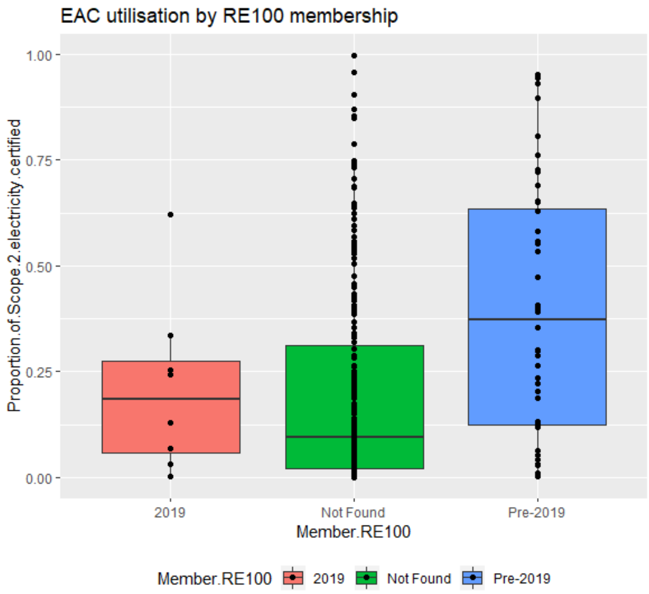


Figure 10: Corporations that were part of the RE100 whilst reporting to the CDP in 2018 (Pre-2019) show significantly higher levels of EAC usage.

Figure 11 (right) shows corporations present in the RE100 membership when disclosing to the CDP in 2018 had significantly higher levels of EAC utilisation (~25%). The RE100 is a group of corporations who advertise commitments to "100% renewable electricity" (RE100, 2019), however these claims can be underpinned by EACs (wholly or otherwise), supporting their connection to green signalling.

Figure 12, overleaf, exemplifies customer-facing corporations (Apparel, Hospitality, Retail & Services) with significantly higher levels of EAC utilisation, whilst corporations operating in less visible, but more price-sensitive industries (Fossil Fuels, Power Generation, Mineral

Extraction) use significantly fewer EACs, supporting a trade-off between the signalling attributes of EACs and realised, but less communicable efficiency-based mitigation.

These two elements of analysis are sufficient to reject Null Hypothesis 2, and state that statistically significant correlations occur between EAC utilisation and industry price sensitivity, and that there are distinct clusters of EAC utilisation when comparing corporations with industry membership against those without.

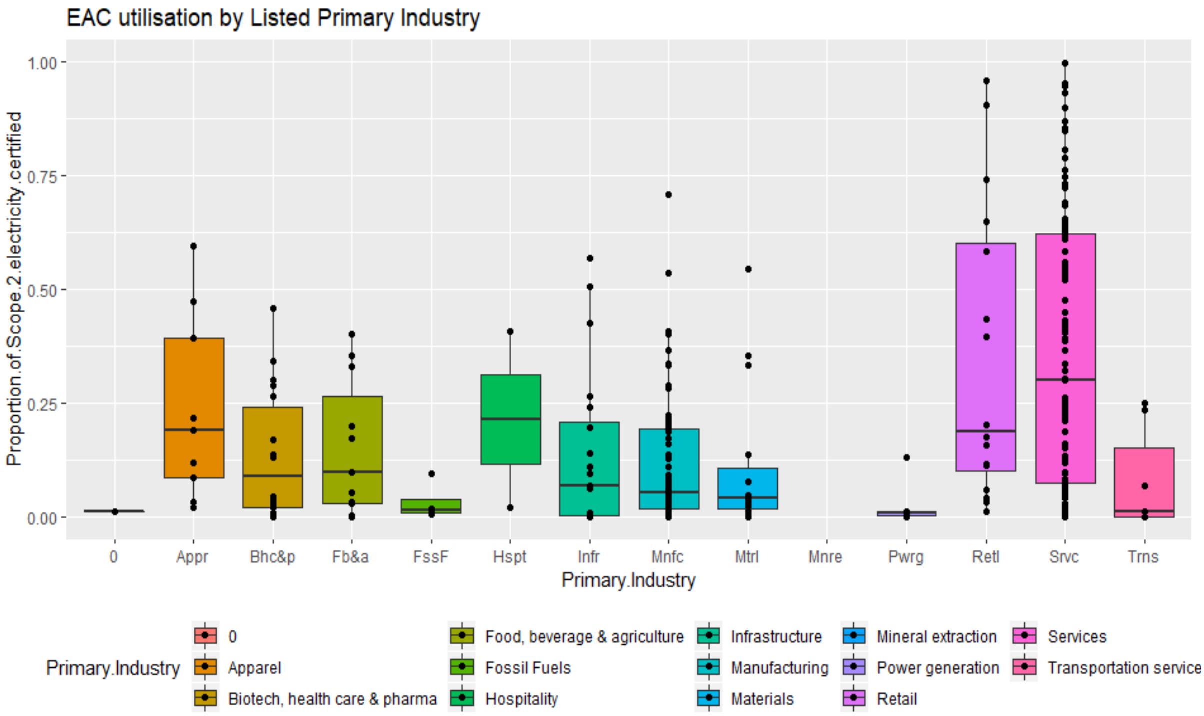


Figure 11: Variation between the EAC usage of industry sectors shows how exposure to the wider consumer, and industry price-sensitivity may influence EAC uptake. Note the high usage of consumer-facing sectors such as retail and services in comparison to price-sensitive, business to business sectors, i.e. manufacturing.

Exploring Causality

A new dataset was constructed, merging the "core" data points (that passed the "sense check") with a dataset of causal variables, to which the Z-score cleaning methodology was applied (to a significance level of 0.05 or critical Z-score of 1.64). NAs were replaced as described in the methodology section, and Kruskal-Wallis Tests applied.

EAC use alone is only ever a proxy, or signal variable for companies, acting as an intermediate to allow a corporation to pursue emissions or governance goals. Interrogating where EAC utilisation is highest will identify how corporations use EACs in response to external risks, and how EACs fit into internal mitigation patterns, by linking EAC use with the other initiatives a corporation pursues. These statistical explorations allow the relative impact of internal and external pressure on EAC utilisation to be derived, with significant test statistics presented in Table 3, overleaf. It was found that linear models were improved by grouping like variables: i.e. numerical risk variables such as cost of risk management, and time horizon of risk assessments; and by dropping non-significant variables. The MASS package's drop-term function was used to test for significant interactions and build the models below. The tests that were listed in Table 2 but have not been listed below gave insignificant results, but their outputs can nevertheless be found in Appendix E.

Table 3: A summary of significant causal relationships between EAC use, examined at a 0.05 level of significance throughout. Full model outputs can be found in appendix E.

<table>
<tr><th>Kruskal-Wallis Expression</th><th>Chi-squared</th><th colspan="2">Pr(>|t|)</th></tr>
<tr><td>Cost.efficiency.of.mitigation..Other…..tCO$_2$e. by Utilising.EAC..x</td><td>6.61</td><td colspan="2">0.010</td></tr>
<tr><td>Low.Carbon.Savings.Intensity....TCO$_2$e. by Utilising.EAC..x</td><td>6.02</td><td colspan="2">0.014</td></tr>
<tr><td>Adjusted.Average.Investment..Other. by Utilising.EAC..x</td><td>23.8</td><td colspan="2">1.07e-06</td></tr>
<tr><td>Low.Carbon.Purchases.Adjusted.Investment by Utilising.EAC..x</td><td>5.09</td><td colspan="2">0.024</td></tr>
<tr><td>Change.in.Emissions.Factor.due.to.Certification by Utilising.EAC..x</td><td>7.40</td><td colspan="2">6.51e-03</td></tr>
<tr><td>Total.Initiative.Mitigation by Utilising.EAC..x</td><td>43.4</td><td colspan="2">4.44e-11</td></tr>
<tr><td>Efficiency.initiatives.Mitigation by Utilising.EAC..x</td><td>24.4</td><td colspan="2">7.82e-07</td></tr>
<tr><td>Proportion.of.Scope.2.electricity.certified.y by X.Market..Risks</td><td>18.5</td><td colspan="2">9.60e-05</td></tr>
<tr><td>Proportion.of.Scope.2.electricity.certified.y by X.Reputation..Risks</td><td>22.9</td><td colspan="2">1.09e-05</td></tr>
<tr><td>Proportion.of.Scope.2.electricity.certified.y by Frequency.of.Risk.Assessment</td><td>20.3</td><td colspan="2">2.46e-03</td></tr>
<tr><th>Linear Modelling Output</th><th>F Statistic (P value)</th><th>T-Value</th><th>Pr(>|t|)</th></tr>
<tr><td><u>Causal Model 1:</u>
Proportion.of.Scope.2.electricity.certified.y ~ Summed.cost.of.risk.management (1) + Time.Horizon.Risk.Assessments (2)</td><td>F-statistic: 4.84 on 2 and 1552 DF</td><td>1: -2.50
2: 2.03</td><td>1: 2.03
2: 0.042</td></tr>
</table>

	(p-value: 0.008)		
<u>Causal Model 2:</u> Proportion.of.Scope.2.electricity.certified.y ~ Num.Scope.2M.initiatives:Num.Scope.3.initiatives (**1**) + Num.Scope.1.initiatives:Num.Scope.3.initiatives **(2)** + Num.Scope.2M.initiatives **(3)** + Num.Scope.3.initiatives **(4)**	F-statistic: 23.9 on 4 and 1550 DF, (p-value: < 2.2e-16)	1: 2.72 2: -4.34 3: 6.13 4: 5.04	1: 6.56e-03 2: 1.51e-05 3: 1.15e-09 4: 5.28e-07

It was found that EAC use links to increased purchasing of Low Carbon energy, but decreased savings resulting from this investment, with no significant effect on low-carbon mitigation cost-effectiveness (£/TCO_2e). EAC use is linked to higher costs of mitigation (£/TCO_2e) for efficiency and "other" initiatives, with lower resultant investment and mitigation outcomes, but no significant change to financial returns. Overall EAC use links to reduced economic efficiency, higher reductions in emissions factors, but also lower Total Mitigation outcomes.

Additionally, the proportion of a corporation's Scope 2 electricity certified by EACs (EV2) increases with risk assessment generally, where increased Frequency of Risk Assessment and longer Time Horizons of Risk Assessment correlated with greater EAC use. Similar trends were found when examining a proxy for external pressure: the presence/evaluation of Market/Reputational risk, where greater risk correlated to greater EAC usage. Policy and Legal risk, on the other hand, did not link significantly to EAC utilisation, distinguishing the links to Market and Reputational Risk. EAC utilisation also correlates with the number of initiatives offering no internal efficiency/process improvements (Num.Scope.2M.initiatives, Num.Scope.3.initiatives & Num.Scope.2M.initiatives:Num.Scope.3.initiatives). It is seen that both EAC utilisation, and non-internal initiatives (market-based or supply chain) are encouraged by the presence and assessment of Market and Reputational risk, and though both of these are very real in theory, and when emerging in practice; they differ from the concrete physical and financial risks faced by many industries and assets.

That difference, and the realisation of risk in financial planning, is revealed by the inverse correlation between the cost of risk management and EAC utilisation, as EACs do nothing to address physical risk, and their effectiveness in addressing reputational and market risks is entirely dependent on how collective systems view their effectiveness. The Summed Cost of Risk Management (where greater costs of risk management lower EAC usage) is supported by other markers of internal pressure, namely the combination of Scope 1 and Scope 3 initiatives, which mark internal actions (Scope 1 generation of energy), and the transference of internal pressure to the supply chain (Scope 3). Above the 0.05 level of significance, but below the 0.1 level of significance was the inverse correlation between a corporation's reported "Value of Financial Opportunities", with proportion EAC decreasing as this figure increased (T-value = -1.65, Pr(>|t|) = 0.099). This connection is logical where corporations are making cost-benefit decisions between theoretical/externalised instruments (like EACs) and real life abatement opportunities: the greater the return of the abatement opportunities are, the less likely a corporation is to invest in a theoretical/externalised alternative.

Modelling Conclusions

It is worth at this stage reconsidering the fit and accuracy of the models presented so far, to evaluate where they fail to describe and predict the outcomes of EAC utilisation. In order to do this, APPENDIX F was produced, analysing the diagnostic plots of Causal Models 1 and 2 in depth. This section shall present the conclusions of this work, with wider relevance, in order to inform the discussions of how this work may be improved.

Both Causal Model 1 and 2 show non-linearity, with non-normal skewing around the y-intercepts, due to zero inflation in the dependant. Evidence of non-linear relationships includes the prediction of non-allowable values, such as proportions below zero in Causal Model 1. Some evidence of zero-inflation exists for the independent variables of both causal models, though when considering Causal Model 1, this is likely due to corporations misreporting or misrepresenting their risk assessment, with 0 listed as the Summed Cost of Risk Management, and the Time Horizon of Risk Assessment for many corporations. The theoretical fit of zero-inflation for the independent variables of Causal Model 2 is much better, as these are all count variables, where zero-inflation typically emerges. Both Causal Models have poor predictive abilities and poor data fit, likely due to one predictor being assigned too much significance, as demonstrated by comparing diagnostic plots with output plots (Figures 9-10, Appendix F).

One-inflation is present in the modelling outcomes of NH1 due to the presence of location-based corporations within a market-based variable, the significance of which will be discussed later. The lack of data for market-based proportions above 1.5 has lead to possible overfitting, with the lack of data likely related to stategic disclosure: corporations with a high market-based emissions figure may simply choose to only report location-based figures. This lack of data leads to a divergence of the 95% confidence interval and the line of best fit to the right of the y-axis (Figure 9). There is more clustering for corporations with an EV1 of 0-0.25 than for the range 0.25-0.5, which links to a differing use of MBIs and with Herold's work stating clusters of strategic certification exist.

——A Discussion of Implications, Limitations and Proposals for Further Research——

Wider Implications: the Location-based Group: evidence of social responsibility & excellence

Considering the findings of NH1.1, the significant relationship exists only for the location-based group who are utilising EACs (Certified Assurers), without realising their signalling benefits through a market-based methodology. This group represents 96 (23.9%) of 401 corporations who are realising the organisational benefits of EACs through internal accounting, best practice and signalling; without realising the external signalling benefits of the zero emissions factor. The location-based group not reporting EAC utilisation (Uncertified Assurers) is a similar proportion (22.7%), and together they represent 46.6% of the cohort. Though it is not possible to state whether non-excellent corporations exist in this group, or excellent corporations exist outside of this group, the location-based method and the "excellence" strategy both share the strongest degree of assurance, and Herold found a similar proportion of "excellence" in the logistics sector (45% compared to 46.6%), which would not discredit the link between these groups.

Wider Implications: Certification Strategies and Trade-Offs

The separation between EAC signalling and the creation of new renewable generation is visualised - and integrated with competing action - , in Appendix G. Considering NH1.2, further evidence of corporations trading off realised and non-realised elements of signalling and organisational improvements was found, notably the increase in model fitting and gradient slope for corporations trading-off the response and EV1 whilst using EACs (185 or 46.1% of the cohort). It was found whilst investigating NH1.3 that increased EAC use (EV2) is correlated with smaller values of EV1, but this would only act to accentuate the relationship found for NH1.2. Further evidence that EACs accentuate rather than replace the existing trade off between market-based and internal abatement exists in the mean response values of the groups, with corporations in the Certified Signaller group having the smallest response reductions of the EU ETS cohort.

Both NH1.1 and NH1.3 could not connect differences in the extent of the response to EAC use without considering market-based reporting. Significant results from tests exporing NH2 and causality show that the trade-off occurs between the opportunity costs of EAC use and various realisable benefits of EACs for each group (internal organisational benefits for the Certified Assurer group, external emissions reductions signals for the Certified Signaller group). This is evidenced by correlations linking EAC usage with strategic industry groupings based upon price sensitivity and consumer exposure; and a decrease in cost-effectiveness for low-carbon financial and efficiency mitigation outcomes. Appendix G demonstrates how parallel subsidisation leads to imperfect competition, almost negligible income from EAC sales and a lack of realisation of "Greenness", whilst the implementation of centralised policy allows green signals of excellence to be derived for corporate-consumer interfaces with high levels of information assymetry. These consumers include investors, whose interpretation of the role of the CDP determines EACs' acceptability in accounting and incentivisation.

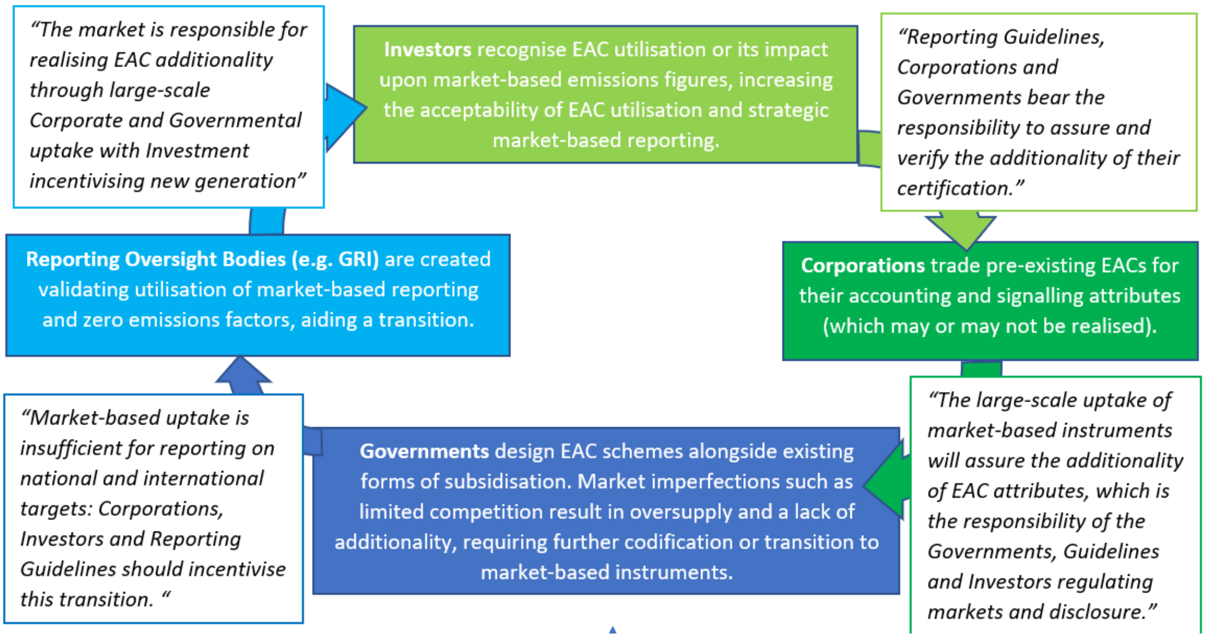


Figure 13: The cyclical deference of responsibility between the institutions overseeing (reporting oversight bodies), assessing (investors), instituting (governments) and implementing (corporations) mitigation action through the usage of Market-based instruments such as the EAC.

Wider Implications: The Effectiveness and Appropriation of EACs

The EACs offered currently from UK generators are subsidised in parallel by all bill-payers, deflating the price below the real cost of incentivising new generation, leading to appropriation rather than additionality where signalling benefits are utilised. These corporations may be acting within Tang and Luo's definition of the CDP "code" in order to either codify this appropriation as an "acceptable" principle, or to codify market-based accounting as acceptable or excellent. The lack of consistency in reporting approaches and the lack of additionality within EAC capacity incentivisation lead to large-scale double-counting of renewables through combinations of location-based and market-based reporting, with little acknowledgement amongst most corporations. Hence the divergence of these perspectives and outcomes for EAC utilisation could be attributed to a cyclical deference of responsibility between the Investor, Corporation, Government and Certification Body (Figure 13, previous page), where both accounting and incentivisation are considered, whilst neither is realised. A set of recommendations tailored for each perspective has been produced within Table 4, below, categorised by price or quantity approach and degree of centralisation.

Table 4: A set of recommendations that would interrupt and address the cycle of deference above in Figure 14, categorised by a price or quantity focus, and their degree of centralisation, with the most centralised suggestion at the top. The colour coding corresponds to the institution in Figure 14.

Institution	Price-based	Quantity-based
Reporting Oversight Bodies **(Centralised)**	Market-based instruments that produce theoretical benefits require additional attestation and verification, a mandatory surcharge could be added by verification institutions to represent the cost of this verification, and the uncertainty it must overcome, internalising these costs.	Where theoretical benefits are realised over a longer timescale, a reflexive monitoring system could be put in place, such that where market-based instruments proved ineffectual, the "attributes" could be rescinded in later carbon budgets.
Governments	Governments could set mandatory demand targets for consumers within grid systems, i.e. in the UK 40% of grid generation is renewable and funded by the general bill-payer. All consumers could therefore be provided with certification for 40% of their consumption, to be returned annually. Mandatory demand targets slightly above the mandated supply level would allow for attribute trading whilst avoiding oversupply, with fines realising a cost/price for attributes.	Governments could cancel attributes derived from generation that has already been subsidised, preventing the oversupply, and ensuring suppliers charge a cost for attributes which is entirely reflective of the price of their production.
Investors	Investors could weight forms of mitigation by the strength and speed of their realisation, so that penalties are applied for less absolute mitigation when considered by ESG metrics.	Institutional investors could set equivalence levels for different forms of mitigation based upon their effectiveness-to-date. E.g. 40% of UK power comes from public-subsidised renewable generation, corporations should therefore purchase but not appropriate additional attributes (2/3rds extra) to maintain these public attributes.

Corporations **(Decentralised)**	By offering a surcharge that reflects the real cost of additional subsidisation, corporations can effectively incentivise additional capacity, in return for higher-quality attestation, and longer-term appropriation of this additional capacity	Where internal carbon trading occurs, equivalence levels could be set between mitigation initiatives, to be reviewed reflexively, such that where targets are set for different sectors of a business, efficient marginal abatement can be reached, reflecting realised rather than theoretical mitigation.

Wider Implications: Factors affecting outcomes and the realisation of change:

NH2 shows that the utilisation of EACs is dependent on the factors introduced by Herold & Lee, showing the involvement of EACs in strategies of certification and disclosure. This is especially the case for those relating to external signalling, for example via the RE100, and for consumer-facing sectors (Apparel, Hospitality, Retail). Likewise, the relevance of price sensitivity as highlighted by Genҫ was revealed, showing that where the internal abatement (such as the response) has strong realisable benefits for a corporation, EACs will be avoided. This occurs in sectors with high energy intensities (Materials and Manufacturing), where investors are less likely to view EACs as forms of realised abatement, or as a favourable green signal, as the competitiveness of corporations within energy intensive sectors depends more on the marginal utility of energy and the realisation of cost savings through energy efficiency than the ability for these corporations to signal "greenness". These sectors may be less likely to consider EACs as a "green signal" regardless, as they link closely to energy suppliers, and many corporations may generate their own renewable energy, and therefore investors in these sectors likely are aware of issues of EAC effectiveness.

Finally considering the resultant effects of this analysis, the data shows that the proportional increase in the response of the Certified Assurer group (mean reductions were 7.16% higher across 96 companies) outweighs the proportional decrease of the response in the Certified Signaller group (mean reductions were 0.71% lower across 185 corporations). This may be counterintuitive for those considering the green signals of the signalling group as legitimate and representative of wider corporate action. The Certified Assurer group may occupy energy intensive or excellent sectors of the market but the analysis showed in this case that this group skewed the EAC groups to show an increase in the extent of response action.

Moving beyond the response figures overall data shows EAC utilisation is linked to reduced investment in efficiency-based mitigation initiatives, with higher resultant costs of mitigation (£/TCO_2e) and no significant difference in financial returns for these initiatives. EAC use correlates with an increase in the number of market-based Scope 2 initiatives, showing a general focus on low-carbon purchasing. Low-carbon energy purchases also make up a greater proportion of initiative spending for Certified corporations, with lower financial savings (£ saved/£ invested) and higher mitigation costs (£/TCO_2e) resulting from these low-carbon initiatives within the EAC group. Both these statements show that the EAC utilisation and low-carbon purchases are not motivated by cost-effective mitigation, or financial returns, but rather the appropriation and utilisation of green signals. This conclusion is supported by the connection of EACs to increased market and reputational risk, the clustering of EAC use across consumer-facing industries and industry groups, and the reduction of EAC utilisation as the cost of risk management, or the value of financial opportunities rises for corporations.

The Project's Limitations: Lessons for Modelling

The methodology utilised and the analysis conducted were not perfect. Overall, the statistical analysis was fairly disparate, attempting to connect variables that would be both upstream and downstream from EAC utilisation in a causal relationship (i.e. reputational risk and cost-efficiency of low-carbon purchases). A secondary variable should be formed that combines the use of reporting methodology and the use of EACs, either as a continuous composite of the proportions EV1 and EV2, or as a categorical set of groups. This secondary variable should replace the EAC categorical variable for further causal examinations, as the Certified Assurer and Certified Signaller groups cannot currently be separated, though the latter forms a larger proportion of the market-based cohort.

The use of simple modelled relationships removed some opportunities for over-fitting, yet the predictive ability of the linear model developed was still very poor, particularly for values of EV1 above one. This section of the graph was underpopulated and although no singular, high leverage point existed, it is likely over-fitting occurs to the right of the y-axis. These issues could be attributed to the data quality, which suffered from inconsistent reporting methodologies, missing data, and reporting errors (e.g. 3000% of Scope 2 electricity being certified). Adding data from previous years reporting and instituting harsher data quality requirements could improve this aspect. Another issue affecting the model's predictive ability comes from zero-inflation within EV2 and "one-inflation" within EV1, exacerbated by the replacement of NAs within this methodology. This was justified, to allow model comparison, as determining significant variables to input into models was more relevant than their predictive ability. However, a clear theoretical disconnect exists between the use of linear modelling and the analysis of bounded variables (proportions 0-1 for example). Though models such as the Beta Distribution are specialised for modelling continuous proportions, they are not suitable for considering all market-based reporting, which has a lower bound of zero, but no upper bound, with calid observations occurring at 0 and 1 (Swearingen, et al., 2012). Proposals to address this lack of suitable distributions are presented in the next section.

Unfortunately, the sampling methodology used was also likely too simple, simply selecting corporations listed in a “block” of EAC-utilising EU nations. A more appropriate sampling methodology would select a sample of corporations from around the globe that were representative of the general make up of Certified and Uncertified groups. A more complex sampling methodology would likely need to be developed in order to integrate the data from previous year’s reporting, in order to increase the number of datapoints, 2014-2016 data could be added, provided changes in year-to-year reporting methodology were resolved

The Project’s Limitations: Lessons for Reporting

The CDP could do more to ensure that proportions within their reporting methodologies are appropriately bounded, with some corporations reporting emissions reductions or certification figures higher than their own emissions or Scope 2 figures. Additionally the CDP seem to be forgiving of gaps in data, with many corporations having incomplete or invalid responses getting fairly high CDP scores. For example Dixon’s Carphone, which had to be removed to due discrepancies in their efficiency-based and year-to-year emissions reductions, received a score of “B”, the third highest. The CDP should apply conditional logic to ask corporations to double check, or provide more detail for figures where they may outlie, or disallow blank responses or non-valid responses (i.e. non-low-carbon emissions factors of zero, or zero cost initiatives); or failing this, apply appropriate penalties for corporations’ mis-reporting. Issues of zero-inflation, particularly for costs and savings, are particularly relevant as they result in non-defined values for secondary variables, causing issues with changing sample sizes and model comparisons. Finally, some of the CDP categorisations seem too broad for the specific analysis above, i.e. “Low-Carbon Purchases” within the initiative reporting covers everything from power purchase agreements to market-based approaches including EAC utilisation. This echoes Gowdy’s (2018) point regarding the need for codifying the opaque terminology of “Green Tariffs”, with 9 available form of low-carbon purchasing available through the CDP.

Proposals for Further Research

The prior section spoke of a theoretical disconnect between the distribution of the explanatory variables, notably EV1, and the modelling techniques applied. One solution for the one-inflation present in EV1 consists of segregating corporations who are selling market-based instruments from those buying them, such that the dataset could be bound from 0-1, and a modified form of Beta distribution applied, called the Zero-One Inflated Beta model. This mixture model has three processes: distinguishing zeroes from non-zeros (modelling 100% Renewable Electricity certification/disclosure); distinguishing ones from non-ones (modelling non-market vs market based approaches); and modelling the effects of lying between these extremes (Grace-Martin, 2020).

Considering the unification of the resultant models, the modelling methodology could integrate the causal variables alongside EAC utilisation, though so many possible variables could influence outcomes it would be difficult to determine their relative significance and combining too many variables without a strong theoretical link could lead to more overfitting. In addition, the covariance of many of the variables tested could exaggerate the relationships present, and one would expect a whole basket of random effects acting upon the multitude of variables and their outcomes. As these random effects may vary with other population variables, or over groups (i.e. EAC group has higher variance); and alongside non-random effects; a "Mixed Effect Model" can be applied to determine the outcomes of applying these fixed and random effects on an "unobserved variable". This is particularly useful for considering internal/external pressure and strategies for disclosure where there is no data describing a complete view of the distributions in question. This allows some degree of interrogation of levels of interest that have not been sampled, improving the utility of proxy variables and allowing for exploration of causal networks. Though different reporting methodologies would have to be consolidated, the introduction of the 2014-2016 data would increase the number of observations present in the data, and allow for the dataset to be split into two halves, one to produce models, another to test their predictive ability, which would also address issues of overfitting. Additionally, the datasets for these years could be better integrated with Herold's 2018 work, analysing the same time period.

Comparing the EAC utilisation within Herold's groupings would improve the theoretical link this thesis has developed as well as better place EACs within the matrix of internal and external pressure which is theorised to motivate strategic corporate disclosure. This could be done via access to the groupings put together by Herold directly, or by reproducing his initial analysis, though access to original or ESG data is required for each option respectively. The analysis could better link with price-sensitivity by integrating the emissions intensity metrics and targets reported within the CDP dataset. This may assist the methodology in separating the likelihood that EACs are being utilised for accounting or signalling purposes and add insight into whether the Certified Assurer group represents a differing demographic or disclosure strategy. By improving the understanding of how financial returns, green signalling and disclosure motivate corporate action, more can be said about why corporations certify strategically, and what this may mean for wider trends of CVA.

In Conclusion

The existence of the CDP speaks to the power of CVA, as a shareholder interface motivating and disclosing corporate change, but one would expect a spectrum of levels and modes of corporate engagement. It is undeniable that the management of relevant risks, and the responsibility of a corporation for its actions are at the forefront of society's expectations for corporations. The development of Frederick's CSR (1994) shows that what society considers credible and appropriate may change over time with societal pressures and therefore corporations should be responsive, and that response should be extensive and effective.

It is within this context that the influence and implications of EAC utilisation upon the CDP cohort may be assessed, with the last two questions Frederick (1994) posed reframed below:

- Does EAC utilisation alter the extent of corporate mitigation action?
- Does EAC utilisation alter the effectiveness of corporate mitigation action?

Does EAC utilisation alter the extent of corporate mitigation action?

Only the Certified Assurer group is distinguished by both their use of EACs and increased response action. These location-based corporations show significantly greater emissions reductions due to energy efficiency action. Herold and Lee linked frameworks of best practice and systems of improved accountancy and transparency, as may be offered by EACs, with above-industry-average internal carbon management practices (such as the response) (2018). External practices like EAC utilisation were found to be driven by stakeholder engagement and Verification & Assurance within these "Excellent" corporations, favouring EAC utilisation within accountancy and transparency (ibid.).

There is no significant difference in the extent of the response for the market-based group generally, where EACs are not used solely for internal accountancy but form a part of wider strategies of action and disclosure, with the green signalling qualities of EACs realisable through a market-based reporting methodology. Because of this, EACs, their benefits, and the opportunity cost they represent are considered alongside other actions, like investing in the response, or sourcing renewable energy through alternate means, such as PPAs. However, the investigations into NH1.2, show that a trade-off occurs between market-based signalling, and the response, with EACs interacting to strengthen this relationship. The balance between the external signalling and response action is not determined by the utilisation of EACs alone however, but rather by factors including the position of a corporation in a market and the relative internal/external pressure put upon that corporation.

This can be seen through the variance of EAC utilisation between primary industries, with price-sensitive business-to-business sectors such as Manufacturing utilising significantly fewer EACs than consumer-facing industries considering primarily reputational risk (such as Retail or Hospitality). This supports the work of Genç (2013), and links to Herold and Lee's investigation into external and internal pressure (2018). This variation within and across sectors is also revealed by corporate industry membership, particularly the evidence from investigation into RE100 corporations, who externally promote the use of "100% renewable electricity". These corporations have significantly higher EAC utilisation, underpinning their self-promotion in response to external pressure, or a need to support brand value.

All the above hints at the position of EACs within the complex causal network of corporate decision-making, where EACs do little to determine overall corporate strategy, yet play essential but differing roles in realising different corporate strategies. This allows EACs to be used in determining which strategy a corporation may be following, what the corporation considers essential to their carbon management, and what pressures a corporation faces. This provides valuable insight into pathways of carbon management and disclosure, which may reveal the extent of current and planned corporate actions. Although EACs may interact when realising corporate action derived from social pressure, this social pressure is distinct and dynamic for each corporation and societal expectations are prone to change. Therefore, EACs should not be considered to alter the extent of corporate action. Instead EACs modify the effectiveness of corporate initiatives, whether investing in market-based instruments or other forms of mitigation, which together form a corporation's strategic response to societal expectations.

Does EAC utilisation alter the effectiveness of corporate mitigation action?

Another approach to separate the extent of mitigation (based upon market position and pressures) from the effectiveness of mitigation (enacted through use of EACs and other mitigation action) comes from considering the total mitigation reported in the "Initiatives" sections of Certified and Uncertified corporations. Here it is seen that Certified corporations have lower total mitigation figures from their initiatives. However it is unclear whether this is due to the lack of opportunities for significant mitigation, or the higher proportion of low-carbon purchases (i.e. EACs) making up these initiatives.

Statistical tests examining causality showed Certified corporations spend significantly more on the purchase of low-carbon energy, and these purchases make up a significantly greater proportion of their mitigation initiatives. What can be said is that these Certified low-carbon purchases do not mitigate any more cost-effectively than low-carbon purchases without EACs. In fact, Certified corporations have less cost-effective mitigation outside of low-carbon purchases. One may presume then that these Certified corporations are favouring financial over mitigation benefits; in reality, these corporations do not show significantly improved returns on investment (annual savings per pound spent mitigating) for their general initiatives, actually having lower savings intensities for low-carbon purchases than the Uncertified group.

The focus within the Certified group on low-carbon instruments, despite their lack of cost-effectiveness in mitigation or providing financial returns, allows only one beneficial outcome to be driving their purchase: their use in green signalling, where the effective communication of action is as important as the effectiveness of the action in the first place. This trade-off between financial benefits and green signalling is further supported by their significant correlation with reputational risk, as well as the fall in EAC utilisation present within corporations with increasing costs of risk management, or increasing values for financial opportunities.

The influence and implications of EAC utilisation

So how does the utilisation of EACs affect CVA? Two conclusions are offered by the two groups: Certified Signallers, utilising the signalling benefits of EACs through market-based reporting, and Certified Assurers, utilising EACs as part of systems of accountancy and transparency, where a location-based methodology excludes their use in direct signalling.

The latter group offers a positive link between EAC utilisation and the response, showing that these corporations are “Excelling” with both Stakeholder Engagement and Verification & Assurance action. Here EACs allow better accountancy of energy use and emissions factors, with certification improving the transparency of action through the separation of market-based accounting, and location-based emissions outcomes. The separation of these aspects improves responsiveness, as the credibility of market-based instruments may vary with time or audience, and the unproven additionality of these instruments may undermine reporting trust. In this way these Certified Assurer corporations are meeting Tang and Luo’s expectations by codifying acceptable and excellent carbon disclosure.

The opposite side of Tang and Luo's description of the CDP as a "code" allows corporations to define and follow a set of principles within the CDP's sphere. Corporations appropriating the "public commodity" of low-carbon attributes through EACs (RECs.org, 2020) to be used in green signalling could be viewed as embedding irresponsible principles within the CDP.

The trade-off between market-based signalling outcomes, offered by EACs, and internal efficiency action within the market-based group hints at some worrisome outcomes of the principle described above. EACs are examples of high risk interventions where they substitute high credibility action with low credibility action, i.e. truly additional renewable energy initiatives such as internal renewable energy generation or PPAs can be substituted for theoretical demand creation, where realisation of this additional capacity is entirely dependent on policy-makers and international market forces **(**Figure 14**)**.

As well as increasing risk for certain initiatives, EAC purchase has two problematic aspects as revealed by this thesis. To begin, market-based corporations use EACs for market-based emissions reductions, which are traded-off for other emissions reduction programmes, such as from energy efficiency actions (Figure 6). This pursuit of "soft", "low-cost" mitigation could lower public benefit by failing to address plateauing industry emissions, which misses the ~25% emissions reductions available through energy intensity improvements (Waters, 2019).

The above is an issue of cost-driven corporate strategy, but more troublesome are corporations using EACs to signal green attributes without sufficient Verification & Assurance. The literature review found research linking EACs with ineffective demand creation, costs that are uncompetitive and unrepresentative in our current renewable energy market, and the private appropriation of public commodities. The strategic disclosure of "concrete" market-based emissions reductions underpinned solely or mostly by this certification is at best speculative, and at worst manipulative, and would fall under the banner of greenwashing. The use of EACs could provide an example of the most widespread, accepted form of greenwashing across markets today, whether intentional or not.

Yet the interpretations of the CDP as a "code" do not exclude EACs. In fact they offer hope through the codification of "excellent" disclosure, whilst recent interviews with industry leaders show that the principle of private appropriation through EACs may be deemed less acceptable by the day (The Times, 2019). Meanwhile industry groups such as the RE100 attempt to salvage their reputation through technical documents such as "Making credible renewable electricity usage claims" (Braslawsky, Jones and Sotos, 2016).

Change to EAC markets or utilisation needs to be addressed to stop the “credibility collapse” or “price collapse” of the instrument. Were the ineffectiveness of EACs to incentivise new capacity to continue, and the appropriation of public attributes discovered by consumers, the credibility of the instrument, and therefore its signalling utility, may collapse. Likewise were the price of an EAC to suddenly jump to the of true cost of private demand creation (through PPAs for example), it is likely corporations would abandon non-contracted EACs for mechanisms like PPAs that provide the same benefits, alongside exclusivity.

Recommendations Moving Forward

Two major issues stand between the utilisation of EACs and achieving their desired outcomes: motivating net increases in renewable generation capacity; and providing a system of effective accounting and attestation for renewable energy. Below are recommendations addressing these issues based upon the findings of this thesis.

In order to address the need for increasing energy efficiency measures alongside renewable capacity, it is proposed that binding, long-term targets are set out for corporations to achieve demand and energy intensity reduction activities alongside current initiatives. Existing work suggests that similar tradeable certificate schemes could be appropriate, provided lessons are learnt from existing EAC markets, notably that targets are expressed with both policy time frame and certainty, and that the market for certificates is liquid and transparent, whilst providing low transaction costs and technology-neutrality (Oikonomou and Mundaca, 2008). To avoid action which is disparate and self-serving, the target should encourage innovation alongside selecting the “low-hanging fruit” (ibid.). One way to do this would be to provide low-discount-rate financial assistance for innovative projects with larger costs and uncertainties, where loans require financial returns within a set range, such that “low-hanging fruit” are not subsidised unnecessarily (avoiding the appropriation of public funds). This would allow for investment down to an evidence-based discount rate, building on the work of the Stern Review (Weitzman, 2007), whilst avoiding the over-allocation of public aid.

In order to provide renewable capacity increases and EAC attestation that is valid, the lack of additionality within EAC demand-creation must be addressed. This will require removing some of the over-supply of EACs in the market and raising the price of EAC purchases to the true cost of renewable energy subsidisation. The over-supply could be addressed in several ways, but the first would be simply to only allow EAC certification above the mandated supply, where projects have not already been financed i.e. the billpayer funds subsidies for 40% renewable supply capacity in the UK, this 40% would not be eligible for certification.

The other side of the same coin would be to mandate a 40% demand target for within the UK grid system, in order to ensure that national EAC utilisation is at least 40% across all sectors, with extra utilisation requiring additional certificates from inside or outside of the UK's EAC market, which would require the financing of additional capacity (Nielson and Jeppesen, 2003). Finally, the Chinese EAC system is mutually exclusive with other subsidies: generators may claim one or the other, but not both (Qiao et al., 2018). This means that where additional financial benefits are claimed, the capacity does not count towards the generator's compliance with national targets, and therefore additional capacity must be purchased or built elsewhere within the nation. There are questions around cross-border trade of EACs, and a need for standardisation of schemes across borders, not only to avoid the appropriation of public commodities internationally (Recs.org, 2020) and issues arising with investor uncertainty (Finjord et al., 2018), but also to ensure additionality is realised globally. These measures should be rolled out with care and deliberation across national and international structures, following the best practices found across innovators, in order to avoid the collapse of EAC markets, which may currently be in states of limited competition (Maroulis, 2019; Tamás et al., 2010); and ensure necessary market transparency (Voogt et al., 2005).

Realising the theoretical demand creation of EACs will go some way to increasing the validity of their attestation, but similarly to Oikonomou and Mundaca's suggestions for tradable "white" certificates, both EAC targets and certifiable outcomes should be expressed with their temporal aspects, and a level of certainty, such that reporting outcomes are responsive to the realisation of abatement outcomes. Increasing public benefit-private cost ratios through the realisation of abatement may reduce some excessive secrecy in reporting (Haeberle and Henderson, 2016). Executive incentives could be linked not to the realisation of financial or emissions targets, but the level of transparency and accuracy connecting corporate targets, disclosure and realised outcomes.

It is proposed that "energy efficiency" is added to the CDP register of initiatives, with subcategories such as "lighting" or "HVAC", which would avoid the need to approximate the existence of these measures through the interrogate and interpretation of CDP records listed "Process" or "other". Additionally reports of zero-cost initiatives, or reports of zero-emissions factors for non-renewable energy sources should trigger follow up questions within the CDP, as these are rarely valid and degrade data quality. Interrogation of terms such as "green tariff" should occur by market regulators (e.g. the UK's Ofgem), to ensure transparency of green marketing and uphold customer confidence in ethical corporate action (Gowdy, 2018).

Upholding confidence in ethical corporate action may counter Harmes' (2011) concerns for arbitrage in undermining the investor-led mitigation business case.

The EAC will not be a silver bullet for the cost-effective financing of capacity within the renewable energy sector: work needs to be done within and across borders to realise the instrument's effectiveness. Responsiveness to society's perceptions and expectations of the instrument should drive corporations to cooperate with governments to bring about an effective EAC market.

Until then the instrument remains a valuable lens: for considering the balance of internal and external pressure upon corporations; for considering the propensity of different industries and business models to accept the risk of price elasticity and reputational responsibility; and for revealing patterns of strategic disclosure across sectors and industry groups.

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APPENDIX A

Term, Acronym or Initialisation	Definition
EAC	Energy Attribute Certificate: A tradable form of certification that attributes properties such as an emissions factor to a specified quantity of generated electricity, which can be traded separately from said electricity.
CVA	Corporate Voluntary Action
ETS	Emission Trading Scheme
MBI	Market Based Instrument
CSR	Corporate Social **Responsiveness**, as defined by Frederick (1994)
CDP	Formerly the Carbon Disclosure Project, now just the CDP
EU	European Union
ESG	Environmental, Social and Governance (metrics/scores)
Assurers	The group of corporations using the location-based method have been given the shorthand "Assurers" due to the fact that the location-based reporting methodology uses a grid emissions factor, usually assured at a national level, with a greater level of implicit assurance.
Signallers	The group of corporations using the market-based method have been given the shorthand "Signallers", given that the majority of this cohort are using the market-based method to report an emissions factor below the grid factor (often 0), in order to signal the "greenness" of their energy consumption. Note this group also contains corporations with market-based proportions (EV1) above 1, showing they are selling market-based instruments.
Certified	The group of corporations with non-zero proportions of Scope 2 electricity certified by EACs (EV2) have been given the "Certified" shorthand. These EACs may be used for their zero-emissions factors (Signaller group) or for internal accounting and as part of best practice (Assurer group)
Uncertified	The group of corporations where no evidence of Scope 2 electricity EAC certification has been found.
EAC utilisation	Any listed certification of Scope 2 electricity connected to "tradable certificates" or like has been deemed EAC utilisation, though many forms of EAC exist (see below), and they may be provided alongside other forms of contractual instrument such as power purchase agreements
GOs	EU Guarantees of Origin
REGOs	UK Renewable Energy GOs
RECs	The US' Renewable Energy Certificates
I-RECs	The primary international EAC system: the International Renewable Energy Certificates
PPAs	Power Purchase Agreement, a private contractual arrangement to purchase energy and its attributes from a given generator/supplier. These are another form of low carbon purchasing
Low Carbon Purchasing	A hierarchy of different contractual instruments from which emissions factors can be derived
Additionality	The attribute of being "additional" to what already exists, i.e. if I were to purchase a pair of shoes, and someone were to take my current pair of shoes off, wrap them up, and give them back to me, they would not be additional.

	The GHG guidelines states that "The Scope 2 Guidance and corporate GHG accounting framework is based on attributional accounting, which in this context means allocating electricity emissions to end-users—but not the "impact" of a given action or activity outside of the inventory boundary. "Additionality" is a core concept of offset credits quantified using the project-level methodology to ensure that the offset was the decisive reason a project was implemented; but it's not a core concept for contractual electricity supply data in scope 2. Projects may be implemented for a variety of reasons—regulatory, favorable economics, or active consumer-driven demand—but the underlying GHG emissions information from that power plant would be the same. It's a matter of which instruments convey those emissions to which customers—and policy makers, 3rd party certification (like Green-e) and supplier programs can all influence this through program design and eligibility. The only requirements the Guidance has for contractual instruments in the market-based method are the Scope 2 Quality Criteria, which aim to ensure accurate allocation and eliminate emissions double counting between end-users. For more reading on the concept of additionality in scope 2, see Chapter 11 (How Companies Can Drive Electricity Supply Changes with the Market-Based Method)." (Top Ten Questions about the Scope 2 Guidance | Greenhouse Gas Protocol, n.d.)
FiT	Feed-in tariff, a UK scheme to subsidise renewable electricity generation at various scales
RE100	Convened by The Climate Group in partnership with CDP, the RE100 is an ambitious global initiative to "engage, support and showcase influential companies committed to using 100% renewable power." (RE100, 2020)
Extent of corporate mitigation action	The degree to which a corporation has engages with instruments, initiatives and internal action in order to attempt to bring about change. For example, a corporation may purchase all new LED lights, showing a good extent of action, but were all those lights defective, or if they were later replaced again with less efficient lighting, the overall effectiveness of the change is lower than the extent of the change.
Effectiveness of corporate mitigation action	The degree to which a corporation realises change through their engagement with initiatives, instruments and internal action. For example a corporation may only have one initiative, purchase and maintain a new plant, but if that plant is extremely efficient and there are large resultant emissions reductions realised through the change, the corporation has not engaged to a large extent, but with great effectiveness.
Explanatory Variable 1 (EV1)	A corporation's reported market-based figure, expressed as a proportion of their location figure, such that market-based emissions reductions correlate to EV1 values less than 1, with corporations reporting no market-based figure, or no change having EV1 values of exactly 1, and with corporations selling market-based instruments having values of EV1 greater than one. This variable is bounded at 0, but may hold any value above one in theory.
Explanatory Variable 2 (EV2)	The Proportion of Scope 2 electricity a corporation has consumed that is certified by EACs, this variable is bounded 0-1.
The response	Emissions changess derived from initiatives categorised as addressing a "Process" or "Other" (energy efficiency actions). In the R studio code this

	is abbreviated to "Reported.Emissions.Change..Physical...Other.Efficiency.". Though the response mainly shows reductions, there are also positive changes. I.e. A corporation may start running a piece of machinery day and night, increasing emissions from that process, but decreasing emissions intensity. These initiatives should provide both a monetary and a carbon saving, and therefore one can distinguish what likely drives a corporate initiative
CDP score	The CDP grade assigned as part of their Public Investor Climate Score system.

APPENDIX B

Description of Her'ld's Corporate Carbon Disclosure Strategies (N.B. emphasis added).

Title of Strategy	Herold's Description (2018)
Excellence (Holistic engagement, internal pressure is held widely, external pressure leads to adoption of tangible commitments, a focus on Verification and Assurance)	"Excellence strategies with regard to carbon disclosure relies on the assumption that the **climate change values and principles exhibited by top management will be shared widely** and held by all organizational members, leading to a unity between organizational members Corporate voluntary action: A valuable but incomplete solution to climate change and energy security challenges. [17]. From a stakeholder perspective, the **high external pressures reflect an approach aimed at making carbon information comparable by an active engagement to work on the standards and transparency of carbon-related activities in the logistics industry [38]. This may include the adoption of technical international and industry procedures and following official international guidelines (e.g., GRI)** as well as engagement in public policy climate change activities, working directly with policy-makers, trade associations, research organizations and non-profit organization." (Herold, 2018, emphasis added)
Acquiescence (Follow the cost-saving actions)	"Organizational acquiescence reflects to **organization's conscious intent to conform to institutional pressures and its expectation that conformity will be self-serving to organizational interests** [22]. In the context of carbon disclosure, it is argued that related activities reflect the corporate actions taken by a company to achieve carbon-related accomplishments in order **to reduce its carbon footprint in line with cost reductions** [9,33,34,35]. Because companies have **high internal pressures**, the integration of climate change values is reflected in organizational structures and is exhibited by top management and shared by organizational members [19]. Moreover, because these companies face **low external pressures**, there is **no need for the company's management to include demands from stakeholders for carbon disclosure beyond market-driven initiatives**." (Herold, 2018, emphasis added)

Avoidance (Save face, regardless of whether action is tangible.)	"Avoidance is motivated by the **desire to circumvent the conditions that make conforming behavior necessary** [22]. With regard to carbon disclosure, it is argued this strategy can be **related to reputation management**, which Schaltegger and Burritt [36] described as a company's focus on societal, political and media attention. Because these companies have **low internal pressures, carbon-related activities and their disclosure may be closely linked to the PR department to gain the support of the company's most immediate audiences** [9]. Moreover, because these companies face low external pressures, management may employ self-interested or narcissist behavior, with claims of carbon-related achievements that are not accompanied by corporate action and reflects the use of rhetorical statements designed to create an impression of environmental responsibility [36]. As a result, **companies have to deal with uncoordinated action from stakeholders and thus with little demand for full carbon disclosure, nor being pushed to implement any carbon-related initiatives that lead to a reduction of the carbon footprint."** (Herold, 2018, emphasis added)
Compromise (Minimal engagement, as required to satisfy stakeholder demands)	"Compromise is employed in the spirit of **conforming to and accommodating external rules and norms, but in contract to acquiescence, compliance is only partial and organizations are more active in promoting their own interests** [22]. In the context of carbon disclosure, we argue that these companies engage in consultations with well-organized stakeholders to discuss the company's carbon-related practices mainly in order to maintain legitimacy. **Due to the high external pressures, however, stakeholder will continually ask for accountability regarding carbon emissions**, which may include requests to adopt technical international and industry procedures and to follow official international guidelines. However, because **these companies have low internal pressures, they will neglect organizational adaption strategies for climate change and react as little as possible to fulfil only the minimum and mandatory carbon disclosure requirements** [37]. Together, these factors result in a minimal engagement with the challenges arising from climate change." (Herold, 2018, emphasis added)

APPENDIX C

A list of the Variable Names and Cell contents/formula produced within Excel, directly from the CDP CSV files, prior to export to R Studio.

Variable Name	Cell Contents/Formula
Organisation	3i Group
Listed Nation	United Kingdom of Great Britain and Northern Ireland
Primary Industry	=VLOOKUP('5,'Summary D'ta'!B$2:O$1805,13)
Total Scope 2 Consumption (MWh)	=IF(SUMIFS(C8.2a!Q$2:Q$12629,C8.2a!B$2:B$12629,Sheet1!B5,C8.2a!L$2:L$126"9,"Total energy consumpt"on")=0,NA(),SUMIFS(C8.2a!Q$2:Q$12629,C8.2a!B$2:B$12629,Sheet1!B5,C8.2a!L$2:L$126"9,"Total energy consumpt"on"))

Summed Certified Consumption (MWh)	=SUMIFS(C8.2f!O$2:O$2873,C8.2f!B$2:B$2873,B5,C8.2f!$R$2:$R$2873,TRUE)
Average Non-renewable emissions factor (tCO_2e/MWh)	=ISNUMBER(IF(COUNTIF(C8.2f!B$2:B$2873,B5)>1,AVERAGEIFS(C8.2f!P$2:P$2873,C8.2f!B$2:B$2873,B5,C8.2f!R$2:R$2873,TRUE),VLOOKUP(B5,C8.2f!B$2:P$2873,15))) COUNTIF(C8.2f!B$2:B$2873,B5)>1 AVERAGEIFS(C8.2f!P$2:P$2873,C8.2f!B$2:B$2873,B5,C8.2f!R$2:R$2873,TRUE)
Average Combined Emissions Factor (tCO_2e/MWh)	=IF(ISNUMBER(IF(COUNTIF(C8.2f!B6:DFM6,B5)>1,AVERAGEIF(C8.2f!B6:DFM6,B5,C8.2f!B20:DFM20),VLOOKUP(B5,C8.2f!A6:DFL20,15))),(IF(COUNTIF(C8.2f!B6:DFM6,B5)>1,AVERAGEIF(C8.2f!B6:DFM6,B5,C8.2f!B20:DFM20),VLOOKUP(B5,C8.2f!A6:DFL20,15))),NA())
Reported Scope 1 Emissions (tCO_2e)	=SUMIFS(C6.1!M$2:M$7101,C6.1!B$2:B$7101,Sheet1!B5,C6.1!L$2:L$71”1,"Ro” 1")
Reported Scope 2 Emissions (Location) (tCO_2e)	=SUMIFS(C6.3!B17:JQO17,C6.3!$B2:$B7217,Sheet1!$A2,C6.3!$L2:$L72”7,"Ro” 1")
Reported Scope 2 Emissions (Market) (tCO_2e)	=IF(ISNUMBER(INDEX(C6.3!N$2:N$7217,MATCH(Sheet1!$A2,C6.3!B$2:B$7217,0))),SUMIFS(C6.3!N$2:N$7217,C6.3!$B$2:$B$7217,Sheet1!$A2,C6.3!$L2:$L72”7,"Ro” 1"),NA())
Gross Combined Reported Emissions (Scope 1+ 2)	=IF(ISNUMBER(VLOOKUP(B5,C6.10!B6:EEB18,13)),VLOOKUP(B5,C6.10!B6:EEB18,13),NA())
Summed Emissions (Scope 1 + 2L)	=B13+B12
Proportion of Scope 2 electricity certified	=IF(AND(B8>0,B9>0),B9/B8,NA())
Change in Emissions Factor due to Certification	=IFERROR(((B11-B10)*(B9/B8)),NA())
Proportion Market based	=IFERROR(B14/B13,NA())

Member RE100	=IF(ISNUMBER(MATCH('5,'C:\Users\conno\Downloads\[RE100 Start.xlsx]She't3'!$C$2:$C$208, 0)), IND‘X('C:\Users\conno\Downloads\[RE100 Start.xlsx]She't3'!$C$2:$D$208, MATCH('5,'C:\Users\conno\Downloads\[RE100 Start.xlsx]She't3'!$C$2:$C$208, 0), 2), NA())
Utilising Market method	=ISNUMBER(B19)
Utilising EAC?	=IF(B9>0,TRUE,FALSE)
Reported Emissions Change (RenEn)	=IF(B$16<>0,SUMIFS(C7.9a!$Q$2:$Q$19845,C7.9a!$B$2:$B$19845,B$5,C7.9a!$L$2:$L$198"5,"Change in renewable energy consumpt"on")/B$16,0)
Reported Emissions Change (Physical)	=IF(B$16<>0,SUMIFS(C7.9a!$Q$2:$Q$19845,C7.9a!$B$2:$B$19845,B$5,C7.9a!$L$2:$L$198"5,"Change in physical operating conditi"ns")/B$16,0)
Reported Emissions Change (Physical + Other Efficiency)	=B$16<>0 IFERROR(SUMIFS(C7.9a!$Q$2:$Q$19845,C7.9a!$B$2:$B$19845,B$5,C7.9a!$L$2:$L$198"5,"Change in physical operating conditi"ns"),0) SUMIFS(C7.9a!$Q$2:$Q$19845,C7.9a!$B$2:$B$19845,B$5,C7.9a!$L$2:$L$198"5,"Other emissions reduction activit"es") 0
Efficiency initiatives Mitigation	=SUMIFS(C4.3b!O$2:O$7549,C4.3b!B$2:B$7549,B5,C4.3b!M$2:M$75"9,"*efficien"y*")
Efficiency initiatives Mitigation (%)	=IF(B26<>0,B26/B16,NA())
Low Carbon Purchase initiatives Mitigation	=SUMIFS(C4.3b!O$2:O$7550,C4.3b!B$2:B$7550,B5,C4.3b!P$2:P$75"0, "*Scope 2 (market-base")*",C4.3b!M$2:M$755“, " Low-carbon energy purch"se")
Low Carbon Purchase initiatives Mitigation (%)	=IF(B28<>0,B28/B16,NA())
Average Investment Required (Other)	=(IF((COUNTIFS(C4.3b!W$2:W$75"0,"FA"SE",C4.3b!B$2:B$7550,B5))>0,SUMIFS(C4.3b!S$2:S$7550,C4.3b!B$2:B$7550,B5,C4.3b!B27:KDJ27,FALSE)/COUNTIFS(C4.3b!W$2:W$75"0,"FA"SE",C4.3b!B$2:B$7550,B5)))
Adjusted Average Investment (Other)	=B30/VLOOKUP(VLOOKUP('5,'–0 - Introduct'on'!$B$2:$N$1805,1'),'–0 - Introduct'on'!$U$22:$W$59,3)

Average Monetary savings (Other)	=(IF(COUNTIFS(C4.3b!W$2:W$75”0,"FA”SE",C4.3b!B$2:B$7550,B5)>0,SUMIFS(C4.3b!R$2:R$7550, C4.3b!B$2:B$7550,B5,C4.3b!W$2:W$75”0,"FA”SE")/COUNTIFS(C4.3b!W$2:W$75”0,"FA”SE",C4.3b!B$2:B$7550,B5)))
Adjusted Average Monetary Savings (Other)	=B32/VLOOKUP(VLOOKUP(’5,'–0 - Introduct’on'!$B$2:$N$1805,1’),'–0 - Introduct’on'!$U$22:$W$59,3)
Low-Carbon Purchases Investment Required	=IF((COUNTIFS(C4.3b!W$2:W$75”0,"T”UE",C4.3b!B$2:B$7550,B5))>0,(SUMIFS(C4.3b!S$2:S$7550,C4.3b!B$2:B$7550,B5,C4.3b!W$2:W$75”0,"T”UE")/(COUNTIFS(C4.3b!W$2:W$75”0,"T”UE",C4.3b!B$2:B$7550,B5))),NA())
Low-Carbon Purchases Adjusted Investment	=B34/VLOOKUP(VLOOKUP(B’5,'–0 - Introduct’on'!$B$2:$N$1805,1’),'–0 - Introduct’on'!$U$22:$W$59,3)
Low-Carbon Purchases Monetary savings	=IF((COUNTIFS(C4.3b!W$2:W$75”0,"T”UE",C4.3b!B$2:B$7550,B5))>0,(SUMIFS(C4.3b!R$2:R$7550,C4.3b!B$2:B$7550,B5,C4.3b!W$2:W$75”0,"T”UE")/(COUNTIFS(C4.3b!W$2:W$75”0,"T”UE",C4.3b!B$2:B$7550,B5))),NA())
Low-Carbon Purchases Adjusted Monetary Savings	=B36/VLOOKUP(VLOOKUP(B’5,'–0 - Introduct’on'!$B$2:$N$1805,1’),'–0 - Introduct’on'!$U$22:$W$59,3)
Total Initiative Mitigation	=SUMIF(C4.3b!B$2:B$7550,B5,C4.3b!O$2:O$7550)
Num Scope 1 initiatives	=COUNTIFS(C4.3b!$B$2:$B$7550,B$5,C4.3b!$P$2:$P$75”0,"*Scope”1 *")
Num Scope 2L initiatives	=COUNTIFS(C4.3b!$B$2:$B$7550,B$5,C4.3b!$P$2:$P$75”0,"*Scope 2 (location-base”)*")
Num Scope 2M initiatives	=COUNTIFS(C4.3b!$B$2:$B$7550,B$5,C4.3b!$P$2:$P$75”0,"*Scope 2 (market-base”)*")
Num Scope 3 initiatives	=COUNTIFS(C4.3b!$B$2:$B$7550,B$5,C4.3b!$P$2:$P$75”0,"*Scope”3 *")
Total Number of Initiatives	=COUNTIFS(C4.3b!B$2:B$7550,B5,C4.3b!$P$2:$P$75”0”"*")
Average Annual ROI	=IFERROR(B32/B30,NA())
Cost efficiency of mitigation (Other) (£/tCO_2e)	=IFERROR(B31/B26,NA())
Low Carbon Cost	=B35/B28

Efficiency of mitigation (£/tCO$_2$e)	
Average Savings Intensity (Other) £/TCO$_2$e	=IF(AND(B26<>0,B33<>0),B33/B26,NA())
Low Carbon Savings Intensity (£/TCO$_2$e)	=IF(B28<>0,B37/B28,9999)
CDP Score	=VLOOKUP(VLOOKUP('5,'Public Investor Climate Sco'es'!$B$2:$E$5920,4),CONSOLIDATED!$AL$3:$AM$13,2)
Y Variables missing?	=SUM(IF(ISERROR(B23:B48),1))
Z-Outlier Cost Efficiency Mitigation	=IFERROR((B45-(VLOOKUP(B$7,Sheet2!$A$1:$G$15,2)))/(VLOOKUP(B$7,Sheet2!$A$1:$G$15,5)),NA())
Z-Outlier Low Carbon Cost Efficiency Mitigation	=IFERROR((B46-(VLOOKUP(B$7,Sheet2!$A$1:$G$15,3)))/(VLOOKUP(B$7,Sheet2!$A$1:$G$15,6)),NA())
Z-Outlier Average Mitigation Intensity (Other)	=IFERROR((B47-(VLOOKUP(B$7,Sheet2!$A$1:$G$15,4)))/(VLOOKUP(B$7,Sheet2!$A$1:$G$15,7)),NA())
Z-Outlier?	=OR(IFERROR(OR(-1.5>B51,B51>1.5),FALSE),IFERROR(OR(-1.5>B52,B52>1.5),FALSE),IFERROR(OR(-1.5>B53,B53>1.5),FALSE))
Sense Check	=AND(IFERROR(B29<=1,TRUE),IFERROR(B27<=1,TRUE),IFERROR(B25>=-1,TRUE),IFERROR(B24>=-1,TRUE),IFERROR(B23>=-1,TRUE))

APPENDIX D

The complete R code used to process the outputs of the Excel Spreadsheet, generating statistical and graphical outputs. Octothorpes (#) denote that the following line of text is a comment. These comments provide explanations to what is occurring in the code, and its significance.

```
##DOUBLE CHECK WORKING DIRECTORY
getwd()

### Attach packages, resolve conflicts
install.packag“s("taR”fx")
install.packag“s("p”cl")
install.packag“s("ggpm”sc")
install.packag“s("M”LM")
```

```
install.packag“s("M”LM")
library(MGLM)
library(ggpmisc)
library(ggplot2)
library( taRifx )##For reclassing cols
library(dplyr)
library(ggplot2)
library(rlang)
library(tidyverse)
library(conflicted)
libra   rusrrr)
library(beanplot)
library(MASS)
library(pscl)
library(gamlss)
libra“y("gridEx”ra")
##library(nnet)
conflict_pref“r("mut”te“, "dp”yr")
conflict_pref“r("sel”ct“, "dp”yr")
conflict_pref“r("summar”se“, "dp”yr")
conflict_pref“r("fil”er“, "dp”yr")
conflict_pref“r("fi”st“, "dp”yr")
conflict_pref“r("separ”te“, "ti”yr")
conflict_pref“r("un”te“, "ti”yr")

rm(list = ls())
cdpIn<-read.c‘v('../Data/CDP_Out.’sv')  ### PARENT FOLDER/DATA/CSV_NAME
cdpCausal<-read.c‘v('../Data/CDP_Out_Causal.’sv')
sapply(cdpIn, class)
sapply(cdpCausal, class)


####### 1: HANDLING N/A and #DIV/0! FIRST
cdpNA <- cdpIn %>% replace(”=="#”/A", NA)
cdpNA <- cdpNA %>% replace(”=="#DIV”0!", NaN)

####### 2L HANDLING TYPE- FACTOR TO NUMERIC
cdpNA[,4:42] <-  lapply(japply(cdpNA[,4:42], which(sapply(cdpNA[,4:42],
class”=="fac”or")),as.numeric)
sapply(cdpNA, class)

####### 3: REMOVING NON-VALID DATA POINTS (Proportions greater than 1)
cdpCore = subset(cdpNA, Sense.Check == TRUE)

## Graphing the change in zero inflation from steps 1-3
par(mfrow=c(1,2))
f1<-hist(cdpNA$Proportion.of.Scope.2.electricity.certified, col“= "”ed", xlab“=
"Proportion ”AC", main = NULL)
f2<-hist(cdpCore$Proportion.of.Scope.2.electricity.certified, col“= "gr”en", xlab“=
"Proportion ”AC", main = NULL)
```

```
par(mfrow=c(1,1))

####### 4: DEFINing FUNCTIONS FOR DATA CLEANUP
## Define z-score function
cleanDirty <- function(dirty, sigStDevs){
  clean <- dirty[which(sigStDevs*-1 <= scale(dirty) & scale(dirty) <= sigStDevs)]
  return(clean)
}

cleanDF <- function(df, dirty, sigStDevs){
  clean <- df[which(sigStDevs*-1 <= scale(dirty) & scale(dirty) <= sigStDevs),]
  return(clean)
}

## Showing post data-cleanup change
par(mfrow=c(1,2))
f3<-hist(cdpNA$Reported.Emissions.Change..Physical...Other.Efficiency., col“= "”ed",
xlab“= "Emissions Change (Efficien”y)", main = NULL)
text(f3$mids,f3$counts,labels=f3$counts, adj=c(0.5, -0.5))
f4<-hist(cleanDirty(cdpNA$Reported.Emissions.Change..Physical...Other.Efficiency.,1.5),
col“= "gr”en", xlab“= "Emissions Change (Efficien”y)", main = NULL)
text(f4$mids,f4$counts,labels=f4$counts, adj=c(0.5, -0.5))
par(mfrow=c(1,1))


### THIS REDUNDANT SECTION ALLOWS THE VERIFIED DATA TO BE
SEPARATED BY ANY LIST OF NATIONS

### nation[] “- "United Kingdom of Great Britain and Northern Irel”nd"
### nation <-“c("United Kingdom of Great Britain and Northern Irel”nd“, "Denm”rk“,
"It”ly“, "Germ”ny“, "Sp”in“, "Netherla”ds“, "Irel”nd“, "Fra”ce“, "Swe”en“, "Finl”nd“,
"Gre”ce“, "Guern”ey“, "Aust”ia“, "Belg”um“, "Luxembo”rg“, "Portu”al“, "Pol”nd“,
"Ma”ta“, "Hung”ry“, "Czec”ia“, "Cyp”us")

####### 5 ##### SPLITTING BY EU NATIONS UTILISING EACS
cdpEU <- cdpCore[gre‘l('United Kingdom of Great Britain and Northern
Ireland|Denmark|Italy|Germany|Spain|Netherlands|Ireland|France|Sweden|Finland|Greece|G
uernsey|Austria|Belgium|Luxembourg|Portugal|Poland|Malta|Hungary|Czechia|Cyp’us',
cdpCore$Listed.Nation),]

## Showing the effects of dataclean up on the EU dataset
par(mfrow=c(2,1))
beanplot::beanplot(Reported.Emissions.Change..Physical...Other.Efficiency. ~
Utilising.EAC., data = cdpEU, col“= "lightg”ay")
clean<-
cleanDF(cdpEU,cdpEU$Reported.Emissions.Change..Physical...Other.Efficiency.,1.5)
beanplot::beanplot(Reported.Emissions.Change..Physical...Other.Efficiency. ~
Utilising.EAC., data = clean, col“= "lightg”ay")
par(mfrow=c(1,1))
rm(clean)
```

```
par(mfrow=c(2,2))
f5<-hist(cdpEU$Proportion.Market.based, col“= "b”ue", xlab“= "Market Based/Location
Based Emissi”ns", main = NULL)
text(f5$mids,f5$counts,labels=f5$counts, adj=c(0.5, -0.5))
f6<-hist(cdpEU$Proportion.of.Scope.2.electricity.certified, col“= "b”ue", xlab“=
"Proportion Scope 2 Certif”ed", main = NULL)

f7<-hist(cdpCore$Proportion.Market.based, col“= "”ed", xlab“= "Market Based/Location
Based Emissi”ns", main = NULL)
text(f7$mids,f7$counts,labels=f7$counts, adj=c(0.5, -0.5))
f8<-hist(cdpCore$Proportion.of.Scope.2.electricity.certified, col“= "”ed", xlab“=
"Proportion Scope 2 Certif”ed", main = NULL)
par(mfrow=c(1,1))
rm(clean)

## Defining a convenience function for plotting regressions


ggplotRegression <- function (fit) {

  require(ggplot2)

  ggplot(fit$model, aes_string(x = names(fit$model)[2], y = names(fit$model)[1])) +
    geom_point() +
    stat_smooth(method“= ”lm", col“= "”ed") +
    labs(title = pas“e("Adj R2“= ",signif(summary(fit)$adj.r.squared, 5),
                  “  "Intercep” =",signif(fit$coef[[1]],5 ),
                  “  " Slop” =",signif(fit$coef[[2]], 5),
                  “  " ” =",signif(summary(fit)$coef[2,4], 5)))
}


################################ DATA TESTING

####### NULL HYPOTHESIS 1: There will be no statistically significant correlation
between the proportion of scope 2 electricity certified by EACs and ####### corporate
expenditure on emissions reduction through “Process” and “Other” emissions reduction
activities.


####### 6 #### PREPARATION OF DATASETS
## Clear dataframe and trim area excluded for given level of significance
rm(cdpNH1)
## testing for 0.05 sig = 1.64 Z score for area of exclusion
rm(NH1)
cdpNH1<-cleanDF(cdpEU,
cdpEU$Reported.Emissions.Change..Physical...Other.Efficiency.,1.64)
cdpNH1<-subset(cdpNH1, Organisation “= "Dixons Carph”ne")
```

```
## For testing later in general linear models
cdpNH1$propEff <- ((cdpNH1$Summed.Emissions..Scope.1...2L.+
cdpNH1$Summed.Emissions..Scope.1...2L.*cdpNH1$Reported.Emissions.Change..Physic
al...Other.Efficiency.)/cdpNH1$Summed.Emissions..Scope.1...2L.)

## This is a dataset of only complete cases to be used for comparing models
rm(NH1,NH1.location,NH1.market)
resp<-cdpNH1$Reported.Emissions.Change..Physical...Other.Efficiency.
prop.MB<-cdpNH1$Proportion.Market.based %>% replace(is.na(.), 1)
prop.Eff<-cdpNH1$propEff
prop.e.c<-cdpNH1$Proportion.of.Scope.2.electricity.certified %>% replace(is.na(.), 0) ###
NA = No certification or market based assumed,
                                                           ### mantain complete data for
categoricals comparison
useEAC<-cdpNH1$Utilising.EAC.
useMB<-cdpNH1$Utilising.Market.method
ind<-cdpNH1$Primary.Industry
NH1<-data.frame(resp, prop.MB, prop.e.c, useEAC, useMB, ind, prop.Eff)
NH1<-cleanDF(NH1,NH1$prop.MB, 1.64)

## Dividing by reporting methodology for investigations into group differences
NH1.location<-subset(NH1, NH1$useMB == FALSE)
NH1.market<-subset(NH1, NH1$useMB == TRUE)

## Dividing again for predictive element later
NH1.train<-NH1[1:202,]
NH1.test<-NH1[203:404,]



##### Define model (Energy Efficiency reductions are traded off against credentials
derived from a low proportion-market-based, resulting from a high proportion of scope 2
electricity certified, and strategic communication of this through Market Method):

### EACs offer signalling via the utilisation of a market method, and therefore we can
compare their significance where a market method is and is not utilised.

## Before going further we should check the presence and direction of effect
globall   ruskalkal.test(Reported.Emissions.Change..Physical...Other.Efficiency. ~
Utilising.EAC., data = subset(cleanDF(cdpCore,
cdpCore$Reported.Emissions.Change..Physical...Other.Efficiency.,1.645),
Utilising.Market.method ==
TRUE   ruskalkal.test(Reported.Emissions.Change..Physical...Other.Efficiency. ~
Utilising.EAC., data = subset(cleanDF(cdpCore,
cdpCore$Reported.Emissions.Change..Physical...Other.Efficiency.,1.645),
Utilising.Market.method == TRUE))

## A brief visual comparison
boxplot(data = cleanDF(cdpCore,
cdpCore$Reported.Emissions.Change..Physical...Other.Efficiency.,1.645),
```

```
Reported.Emissions.Change..Physical...Other.Efficiency.~Utilising.EAC.+Utilising.Market
.method, main“= "Global Energy Efficiency changes by use of EACs and MB report”ng")
boxplot(data = cdpEU, resp~useEAC+useMB, main“= "EU ETS Energy Efficiency
changes by use of EACs and MB report”ng")

###### 7A # We can confirm the interaction of these elements is
significan   ruskalkal.test(resp ~ useMB, data = cdpNH1)
##Use of market method alone is n   ruskal   antant, neither are EAC   ruskalkal.test(resp ~
useEAC, data = cdpNH1)
###### 7B # Separating by market method we see an interaction
howeve   ruskalkal.test(resp ~ useEAC, data = NH1.market) ### market-based disclosure
shows no significan   ruskalkal.test(resp ~ useEAC, data = NH1.location) ###### but
significance clustered around non-market

###### 7C # Boxplot
f9 <- ggplot(data = NH1.market, aes(y = resp, x = useEAC, fill = useEAC)) +
  geom_boxplot()+
  geom_point(aes(x = useEAC))+
  ggtit“e("Market-based report”ng") +
  theme(legend.position“= "n”ne")
f10 <- ggplot(data = NH1.location, aes(y = resp, x = useEAC, fill = useEAC)) +
  geom_boxplot()+
  geom_point(aes(x = useEAC))+
  ggtit“e("Location-based report”ng") +
  theme(legend.position“= "n”ne")
grid.arrange(f9, f10, ncol=2)

## This is because for corporations utilising the market based methodology can use many,
or relatively few instruments, but we do have a continuous variable for comparing Market
method utilisation, the proportion market based, which will replace our categorical across
the whole dataset:

###### 8
MASS::dropterm(lm(resp ~ prop.MB*useEAC, data = NH1), test“=”"F")
plot(lm(resp ~ prop.MB:useEAC, data = NH1))
summary(lm(resp ~ prop.MB:useEAC, data = NH1))
ggplotRegression(lm(resp ~ prop.MB:useEAC, data = NH1)) ##This plot shows significant
relationship onl##

### Separating the interaction has the highest AIC, and best theoretical fit (EAC signalling
only through market based reporting) therefore feed forward:
NH1.lm1 = lm(resp ~ prop.MB:useEAC, data = NH1)
summary(NH1.lm1)
anova(NH1.lm1)

## Defining the average non-EAC response for use in upcoming graph
cept<-mean(subset(NH1, useEAC == FALSE)$resp)
my.formula<- y ~ x

## Graphing main replationship: Vlear with no datapoints
```

```
ggplot(NH1, aes(x = prop.MB, y = resp, shape=useEAC, colour=useEAC, fill=useEAC)) +
  ##geom_point()+
  geom_smooth(meth”d=”lm") +
  labs(title“= "Proportion Market-based vs Emissions Change (Efficiency) by EAC ”se",
x‘= 'Proportion Market Ba’ed', y‘= 'Reported Emissions Change (Oth’r)')+
  geom_hline(aes(yintercept= cept), label“= "Average for non-EAC corporati”ns")+
  stat_poly_eq(aes(label = paste(..eq.label.., ..rr.label.., sep“= "”~~")), formula =
my.formula, parse = TRUE, label.y“= "bot”om")+
  geom_text(aes( 1.75, cept, label“= "Mean non-EAC mitigat”on", vjust = -1), size = 3,
col“= "bl”ck")


## Graphing main replationship: more cluttered but showing distribution of datapoints
my.formula<- y ~ x
ggplot() +
  geom_point(data = NH1.market,
           aes(x = prop.MB, y = resp,
               color = useEAC, group = useEAC)) +
  geom_point(data = NH1.location, shape = 0,
           aes(x = prop.MB, y = resp,
               color = useEAC, group = useEAC)) +
  geom_smooth(data =NH1,
            aes(x = prop.MB, y = resp,
                col = useEAC, group = useEAC),
            meth”d=”lm", se=TRUE, fullrange=FALSE, level=0.95,show.legend = TRUE)+
  labs(title“= "gg: proportion EAC vs cost of mitigat”on", x‘= 'Proportion Market Ba’ed',
y‘= 'Reported Emissions Change (Oth’r)')+
  geom_hline(aes(yintercept= cept))+
  ##scale_x_continuous(limits = c(0, 2)) +
  stat_poly_eq(aes(label = paste(..eq.label.., ..rr.label.., sep“= "”~~")), formula =
my.formula, parse = TRUE, label.y = c(0.9, 0.5)
  )


## Now the overall effect has been established, now we can examine the proportion EAC
utilisation, but to maintain comparability we move to NH1.market, as all cases are
complete. We start by considering how these two variables interlink:
summary(lm(prop.MB ~ prop.e.c, NH1.market))
ggplotRegression(lm(prop.MB ~ prop.e.c, NH1.market))

####### 9 # Analysis of continuous EAC variable
## The initiative response
sapply(cdpNH1, class)
summary(lm(data = subset(cdpNH1, Utilising.Market.method == TRUE),
Efficiency.initiatives.Mitigation ~  Proportion.of.Scope.2.electricity.certified))
ggplotRegression(lm(data = subset(cdpNH1, Utilising.Market.method == TRUE),
Efficiency.initiatives.Mitigation ~  Proportion.of.Scope.2.electricity.certified))

## We can see that Proportion Scope 2 influences Proportion Market based if nothing else:
```

```
cor(NH1.market$prop.MB,NH1.market$prop.e.   ruskalkal.test(data=NH1, prop.e.c ~
useMB)
## A graph showing the difference in EAC utilisation with reporting methodology
ggplot(data = cdpNH1, aes(y = Proportion.of.Scope.2.electricity.certified, x =
Utilising.Market.method, fill = Utilising.Market.method)) +
  geom_boxplot()+
  geom_point(aes(x = Utilising.Market.method))

## The proportion EAC is n   ruskal   antant alone however for market based
summary(lm(resp ~ prop.e.c,data = NH1.market))
ggplotRegression(lm(resp ~ prop.e.c,data = NH1.market))+
  labs(subtitle“= "Efficiency change (Efficiency) vs Proportion EAC utilised (”B)")
## Significant for location
summary(lm(resp ~ prop.e.c, data = NH1.location))
ggplotRegression(lm(resp ~ prop.e.c, data = NH1.location))

## We could try combining the interaction between Scope 2 certification and the resultant
market proportions, we can get close to 0.1 significance. The proportion has to be inverted
(1-proportion) such that it scales in the same direction- higher number means less
utilisation.
NH1.market$invProp <- (1-NH1.market$prop.e.c)
NH1.market$dualProp <- (NH1.market$prop.MB*NH1.market$invProp)
## We can see that dual prop does not invalidate interactions
summary(lm(resp ~ dualProp,data = NH1.market))
ggplotRegression(lm(resp ~ dualProp,data = NH1.market)) ### but contributes to the
effect: T value also negative

## Recall that these two variables co-vary significantly. Although it is important to consider
the effects of this co-variance, we will avoid trying to form a linear regression with them
together due to the bias in fitting parameters that result“: "it is common to find that
independent variables are correlated, and such correlations lead to biased parameter
estimates or significance te”ts"

## We have a model ready for comparison against other models: NH1.lm1 ##
summary(lm(resp ~ prop.MB, data = NH1)) ## MB proportion alone has a higher p value
and a lower R value than our model
summary(lm(resp ~ ind, data = NH1)) ## not significant

## EACs better predictor than market based alone or corporate industry
summary(NH1.lm1)
plot(NH1.lm1)

##Second plot for EAC models shows higher dependant dispersion at highest and
lowestquartiles, possibly evidence of non-gaussian distribution?
hist(x = cdpNH1.train$Reported.Emissions.Change..Physical...Other.Efficiency.)

## Recall the propEff, a variable re-written in a non-negative form describing t“e "redu”ed"
emissions as a proportion of initial emissions, however as some corporations had positive
emissions changes (i.e. not reductions), this data is still not bounded 0-1.
```

```
##cdpNH1$propEff <- ((cdpNH1.train$Summed.Emissions..Scope.1...2L.+
cdpNH1.train$Summed.Emissions..Scope.1...2L.*cdpNH1.train$Reported.Emissions.Chan
ge..Physical...Other.Efficiency.)/cdpNH1.train$Summed.Emissions..Scope.1...2L.)
sapply(cdpNH1,class)
summary(lm(propEff ~ prop.e.c, data = cdpNH1))
hist(x = cdpNH1$propEff)


##data greater than 1 exists, binomial cannot be applied until this is resolved, and
theoretical link is poor (no Bernoulli trials present)
summary(glm(prop.Eff ~ prop.MB:useEAC, data = NH1, family = quasi()))
##(Dispersion parameter for quasi family taken to be 0.007929924)
summary(glm(prop.Eff ~ prop.MB:useEAC, data = NH1, family = inverse.gaussian()))
##Less Promising, lets try gamma
NH1.glm = glm(prop.Eff ~ prop.MB:useEAC, data = NH1, family = Gamma())
summary(NH1.glm)

par(mfrow=c(2,2))
plot(NH1.glm)

par(mfrow=c(2,2))
plot(NH1.lm1)
## Gamma is the most Promising so far, one high leverage points may be skewing fit
though

###### 10 # Compare existing model with GLMs.
## Confirm not to drop term interactions and compare models AIC:
MASS::dropterm(NH1.lm1, test“=”"F")
MASS::dropterm(NH1.glm, test“=”"F")
## Linear Model preferred

## Save Linear Model Output as DF
NH1.lm.df<-broom::tidy(NH1.lm1)
plot(NH1.lm1)
summary(NH1.lm1)
##Residual standard error: 0.08303 on 401 degrees of freedom
##Multiple R-squared:  0.02213,       Adjusted R-squared:  0.01722
##F-statistic: 4.503 on 2 and 398 DF,  p-value: 0.01164

## REJECT NULL HYPOTHESIS 1

## Consider the resulting importance based upon the make-up of the sample group:
group_by(NH1, useEAC, useMB) %>% summarise(n())
group_by(NH1, useEAC, useMB) %>% summarise(mean(resp))
mean(NH1$resp)
## 91 (22.7%) Location Non-EAC, 96 (23.9%) Location EAC, 29 (7.2%) Market non-
EAC, 185 (46.1%) Market EAC.

##### 11 # CAVEAT: LOW PREDICTIVE ABILITY FOR GIVEN SAMPLE SIZE
NH1.lm2 = lm(resp ~ prop.MB:useEAC, data = NH1.train)
```

```
## Alternative for confidence predict.lm(NH1.lm2,newdata=NH1.test,
interv”l="confide”ce")
pred.NH1.1 <- predict.lm(NH1.lm2,newdata=NH1.test, interv”l="predict”on")
NH1.1.bound<- cbind(NH1.train,pred.NH1.1)
p <- ggplot(data = NH1.1.bound, aes(x = prop.MB, y = resp, shape=useEAC,
colour=useEAC, fill=useEAC)) +
  geom_point() +
  stat_smooth(method = lm) +
  labs(title“= "The range of all values predicted for ”M1", subtitle“= "based upon half of the
EU ETS d”ta")
# 3. Add prediction intervals
p + geom_line(aes(y = lwr), color“= "”ed", linetype“= "das”ed")+
  geom_line(aes(y = upr), color“= "”ed", linetype“= "das”ed")


pred.NH1.2 <- predict.lm(NH1.lm2,newdata=NH1.test, interv”l="predict”on")
NH1.2.bound<- cbind(NH1.train,pred.NH1.2)
p <- ggplot(NH1.2.bound, aes(prop.MB,resp)) +
  geom_point() +
  stat_smooth(method = lm)
# 3. Add prediction intervals
p + geom_line(aes(y = lwr), color“= "”ed", linetype“= "das”ed")+
  geom_line(aes(y = upr), color“= "”ed", linetype“= "das”ed"##

####### NULL HYPOTHESIS 2: There will be no statistically significant correlation or
clustering relating the industry price sensitivity, or membership with industry groups
respectively, and the utilisation of EACs.

####### 1 ### Clean up
cdpNH2<-cleanDF(cdpCore,
cdpNA$Reported.Emissions.Change..Physical...Other.Efficiency.,2.3262)
hist(x = cdpNH2$Proportion.Market.based)
cdpNH2<-cleanDF(cdpNH2, cdpNH2$Proportion.Market.based,2.3262)
hist(x = cdpNH2$Proportion.Market.based)
hist(x = cdpNH2$Proportion.of.Scope.2.electricity.certified)

####### 2 ## Test membership to industry
grou   ruskalkal.test(Proportion.of.Scope.2.electricity.certified ~ Member.RE100, data =
cdpNH2)
bp <- ggplot(data = cdpNH2, aes(y = Proportion.of.Scope.2.electricity.certified, x =
Member.RE100, fill = Member.RE100), legend.) +
  geom_boxplot()+
  geom_point(aes(x = Member.RE100)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "EAC utilisation by RE100 members”ip")
bp   ruskalkal.test(Proportion.Market.based ~ Member.RE100, data = cdpNH2)
bp <- ggplot(data = cdpNH2, aes(y = Proportion.Market.based, x = Member.RE100, fill =
Member.RE100)) +
  geom_boxplot()+
```

```
  geom_point(aes(x = Member.RE100)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Proportion Market-Based utilisation by RE100 members”ip")
b   ruskalkal.test(Proportion.Market.based ~ Utilising.EAC., data = cdpNH2)
bp <- ggplot(data = cdpNH2, aes(y = Proportion.Market.based, x = Utilising.EAC., fill =
Utilising.EAC.)) +
  geom_boxplot()+
  geom_point(aes(x = Utilising.EAC.))
bp

################################ 3 ### Testing by Primary
Indust   ruskalkal.test(Proportion.of.Scope.2.electricity.certified ~ Primary.Industry, data =
cdpNH2)
bp <- ggplot(data = cdpNH2, aes(y = Proportion.of.Scope.2.electricity.certified, x =
Primary.Industry, fill = Primary.Industry)) +
  geom_boxplot()+
  geom_point(aes(x = Primary.Industry))+
  scale_x_discrete(labels = abbreviate) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "EAC utilisation by Listed Primary Indus”ry")
bp   ruskalkal.test(Proportion.of.Scope.2.electricity.certified ~ CDP.Score, data = cdpNH2)
###CDP score is not significant

################################Exploring causali–y - what makes these
groups/subsets different?

##### Data Clean-up
cdpCausal<-read.c‘v('../Data/CDP_Out_Causal.’sv')
sapply(cdpCausal,class)
cdpCausal$Proportion.of.Scope.2.electricity.certified <-
as.numeric(levels(cdpCausal$Proportion.of.Scope.2.electricity.certified))[cdpCausal$Propo
rtion.of.Scope.2.electricity.certified]
cdpCausal$X.Policy...Legal..Risks <- as.factor(cdpCausal$X.Policy...Legal..Risks)
cdpCausal$X.Market..Risks <- as.factor(cdpCausal$X.Market..Risks)
cdpCausal$X.Reputation..Risks <- as.factor(cdpCausal$X.Reputation..Risks)
hist(cdpCausal$Summed.cost.of.risk.management)
cdpCausal <- cleanDF(df=cdpCausal, dirty=cdpCausal$Summed.cost.of.risk.management,
1.64)
hist(cdpCausal$Time.Horizon.Risk.Assessments)
cdpCausal <- cleanDF(df=cdpCausal, dirty=cdpCausal$Time.Horizon.Risk.Assessments,
1.64)

par(mfrow=c(1,1))
cdpJoined<-merge(cdpCore,cdpCausal, by“= "Organisat”on")
cdpJoined$Proportion.of.Scope.2.electricity.certified.y <-
cdpJoined$Proportion.of.Scope.2.electricity.certified.x %>% replace(is.na(.), 0)
sapply(cdpJoined,class   ruskalkal.test(Average.Annual.ROI ~ Utilising.EAC..x, data =
cdpJoined)
```

```
## This section shows how EAC/MB use links to disclosure with greater coverage and
higher CDP scores. Links to broader external signalling, more relevant for
reputational/brand value considerations

## Initials tests show the CDP scores are higher for market-based corporations, and have a
higher lower bound where EACs are use   ruskalkal.test(CDP.Score.y ~ Utilising.EAC..x,
data = subset(cdpJoined, Utilising.Market.method == TRUE   ruskalkal.test(CDP.Score.y ~
Utilising.EAC..x, data = subset(cdpJoined, Utilising.Market.method ==
FALSE   ruskalkal.test(Y.Variables.missing. ~ Utilising.EAC..x, data = subset(cdpJoined,
Utilising.Market.method == FALSE))

bp1 <- ggplot(data = subset(cdpJoined, Utilising.Market.method== TRUE), aes(y =
CDP.Score.y , x = Utilising.EAC..x, fill“= "”ed")) +
  geom_boxplot()+
  geom_point(aes(x = Utilising.EAC..x)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Market-based report”ng")
bp2 <- ggplot(data = subset(cdpJoined, Utilising.Market.method== FALSE), aes(y =
CDP.Score.y, x = Utilising.EAC..x, fill“= "b”ue")) +
  geom_boxplot()+
  geom_point(aes(x = Utilising.EAC..x)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Location-based report”ng")
grid.arrange(bp1, bp2, ncol=2)

bp1 <- ggplot(data = subset(cdpJoined, Utilising.Market.method== TRUE), aes(y =
Y.Variables.missing., x = Utilising.EAC..x, fill“= "”ed")) +
  geom_boxplot()+
  geom_point(aes(x = Utilising.EAC..x)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Market-based report”ng")
bp2 <- ggplot(data = subset(cdpJoined, Utilising.Market.method== FALSE), aes(y =
Y.Variables.missing., x = Utilising.EAC..x, fill“= "b”ue")) +
  geom_boxplot()+
  geom_point(aes(x = Utilising.EAC..x)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Location-based report”ng")
grid.arrange(bp1, bp2, ncol=2)
##### Section end


## Examining reporting of zero-cost initiatives- a major barrier to linki   ruskal   antves to
cost-effectiveness.
par(mfrow=c(2,2))
f1<-hist(x = cleanDirty(dirty = subset(cdpJoined, Utilising.Market.method== TRUE &
Utilising.EAC..x==TRUE)$Low.Carbon.Purchases.Adjusted.Investment, 1.645), col“=
"”ed", xlab“= "Cost of Low Carbon Purcha”es", main“= "MARKET + ”AC")
f2<-hist(x = cleanDirty(dirty = subset(cdpJoined, Utilising.Market.method== FALSE &
Utilising.EAC..x==TRUE)$Low.Carbon.Purchases.Adjusted.Investment, 1.645), col“=
"”ed", xlab“= "Cost of Low Carbon Purcha”es", main“= "LOCATION + ”AC")
```

```
f3<-hist(x = cleanDirty(dirty = subset(cdpJoined, Utilising.Market.method== TRUE &
Utilising.EAC..x==FALSE)$Low.Carbon.Purchases.Adjusted.Investment, 1.645), col“=
"”ed", xlab“= "Cost of Low Carbon Purcha”es", main“= "MARKET AL”NE")
f4<-hist(x = cleanDirty(dirty = subset(cdpJoined, Utilising.Market.method== FALSE &
Utilising.EAC..x==FALSE)$Low.Carbon.Purchases.Adjusted.Investment, 1.645), col“=
"”ed", xlab“= "Cost of Low Carbon Purcha”es", main“= "LOCATION AL”NE")
par(mfrow=c(1,1))

count(subset(cdpJoined, Utilising.Market.method== TRUE & Utilising.EAC..x==TRUE),
vars = Low.Carbon.Purchases.Adjusted.Investment) ## 38.6% zero cost
count(subset(cdpJoined, Utilising.Market.method== FALSE & Utilising.EAC..x==TRUE),
vars = Low.Carbon.Purchases.Adjusted.Investment)
count(subset(cdpJoined, Utilising.Market.method== TRUE & Utilising.EAC..x==FALSE),
vars = Low.Carbon.Purchases.Adjusted.Investment)
count(subset(cdpJoined, Utilising.Market.method== FALSE &
Utilising.EAC..x==FALSE), vars = Low.Carbon.Purchases.Adjusted.Investment)

## This difference in investment is significant:
## EAC/MB use inflates both Zero cost and high cost Efficiency
initiativ   ruskalkal.test(Low.Carbon.Purchases.Adjusted.Investment ~ Utilising.EAC..x,
data = cleanDF(df=cdpJoined,
dirty=cdpJoined$Low.Carbon.Purchases.Adjusted.Investment, 1.64))
bp <- ggplot(data = cleanDF(df=cdpJoined,
dirty=cdpJoined$Low.Carbon.Purchases.Adjusted.Investment, 1.64), aes(y =
Low.Carbon.Purchases.Adjusted.Investment, x = Utilising.EAC..x, fill = Utilising.EAC..x))
+
  geom_boxplot()+
  geom_point(aes(x = Utilising.EAC..x)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Cost of Mitigation (£/tCO2e) utilisation by EAC ”se")+
  ylim(c(0,10000))
bp

## Below EAC use    ruskal   ant   ytly linked to higher costs of mitigation
(othe   ruskalkal.test(Cost.efficiency.of.mitigation..Other.....tCO2e. ~ Utilising.EAC..x, data
= cleanDF(df=cdpJoined, dirty=cdpJoined$Cost.efficiency.of.mitigation..Other.....tCO2e.,
1.64))
bp <- ggplot(data = cleanDF(df=cdpJoined,
dirty=cdpJoined$Cost.efficiency.of.mitigation..Other.....tCO2e., 1.64), aes(y =
Cost.efficiency.of.mitigation..Other.....tCO2e., x = Utilising.EAC..x, fill =
Utilising.EAC..x)) +
  geom_boxplot()+
  geom_point(aes(x = Utilising.EAC..x)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Cost of Mitigation (Other) (£/tCO2e) utilisation by EAC ”se")+
  ylim(c(0,10000))
bp

## Below EAC use shows no significant link to higher cost efficiency of mitigation
(othe   ruskalkal.test(Low.Carbon.Cost.Efficiency.of.mitigation....tCO2e.   ~
```

```
Utilising.EAC..x, data = cleanDF(df=cdpJoined,
dirty=cdpJoined$Low.Carbon.Cost.Efficiency.of.mitigation....tCO2e.  , 1.64))
bp <- ggplot(data = cleanDF(df=cdpJoined,
dirty=cdpJoined$Low.Carbon.Cost.Efficiency.of.mitigation....tCO2e.  , 1.64), aes(y =
Low.Carbon.Cost.Efficiency.of.mitigation....tCO2e.  , x = Utilising.EAC..x, fill =
Utilising.EAC..x)) +
  geom_boxplot()+
  geom_point(aes(x = Utilising.EAC..x)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Cost of Low-Carbon Mitigation (£/tCO2e) utilisation by EAC ”se")
bp

## Below EAC use shows no significant link to higher returns through efficiency mitigation
(othe   ruskalkal.test(Average.Savings.Intensity..Other....TCO2e ~ Utilising.EAC..x, data =
cleanDF(df=cdpJoined, dirty=cdpJoined$Average.Savings.Intensity..Other....TCO2e,
1.64))
bp <- ggplot(data = cleanDF(df=cdpJoined,
dirty=cdpJoined$Average.Savings.Intensity..Other....TCO2e, 1.64), aes(y =
Average.Savings.Intensity..Other....TCO2e, x = Utilising.EAC..x, fill = Utilising.EAC..x))
+
  geom_boxplot()+
  geom_point(aes(x = Utilising.EAC..x)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Cost of Mitigation (£/tCO2e) utilisation by EAC ”se")
bp ## GENERAL SAVINGS INTENSITY IS INSIGNIFICANT

## Below EAC use is significantly linked to LOWER returns through low-carbon
mitigati   ruskal   antv   ruskalkal.test(Low.Carbon.Savings.Intensity....TCO2e. ~
Utilising.EAC..x, data = cleanDF(df=cdpJoined,
dirty=cdpJoined$Low.Carbon.Savings.Intensity....TCO2e., 1.64))
bp <- ggplot(data = cleanDF(df=cdpJoined,
dirty=cdpJoined$Low.Carbon.Savings.Intensity....TCO2e., 1.64), aes(y =
Low.Carbon.Savings.Intensity....TCO2e., x = Utilising.EAC..x, fill = Utilising.EAC..x)) +
  geom_boxplot()+
  geom_point(aes(x = Utilising.EAC..x)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Cost of Mitigation (£/tCO2e) utilisation by EAC ”se")
bp ## NON-EAC LOW CARBON SAVINGS INTENSITY IS SIGNIFICANTLY
HIGHER (more return)

## Here the mechanism for EAC signalling is demonstrated: EAC use lowers emission
facto   ruskalkal.test(Change.in.Emissions.Factor.due.to.Certification ~ Utilising.EAC..x,
data = cleanDF(df=cdpJoined,
dirty=cdpJoined$Change.in.Emissions.Factor.due.to.Certification, 1.64))
bp <- ggplot(data = cleanDF(df=cdpJoined,
dirty=cdpJoined$Change.in.Emissions.Factor.due.to.Certification, 1.64), aes(y =
Change.in.Emissions.Factor.due.to.Certification, x = Utilising.EAC..x, fill =
Utilising.EAC..x)) +
  geom_boxplot()+
  geom_point(aes(x = Utilising.EAC..x)) +
```

```
  theme(legend.positi”n="bot”om") +
  labs(title“= "Cost of Mitigation (£/tCO2e) utilisation by EAC ”se")
bp ## EAC utilisation links to higher change due to emissions factors

## EAC corporations reported greater Mitigation Outcomes from Low-Carbon Purchases,
but not quite 0.05 significan   ruskalkal.test(Low.Carbon.Purchase.initiatives.Mitigation....
~ Utilising.EAC..x, data = cleanDF(df=cdpJoined,
dirty=cdpJoined$Low.Carbon.Purchase.initiatives.Mitigation...., 1.64))
bp <- ggplot(data = cleanDF(df=cdpJoined,
dirty=cdpJoined$Low.Carbon.Purchase.initiatives.Mitigation...., 1.64), aes(y =
Low.Carbon.Purchase.initiatives.Mitigation...., x = Utilising.EAC..x, fill =
Utilising.EAC..x)) +
  geom_boxplot()+
  geom_point(aes(x = Utilising.EAC..x)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Reported Mitigation Outcomes of Low-Carbon Purchases by EAC ”se")
bp

## EAC corporations reported significantly lower total Mitigation
Outcom   ruskalkal.test(Total.Initiative.Mitigation ~ Utilising.EAC..x, data =
cleanDF(df=cdpJoined, dirty=cdpJoined$Total.Initiative.Mitigation, 1.64))
bp <- ggplot(data = cleanDF(df=cdpJoined, dirty=cdpJoined$Total.Initiative.Mitigation,
1.64), aes(y = Total.Initiative.Mitigation, x = Utilising.EAC..x, fill = Utilising.EAC..x)) +
  geom_boxplot()+
  geom_point(aes(x = Utilising.EAC..x)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Total Reported Mitigation Outcomes by EAC ”se")
bp

## This shows EAC corporations report significantly lower efficiency initiative mitigation
outcome   ruskalkal.test(Efficiency.initiatives.Mitigation ~ Utilising.EAC..x, data =
cdpJoined) ## SIG
mean(subset(cleanDF(df=cdpJoined, dirty=cdpJoined$Efficiency.initiatives.Mitigation,
1.64), Utilising.EAC..x == FALSE)$Efficiency.initiatives.Mitigation)
mean(subset(cleanDF(df=cdpJoined, dirty=cdpJoined$Efficiency.initiatives.Mitigation,
1.64), Utilising.EAC..x == TRUE)$Efficiency.initiatives.Mitigation)

bp <- ggplot(data = cleanDF(df=cdpJoined,
dirty=cdpJoined$Efficiency.initiatives.Mitigation, 1.64), aes(y =
Efficiency.initiatives.Mitigation, x = Utilising.EAC..x, fill = Utilising.EAC..x)) +
  geom_boxplot()+
  geom_point(aes(x = Utilising.EAC..x)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Reported Efficiency Mitigation Initiative Outcomes by EAC ”se")
bp

### THIS SHOWS THAT RESPONSE INCREASES WITH RISK
GENERAL   ruskalkal.test(Reported.Emissions.Change..Physical...Other.Efficiency. ~
Frequency.of.Risk.Assessment, data = cleanDF(df=cdpJoined,
dirty=cdpJoined$Reported.Emissions.Change..Physical...Other.Efficiency., 1.64)) ###
```

```
Response changes with risk generally, but may be a byproduct of selection of reporting
metho   ruskalkal.test(Reported.Emissions.Change..Physical...Other.Efficiency. ~
Frequency.of.Risk.Assessment, data = subset(cleanDF(df=cdpJoined,
dirty=cdpJoined$Reported.Emissions.Change..Physical...Other.Efficiency., 1.64),
Utilising.Market.method == TRUE))
   ruskalkal.test(Reported.Emissions.Change..Physical...Other.Efficiency. ~
Frequency.of.Risk.Assessment, data = subset(cleanDF(df=cdpJoined,
dirty=cdpJoined$Reported.Emissions.Change..Physical...Other.Efficiency., 1.64),
Utilising.Market.method == FALSE))

## These figures show the complexity involved, some i.e. market corporations show low
response for two year group, but location based corporations show high response for the
same group:
f11<-ggplot(data = subset(cleanDF(df=cdpJoined,
dirty=cdpJoined$Reported.Emissions.Change..Physical...Other.Efficiency., 1.64),
Utilising.Market.method == TRUE), aes(y =
Reported.Emissions.Change..Physical...Other.Efficiency., x =
Frequency.of.Risk.Assessment, fill = as.factor(Utilising.Market.method))) +
  geom_boxplot()+
  ##geom_point(aes(x = Frequency.of.Risk.Assessment)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Response by Frequency of Risk Assessm”nt")
f12<-ggplot(data = subset(cleanDF(df=cdpJoined,
dirty=cdpJoined$Reported.Emissions.Change..Physical...Other.Efficiency., 1.64),
Utilising.Market.method == FALSE), aes(y =
Reported.Emissions.Change..Physical...Other.Efficiency., x =
Frequency.of.Risk.Assessment, fill = as.factor(Utilising.Market.method))) +
  geom_boxplot()+
  ##geom_point(aes(x = Frequency.of.Risk.Assessment)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Response by Frequency of Risk Assessm”nt")
grid.arrange(f11, f12, ncol=2)

## This shows that EAC corporations spend significantly less on Other (efficiency)
mitigation initiative   ruskalkal.test(Adjusted.Average.Investment..Other. ~
Utilising.EAC..x, data = cdpJoined)
mean(subset(cleanDF(df=cdpJoined,
dirty=cdpJoined$Adjusted.Average.Investment..Other., 1.64), Utilising.EAC..x ==
FALSE)$Adjusted.Average.Investment..Other.)
mean(subset(cleanDF(df=cdpJoined,
dirty=cdpJoined$Adjusted.Average.Investment..Other., 1.64), Utilising.EAC..x ==
TRUE)$Adjusted.Average.Investment..Other.)

## This shows the increased use of EACs with more frequent risk
assessme   ruskalkal.test(Proportion.of.Scope.2.electricity.certified.y ~
Frequency.of.Risk.Assessment, data = cdpJoined)
plot(data = cdpJoined, Proportion.of.Scope.2.electricity.certified.y ~
Frequency.of.Risk.Assessment)
```

```
## Significance is again eroded by segregation by reporting methodology, likely due to co-correlatio   ruskalkal.test(Proportion.of.Scope.2.electricity.certified.y ~ Frequency.of.Risk.Assessment, data = subset(cdpJoined, Utilising.Market.method == TRUE))         ruskalkal.test(Proportion.of.Scope.2.electricity.certified.y ~ Frequency.of.Risk.Assessment, data = subset(cdpJoined, Utilising.Market.method == FALSE))

f11<-ggplot(data = subset(cleanDF(df=cdpJoined, dirty=cdpJoined$Reported.Emissions.Change..Physical...Other.Efficiency., 1.64), Utilising.Market.method == TRUE), aes(y = Proportion.of.Scope.2.electricity.certified.y, x = Frequency.of.Risk.Assessment, fill = as.factor(Utilising.Market.method))) +
  geom_boxplot()+
  ##geom_point(aes(x = Frequency.of.Risk.Assessment)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Response by Frequency of Risk Assessm”nt")
f12<-ggplot(data = subset(cleanDF(df=cdpJoined, dirty=cdpJoined$Reported.Emissions.Change..Physical...Other.Efficiency., 1.64), Utilising.Market.method == FALSE), aes(y = Proportion.of.Scope.2.electricity.certified.y, x = Frequency.of.Risk.Assessment, fill = as.factor(Utilising.Market.method))) +
  geom_boxplot()+
  ##geom_point(aes(x = Frequency.of.Risk.Assessment)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "Response by Frequency of Risk Assessm”nt")
grid.arrange(f11, f12, ncol=2)

####### More detailed analysis of ri   ruskalkal.test(Proportion.of.Scope.2.electricity.certified.y ~ X.Policy...Legal..Risks, data = cdpJoined)        ### Legal Risks = Insignifica   ruskalkal.test(Proportion.of.Scope.2.electricity.certified.y ~ X.Market..Risks, data = cdpJoined)                ### Increased Market Risks = Sig EAC increase
ggplot(data = cdpJoined, aes(y = Proportion.of.Scope.2.electricity.certified.y, x = X.Market..Risks, fill = X.Market..Risks)) +
  geom_boxplot()+
  geom_point(aes(x = X.Market..Risks)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "EAC utilisation by Reported Market R”sk")   ruskalkal.test(Proportion.of.Scope.2.electricity.certified.y ~ X.Reputation..Risks, data = cdpJoined)            ### Increased Reputation Risks = Sig EAC increase
ggplot(data = cdpJoined, aes(y = Proportion.of.Scope.2.electricity.certified.y, x = X.Reputation..Risks, fill = X.Reputation..Risks)) +
  geom_boxplot()+
  geom_point(aes(x = X.Reputation..Risks)) +
  theme(legend.positi”n="bot”om") +
  labs(title“= "EAC utilisation by Reported Reputation R”sk")

## As cost of risk management increases, proportion EAC decreases significantly
summary(lm(Proportion.of.Scope.2.electricity.certified.y ~ Summed.cost.of.risk.management, data = cdpJoined))
```

```
ggplotRegression(lm(Proportion.of.Scope.2.electricity.certified.y ~
Summed.cost.of.risk.management, data = cdpJoined)) ### Model fit poor due to double
zero inflation

summary(lm(Proportion.of.Scope.2.electricity.certified.y ~
Time.Horizon.Risk.Assessments, data = cdpJoined)) ### almost 0.05 significant

summary(lm(Proportion.of.Scope.2.electricity.certified.y ~
Value.of.Financial.Opportunities, data = cdpJoined)) ### Financial Opportunities not
significant

summary(lm(Proportion.of.Scope.2.electricity.certified.y ~
Summed.cost.of.risk.management + Time.Horizon.Risk.Assessments, data = cdpJoined))
## Modelling Numeric Risk Variables together increases fit:
causal1.lm = lm(Proportion.of.Scope.2.electricity.certified.y ~
Summed.cost.of.risk.management + Time.Horizon.Risk.Assessments, data = cdpJoined)

par(mfrow=c(2,2))
plot(causal1.lm) ### model fit abhorrent- not an LM, possibly exponential?
par(mfrow=c(1,1))

##Attempting to plot numerical risk model:
ggplot(cdpJoined, aes(y = Proportion.of.Scope.2.electricity.certified.y, x =
Summed.cost.of.risk.management, col = Time.Horizon.Risk.Assessments)) +
  geom_point(data = cdpJoined, aes(y = Proportion.of.Scope.2.electricity.certified.y, x =
Summed.cost.of.risk.management, col = Time.Horizon.Risk.Assessments))+
  geom_smooth(meth”d=”lm") +
  labs(title“= "Proportion EAC vs Cost of Risk Management by Time Horizon of Risk
Assessm”nt", y‘= 'Proportion of Scope 2 electricity certif’ed') +
  theme(legend.positi”n="bot”om") +
  stat_poly_eq(aes(label = paste(..eq.label.., ..rr.label.., sep“= "”’~~")), formula =
my.formula, parse = TRUE, label.y“= "bot”om")



###### We can now examine initiatives
summary(lm(Proportion.of.Scope.2.electricity.certified.y ~
Num.Scope.1.initiatives*Num.Scope.2L.initiatives*Num.Scope.2M.initiatives*Num.Scope
.3.initiatives, data = cdpJoined))
#### carry forward most significant
causal2.lm = lm(Proportion.of.Scope.2.electricity.certified.y ~
Num.Scope.2M.initiatives:Num.Scope.3.initiatives  +
Num.Scope.1.initiatives:Num.Scope.3.initiatives + Num.Scope.2M.initiatives +
Num.Scope.3.initiatives, data = cdpJoined)
summary(causal2.lm)
par(mfrow=c(2,2))
plot(causal2.lm) ### model fit abhorrent- not an LM
par(mfrow=c(1,1))
ggplotRegression(causal2.lm)

## These show increase in EAC use with external facing intitatives (scope 2m/3)
```

```
ggplot(cdpJoined, aes(y = Proportion.of.Scope.2.electricity.certified.y, x =
Num.Scope.2M.initiatives + Num.Scope.3.initiatives, col = Num.Scope.1.initiatives)) +
  geom_point(data = cdpJoined, aes(y = Proportion.of.Scope.2.electricity.certified.y, x =
Num.Scope.2M.initiatives + Num.Scope.3.initiatives, col = Num.Scope.1.initiatives))+
  geom_smooth(meth”d=”lm") +
  labs(title“= "Proportion EAC vs Cost of Risk Management by Time Horizon of Risk
Assessm”nt", y‘= 'Proportion of Scope 2 electricity certif’ed') +
  theme(legend.positi”n="bot”om") +
  stat_poly_eq(aes(label = paste(..eq.label.., ..rr.label.., sep“= "”~~")), formula =
my.formula, parse = TRUE, label.y“= "”op")

##### This models better than 2M alone:
summary(lm(Proportion.of.Scope.2.electricity.certified.y ~ Num.Scope.2M.initiatives, data
= cdpJoined))

##Can we combine models 1 and 2?
summary(lm(Proportion.of.Scope.2.electricity.certified.y ~
Summed.cost.of.risk.management + Time.Horizon.Risk.Assessments +
Num.Scope.2M.initiatives:Num.Scope.3.initiatives  +
Num.Scope.1.initiatives:Num.Scope.3.initiatives + Num.Scope.2M.initiatives +
Num.Scope.3.initiatives, data = cdpJoined))

causal3.lm = lm(Proportion.of.Scope.2.electricity.certified.y ~
Summed.cost.of.risk.management + Num.Scope.2M.initiatives:Num.Scope.3.initiatives  +
Num.Scope.1.initiatives:Num.Scope.3.initiatives + Num.Scope.2M.initiatives +
Num.Scope.3.initiatives, data = cdpJoined)

summary(causal3.lm)
ggplotRegression(causal3.lm)
plot(causal3.lm) ### These show the non-linearity of the relationships we are modelling

##### To conclude EACs raise low carbon investment, but with decreased savings and no
effect on mitigation intensity (£/TCO2e), nor a significant effect on total outcomes

##### EACs link to higher costs of non-LC mitigation, but not significantly higher non-LC
returns.

##### EACs link to higher emission factor reductions but also lower Total mitigation
outcomes.

##### EACs link to lower efficiency initiative outcomes and lower spending on these
initiatives.


##### To conclude initiatives and risk, the proportion certified increases with terms derived
from external pressure, offering no internal efficiency/process improvements:
(Num.Scope.2M.initiatives, Num.Scope.3.initiatives &
Num.Scope.2M.initiatives:Num.Scope.3.initiatives)
```

the proportion certified decreases with terms derived from internal pressure, that compete with EACS (Num.Scope.3.initiatives:Num.Scope.1.initiatives), or cannot be addressed by EACs (Summed.cost.of.risk.management)

APPENDIX E

A summary of text-based console outputs from R analysis.

```
ruskalkal.test(Reported.Emissions.Change..Physical...Other.Efficiency. ~ Utilising.EAC., data = subset(cleanDF(cdpCore, cdpCore$Reported.Emissions.Change..Physical...Other.Efficiency.,1.645), Utilising.Market.method == TRUE))

        Kruskal-Wallis rank sum test

data:  Reported.Emissions.Change..Physical...Other.Efficiency. by Utilising.EAC.
Kruskal-Wallis chi-squared = 0.0068582, df = 1, p-value = 0.934
ruskalkal.test(Reported.Emissions.Change..Physical...Other.Efficiency. ~ Utilising.EAC., data = subset(cleanDF(cdpCore, cdpCore$Reported.Emissions.Change..Physical...Other.Efficiency.,1.645), Utilising.Market.method == FALSE))

        Kruskal-Wallis rank sum test

data:  Reported.Emissions.Change..Physical...Other.Efficiency. by Utilising.EAC.
Kruskal-Wallis chi-squared = 5.4109, df = 1, p-value = 0.02001
```

1. EU ETS Significance check:

```
> # We can confirm the interaction of these elements is significant:   ruskalkal.test(resp ~ useMB, data = cdpNH1)

        Kruskal-Wallis rank sum test

data:  resp by useMB
Kruskal-Wallis chi-squared = 1.1443, df = 1, p-value = 0.2847

> ##Use of market method alone is n   ruskal   antant, neither are EACs:   ruskalkal.test(resp ~ useEAC, data = cdpNH1)

        Kruskal-Wallis rank sum test

data:  resp by useEAC
Kruskal-Wallis chi-squared = 0.98615, df = 1, p-value = 0.3207

> ###### 7B # Separating by market method we see an interaction however:   ruskalkal.test(resp ~ useEAC, data = NH1.market) ### market-based disclosure shows no significance

        Kruskal-Wallis rank sum test

data:  resp by useEAC
Kruskal-Wallis chi-squared = 0.19196, df = 1, p-value = 0.6613
ruskalkal.test(resp ~ useEAC, data = NH1.location) ###### but significance clustered around non-market
```

```
        Kruskal-Wallis rank sum test

data:  resp by useEAC
Kruskal-Wallis chi-squared = 11.729, df = 1, p-value = 0.0006154
```

2. Linear Modelling, Dropterm term deletions and MB:EAC interaction

```
MASS::dropterm(lm(resp ~ prop.MB*useEAC, data = NH1), test“=”"F")
Single term deletions

Model:
resp ~ prop.MB * useEAC
              Df Sum of Sq    RSS     AIC F Value  Pr(F)
<none>                     2.7436 -1990.9
prop.MB:useEAC  1 0.0029669 2.7466 -1992.4 0.42932 0.5127
> summary(lm(resp ~ prop.MB:useEAC, data = NH1))

Call:
lm(formula = resp ~ prop.MB:useEAC, data = NH1)

Residuals:
     Min       1Q   Median       3Q      Max
-0.64692 -0.01392  0.02095  0.03984  0.23975

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)          -0.02478    0.01004  -2.469  0.01397 *
prop.MB:useEACFALSE -0.02130    0.01176  -1.812  0.07078 .
prop.MB:useEACTRUE  -0.03997    0.01345  -2.972  0.00314 --
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.08303 on 398 degrees of freedom
Multiple R-squared:  0.02213,            Adjusted R-squared:  0.01722
F-statistic: 4.503 on 2 and 398 DF,  p-value: 0.01164

NH1.lm1 = lm(resp ~ prop.MB:useEAC, data = NH1)
anova(NH1.lm1)
Analysis of Variance Table

Response: resp
                Df  Sum Sq   Mean Sq F value  Pr(>F)
prop.MB:useEAC   2 0.06209 0.0310436  4.5034 0.01164 *
Residuals      398 2.74359 0.0068935                --
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

3. Differences in EAC utilisation between corporations using MB and location-based reporting (co-correlation of EAC use and proportion market based).

```
kruskal.test(data=NH1, prop.e.c ~ useMB)

        Kruskal-Wallis rank sum test

data:  prop.e.c by useMB
Kruskal-Wallis chi-squared = 49.577, df = 1, p-value =
1.908e-12
```

4. Model summaries showing that the Gamma distribution is the best alternative to the linear model, but fit is no better.

```
##data greater than 1 exists, cannot be binomial
> summary(glm(prop.Eff ~ prop.MB:useEAC, data = NH1, family = quasi()))

Call:
glm(formula = prop.Eff ~ prop.MB:useEAC, family = quasi(), data = NH1)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.64692  -0.01392   0.02095   0.03984   0.23975

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)          0.97522    0.01004  97.153  < 2e-16 ***
prop.MB:useEACFALSE -0.02130    0.01176  -1.812  0.07078 .
prop.MB:useEACTRUE  -0.03997    0.01345  -2.972  0.00314 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for quasi family taken to be 0.006893454)

    Null deviance: 2.8057  on 400  degrees of freedom
Residual deviance: 2.7436  on 398  degrees of freedom
AIC: NA

Number of Fisher Scoring iterations: 2

> ##(Dispersion parameter for quasi family taken to be 0.007929924)
> summary(glm(prop.Eff ~ prop.MB:useEAC, data = NH1, family = inverse.gaussian()))

Call:
glm(formula = prop.Eff ~ prop.MB:useEAC, family = inverse.gaussian(),
    data = NH1)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.28113  -0.01504   0.02166   0.04203   0.23655

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)          1.05019    0.02310  45.467  < 2e-16 ***
prop.MB:useEACFALSE  0.04880    0.02722   1.793  0.07380 .
```

```
prop.MB:useEACTRUE   0.09318    0.03166   2.943  0.00344 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for inverse.gaussian family taken to be 0.00819226)

    Null deviance: 6.6167  on 400  degrees of freedom
Residual deviance: 6.5444  on 398  degrees of freedom
AIC: -570.7

Number of Fisher Scoring iterations: 4

> ##Less Promising, lets try gamma
> NH1.glm = glm(prop.Eff ~ prop.MB:useEAC, data = NH1, family = Gamma())
> summary(NH1.glm)

Call:
glm(formula = prop.Eff ~ prop.MB:useEAC, family = Gamma(), data = NH1)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.98080  -0.01465   0.02138   0.04146   0.23727

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)          1.02500    0.01102  92.981  < 2e-16 ***
prop.MB:useEACFALSE  0.02333    0.01296   1.799  0.07275 .
prop.MB:useEACTRUE   0.04428    0.01499   2.953  0.00333 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Gamma family taken to be 0.007733093)

    Null deviance: 4.6366  on 400  degrees of freedom
Residual deviance: 4.5679  on 398  degrees of freedom
AIC: -691.97

Number of Fisher Scoring iterations: 4
```

5. Drop term comparison of the GLM and LM

```
MASS::dropterm(NH1.lm1, test = "F")
Single term deletions

Model:
resp ~ prop.MB:useEAC
               Df Sum of Sq    RSS     AIC F Value   Pr(F)
<none>                      2.7436 -1992.9
prop.MB:useEAC  2  0.062087 2.8057 -1987.9  4.5034 0.01164 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
> MASS::dropterm(NH1.glm, test = "F")
Single term deletions

Model:
prop.Eff ~ prop.MB:useEAC
              Df Deviance     AIC F value   Pr(F)
<none>            4.5679 -691.97
prop.MB:useEAC  2   4.6366 -687.08  2.9957 0.05113 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

6. NH2: EAC utilisation/proportion MB by factors including: RE100 membership

```
kruskal.test(Proportion.of.Scope.2.electricity.certified ~ Member.RE100, data = cdpNH2)


	Kruskal-Wallis rank sum test

data:  Proportion.of.Scope.2.electricity.certified by Member.RE100
Kruskal-Wallis chi-squared = 16.407, df = 2, p-value = 0.0002737

kruskal.test(Proportion.Market.based ~ Member.RE100, data = cdpNH2)

	Kruskal-Wallis rank sum test

data:  Proportion.Market.based by Member.RE100
Kruskal-Wallis chi-squared = 31.415, df = 2, p-value = 1.508e-07

kruskal.test(Proportion.of.Scope.2.electricity.certified ~ Primary.Industry, data = cdpNH2)

	Kruskal-Wallis rank sum test

data:  Proportion.of.Scope.2.electricity.certified by Primary.Industry
Kruskal-Wallis chi-squared = 57.392, df = 12, p-value = 6.714e-08
```

7. Causal KW tests

```
count(subset(cdpJoined, Utilising.Market.method== TRUE & Utilising.EAC..x==TRUE), vars = Low.Carbon.Purchases.Adjusted.Investment) ## 38.6% zero cost
# A tibble: 85 x 2
   vars     n
  <dbl> <int>
 1     0    53
 2     1     1
 3   372     1
 4   675     1
 5   785     1
 6   835     1
 7   958     1
```

```
 8  2679     1
 9  3000     1
10  3054     1
# ... with 75 more rows
> count(subset(cdpJoined, Utilising.Market.method== FALSE & Utilising.EAC..x==TRUE), vars = Low.Carbo
n.Purchases.Adjusted.Investment)
# A tibble: 4 x 2
   vars     n
  <dbl> <int>
1     0     7
2    67     1
3 13880     1
4    NA    64
> count(subset(cdpJoined, Utilising.Market.method== TRUE & Utilising.EAC..x==FALSE), vars = Low.Carbo
n.Purchases.Adjusted.Investment)
# A tibble: 19 x 2
        vars     n
       <dbl> <int>
 1         0    28
 2       675     1
 3      2500     1
 4      3529     1
 5      4397     1
 6      8634     1
 7     17645     1
 8     25377     1
 9     26274     1
10     74430     1
11     78822     1
12    164208     1
13    191133     1
14    411338     1
15    555990     1
16    863434     1
17   1484213     1
18 152162277     1
19        NA   343
> count(subset(cdpJoined, Utilising.Market.method== FALSE & Utilising.EAC..x==FALSE), vars = Low.Carb
on.Purchases.Adjusted.Investment)
# A tibble: 5 x 2
   vars     n
  <dbl> <int>
1     0     4
2  3087     1
3 33732     1
4 99582     1
5    NA   712
>
> ## This difference in investment is significant:
> ## EAC/MB use inflates both Zero cost and high cost Efficiency initiatives
```

```
> kruskal.test(Low.Carbon.Purchases.Adjusted.Investment ~ Utilising.EAC..x, data = cleanDF(df=cdpJoined, dirty=cdpJoined$Low.Carbon.Purchases.Adjusted.Investment, 1.64))

	Kruskal-Wallis rank sum test

data:  Low.Carbon.Purchases.Adjusted.Investment by Utilising.EAC..x
Kruskal-Wallis chi-squared = 5.0939, df = 1, p-value = 0.02401


kruskal.test(Cost.efficiency.of.mitigation..Other.....tCO2e. ~ Utilising.EAC..x, data = cleanDF(df=cdpJoined, dirty=cdpJoined$Cost.efficiency.of.mitigation..Other.....tCO2e., 1.64))

	Kruskal-Wallis rank sum test

data:  Cost.efficiency.of.mitigation..Other.....tCO2e. by Utilising.EAC..x
Kruskal-Wallis chi-squared = 6.6122, df = 1, p-value = 0.01013

kruskal.test(Low.Carbon.Cost.Efficiency.of.mitigation....tCO2e.   ~ Utilising.EAC..x, data = cleanDF(df=cdpJoined, dirty=cdpJoined$Low.Carbon.Cost.Efficiency.of.mitigation....tCO2e.  , 1.64))

	Kruskal-Wallis rank sum test

data:  Low.Carbon.Cost.Efficiency.of.mitigation....tCO2e. by Utilising.EAC..x
Kruskal-Wallis chi-squared = 1.0471, df = 1, p-value = 0.3062

kruskal.test(Average.Savings.Intensity..Other....TCO2e ~ Utilising.EAC..x, data = cleanDF(df=cdpJoined, dirty=cdpJoined$Average.Savings.Intensity..Other....TCO2e, 1.64))

	Kruskal-Wallis rank sum test

data:  Average.Savings.Intensity..Other....TCO2e by Utilising.EAC..x
Kruskal-Wallis chi-squared = 0.96278, df = 1, p-value = 0.3265

> kruskal.test(Low.Carbon.Savings.Intensity....TCO2e. ~ Utilising.EAC..x, data = cleanDF(df=cdpJoined, dirty=cdpJoined$Low.Carbon.Savings.Intensity....TCO2e., 1.64))

	Kruskal-Wallis rank sum test

data:  Low.Carbon.Savings.Intensity....TCO2e. by Utilising.EAC..x
Kruskal-Wallis chi-squared = 6.0152, df = 1, p-value = 0.01418

## Here the mechanism for EAC signalling is demonstrated: EAC use lowers emission factors
> kruskal.test(Change.in.Emissions.Factor.due.to.Certification ~ Utilising.EAC..x, data = cleanDF(df=cdpJoined, dirty=cdpJoined$Change.in.Emissions.Factor.due.to.Certification, 1.64))

	Kruskal-Wallis rank sum test

data:  Change.in.Emissions.Factor.due.to.Certification by Utilising.EAC..x
Kruskal-Wallis chi-squared = 7.4012, df = 1, p-value = 0.006518
```

```
## EAC corporations reported significantly lower total Mitigation Outcomes
> kruskal.test(Total.Initiative.Mitigation ~ Utilising.EAC..x, data = cleanDF(df=cdpJoined, dirty=cdpJoined$Total.Initiative.Mitigation, 1.64))

	Kruskal-Wallis rank sum test

data:  Total.Initiative.Mitigation by Utilising.EAC..x
Kruskal-Wallis chi-squared = 43.412, df = 1, p-value = 4.435e-11

## This shows EAC corporations report significantly lower efficiency initiative mitigation outcomes:
> kruskal.test(Efficiency.initiatives.Mitigation ~ Utilising.EAC..x, data = cdpJoined) ## SIG

	Kruskal-Wallis rank sum test

data:  Efficiency.initiatives.Mitigation by Utilising.EAC..x
Kruskal-Wallis chi-squared = 24.402, df = 1, p-value = 7.818e-07

> mean(subset(cleanDF(df=cdpJoined, dirty=cdpJoined$Efficiency.initiatives.Mitigation, 1.64), Utilising.EAC..x == FALSE)$Efficiency.initiatives.Mitigation)
[1] 15076.1
> mean(subset(cleanDF(df=cdpJoined, dirty=cdpJoined$Efficiency.initiatives.Mitigation, 1.64), Utilising.EAC..x == TRUE)$Efficiency.initiatives.Mitigation)
[1] 12905.08

This shows that EAC corporations spend significantly less on Other (efficiency) mitigation initiatives:
> kruskal.test(Adjusted.Average.Investment..Other. ~ Utilising.EAC..x, data = cdpJoined)

	Kruskal-Wallis rank sum test

data:  Adjusted.Average.Investment..Other. by Utilising.EAC..x
Kruskal-Wallis chi-squared = 23.791, df = 1, p-value = 1.074e-06

> mean(subset(cleanDF(df=cdpJoined, dirty=cdpJoined$Adjusted.Average.Investment..Other., 1.64), Utilising.EAC..x == FALSE)$Adjusted.Average.Investment..Other.)
[1] 4014969
> mean(subset(cleanDF(df=cdpJoined, dirty=cdpJoined$Adjusted.Average.Investment..Other., 1.64), Utilising.EAC..x == TRUE)$Adjusted.Average.Investment..Other.)
[1] 2937020

> kruskal.test(Proportion.of.Scope.2.electricity.certified.y ~ X.Market..Risks, data = cdpJoined)

	Kruskal-Wallis rank sum test

data:  Proportion.of.Scope.2.electricity.certified.y by X.Market..Risks
Kruskal-Wallis chi-squared = 18.502, df = 2, p-value = 9.602e-05

> kruskal.test(Proportion.of.Scope.2.electricity.certified.y ~ X.Reputation..Risks, data = cdpJoined)

	Kruskal-Wallis rank sum test
```

```
data:  Proportion.of.Scope.2.electricity.certified.y by X.Reputation..Risks
Kruskal-Wallis chi-squared = 22.851, df = 2, p-value = 1.091e-05

> kruskal.test(Proportion.of.Scope.2.electricity.certified.y ~ Frequency.of.Risk.Assessment, data = cdpJoined)
### Freq. Risk Assessment = SIGNIFICANT

	Kruskal-Wallis rank sum test

data:  Proportion.of.Scope.2.electricity.certified.y by Frequency.of.Risk.Assessment
Kruskal-Wallis chi-squared = 20.293, df = 6, p-value = 0.002456
```

8. Causal Linear Models

```
Call:
lm(formula = Proportion.of.Scope.2.electricity.certified.y ~ 
    Summed.cost.of.risk.management + Time.Horizon.Risk.Assessments, 
    data = cdpJoined)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.08886 -0.06385 -0.05747 -0.04403  0.93794 

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)    
(Intercept)                    4.896e-02  8.015e-03   6.109 1.27e-09 ***
Summed.cost.of.risk.management -4.784e-13  1.916e-13  -2.496   0.0126 *  
Time.Horizon.Risk.Assessments   1.596e-03  7.857e-04   2.031   0.0424 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.161 on 1552 degrees of freedom
Multiple R-squared:  0.006202,	Adjusted R-squared:  0.004921 
F-statistic: 4.843 on 2 and 1552 DF,  p-value: 0.008004
```

APPENDIX F

This Appendix consists of a “close reading” or detailed analysis of model diagnostic plots, feeding into expanded model conclusions, though outcomes are somewhat redundant and repetitive.

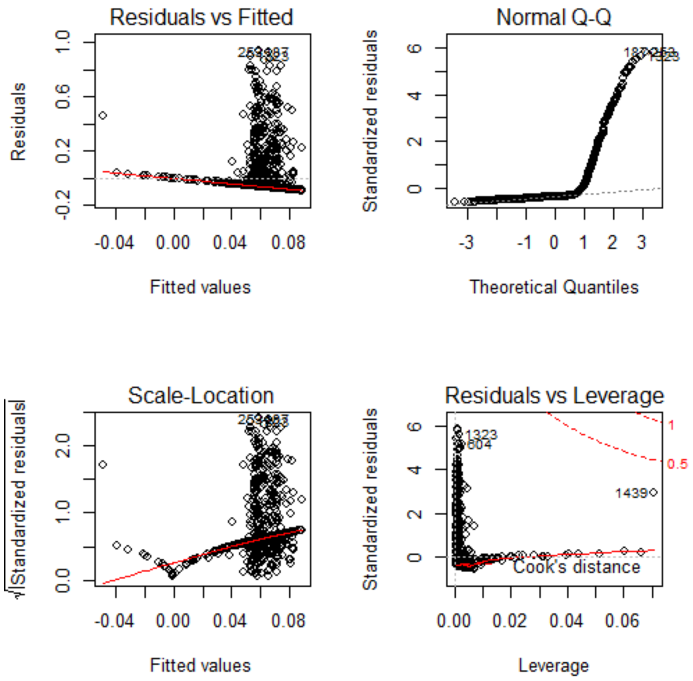


Figure 13: Causal Model 1: Proportion.of.Scope.2.electricity.certified.y ~ summed.cost.of.risk.management + Time.Horizon.Risk.Assessments

Expanded Modelling Conclusions

It is worth at this stage reconsidering the diagnostic plots for the models presented so far, to evaluate where they fail to describe and predict the outcomes of EAC utilisation. In order to do this we consider the diagnostic plots available through base R, which can give insight into the non-linearity of the data. Referring to Figure 15 (left) the first plot of interest “Residuals vs fitted” shows the pattern of residuals across the fitted values. It is clear a pattern is present, for Causal Relationship 1, with a clear linear relationship between -0.04 and 0.04, whereupon larger fitted values have positive residuals, meaning that many reported values are higher than their fitted value. This is reflected in the Normal Q-Q graph, showing heavy non-normal skewing above the first theoretical quartile. One can see from the Scale-Location plot the clear presence of a cluster on the right of the graph, around the fitted value of 0.08, which happens to be the y-intercept. That said despite this cluster showing on the left of the residual vs leverage plot, one can see that these points are distributed across positive residuals without too much leverage individually. Together, these points lead to the conclusion that a heavy non-normal skewing occurs around the y-intercept, due to the clustering of many points, distributed above their fitted value. One can also state that the plot is poorly fitted above fitted values of 0.00, with values higher than expected, it is likely that a non-linear decay, such as an exponential decay, is present within the trend. Both of these allow the statement that this is a non-normal distribution, with a non-linear relationship, and is likely inflated around zero due to the clustering and skewing present at the

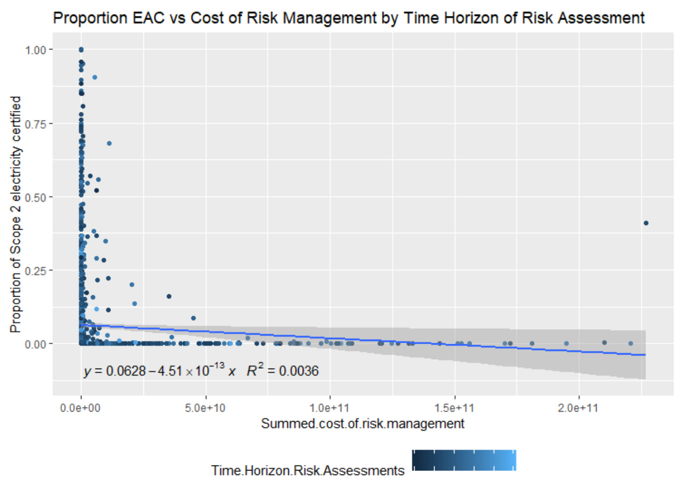


Figure 12: A graph showing the prediction of non-valid (less than zero) values for EV2

intercept. Looking at the resultant plot for the graph, these conclusions are supported (Figure 14, previous page), and the divide between theory and model fit is revealed, with the model prediction non-valid proportions below zero.

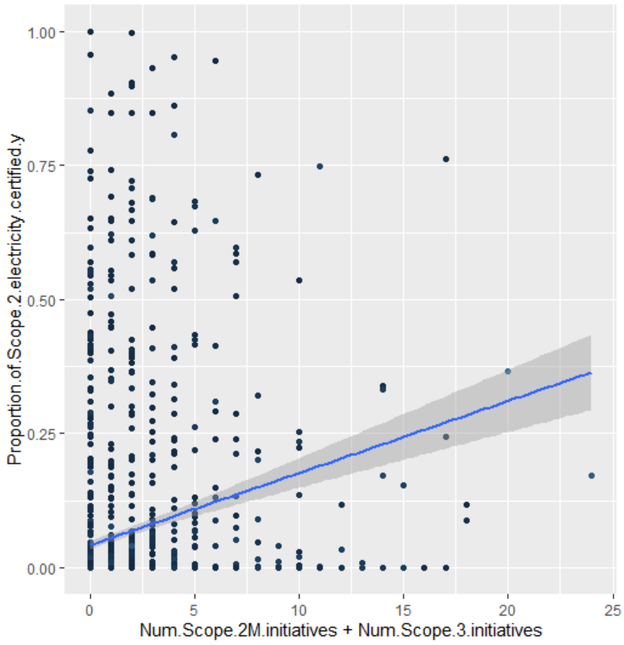


Figure 14

Analysing the second causal model, (Figure 16 & 17, below) many of the issues from the prior model can also be identified, somewhat unsurprisingly given the dependant variable has not changed, not its non-normal, bounded distribution, showing zero inflation due to the clustering on the left of the scale location graph. However the model fit is worse in the lower quantiles, with the Normal Q-Q graph showing depressed residuals, showing something is causing the smallest values to be even lower than fitted. This could be due to the presence of high leverage negative residuals, as show in the bottom right plot. It is unclear why negative fitted values occur, but clearly as proportions less that 0 cannot exist, this is incorrect, and looking at the plot of the model it is clear that the presence of multiple predictors; some of which correlate the response, whilst for others the inverse is true; has lead to one predictor being assigned too much significance. The steep pitch of the scale location plot and the contrast between a zero-inflated negative gradient, and the actual best fit line in the graph (Figure 17, above)

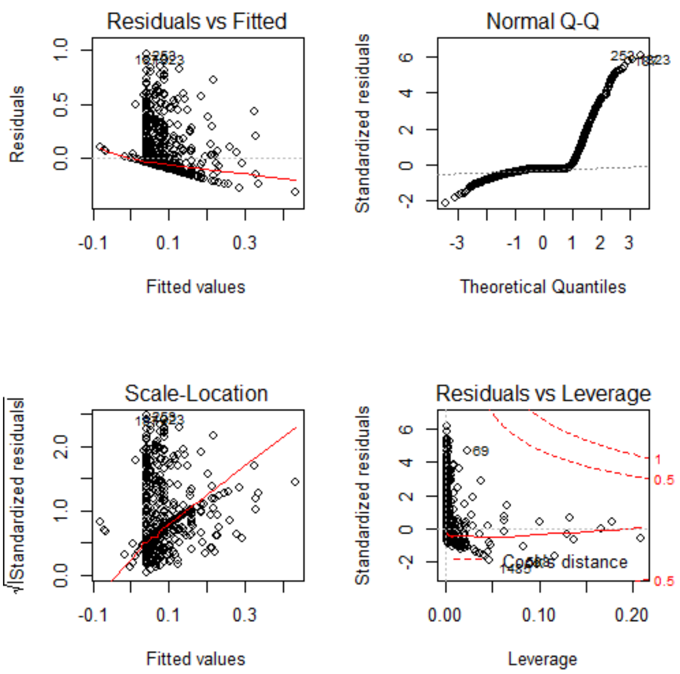


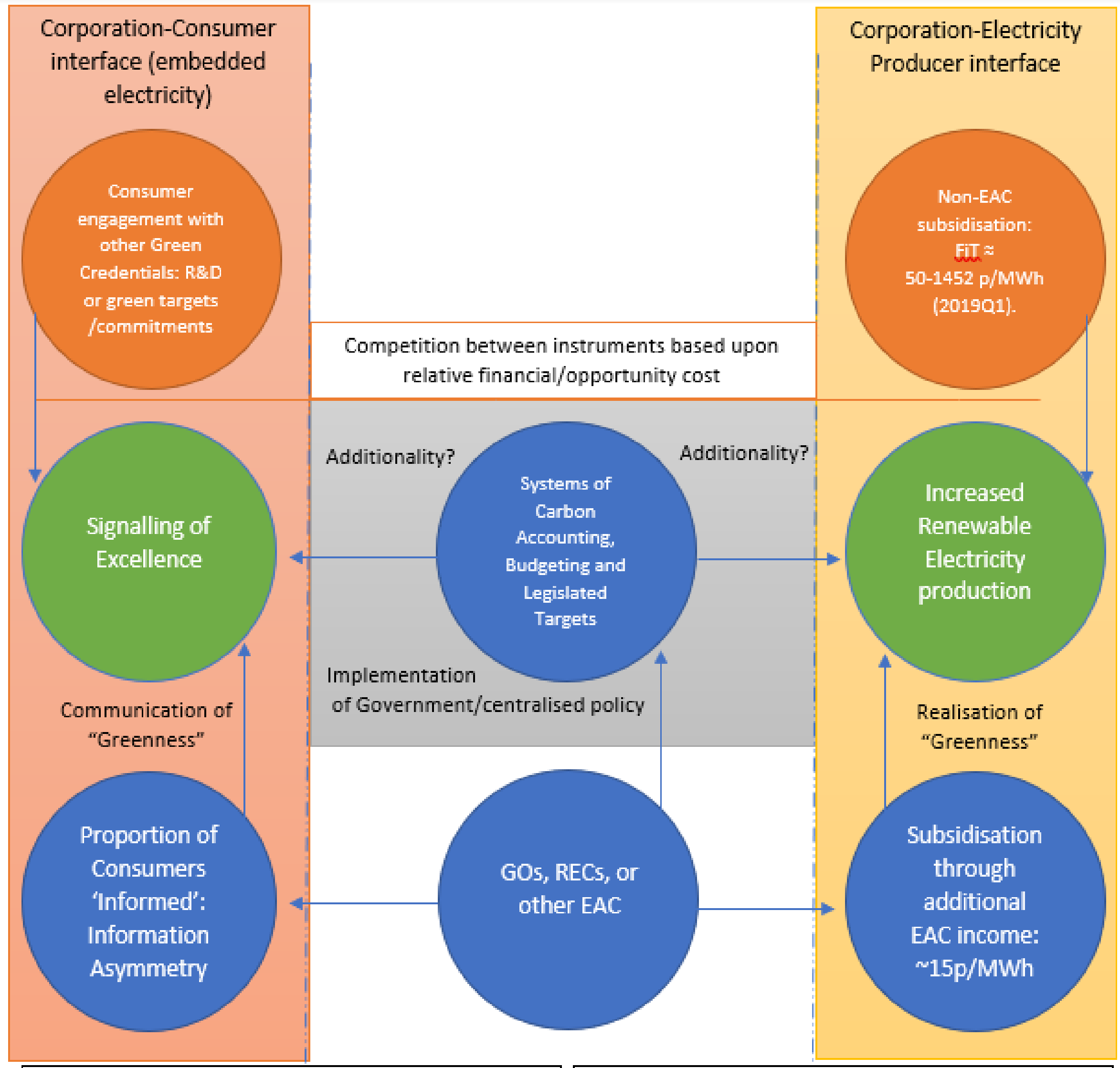
Figure 15 Causal Model 2: Causal Model 2: Proportion.of.Scope.2.electricity.certified.y ~ Num.Scope.2M.initiatives:Num.Scope.3.initiatives + Num.Scope.1.initiatives:Num.Scope.3.initiatives + Num.Scope.2M.initiatives + Num.Scope.3.initiatives.

demonstrate this, and therefore why care should be taken with building up a model with many layers.

Returning to the modelling outcomes of NH1, and referring again to Figure 9, there is more to be considered. Firstly the residuals and fitted values are distributed fairly evenly, with the fit line almost horizontal, though the lowest fitted values show positive skewing. The clusters present at approximately -0.045 and -0.065 likely correlate to the intercept of the Certified and Uncertified groups with the y-axis, where clustering (or one-inflation) occurs due to the presence of location-based corporations. The significance of these corporations will be discussed in the following section. The lack of data for market-based proportions above 1.5 has lead to high leverage points, and possible overfitting, as the residuals for these points are near-zero, but have raised the line of fit on the right of the bottom right plot, though no points surpass cook’s distace. This is reinforced by the positive residuals present on the left of the scale-location plot, though the gradient of the fit is not overly steep, it shows the corporations at the far right of figure R4 are doing less efficiency mitigation than expected, reflected by the divergence of the 95% confidence interval and the line of best fit. Finally, many issues derived from the non-normality of the data, as though the fit of the Q-Q graph is between the -1 and 2.5 quartiles, above this there are two divergent points, and below -1 there is a pattern of non-normal skewing. This is likely due to the presence of points below the prediction interval for prop.MB = 0 – 0.25, and it is not clear why corporations in this region exhibit this distribution, but it is possible their utilisation of market-based instruments is different, as there appears to be more points clustered in this region than between 0.25 and 0.5. Recall that Herold’s work states that there are clusters of strategic certification, and it could be expected that groups with differing strategies cluster at different regions across the distribution, and may utilise EACs in differing ways.

APPENDIX G

The graph below shows how competition occurring between EACs and other actions, based upon their financial and opportunity costs, when enacted through systems of Carbon Accounting, Budgeting and Legislated Targets.



The level of information asymmetry and the perceived tangibility/communicability of corporate action will determine the advantaged gained from Green Signalling.

Different types of action will have different levels of information asymmetry and perceived tangibility/communicability. For example: Repairing pipes may improve water and energy efficiency due to decreased leakage and increased hydraulic head, but the technical nature of this action may lead to a lower level of perceived tangibility compared to the purchase of "Green Electricity" even if the emissions savings from the electricity usage are equivalent.

Certification/production cost ratios are currently very low for certifying existing RE capacity, as the EACs are granted to generators for existing RE capacity, but are not mutually exclusive with other forms of subsidisation.

EACs are given to renewable generators of any size in Great Britain and Northern Ireland, and their value/deployment is not banded, centrally adjusted, or capped at the time of writing.

Despite lower complexity, the income per MWh of EACs sold is only 1-30% of the income derived from the FiT subsidisation available in Quarter 1 of 2019.