BUSINESS RESPONSES TO SUPPLY CHAIN DYNAMICS: IMPLICATIONS FOR SOURCING AND PUBLIC POLICY

By

Zhenzhen Yan

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ABSTRACT

ESSAYS ON BUSINESS RESPONSES TO SUPPLY CHAIN DYNAMICS: IMPLICATIONS FOR SOURCING AND PUBLIC POLICY

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This dissertation studies drivers and consequences of firms' policy decisions from a supply chain perspective. Policy decisions can be both internal and external to the firms and carry substantial implications for firms' performance outcomes. Both internal and external aspects of policy engagement are critical since they help further disciplinary understanding of not only how policy decisions influence the performance of products firms manufacture, but also the fact that firms can reshape their environmental conditions through adopting policy decisions to engage with regulators and impact their own business practices. Specifically, I investigate firms' sourcing policies and their product performance implications – an internal policy set by firms. Within the context of external policy engagement, my research investigates firms' policy responses to external conditions, such as climate change public policies.

The first essay focuses on manufacturing localization, an internal policy set by automakers to relocate manufacturing activities closer to their target market. I apply a causal estimation method to 23-year panel data of the automotive industry complied from diverse data sources including Wards, National Highway and Traffic Safety Authority (NHTSA) recall data to investigate the quality implications of manufacturing localization. The results show an immediate quality decline for localized vehicles, indicated by an increase of 68.203% in the number of recalls (equivalent to 0.552 more recall campaigns) and an increase of customer complaints by 56.831% (equivalent to 9.997 more complaints) in the three years after the manufacturing localization. The increased number of recalls can lead to an extra expense of $2.76 million for a localized vehicle based on

conservative estimations. A cautionary note is thus issued for automakers to adjust their planned budgets to account for warranty claims before the localization. This study provides guidance for firms considering the relocation of their manufacturing activities and for regulators that seek to reduce vehicle recalls.

The second and third essays of my dissertation investigate firms' engagement in influencing climate change policies (EICCP), which refers to firms' strategic actions to influence climate change policymaking processes, aiming at reshaping policies or promoting policy changes in favor of their interests. In the second essay, I conceptualize EICCP and propose a taxonomy for EICCP strategies considering firms' perceptions of external conditions and internal resources. I also create measures for EICCP to empirically validate this taxonomy by performing text analytics with machine-learning techniques on firms' self-disclosure in CDP Climate Change data. Building on the second essay, I undertake a large-scale empirical analysis to investigate antecedents of EICCP in the third essay. Specifically, I examine the regulatory risks associated with climate change and firms' supply network complexity as critical and interrelated factors for firms' EICCP. The latter two essays contribute to the growing literature on climate change and firm responses.

Overall, my thesis responds to the call for policy-related studies in the supply chain field and provides insights for policy decision-makers.

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CHAPTER 1- Introduction

1.1. Introduction

Responding to environmental changes is essential for business success. Firms can respond to such dynamics in two ways: First, firms can revamp their internal processes or operations to adapt to the new environmental conditions. And second, firms can reshape their external environment in favor of their interests. This dissertation focuses on two understudied strategic decisions that belong to these two ways to respond to the ever-present environmental dynamics. The first one is the manufacturing localization decision, which reflects firms' efforts to adapt to global competitive conditions by redefining their manufacturing and sourcing policy. The second one is firms' engagement in climate change policymaking processes, which is indicative of their endeavor to enhance organizational legitimacy and maintain competitive advantages by influencing climate change policies.

The first essay focuses on manufacturing localization, which refers to firms' decision to relocate manufacturing activities closer to the target market. Manufacturing localization can bring substantial changes to production and lead to uncertain quality outcomes. However, investigations into the consequences of manufacturing localization are largely absent, primarily due to the difficulty of tracking the manufacturing performance before and after the relocation of production activities. I overcome these challenges and, using the automotive industry as the empirical context, investigate the overall quality implications of localizing vehicle production closer to the U.S. market. I apply causal estimation to a unique dataset across vehicle profiles, automakers' relocation decisions, recalls, customer complaints and other industry-specific proprietary data spanning more than 23 years. The results show an immediate quality decline for localized vehicles, indicated by an increase of 68.203% in the number of recalls (equivalent to 0.552 more recall campaigns) and an increase of customer complaints by 56.831% (equivalent to 9.997 more complaints) in the three years after the manufacturing localization. The increased number of recalls can lead to an extra expense of $2.76 million for a localized vehicle based on conservative estimations. A cautionary note is thus issued for automakers to adjust their planned budgets to account for warranty claims before the localization. My post-hoc exploration suggests that the quality decline might result from both the learning effects and the difficulties in technological transfer. Overall, by investigating the quality implications of manufacturing localization decisions in the automotive industry, my results provide guidance for firms considering the relocation of their manufacturing activities and for regulators that seek to reduce vehicle recalls.

The second and third essays of my dissertation explore external policy engagement aspects of a firm in the climate change context. Extant studies note policies as irresistible contexts and concentrate on how firms survive the climate change scrutiny by adopting sustainable practices. The attention to firms' endeavor to reversely influence policymaking to redirect or evade regulatory scrutiny is scarce. Yet, the investigation of how firms reshape the regulatory context to solve the problem of practice-policy decoupling and obtain legitimacy under scrutiny over climate impact is important to further the understanding of firms' overall sustainability strategy. In the second essay, I introduce the concept of engagement in influencing climate change policies (EICCP). EICCP refers to firms' strategic actions to influence climate change policymaking processes, aiming at reshaping policies or promoting policy changes in favor of their interests. Building on the literature on corporate political actions and environmental politics, I propose a taxonomy for EICCP strategies considering firms' perceptions of external conditions and internal resources. Then, I validate this taxonomy by examining strategies of EICCP adopted in the real world. Specifically, I perform text analytics with machine-learning techniques on firms' self-disclosure in CDP Climate Change data to identify different strategies and generate automated approaches to coding the strategies pursued by these companies with the aim of analyzing them. The measures I created for EICCP can be applied to future research. In the third essay, I incorporate the data generated from the machine-learning-based strategy identification to undertake a large-scale empirical analysis to investigate antecedents of EICCP. Specifically, I examine the regulatory risks associated with climate change and firms' supply network complexity as critical and interrelated factors for firms' EICCP. The latter two essays contribute to the growing literature on climate change and firm responses.

Overall, my thesis responds to the call for policy-related studies in the supply chain field and provides insights for policy decision-makers.

CHAPTER 2 – Manufacturing Localization and its Performance Implications: An Empirical Study in the Automotive Industry

2.1. Introduction

Uncertainties associated with the management of global supply chains have intensified significantly in recent years, with the Covid-19 pandemic and the far-reaching geopolitical issues such as the U.S.– China trade tensions serving as illustrative examples. Considering the increasing challenges to manage cross-border movements of goods, coupled with the worldwide shortage of labor and supply, manufacturers have been keen to regain control of their supply chains (Cherney, 2020; Gryta and Cutter, 2021). One way to accomplish this is to relocate manufacturing activities closer to the target market, which has been a prevalent option as indicated by several surveys in the recent past (BDO, 2021; Ma et al., 2021; NielsonIQ, 2020). I refer to this phenomenon as manufacturing localization (hereinafter, localization). Localization carries the promise to strengthen a supply chain's resilience (Schwartz, 2022), which is imperative in our current environment in which volatility is here to stay (Rosenbaum, 2021). Furthermore, emerging policies increasingly favor localization (Raza et al., 2021; The White House, 2021), boding well for it to continue to be a priority for many firms going forward (Haex and Buck, 2022; Wellener et al., 2022). Yet, getting closer to the market is easier said than done, often being associated with significant costs—the relocation of production capacity may require substantial investments and reconstruction of a firm's supply and manufacturing networks (Curran, 2021). Moreover, supply chain scholars have indicated that relocation *per se* does not imply resilience—firms may still be challenged by industrial, technological, and operational constraints (Simchi-Levi and Simchi-Levi, 2020).

With such a plethora of challenges and roadblocks on the way toward localization, firms need to have a clear picture of their localization decision's implications. However, while literature is rich in the overall economic potential of localization at the country or regional level (Ma et al., 2021; Raza et al., 2021), a significant void exists for insight into the consequences of localization *at the firm level*. Exceptions include broad-based managerial research on reshoring, which can be considered a special type of localization—in this vein, survey findings suggest that reshoring influences customer-perceived product quality (Cassia, 2020) and employees' citizenship behaviors (Grappi et al., 2020). Where empirical evidence is however missing is the impact of localization on supply chain and operations management derived through secondary data analysis (rather than perceptual data). What may have prevented this research in the past is that collecting rich, secondary data from firms across the world that engage in localization is challenging, if not impossible (Gray et al., 2011, p. 737; 2013, p. 31).

I overcome this challenge in the present study by choosing the automotive industry as my empirical setting and generating a unique panel dataset at the vehicle level compiled from various sources. The automotive industry was chosen since the practice of localization has been prevalent in this industry for decades, making it a fertile ground to study the consequences of localization. For example, Hyundai established a manufacturing plant in Alabama to better serve the U.S. market in 2005 (HMMA, 2006), Volvo opened its first U.S. car assembly plant to assemble sedan and sport utility vehicles in 2015 (CNN, 2015), and Volkswagen established an assembly plant in Kenya to target the East African market in 2016 (Reuters, 2016). Recently, Tesla broke ground for the company's largest battery plant in Berlin-Brandenburg, Germany (Tesla, 2020), to tailor products for the European market (Tech Explore, 2020).

With an average of 30,000 parts that comprise a vehicle and the inherent coordination and manufacturing complexity (Foldy, 2020), the localization decision can bring substantial changes to a vehicle's production operations with the potential for significant quality implications. For example, moving an existing production line and re-establishing it elsewhere can disrupt production planning of the relocated product, while at the same time disrupting the destination plant's operations through the potential redesign of workflows, the reallocation of the workforce and other resources, and the additional coordination now necessary among the product lines (Gopal et al., 2013). These operational changes may yield an increase in production errors due to learning processes and the adaptation to the new manufacturing conditions (Badiru, 1998; Clark and Fujimoto, 1992). It is thus reasonable to expect that localization will negatively impact product quality, at least in the short term. However, getting closer to the target market also allows automakers to reduce manufacturing complexity through the postponement of product customization and the consolidation of customer requirements in a region (Brun and Zorzini, 2009). It also enables automakers to better capture consumer tastes and market trends, offering the opportunity to enhance and tailor product designs accordingly (Ellram et al., 2013). As such, localization may also lead to better vehicle quality through the reduction of manufacturing complexity and superior response to market demands. These differing perspectives establish localization as an intriguing context, motivating my investigation of how localization influences vehicle quality.

Given that automakers have been actively localizing manufacturing operations (HMMA, 2006; CNN, 2015; Reuters, 2016; Tesla, 2020; Tech Explore, 2020), research that uncovers the quality outcomes of such decisions is timely, with the results destined to be impactful given the different trajectories leading to either better or worse quality as outlined above. Using the U.S.

automotive industry as my empirical setting, I seek in this study to uncover the quality implications of relocating vehicle production from foreign plants to domestic plants. My first research question is thus stated as follows: *Does localization result in product quality changes for localized products? (RQ1)*

The impact of a location change on quality is likely dependent on contextual factors at the destination plant, which I thus consider in my analysis. For example, localization to a new plant may negatively influence vehicle quality due to the learning effect, while localization to an existing plant may cause quality problems due to difficulties in technology transfer. With this framing, an intriguing question that remains unanswered is what the mechanisms are through which quality declines after localization. I will aim to provide an answer to this question in my post-hoc analysis.

My second research question aims to assess the likely disruptions to overall plant operations caused by the introduction of the newly localized vehicles in that plant. These disruptions can be reflected in the quality of other vehicles that had already been produced at that location. Considering these potential effects is important since prior literature suggests that the introduction of a new model can lead to a substantial decline in plant-level productivity (Gopal et al. 2013). This lower productivity may then translate into quality implications for *other* existing products manufactured in the plant. I, therefore, investigate the potential impact on product quality for the existing products in that plant, i.e., those vehicles that are not the subject of the localization. My second research question is thus as follows: *Does localization result in changes to product quality for other vehicles produced in the destination plant? (RQ2)*

To address the aforementioned research questions, I compile a secondary dataset that spans from 1996 to 2019 for automobile sales in the U.S. and apply a general difference-in-difference (DID) approach to examine the causal effect of localization. The U.S. provides a unique context to investigate these dynamics since it is the second-largest automobile market in the world, having attracted foreign automakers to invest more than $75 billion for local and nearby production from 1982 to 2018 (ITA, 2018).

To foreshadow my results, I find that localization of vehicle production negatively influences the quality of localized vehicles. Utilizing the number of recalls and complaints as two distinct quality indicators, I observe an increase in both measures *after* the localization, with these effects being persistent even several years after the localization event. Specifically, I find that the number of recalls increases by 68.203%, and the number of complaints increase by 56.831% for localized vehicles. The increased number of recalls alone (0.552 more recall campaigns for localized vehicles after localization than before localization) would cause $2.76 million in extra expenses for a localized vehicle, which is a conservative estimate based on financial damage statistics of historical recalls (Held et al., 2018; Isidore, 2015). The increase in the number of recalls is agnostic to different localization decisions (localization to a new plant vs. localization to an existing plant), but the increase in the number of complaints only happens with localization to a new plant. Further, I find that the introduction of localized vehicles does not trigger more recalls or complaints about *other* vehicles produced in the same plants.

2.2. Literature Review

Research on manufacturing location decisions is rich due to the complexities associated with location-specific dynamics such as geopolitical and cultural dimensions, as well as the ensuing impact on optimal manufacturing network configurations (Brennan et al., 2015; Cheng et al., 2015). As such, research at the firm level has a long history of investigating firms' decision patterns in moving manufacturing facilities from their domestic locations to emerging or developing economies based on a low-cost rationale (e.g., Bock, 2008; Gray et al., 2011; Srai and Ané, 2016).

Another stream of literature on firms' internationalization also investigates offshoring as an indispensable process through which firms improve cost efficiency (e.g., Dunning, 1970; Vahlne and Johanson, 2017; Vernon, 1966). More recently, triggered by discussions on the best global manufacturing locations that do not conform to the low-cost imperative (Ellram et al., 2013), scholars have started to investigate less traditional strategies such as reshoring and manufacturing in high-cost countries (J. V. Gray et al., 2013; Ketokivi et al., 2017). For example, studies noted that manufacturing lead times and local market responsiveness are critical decision factors in relocating operations to high-cost countries (de Treville et al., 2014), as is the consideration of cultural distance in driving quality risk in offshore locations (Gray et al., 2013). Yet others justify the decision to manufacture in high-cost countries based on the interdependencies between production and other value chain activities, such as research and development (Ketokivi et al., 2017). The geographical proximity of upstream and downstream production can also have benefits for the assurance of product quality due to enhanced communication among supply chain stakeholders (Bray et al., 2019). These observations favor manufacturers bringing production activities closer to the respective target markets, instead of relying on import-oriented operations from other countries.

Studies on localization decisions, including reshoring and offshoring literature, provide various rationales for firms' manufacturing location decisions (Foerstl et al., 2016; Fratocchi et al., 2016; Wiesmann et al., 2017). Most of these studies are qualitative and highlight product quality as a key driver for manufacturers to move to higher-cost countries. However, empirical evidence on the actual quality *implications* of manufacturing location/relocation decisions is limited. I aim to fill this void with the present study, and in doing so, I rely on two streams of literature.

The first stream explores the impact of manufacturing location strategies on product quality. By and large, studies in this realm suggest that offshoring manufacturing to other countries is negatively associated with product quality, due to the difficulty of monitoring quality and the lack of skilled labor (da Silveira, 2014; Dana et al., 2007). In this vein, Gray et al. (2011) provide empirical evidence of the quality risks that U.S. pharmaceutical firms incur when adopting offshore manufacturing in Puerto Rico. However, Stentoft et al. (2018) report no significant differences in product quality under domestic production, offshoring, and reshoring scenarios; a caveat here however is that the study focused on perceived quality captured via survey research. The relevance of these studies to the localization–quality link within my context goes back to the possibility that products made in offshored facilities are sold to customers residing in these offshore locations. In this case, offshore manufacturing is equivalent to localization in a lower-cost country. None of these studies specify the target market of the offshore-manufactured products.

The second stream of literature couples the manufacturing location decision with marketing and identifies customer proximity as a key motivation for localization. The distance between the point of production and the point of consumption is a continuing concern for firms due to high shipping costs, long lead times, lack of market responsiveness, and inventory management challenges (The Economist, 2013). However, studies on manufacturing location decisions have identified that moving manufacturing activities closer to the target market is one of the most pursued solutions (e.g., Johansson and Olhager, 2018). From a marketing standpoint, localization makes it easier for firms to understand customer tastes and market trends, improving product design and product performance (Ellram et al., 2013). This is also consistent with operations literature noting that localization allows the postponement of product customization and consolidates a region's customer requirements, reducing overall manufacturing complexity and quality risk (Bailey and De Propris, 2014; Ben-Ner and Siemsen, 2017; Moradlou et al., 2017). These studies, however, do not offer direct evidence of quality performance post localization.

Furthermore, leaving the impact on the focal product aside, the localization decision can also have significant ramifications on the existing products produced in that plant, which is a dynamic that has not been examined. The logic is that the newly introduced vehicles can cause disruptions in the plant's regular operations, for instance in terms of production planning and coordination, resource allocations, and product flows. In this realm, Gopal et al. (2013) demonstrate that a new product introduction reduces a plant's productivity in the automotive industry due to "the engineering changes, retooling, and reprogramming of equipment, resequencing of processes, possible retraining of workers and correction of ongoing errors" (p. 2218). Thus, it is likely that quality challenges in localizing a vehicle may spill over to existing vehicles' production lines, offering further motivation for my investigation. After all, quality challenges happen at the product level, rather than at the plant level.

Finally, my research is also related to studies that have examined the quality implications of manufacturing plant strategies within the automotive industry. Specifically, Shah et al. (2017) examine the impact of utilization on product recalls tied to a specific plant. In contrast to their study, I examine the quality implications of localization decisions. Further, Lacetera and Sydnor (2015) compare the quality of vehicles made by the same manufacturers but assembled in different locations, including Japan and the U.S., using data from U.S. wholesale used-car auctions. While the authors find that there are no significant quality differences between products manufactured in these two countries, they do not provide direct insight into the effect of localization, as the relocation event from Japan to the U.S. is not explicitly considered.

2.3. Methodology

2.3.1 Data and Sample Construction

To examine the quality implications of localization decisions, I use the U.S. automotive market as my empirical setting and study the population of 704 vehicles models that were sold in the U.S. market from 1996 to 2019. I obtain vehicle-level data from two data sources, the Wards Intelligence data set (Wards hereinafter) and the NHTSA/ODI (National Highway Traffic Administration/Office of Defects Investigation) database (NHTSA hereinafter). Each vehicle's profile (including the manufacturer and brand information, classification, and segments), annual sales volume, and location of production are derived from Wards. The count of recalls and complaints about a vehicle each year are provided by NHTSA. Considering that the recalls or complaints might not immediately occur upon a vehicle entering the market, I track the recall and complaint announcements for three years after a vehicle's official launch. Therefore, the data from NHTSA spans from 1996 to 2021. The complied panel contains 6,826 vehicle-year observations.

Spanning the years 1996 to 2019, my panel dataset records each vehicle's source of production for every year. As defined by Wards, domestically produced vehicles are assembled in domestic plants located in the U.S., Canada, and Mexico, and imported vehicles are assembled in foreign plants located in other countries. I am thus able to identify the event of localization as the point in time when automakers relocate the production of a vehicle from a foreign plant to a domestic plant. This setting is consistent with my definition of localization, which is the relocation of manufacturing activities closer to the U.S. market. For example, Honda moved the production of its 2007 Honda CR-V from its Japanese plant to its U.S. plant in East Liberty, Ohio (Honda, 2006).

I manually verified the shift of production location using the automakers' official news releases and other reliable sources such as Automotive News and Autoblog. To investigate the quality change resulting from localization, I restrict my sample to vehicles that were originally produced in foreign plants, ensuring a consistent production condition for all vehicles in the sample. This sample, which I refer to as Panel A hereinafter, contains 365 vehicles. A total of 35 vehicles in Panel A had their production relocated from foreign plants to domestic plants between 1997 and 2019 and maintained such production location until the end of 2019 or until the vehicles were discontinued—this constitutes the treatment group for localization. One vehicle was once localized but then relocated to a foreign plant again. I removed this vehicle from my sample to avoid the confounding effect of multiple relocation decisions. The other 329 vehicles were produced in foreign plants during the time span of my observation, which constitute my control group. A list of the 35 treated vehicles is presented in Panel A of Table 1.1, including their year of localization and plant information.

Among the 35 localized vehicles, 14 vehicles had their production moved to a domestic plant that was opened within three years prior to the relocation. I consider this type of relocation decision as localization to a new plant. I choose three years as a cut-off point, when identifying new plants, instead of only the year when the plant was opened to account for manufacturing changes that potentially go on in the first few years of plant opening. In contrast, the production of the other 21 vehicles was relocated to plants that the automakers had owned for more than three years at the time of relocation, which I refer to as localization to an existing plant. To examine whether introducing the localized vehicles to an existing plant interrupts the plant operation and provokes quality problems for the vehicles produced in this plant, I construct another sample, which I refer to as Panel B. Panel B contains 314 vehicles that were produced in domestic plants during the time span of my observation. Among them, 15 vehicles experienced the introduction of localized vehicles in their plants in only one year in any five-year window, and nine vehicles experienced such disruption in at least two years within a five-year window. I eliminated the nine vehicles that experienced the multiple introductions of localized vehicles to remove confounding effects of disruptions for this vehicle in different years. I choose to use the five-year window since automakers rely on mid-term planning and five years should be enough to ease any changes provoked by the prior introduction of any vehicle. Therefore, the treatment group for the introduction of localized vehicles consists of 15 vehicles, with the control group consisting of the other 290 vehicles that never experienced the introduction of localized vehicles. I list the 15 treated vehicles, the year of intervention, their plant information, and the introduced localized vehicles in Panel B of Table 1.1.

I further removed vehicles that have less than five years of records to ensure the data of each vehicle in the sample is longitudinal. The final sample of Panel A includes 3,241 vehicle-year observations for 274 vehicles, with 34 vehicles in the treatment group and 240 in the control group. The final sample of Panel B contains 2,555 vehicle-year observations for 218 vehicles, with 13 vehicles in the treatment group and 205 vehicles in the control group. Using these final samples versus the full samples yields similar results with identical findings (I report the results for the final samples in the result section).

Table 1.1 Descriptions of treated vehicles

Panel A. List of vehicles in the treatment group of Localization

Vehicle	Year of Localization	Plant	New plant
VOLKSWAGEN CABRIO	1997	Puebla	No
ISUZU AMIGO	1998	Lafayette	No
ACURA TL	1999	Marysville	No
HONDA ODYSSEY	1999	Alliston 2	Yes
NISSAN MAXIMA	2003	Smyrna	No
LEXUS RX330	2004	Cambridge	No
HYUNDAI SONATA	2005	Montgomery	Yes
NISSAN PATHFINDER	2005	Smyrna	No
HYUNDAI SANTA FE	2006	Montgomery	Yes
HONDA CR-V	2007	East Liberty	No
TOYOTA RAV4	2009	Woodstock	Yes
KIA SORENTO	2010	West Point	Yes
TOYOTA HIGHLANDER	2010	Princeton	No
BMW X3	2011	Spartanburg	No
HYUNDAI ELANTRA	2011	Montgomery	No
VOLKSWAGEN PASSAT	2011	Chattanooga	Yes
KIA OPTIMA	2012	West Point	No
NISSAN LEAF	2013	Smyrna	No
HONDA FIT	2014	Celaya	Yes
LEXUS RX450	2014	Cambridge	No
MAZDA MAZDA3	2014	Salamanca	Yes
NISSAN ROGUE	2014	Smyrna	No
VOLKSWAGEN GTI	2014	Puebla	No
MERCEDES-BENZ C CLASS	2015	Vance	No
NISSAN MURANO	2015	Canton	No
LEXUS ES350	2016	Georgetown	No
AUDI Q5	2017	San Jose Chiapa	Yes
KIA FORTE	2017	Monterrey	Yes
SUBARU IMPREZA	2017	Lafayette	No
VOLKSWAGEN TIGUAN	2017	Puebla	No
HYUNDAI ACCENT	2018	Monterrey	Yes
INFINITI QX50	2018	Aguascalientes	No
KIA RIO	2018	Monterrey	Yes
MERCEDES-BENZ SPRINTER VAN	2019	Ladson	Yes
VOLVO S60	2019	Ridgeville	Yes

Note. LEXUS RX330 was dropped from the analysis since it has less than five years of observations.

Table 1.1 (cont'd)
Panel B. List of vehicles in the treatment group of Introduction

Vehicle	Year of Introducing Localized Vehicles	Plant	Localized Vehicles
ISUZU RODEO	1998	Lafayette	ISUZU AMIGO
NISSAN ALTIMA	2003	Smyrna	NISSAN MAXIMA
HONDA ELEMENT	2007	East Liberty	HONDA CR-V
TOYOTA SEQUOIA	2010	Princeton	TOYOTA HIGHLANDER
TOYOTA SIENNA	2010	Princeton	TOYOTA HIGHLANDER
BMW X5	2011	Spartanburg	BMW X3
BMW X6	2011	Spartanburg	BMW X3
INFINITI JX	2013	Smyrna	NISSAN LEAF
SUZUKI EQUATOR	2013	Smyrna	NISSAN LEAF
MERCEDES-BENZ GL	2015	Vance	MERCEDES-BENZ C CLASS
MERCEDES-BENZ M CLASS	2015	Vance	MERCEDES-BENZ C CLASS
NISSAN NV	2015	Canton	NISSAN MURANO
NISSAN TITAN	2015	Canton	NISSAN MURANO
TOYOTA AVALON	2016	Georgetown	LEXUS ES350
NISSAN KICKS	2018	Aguascalientes	INFINITI QX50

Note. INFINITI JX was dropped from the main analysis since it has less than five years of observations.

In my main analysis, I use three years of data in the pre-localization and pre-introduction phases and three years in the post-localization and post-introduction phases. I select this time span based on the expectation that manufacturers will work to continuously improve product quality such that the impact of manufacturing localization on car quality lasts only for a short term (Bandyopadhyay and Jenicke, 2007; Staeblein and Aoki, 2015). Further, a period of three years is reasonably long that any impact on quality can be captured clearly.

2.3.2. Model and Estimation

I use a difference-in-differences (DID) design to estimate how localization influences the quality of the localized vehicles and the other vehicles in localized vehicles' destination plants within a 23-year window across 14 events of localization to a new plant and 21 events of localization to an existing plant. DID was deemed as the most appropriate design for investigating the treatment effects of an intervention (i.e., the localization and introduction of localized car models in a domestic plant). I noted that in this study, the events of manufacturing localization, and consequently the events of the introduction of localized vehicles, did not happen in the same year for all vehicles. For example, BMW localized the production of the vehicle BMW X3 in the U.S. in 2011, while Nissan made the localization decision for Nissan Rogue in 2014 (see Table 1.1). To account for this varying treatment timing, I utilize the staggered DID analysis with the two-way fixed effect (TWFE) regression model, which has become prevalent in staggered DID designs over the past two decades (Baker et al., 2022). Following Baker et al.'s (2022) notation, the model specification is as follows:

$$y_{it} = \alpha_i + \lambda_t + \delta^{DD} D_{it} + \varepsilon_{it} \ ,$$

where α_i and λ_t specify the unit and time fixed effects, respectively. D_{it} is the indicator for the treated group in the post-treatment periods, with δ^{DD} being the estimate of an average treatment effect across all treatment years. However, recent econometric studies in DID applications posit that the average treatment effect (ATE) or the average treatment effect on the treated (ATT) estimated by the TWFE regression model may not be valid and interpretable (e.g., Callaway and Sant'Anna, 2021; Imai and Kim, 2021; Sun and Abraham, 2021). Specifically, Goodman-Bacon (2021) indicates that the TWFE treatment-effect estimate is a weighted average of all possible constituent 2x2 DID estimates. To overcome the challenge that the late treatment events confound the early treatment events in the estimation, I conduct a stacked regression following Cengiz et al. (2019). This approach considers the time-varying treatments and treatment heterogeneity in a generalized DID setting via two steps. The first step consists in creating a separate dataset for each year of treatment that contains observations of vehicles that were treated that year, with all others that are not treated at any time serving as "clean controls". For each dataset, I use the year of treatment as the demarcation point to identify the three pre-treatment and post-treatment periods for both treated vehicles and control vehicles, respectively. I then stack the treatment-time-specific datasets together to generate the complete data for the main analysis. The second step is to perform the DID analysis on the stacked data using the following specifications.

To estimate the treatment effect of localization, I use Panel A and model vehicle quality as described below:

$$Y_{itg} = f\left(\alpha_{ig} + \lambda_{tg} + \delta^{DD} Localization_{it} + \psi_{it} X_{it} + \varepsilon_{itg}\right), \tag{1}$$

where Y_{itg} is a vector of outcome variables including the number of recalls and the number of customer complaints; *i* indexes the vehicle; *t* indexes the model year; and *g* indexes the treatment year. The link function, f, denotes a Poisson regression considering that both outcome variables are count variables. α_{ig} and λ_{tg} are the vehicle and time fixed effects for treatment year *g*, respectively. $Localization_{it}$ is a dichotomous variable that is equal to 1 if the vehicle has had its production localized from a foreign to a domestic plant, and is 0 otherwise. δ^{DD} is the estimate of an average treatment effect across all treatment years. X_{it} is a vector of time-varying covariates, including the annual sales volume and cumulative sales volume since a vehicle's first generation, which controls for economies of scale (Ball et al., 2018; Shah et al., 2017) and automakers' learning experiences in addressing quality concerns (Haunschild and Rhee, 2004).

I also investigate how the introduction of localized vehicles influences the quality of other vehicles produced in that plant by analyzing Panel B, estimating the following model:

$$Y_{itg} = f(\alpha_{ig} + \lambda_{tg} + \delta^{DD} Introduction_{it} + \psi_{it} X_{it} + \varepsilon_{itg}). \tag{2}$$

$Introduction_{it}$ is a dichotomous variable that is equal to 1 if a localized vehicle had been introduced to the plant of vehicle *t* in year *i*, and is 0 otherwise. The rest of the variables are the same as those in equation (1). Details on the construction of the variables and measures are included in the Appendix, and summary statistics are included in Table 1.2. I perform fixed effects estimation for each model and cluster the standard errors at the vehicle level.

2.3.3. Validity of DID Approach

The prerequisite of conducting DID analysis is that treatment and control groups have parallel underlying trends in the dependent variables. It is therefore important to examine pre-treatment trends to ensure that vehicles in the treatment group and those in the control group have no significant statistical differences in the number of recalls and the number of customer complaints conditional on the controls. To do so, I examine the dynamic treatment effects by including the leads and lags of the treatment variable instead of using the binary treatment indicator as in equations (1) and (2). The models for the two treatments of interest take the following forms:

$$Y_{itg} = f(\alpha_{ig} + \lambda_{tg} + \sum_{\tau=-3}^{2} \delta_{\tau}{}^{DD} Localization_{it}^{\tau} + \psi_{it} X_{it} + \varepsilon_{itg}), \quad (3)$$

$$Y_{itg} = f(\alpha_{ig} + \lambda_{tg} + \sum_{\tau=-3}^{2} \delta_{\tau}{}^{DD} Introduction_{it}^{\tau} + \psi_{it} X_{it} + \varepsilon_{itg}), \quad (4)$$

where $Localization_{it}^{\tau}$ is the treatment indicator variable that is equal to 1 if the vehicle *i* had its production localized from a foreign to a domestic plant τ years from year *t*, and is 0 otherwise, with $\tau = 0$ representing the first year following the localization, and $\tau = -1$ denoting the first year before treatment. Similarly, $Introduction_{it}^{\tau}$ is the treatment indicator variable that is equal to 1 if the vehicle *i* experienced the introduction of localized vehicles in its plant τ years from year *t*, and is 0 otherwise. The remainder of the variables are the same as those in equation (1). If my models are properly identified, the $\delta_{\tau}{}^{DD}$ should remain insignificant for $\tau < 0$ (i.e., the pre-treatment periods).

Table 1.2 Summary statistics

Variables	Descriptions	Obs.	Mean	SD	Min.	Max.
Recalls	Number of recalls within three years from the launch of a vehicle	6,826	1.258	2.011	0	26
Complaints	Number of complaints within three years from the launch of a vehicle	6,826	20.572	52.865	0	1080
Localization	Indicator for the manufacturing localization of vehicle assembly from foreign to domestic plants	6,826	0.039	0.194	0	1
Introduction	Indicator for the introduction of a localized model in a domestic plant	6,826	0.034	0.181	0	1
Log (Sales)	Log transformation of the number of cars sold for a vehicle in a year	6,826	9.513	2.469	0	13.727
Log (Cumulative Sales)	Log transformation of the overall number of cars sold for a vehicle since its launch	6,826	11.650	2.162	0	16.678

Table 1.3 presents the test results for the parallel trends assumption. The test suggests that the parallel trends assumption is satisfied for my data prior to both treatments.

Table 1.3 Testing for parallel trends assumption

	Panel A			Panel B	
	Recalls	Complaints		Recalls	Complaints
	(1)	(2)		(3)	(4)
Localization^{-3}	-0.296	0.127	Introduction^{-3}	0.066	-0.134
	(0.305)	(0.167)		(0.292)	(0.332)
Localization^{-2}	0.152	0.083	Introduction^{-2}	0.160	-0.160
	(0.163)	(0.122)		(0.244)	(0.244)
Observations	9,304	9,980	Observations	4,977	4,635
Log-likelihood	-10,885.485	-41,179.264	Log-likelihood	-7,397.410	-44,517.739
Pseudo R2	0.311	0.73	Pseudo R2	0.298	0.729

Note. *** p< 0.001, ** p< 0.01, * p< 0.05, + p< 0.1. Table 1.3 reports the estimated coefficients and their robust standard errors (in parenthesis) for the key terms in equations (3) and (4) regarding the number of recalls and the number of customer complaints. As all coefficients are insignificant, I conclude that the assumption of parallel trends is satisfied. The superscripts give the value of τ such that Localization^{-3} means three years before localization.

2.4. Results

2.4.1. Overall Effects of Localization on Vehicle Quality

The results for the treatment effect of localization on vehicle quality based on equation (1) are captured in Table 1.4, Panel A. From columns (1) and (3) I observe that the number of recalls increases by 68.203% after a localization, which equates to 0.552 more recall campaigns than the average number of recall campaigns before the treatment (0.810 recall campaigns). Also, the number of complaints increases by 56.831% after localization, which represents 9.977 more complaints than the average number of complaints in the pre-treatment scenario (17.556 complaints). Overall, the results thus show that localization leads to a significant quality decline for localized vehicles.

To assess the dynamic treatment effects of localization, I replace the binary treatment variable (*Localization*) with a series of dummy variables for each year of localization (Localization Time 1 to Time 3). These three dummy variables take on the value of 1 if the localization has been occurring for one, two, or three years, respectively, and 0 otherwise. The results in columns (2) and (4) of Table 1.4 show that the quality decline of localized vehicles diminishes with time and is no longer significant after two years, indicating a temporary impact.

Table 1.4 Estimates of the treatment effects on vehicle quality

Panel A. Manufacturing localization and the quality of localized vehicles

	Recalls		Complaints	
	(1)	(2)	(3)	(4)
Localization	0.520*		0.450*	
	(0.217)		(0.221)	
$Localization^1$		0.545*		0.362+
		(0.229)		(0.204)
$Localization^2$		0.696**		0.590*
		(0.218)		(0.296)
$Localization^3$		0.253		0.355
		(0.281)		(0.275)
Post	0.007	-0.007	-0.043	-0.048
	(0.021)	(0.015)	(0.058)	(0.056)
Sales	0.633***	0.635***	1.013***	1.011***
	(0.068)	(0.068)	(0.179)	(0.180)
Cumulative Sales	-0.122**	-0.123**	-0.159**	-0.158**
	(0.043)	(0.043)	(0.050)	(0.050)
Constant	-3.350***	-3.331***	-5.935**	-5.908**
	(0.926)	(0.927)	(1.856)	(1.878)
Observations	9,301	9,301	9,974	9,974
Log-pseudolikelihood	-10,886.376	-10,883.138	-41,108.101	-41,088.269
Pseudo R2	0.310	0.311	0.730	0.730

Note. Robust standard errors in parentheses. *** p< 0.001, ** p< 0.01, * p< 0.05, + p< 0.1

Table 1.4 (cont'd)

Panel B. Introduction of localized vehicles in a plant and the quality of other vehicles in the plant

	Recalls		Complaints	
	(1)	(2)	(3)	(4)
Introduction	-0.050		-0.062	
	(0.170)		(0.229)	
Introduction^1		0.016		-0.216
		(0.259)		(0.155)
Introduction^2		0.298		0.204
		(0.222)		(0.463)
Introduction^3		-0.579+		-0.204
		(0.340)		(0.251)
Post	0.165	0.171	0.498**	0.498**
	(0.197)	(0.198)	(0.155)	(0.155)
Sales	0.517***	0.519***	1.523***	1.524***
	(0.141)	(0.142)	(0.152)	(0.152)
Cumulative Sales	-0.080**	-0.080**	-0.160***	-0.160***
	(0.030)	(0.030)	(0.041)	(0.041)
Constant	-3.681*	-3.687*	-11.310***	-11.319***
	(1.546)	(1.549)	(1.983)	(1.984)
Observations	4,223	4,223	3,957	3,957
Log-pseudolikelihood	-6,281.424	-6,277.903	-36,899.029	-36,887.849
Pseudo R2	0.305	0.305	0.742	0.742

Note. Robust standard errors in parentheses. *** p< 0.001, ** p< 0.01, * p< 0.05, + p< 0.1

The results for the treatment effect of introducing localized vehicles to a plant on the quality of other vehicles in those plants are captured in Table 1.4, Panel B. As can be seen in columns (1) and (3), there is no evidence of statistical differences across treated and untreated vehicles in the number of recalls or the number of complaints. The time-varying treatment effects reported in columns (2) and (4) show the same results. I, thus, conclude that introducing localized vehicles to a plant does not influence the quality of the existing vehicles in the plant.

2.4.2 Post-Hoc Analysis

To investigate the mechanism through which the localization leads to the quality decline for localized vehicles, I further differentiate the treatment effects of two types of localization decisions.

The first decision type is the localization to a new plant, which is when automakers localized a vehicle to a plant that was opened within three years of the time of localization. Localization to a new plant might negatively influence the vehicle quality due to the learning effect, with however the quality expected to improve over time (G. Li and Rajagopalan, 1998). The second decision type is localization to an existing plant, which refers to automakers' decision to localize a vehicle to a plant that has been operating for more than three years. Vehicles having a lower level of quality after localization to an existing plant might suggest that the plants experienced difficulties in technology transfer. This is especially relevant when the destination plants were built many years ago.

The results in Table 1.5 reaffirm the quality decline triggered by both types of localization decisions. Specifically, Localization to an Existing Plant significantly increases the number of recalls of the localized vehicles, while the effect of Localization to a New Plant is marginal. However, only Localization to a New Plant leads to a greater number of customer complaints. Overall, both mechanisms considered contribute to the quality decline of localized vehicles.

2.5. Conclusion and Implications

I investigated whether the relocation of vehicle production to the target market can influence the quality of localized vehicles and the quality of existing vehicles in those plants in which the localized vehicles were introduced. Causal data analysis of vehicles sold in the U.S. market indicates that localization increases the number of recalls and customer complaints for localized car models, indicating a decline in quality. Specifically, a localized vehicle has 68.203% more recalls and 56.831% more complaints in three years following the launch year of this vehicle. The pattern of time-varying treatment effects shows that the increase in quality concerns is temporary and diminishes over time. The increase of recalls is robust to the conditions of the destination plants—both localization to a new plant and localization to an existing plant leads to more recalls. Since the introduction of localized vehicles in a plant can interrupt existing plant operations, existing vehicles in the plant, in theory, may also experience quality losses. However, I did not find evidence that the number of recalls or complaints for existing vehicles increased after the introduction of localized vehicles.

Table 1.5 Estimates of the treatment effects of localization on vehicle quality, differentiating the plant history (Panel A)

	Recalls	Complaints
	(1)	(2)
Localization to an Existing Plant	0.678*	0.108
	(0.340)	(0.334)
Localization to a New Plant	0.305+	0.731**
	(0.182)	(0.244)
Post	0.011	-0.044
	(0.020)	(0.058)
Sales	0.633***	1.012***
	(0.068)	(0.179)
Cumulative Sales	-0.122**	-0.161**
	(0.043)	(0.049)
Constant	-3.352***	-5.816**
	(0.927)	(1.839)
Observations	9,301	9,974
Log-pseudolikelihood	-10,885.343	-41,054.386
Pseudo R2	0.311	0.730

Note. Robust standard errors in parentheses. *** p< 0.001, ** p< 0.01, * p< 0.05, + p< 0.1

While automakers do not usually disclose the cost of recalls, I aim to estimate the cost of recall campaigns to evaluate part of the economic value lost due to an increased number of recall campaigns for localized vehicles based on aggregated numbers. The 2016 data of the NHTSA Recall Annual Report, which records the number of recall campaigns and the number of vehicles affected per year, shows that there was a total of 919 recall campaigns that affected over 50.14 million vehicles. With more than $10.3 billion spent on warranty and recall accruals in 2016 (Held et al., 2018), each recall campaign is estimated to cost $11.21 million and to affect an average of 54,559 vehicles, yielding a recall cost of $205.28 per vehicle. More specific cases, such as General Motor's 2014 recalls, suggest that the company spent $4.10 billion to recall 30.4 million cars (Isidore, 2015), with $134.87 specified as the recall cost per vehicle. Using these estimations of the recall cost per vehicle as a foundation, I estimate the cost per recall campaign to be between $4.99 and $7.60 million in the 20 years between 2000 to 2019 (see Table 1.6 for further detail). A conservative estimate that I can thus develop is that with 0.552 more recall campaign for a localized vehicle, the associated cost can be $2.76 million; this number may however be much larger based on the fines NHTSA can impose on automakers, the repairs needed, or products to be replaced to correct the quality defect. It can become particularly costly when an entire battery for an electric vehicle needs to be replaced (Isidore and Valdes-Dapena, 2021). Due to recalls following localization jeopardizing substantial financial losses, a cautionary note is issued to automakers to budget warranty spending and accrual with the potential quality decline after localization. Based on the data I collected from a North American automotive manufacturer, the warranty per car unit has an average cost of about $88. With the estimated recall cost per car unit that I specified above, I suggest that automakers increase the budget on warranty by at least 53.261% to prevent further operational disruptions triggered by this financial distress.

Several intriguing research avenues exist that can build on my work. For example, it is possible that the localization of an entire (or large parts of a) supply chain may reduce recalls. Prior literature has indicated that quality defects of vehicles increase as the distance between upstream component suppliers and downstream assembly plants increases (Bray et al., 2019), which is likely to happen when the manufacturing localization does not come with an extensive supply localization. This is especially true for high-end vehicles as well as vehicles with numerous subcomponents and large production volumes. In those cases, process-level changes, including standardization, modularity, and small batch production, are helpful to mitigate the negative impact of localization on vehicle quality.

From the perspective of regulators, closer attention to the shifts in manufacturing locations can help reduce automotive recalls. Protocols can be developed to specify how automakers should manage the localized vehicles and the required analysis and procedures of plant relocation—this may mitigate the problem of quality decline identified in my research.

Table 1.6 Estimation of cost per recall campaign

			Recall Cost per Unit of Car Estimation 1	Recall Cost per Unit of Car Estimation 2
			$134.87	$205.28
Year	Number of Recalls	Number of Vehicles Affected	Cost per Recall Estimation 1	Cost per Recall Estimation 2
2000	541	24,636,743	$6.14	$9.35
2001	453	13,626,263	$4.06	$6.17
2002	434	18,435,673	$5.73	$8.72
2003	527	19,062,913	$4.88	$7.43
2004	600	30,806,580	$6.92	$10.54
2005	562	18,962,510	$4.55	$6.93
2006	490	11,203,534	$3.08	$4.69
2007	587	14,816,417	$3.40	$5.18
2008	683	10,207,696	$2.02	$3.07
2009	491	16,125,894	$4.43	$6.74
2010	647	19,691,419	$4.10	$6.25
2011	597	13,612,039	$3.08	$4.68
2012	582	16,486,229	$3.82	$5.81
2013	628	20,260,042	$4.35	$6.62
2014	771	50,032,376	$8.75	$13.32
2015	862	49,863,794	$7.80	$11.87
2016	919	50,138,221	$7.36	$11.20
2017	809	30,689,022	$5.12	$7.79
2018	912	29,455,396	$4.36	$6.63
2019	881	38,583,951	$5.91	$8.99
		Average	$4.99	$7.60

APPENDIX

Construction of Variables and Measures

1. Dependent Variable

Our dependent variable is car quality. We consider auto recalls and complaints as two indicators of quality issues, which we obtained from the NHTSA/DOI database.

Recalls. We measure Recalls using the number of recalls a vehicle of a specific year had within three years since its launch. Considering the mismatch between the year an OEM officially assigns to a vehicle-year and the time the vehicle-year enters the market, we consider the sales of all vehicle-years to always start on August 1st of the year prior to their officially assigned year. The three-year span during which we capture the recalls then refers to the 36 months following the August of the prior year. For example, we consider the 2014 Chevrolet Cruz to having been sold to consumers starting on August 1, 2013. During the following 36 months (i.e., August 1, 2013, to July 31, 2016), General Motors issued eight recalls for this vehicle year – five from August 1, 2013, until July 31, 2014, one from August 1, 2014, until July 31, 2015, and two from August 1, 2015, to July 31, 2016. In the main analysis, we use the three-year forward measure of the number of recalls, which captures, on average, 42.7% of the total number of recalls a vehicle experienced during its life span.

Complaints. The measurement approach for Complaints is consistent with the approach we took to measure recalls. Specifically, we use a three-year forward measure for this variable using the number of complaints that a vehicle of a specific year received within a three-year span, which starts from August 1st of the year prior to the official launch.

2. Independent Variables

Localization. Localization is a binary variable with Localization = 1 indicating the automaker localizing the assembly of the vehicle in the given year, and Localization = 0 indicating the location of the assembly not changing. We obtained this information from the Wards final assembly plant location data for North America and verified the information using the press releases on the plant relocation and plant opening from the automakers' websites and other reliable resources. There was one vehicle (MITSUBISHI OUTLANDER SPORT) that was relocated to foreign plants after being localized. We delete it from our sample to avoid the confounding effect of multiple localization decisions.

Introduction. Introduction is a binary variable. Specifically, Introduction = 1 indicates that a localized vehicle was produced in the year it was introduced, Introduction = 0 indicates otherwise. Since some vehicles were assembled in more than one plant in a given year, it is possible that the introduction of localized vehicles only happened in one plant, while the quality impacts for "other" vehicles manufactured in that plant could be captured in aggregate across all plants in which the same vehicle is manufactured. This can create a problem in isolating the assessment of the impact of localization of a vehicle on other vehicles manufactured in the plant. However, in Panel B, our data suggests that none of the models that had multiple assembly plants experienced the introduction of localized vehicles.

3. Control Variables

We include a number of variables in our analysis to control for heterogeneity at the vehicle level. We also control for vehicle fixed-effects and year fixed-effects. These data were obtained from the Wards sales data. Each of these variables are described below:

Sales. Prior literature suggests that a high level of production volume leads to an increase of quality-related issues, with production volume capturing economies of scales (Ball et al., 2018; Shah et al., 2017). In this study, we use the sales volume as a proxy for production volume. Sales data are available for each vehicle year. Specifically, we aggregated the monthly data into yearly data to match the measurement period of other variables. As noted above, it is common practice in the auto industry that dealers start to sell a vehicle model before its assigned year. Therefore, the sales record of the prior year may capture part of the sales of a given vehicle year. To align the aggregated data with the sales practice, we made the same assumption as the one we presented in the creation of recall variable, i.e., that the sale of a vehicle always starts on August 1st of the year prior to their officially assigned year. As such, the yearly sales data capture the number of vehicles sold during the following 12 months. For example, the sales of the 2010 Honda Accord refer to the volume sold from August 1, 2019, until July 31, 2020. We performed a log transformation for this variable before including it into the analysis.

Cum Sales. Cumulative production volume is also related to quality issues, such as recalls or complaints, because it measures the extent to which manufacturers can learn from the experience to reduce quality concerns (Haunschild & Rhee, 2004). We use the cumulative sales volume as a proxy of cumulative production volume. We construct the variable by calculating the number of vehicles sold for a vehicle from its launch, or from the earliest record in our sample until the last year of record. We performed a log transformation for the one-year lagged variable before including it in the analysis.

REFERENCES

REFERENCES

Badiru, A. B. (1998). Quality Improvement through Learning Curve Analysis. In *Handbook of Total Quality Management* (pp. 87–107). Springer US.

Bailey, D., and De Propris, L. (2014). Manufacturing Reshoring and Its Limits: The UK Automotive Case. *Cambridge Journal of Regions, Economy and Society*, *7*(3), 379–395.

Baker, A. C., Larcker, D. F., and Wang, C. C. Y. (2022). How Much Should We Trust Staggered Difference-in-Differences Estimates? *Journal of Financial Economics*, *144*(2), 370–395.

Ball, G. P., Shah, R., and Wowak, K. D. (2018). Product Competition, Managerial Discretion, and Manufacturing Recalls in the U.S. Pharmaceutical Industry. *Journal of Operations Management*, *58–59*(1), 59–72.

Bandyopadhyay, J. K., and Jenicke, L. O. (2007). Six Sigma Approach to Quality Assurance in Global Supply Chains: A Study of United States Automakers. *International Journal of Management*, *24*(1), 101–107.

BDO. (2021). *2021 BDO manufacturing CFO outlook survey*. https://www.bdo.com/BDO/media/CFO-Outlook-Survey/IND_2021-Manufacturing-CFO-Outlook-Survey_WEB.pdf.

Ben-Ner, A., and Siemsen, E. (2017). Decentralization and Localization of Production: The Organizational and Economic Consequences of Additive Manufacturing. *California Management Review*, *59*(2), 5–23.

Bock, S. (2008). Supporting Offshoring and Nearshoring Decisions for Mass Customization Manufacturing Processes. *European Journal of Operational Research*, *184*(2), 490–508.

Bray, R. L., Serpa, J. C., and Colak, A. (2019). Supply Chain Proximity and Product Quality. *Management Science*, *65*(9), 4079–4099.

Brennan, L., Ferdows, K., Godsell, J., Golini, R., Keegan, R., Kinkel, S., Srai, J. S., and Taylor, M. (2015). Manufacturing in the World: Where Next? *International Journal of Operations and Production Management*, *35*(9), 1253–1274.

Brun, A., and Zorzini, M. (2009). Evaluation of Product Customization Strategies through Modularization and Postponement. *International Journal of Production Economics*, *120*(1), 205–220.

Callaway, B., and Sant'Anna, P. H. C. (2021). Difference-in-Differences with Multiple Time PP. *Journal of Econometrics*, *225*(2), 200–230.

Cassia, F. (2020). 'Manufacturing Is Coming Home': Does Reshoring Improve Perceived Product Quality? *The TQM Journal*, *32*(6), 1099–1113.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The Effect of Minimum Wages on Low-Wage Jobs*. *The Quarterly Journal of Economics*, *134*(3), 1405–1454.

Cheng, Y., Farooq, S., and Johansen, J. (2015). International Manufacturing Network: Past, Present, and Future. *International Journal of Operations and Production Management*, *35*(3), 392–429.

Cherney, M. (2020, December 27). Firms Want to Adjust Supply Chains Post-Pandemic, but Changes Take Time. *Wall Street Journal (Online)*. http://ezproxy.msu.edu/login?url=https://www.proquest.com/newspapers/firms-want-adjust-supply-chains-post-pandemic/docview/2472846898/se-2?accountid=12598.

Clark, K. B., and Fujimoto., T. (1992). *Product Development Performance: Strategy, Organization, and Management in the World Auto Industry.* Harvard Business School Press.

CNN. (2015). *Chinese-owned Volvo to open its first U.S. car plant*. https://money.cnn.com/2015/03/30/news/companies/volvo-new-factory-u-s-/index.html.

Curran, E. (2021, May 21). APEC Sees Challenges in Reshoring as Pandemic Hits Supply Chains. *Bloomberg Newsletter*. https://www.bloomberg.com/news/newsletters/2021-05-27/supply-chains-latest-weighing-costs-and-benefits-of-reshoring.

da Silveira, G. J. C. (2014). An Empirical Analysis of Manufacturing Competitive Factors and Offshoring. *International Journal of Production Economics*, *150*, 163–173.

Dana, L. P., Hamilton, R. T., and Pauwels, B. (2007). Evaluating Offshore and Domestic Production in the Apparel Industry: The Small Firm's Perspective. *Journal of International Entrepreneurship*, *5*(3–4), 47–63.

de Treville, S., Bicer, I., Chavez-Demoulin, V., Hagspiel, V., Schürhoff, N., Tasserit, C., and Wager, S. (2014). Valuing Lead Time. *Journal of Operations Management*, *32*(6), 337–346.

Dunning, J. H. (1980). Toward an Eclectic Theory of International Production: Some Empirical Tests. *Journal of International Business Studies*, *11*(1), 9–31.

Ellram, L. M., Tate, W. L., and Petersen, K. J. (2013). Offshoring and Reshoring: An Update on the Manufacturing Location Decision. *Journal of Supply Chain Management*, *49*(2), 14–22.

Foerstl, K., Kirchoff, J. F., and Bals, L. (2016). Reshoring and Insourcing: Drivers and Future Research Directions. *International Journal of Physical Distribution & Logistics Management*, *46*(5), 492–515.

Foldy, B. (2020, April 2). Auto-Parts Suppliers Teeter as Car Production Halts. *The Wall Street Journal*. https://www.wsj.com/articles/auto-parts-suppliers-teeter-as-car-production-halts-11585828803.

Fratocchi, L., Ancarani, A., Barbieri, P., Di Mauro, C., Nassimbeni, G., Sartor, M., Vignoli, M., and Zanoni, A. (2016). Motivations of Manufacturing Reshoring: An Interpretative

Framework. *International Journal of Physical Distribution & Logistics Management*, *46*(2), 98–127.

Goodman-Bacon, A. (2021). Difference-in-Differences With Variation in Treatment Timing. *Journal of Econometrics*, *225*(2), 254–277.

Gopal, A., Goyal, M., Netessine, S., and Reindorp, M. (2013). The Impact of New Product Introduction on Plant Productivity in the North American Automotive Industry. *Management Science*, *59*(10), 2217–2236.

Grappi, S., Romani, S., and Bagozzi, R. P. (2020). The Effects of Reshoring Decisions on Employees. *Personnel Review*, *49*(6), 1254–1268.

Gray, J. V., Roth, A. V., and Leiblein, M. J. (2011). Quality Risk in Offshore Manufacturing: Evidence from the Pharmaceutical Industry. *Journal of Operations Management*, *29*(7–8), 737–752.

Gray, J. V., Skowronski, K., Esenduran, G., and Johnny Rungtusanatham, M. (2013). The Reshoring Phenomenon: What Supply Chain Academics Ought to Know and Should Do. *Journal of Supply Chain Management*, *49*(2), 27–33.

Gryta, T., and Cutter, C. (2021, November 1). Farewell Offshoring, Outsourcing. Pandemic Rewrites CEO Playbook. *Wall Street Journal (Online)*. http://ezproxy.msu.edu/login?url=https://www.proquest.com/newspapers/farewell-offshoring-outsourcing-pandemic-rewrites/docview/2590139909/se-2?accountid=12598.

Haex, P., and Buck, R. (2022). *Global reshoring & footprint strategy*. https://bciglobal.com/uploads/9/artikelen/global-reshoring-and-footprint-strategy-2022.pdf.

Haunschild, P. R., and Rhee, M. (2004). The Role of Volition in Organizational Learning: The Case of Automotive Product Recalls. *Management Science*, *50*(11), 1545–1560.

Held, M., Marian, A., and Reaves, J. (2018). *The auto industry's growing recall problem—and how to fix it*. https://www.alixpartners.com/media/14438/ap_auto_industry_recall_problem_jan_2018.pdf

HMMA. (2006). *Hyundai celebrates grand opening of its first US plant - Hyundai Motor Manufacturing Alabama, LLC (HMMA)*. https://www.hmmausa.com/hyundai-celebrates-grand-opening-of-its-first-us-plant/.

Honda. (2006, September 26). *2007 Honda CR-V. U.S. Production*. https://hondanews.com/en-US/photos/photo-547a298d6a2fe6a21f1369004c350649-2007-honda-cr-v-u-s-production?firstResultIndex=40&channelsConstraint=channel-3012.

Imai, K., and Kim, I. S. (2021). On the Use of Two-Way Fixed Effects Regression Models for Causal Inference with Panel Data. *Political Analysis*, *29*(3), 405–415.

Isidore, C. (2015, February 4). *GM's total recall cost: $4.1 billion*. CNNMoney.

https://money.cnn.com/2015/02/04/news/companies/gm-earnings-recall-costs/index.html.

Isidore, C., and Valdes-Dapena, P. (2021, February 25). Hyundai's Recall of 82,000 Electric Cars Is One of the Most Expensive in History. *CNN Business*. https://www.cnn.com/2021/02/25/tech/hyundai-ev-recall/index.html.

ITA. (2018). *Automotive Industry Spotlight*. https://www.selectusa.gov/automotive-industry-united-states.

Johansson, M., and Olhager, J. (2018). Comparing Offshoring and Backshoring: The Role of Manufacturing Site Location Factors and Their Impact on Post-Relocation Performance. *International Journal of Production Economics*, *205*, 37–46.

Ketokivi, M., Turkulainen, V., Seppälä, T., Rouvinen, P., and Ali-Yrkkö, J. (2017). Why Locate Manufacturing in a High-Cost Country? A Case Study of 35 Production Location Decisions. *Journal of Operations Management*, *49–51*(1), 20–30.

Lacetera, N., and Sydnor, J. (2015). Would You Buy a Honda Made in the United States? The Impact of Production Location on Manufacturing Quality. *Review of Economics and Statistics*, *97*(4), 855–876.

Li, G., and Rajagopalan, S. (1998). Process Improvement, Quality, and Learning Effects. *Management Science*, *44*(11 PART 1), 1517–1532.

Ma, C., Hauck, M., and Matava, D. (2021). *State of North America manufacturing 2021 annual report*. https://f.hubspotusercontent00.net/hubfs/242200/UA Files/State of North American Manufacturing 2021 Annual Report v1.3.pdf.

Moradlou, H., Backhouse, C., and Ranganathan, R. (2017). Responsiveness, the Primary Reason behind Re-Shoring Manufacturing Activities to the UK: An Indian Industry Perspective. *International Journal of Physical Distribution and Logistics Management*, *47*(2–3), 222–236.

NielsonIQ. (2020). *COVID-19 concerns are a likely tipping point for local brand growth*. https://nielseniq.com/global/en/insights/analysis/2020/covid-19-concerns-are-a-likely-tipping-point-for-local-brand-growth/.

Raza, W., Grumiller, J., Grohs, H., Essletzbichler, J., and Pintar, N. (2021). *Post Covid-19 value chains: options for reshoring production back to Europe in a globalised economy* (Issue March). https://www.europarl.europa.eu/thinktank/en/document/EXPO_STU(2021)653626. https://doi.org/10.2861/118324

Reuters. (2016). *Volkswagen targets East Africa with Kenya car assembly plant*. https://www.reuters.com/article/us-volkswagen-kenya/volkswagen-targets-east-africa-with-kenya-car-assembly-plant-idUSKCN11D1YM.

Rosenbaum, E. (2021, December 2). CEOs across Economy Agree on One 2022 Prediction: More Volatility, No End to Covid. *CNBC*. https://www.cnbc.com/2021/12/02/ceos-across-economy-agree-on-one-big-2022-prediction-more-volatility.html.

Schwartz, N. D. (2022, February 18). Supply Chain Woes Prompt a New Push to Revive U.S. Factories. *International New York Times*. https://link-gale-com.proxy1.cl.msu.edu/apps/doc/A688930535/GIC?u=msu_main&sid=bookmark-GIC&xid=e0e2c2cc.

Shah, R., Ball, G. P., and Netessine, S. (2017). Plant Operations and Product Recalls in the Automotive Industry: An Empirical Investigation. *Management Science*, *63*(8), 2439–2459.

Simchi-Levi, D., and Simchi-Levi, E. (2020). Building Resilient Supply Chains Won't Be Easy. *Harvard Business Review*.

Srai, J. S., and Ané, C. (2016). Institutional and Strategic Operations Perspectives on Manufacturing Reshoring. *International Journal of Production Research*, *54*(23), 7193–7211.

Staeblein, T., and Aoki, K. (2015). Planning and Scheduling in the Automotive Industry: A Comparison of Industrial Practice at German and Japanese Makers. *International Journal of Production Economics*, *162*, 258–272.

Stentoft, J., Mikkelsen, O. S., Jensen, J. K., and Rajkumar, C. (2018). Performance Outcomes of Offshoring, Backshoring and Staying at Home Manufacturing. *International Journal of Production Economics*, *199*, 199–208.

Sun, L., and Abraham, S. (2021). Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects. *Journal of Econometrics*, *225*(2), 175–199.

Tech Explore. (2020). *Tesla to build "world's largest" battery plant near Berlin*. https://techxplore.com/news/2020-11-tesla-world-largest-battery-berlin.html.

Tesla. (2020). *Gigafactory Berlin-Brandenburg*. https://www.tesla.com/gigafactory-berlin.

The White House. (2021). *Building resilient supply chains, revitalizing American manufacturing, and fostering broad-based growth*. https://www.whitehouse.gov/wp-content/uploads/2021/06/100-day-supply-chain-review-report.pdf.

TheEconomist. (2013, January 17). Here, There and Everywhere. *The Economist*, *406*(8819).

Vahlne, J. E., and Johanson, J. (2017). From Internationalization to Evolution: The Uppsala Model at 40 Years. *Journal of International Business Studies*, *48*(9), 1087–1102.

Vernon, R. (1966). International Investment and International Trade in the Product Cycle. *The Quarterly Journal of Economics*, *80*(2), 190.

Wellener, P., Hardin, K., and Beckoff, D. (2022). *2022 manufacturing industry outlook*. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/energy-resources/us-2021-manufacturing-industry-outlook.pdf.

Wiesmann, B., Snoei, J. R., Hilletofth, P., and Eriksson, D. (2017). Drivers and Barriers to Reshoring: A Literature Review on Offshoring in Reverse. *European Business Review*, *29*(1), 15–42.

CHAPTER 3 – Firms' Policy Engagement on Climate Change: Taxonomy Development and Validation

3.1. Introduction

With the increasing awareness of climate change as a pressing sustainability challenge and a major global issue in the last few decades, the governments of many countries and regions have formulated and enacted climate change policies to restrict and reduce greenhouse gas emissions. Up to July 2022, the International Energy Agency's (IEA, 2022) policies database recorded 6,782 regulations, policies, and measures related to the reduction of carbon emission, the improvement of energy efficiency, and the development and deployment of renewable and other clean energy technologies that are in force in 37 countries. The World Bank's Carbon Pricing Dashboard (The World Bank, 2022) has tracked down 68 carbon pricing initiatives, one of the key economic policy instruments, that were implemented or scheduled for implementation in 46 nations and 36 subnational areas, which covers 23% of global greenhouse gas emissions. Many jurisdictions have adopted renewable energy targets, led by the EU's binding target that 27% of the overall energy consumption of the EU should come from renewable sources by 2030 (EEU, 2018), and the U.S.'s state renewable portfolio standards that require a different degree of clean energy consumption in different states (RSP, 2021).

Those emerging public policies or policy changes exert regulatory and policy pressures on firms and have urged businesses to take action. On the one hand, the increased scrutiny motivates firms to improve policy compliance and commit to climate change mitigation and adaptation. Consequently, firms have adopted a variety of approaches to transform or tweak internal operations and engage in sustainable supply chain management to minimize the climate impact. Investigations of those business practices led to a stream of climate change-related research in the operations and supply chain management (OSCM) field, which has identified and discussed approaches that firms incorporate in procurement and sourcing strategies, manufacturing operations, and logistic and transportation management to make or enhance their commitment to the reduction of carbon emissions (Ghadge et al., 2020), including supply chain collaboration and coordination for carbon transparency and other engagements (Jira and Toffel, 2013; Theißen et al., 2014; Tidy et al., 2016; Villena and Dhanorkar, 2020), carbon footprint mapping (K.-H. Lee, 2011; Rizet et al., 2012), low-carbon product and packaging design (Ji et al., 2014; Oglethorpe and Heron, 2010), low-carbon manufacturing strategies (Dadhich et al., 2015; Oglethorpe and Heron, 2010), and low-carbon supply chain strategies (C.-M. Chen, 2017; Jin et al., 2014). These studies note climate change policies as an external context and concentrate on how firms survive the climate change scrutiny by adopting sustainable OSCM.

On the other hand, a context of strict enforcement of climate change policies prompts firms to reversely influence policymaking to redirect or evade regulatory scrutiny. This effort has been evident especially when emerging policies influence the dynamics of an industry and firms residing in an industry (Grover and Dresner, 2022). As an example, consider automakers' varying attempts to reshape the action plans of the targets to gradually phase out sales of new internal combustion engine (ICE) vehicles to achieve zero-emission by 2050 at the latest, which have been specified in 17 national or regional governments' official policies or strategy documents (Automotive World, 2020). While General Motors, Ford, and several other automakers commit to a carbon-neutral stance and advocate for a more aggressive goal of eliminating gas and diesel vehicles by 2035 (Boudette and Davenport, 2021), the remaining automakers led by BMW lobby against the pressing enforcement of ICE bans (Hetzner, 2021). As another example serves the coexisting support and resistance in the oil and gas industry to policies related to decarbonization

(Domonoske, 2021; McCarthy, 2019), which are believed to be the unavoidable but costly path energy companies should take to achieve the goal of The Paris Agreement (Pee et al., 2018).

In contrast to reactively responding to policy changes with improved compliance and adaptation, firms engaging in influence actions seek to reshape or amend the policy and regulatory environments in which they embed through close interactions with government departments, participation in ad-hoc coalitions, lobbying, and imposing market influences (Clapp and Meckling, 2013). Such engagement has been captured by the literature as part of corporate political activities (CPAs) (Bumpus, 2015; Eberlein and Matten, 2009; Okereke and Russel, 2010; Oliver and Holzinger, 2008). However, these issues are understudied from an OSCM perspective.

One exception is a recent conceptual study by Grover and Dresner (2022). They extend the typology of political actions proposed by management researchers (Oliver and Holzinger, 2008), and discuss the applicability of influence-oriented political actions for supply chain risk management. Specific to the context of climate change, only Cory et al.'s (2021) research justifies the relevance of OSCM to firms' attempts to influence policymaking. They empirically demonstrate that firms' embeddedness in the supply chain ecosystem motivates firms to reshape climate change policies in favor of the less sustainable segments of their supply chain. Specifically, the greenhouse gas intensity of the extended supply chain is positively associated with the focal firms' participation in carbon coalitions and lobbying.

The scarcity of discussions on firms' engagement in influencing climate change policies (EICCP) is due to the unbalance in climate change-related research – most existing studies have regarded climate change policies as external conditions to which firms should adapt, while very few studies have paid attention to the impact of firms' political actions on climate change policies (Aragón-Correa et al., 2020; Greiner and Kim, 2021). Yet, the investigation of how firms reshape the regulatory context to solve the problem of practice-policy decoupling and obtain legitimacy under scrutiny over climate impact is important to further the understanding of firms' overall sustainability strategy. Specifically, identifying and examining different strategies of EICCP sets a foundation for the exploration of the dynamics between public policies and sustainable OSCM, responding to the call for more investigation on policy issues from an OSCM perspective (Tokar and Swink, 2019). Further, prior literature indicates that the discourse of sustainability has been marginalized in OSCM to align with firms' intentions to make incremental changes instead of a fundamental shift in practices as well as their concentration on profitability over sustainability (Hardy et al., 2020; Pagell and Shevchenko, 2014). I contend that the investigation of firms' EICCP provides insights into the role of business in the formation of the current discourse of sustainability in the OSCM context and facilitates the revamping of the discourse that leads to more sustainable supply chains. Overall, there is a need to complement climate change-related OSCM studies by incorporating the conceptualization of EICCP and identifying different types of engagements. Within this context, I specifically focus on two research questions: 1) Which criteria need to be considered to differentiate EICCP strategies? and 2) What kind of EICCP strategies do firms adopt? How can these strategies be captured?

To answer those questions, I first introduce the concept of EICCP. Building on the literature on CPA and environmental politics, I also propose a typology for EICCP that differentiates firms' engagement strategies from three dimensions: firms' value perspective and engagement level, firms' participation level in EICCP, and the type of resources devoted to EICCP. Second, I validate the typology by identifying strategies of EICCP adopted in the real world by performing text analytics with automated machine-learning techniques on firms' self-disclosure in CDP Climate Change data. I also evaluate the measures and discuss future research opportunities.

3.2. Literature Review and Theory Development for EICCP

3.2.1. Literature Review

Researchers in economics, political science, and management have long recognized the business responses to government regulations, which is referred to as CPA. At the micro or firm level, CPA has been defined as "strategies to employ an organization's resources to integrate objectives and to undertake coherent actions directed towards the political, social, and legal environment to secure either permanent or temporary advantage and influence over other actors in the process" (Mahon, 1983, pp. 51-52). From a managerial perspective, prior literature posits that firms engage in the public policy process to strengthen their organizational legitimacy in a broader social system as well as to obtain competitive advantages over their competitors (Shaffer, 1995). Due to the heterogeneity in political resources and capabilities, firms perceive the impact of policies differently (Hillman et al., 2004). Consequently, firms choose different ways to engage in policies, with expectations of investments and potential gains (Bonardi et al., 2005). The various ways to engage mainly depend on the structure of firms and industries, the characteristics of different political issues, and the institutional features (Hillman et al., 2004; Lawton et al., 2013).

The multiplicity of firms' engagement strategies enlightens a stream of literature that focuses on developing a taxonomy of CPA to further the understanding of CPA types. With the initial attempts only being to differentiate proactive behaviors from reactive behaviors (Blumentritt, 2003; Meznar and Nigh, 1995), later research proposes various criteria seeking to develop a more holistic taxonomy following different theoretical underpinnings. Representative work includes Hillman and Hitt (1999), which categorizes CPA engagement strategies based on firms' approaches to CPA (relational vs. transactional engagement), participation level (engage as a leader vs. as a follower), and fundamental resources exchanged (information, financial incentives vs. constituency building). The authors apply resources dependence theory and institutional theory to consider the firms' resources or resource constraints, as well as the institutional differences at the country- or subnational-level as important factors for political strategy formulation. Dahan (2005) extends the typology of resources exchanged by proposing other political resources used for CPA. Building on the resource-based view and dynamic capabilities view, Oliver and Holzinger (2008) propose that the effectiveness of firms' CPA strategies differ due to the different dynamic capabilities that firms have developed in the political environment. To achieve effective political management, firms ground the CPA strategies in their value perspectives, which delineate whether firms aim to maintain or create value, and strategic orientation, which suggests whether firms need to influence or comply with policies. Integrating the two criteria yields a typology that is comprised of four strategies: reactive (value maintenance with compliance), anticipatory (value creation with compliance), defensive (value maintenance with influence), and proactive strategies (value creation with influence). Grover and Dresner (2022), presenting an integrated model of CPA and supply chain risk management strategies, extend Oliver and Holzinger's (2008) taxonomy specifying a competitive dynamics perspective. They argue that there exist two additional strategic orientations besides compliance and influence. One is moderation, which refers to firms "acting to moderate their political environments to improve or defend their competitive advantage" (Grover and Dresner, 2022, pp. 53). The other is neutral, which describes firms' attempt to "adopt a free-riding political stance or submit to the political environment" to maintain competitive advantage (Grover and Dresner, 2022, pp. 53).

Discussions on general types of CPA provide a theoretical foundation for the further exploration of firms' political engagement. However, these taxonomies may have limited explanatory power if focused on a specific context such as climate change. This is because the ways firms engage in policymaking depend on the issues and the stages of the policymaking process (Hillman et al., 2004; Keim and Zeithaml, 1986). For example, prior literature contends that the types and intensity of firms' CPA are associated with the degree of saliency for a political issue, which refers to the importance that individuals such as voters place on a certain issue (Keim and Bonardi, 2005; Moniz and Wlezien, 2020). While issues such as healthcare, foreign policy, and abortion, have different levels of saliency (Doherty et al., 2020), firms can adopt different CPA strategies to respond to policy changes on those issues. Therefore, there is a need to provide issue-specific discussions when exploring the potential types of CPA engagements. This study contributes to this discussion by investigating firms' different engagement strategies in climate change-related policymaking.

In addition, while the existing typologies examine several general types of CPA strategies, I further investigate the various engagement efforts within a certain strategy type to further the understanding of firms' responses to climate change policies. This is especially necessary when the exploration of different strategy types are unbalanced, with the influence-oriented engagement in policymaking for climate change issues receiving less academic attention than the adaptation-oriented engagement (Aragón-Correa et al., 2020; Greiner and Kim, 2021). Thus, an examination of the distinct approaches that firms adopt to influence climate change policies is needed. Accordingly, this essay contributes to the development of a holistic framework of business responses to the climate change issue and develops a taxonomy specific to EICCP.

3.2.2. Typologies of EICCP strategies

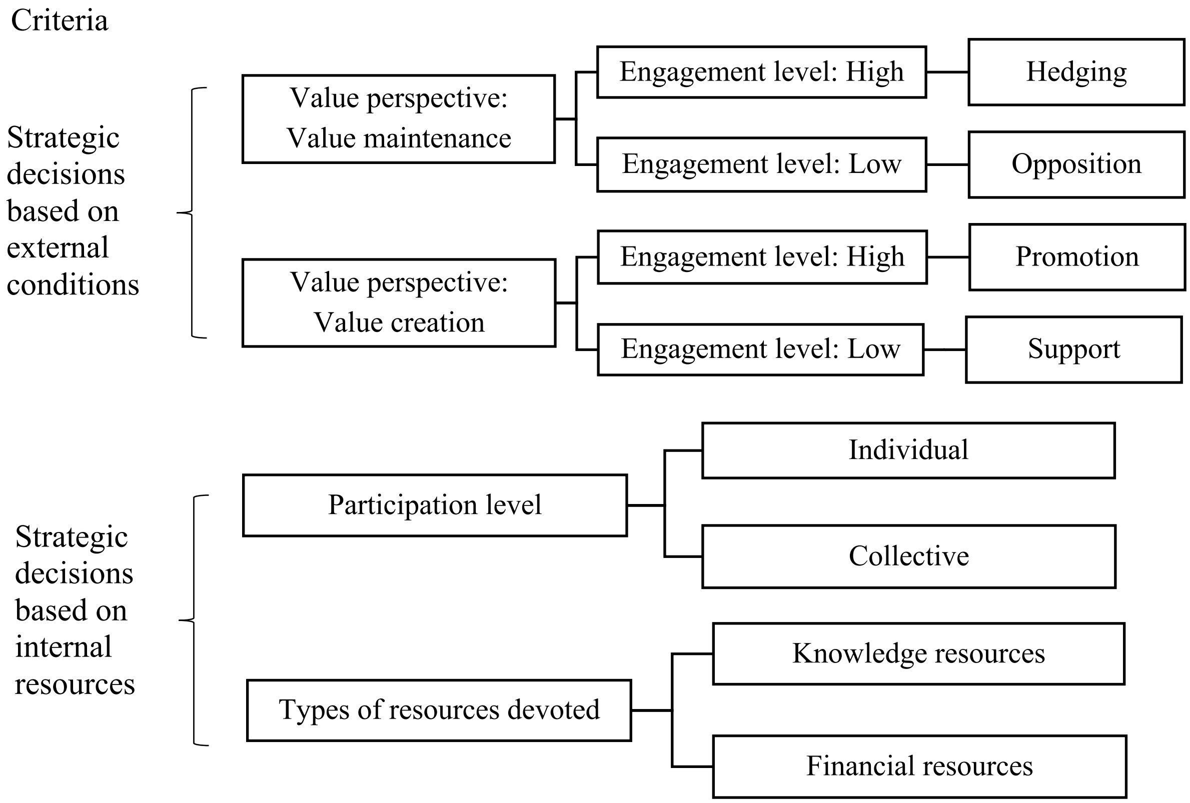
I elaborate on the literature on general CPA to develop the concept of EICCP. Specifically, I define EICCP as strategic actions firms perform to influence climate change policymaking processes, aiming at shaping policies or promoting policy changes in favor of their interests. Since EICCP focuses on influence, it falls into the influence-type of political actions that Oliver and Holzinger (2008) and Grover and Dresner (2022) define. Although extant literature has not studied the types of EICCP strategies, I found studies that focus on business engagement in environmental public policies relevant given that environmental policies embrace climate change policies. My literature review yields two typologies of firms' engagement strategies in environmental policies.

The first taxonomy by Tienhaara (2013) categorizes firms' engagement strategies based on different forms of corporate power firms exercise in the engagement process: structural power, instrumental power, discursive power, and institutional power. Firms that execute structural power move business activities away from the regulated regions, which seek to implicitly influence policymaking by imposing economic sanctions on the region. Instrumental power allows firms to showcase their organizational strength in expertise or resources to shape policy-related decision-making. Discursive power enhances firms' political legitimacy and helps firms couch policymakers' preferences through constituency building or research funding. Firms imposing institutional power possess global corporations' ability to shift environmental issues from regulatory institutions to enabling institutions of trade and investment to avert regulatory risks. Different dimensions of corporate power also inspire the classification of engagement in environmental policies by influence channels corporate power can wield. Clapp and Meckling (2013), for instance, identify and differentiate lobbying, the execution of market influence, rule-setting practices, and issue-framing activities as four distinct ways for firms to engage in environmental policymaking. Although the classification based on firms' power over regulatory agencies provides rationales for the implementation of several political activities including evasion, lobbying, and political advertising, it has also drawbacks in supporting the follow-up empirical investigation. This is specifically due to the differences among the proposed forms of power being obscure (Barnett and Duvall, 2004). The inconsistent interpretation of power and the inherent interrelation among distinct forms of power have therefore resulted in different classification models and the increased difficulty of model applications (Tienhaara, 2013).

The second taxonomy by Meckling (2015) proposes four engagement strategies that are more exclusive from the other types. Combining regulatory pressure and distributional effect as the basis of classification, this typology identifies opposition, hedging, support, and non-participation as four types of business strategies firms take when engaging in environmental policies. Regulatory pressure derives from firms' interpretation of "its multi-layered institutional environment and its mixed signals with regard to demand for regulatory action on a given environmental issue" (Meckling, 2015, p. 22), which considers the impact of external factors on firms' decision-making. The distributional effect captures the cost versus the benefits of the engagement considering "firms' heterogeneity due to market position and technology portfolio" (Meckling, 2015, p. 21). Since this classification method concentrates on firms' perceptions of external and internal risks associated with influencing environmental policymaking, I can measure the engagement strategies using firms' self-disclosure on environmental policy engagement as the source of data. Also, the classification criteria are compatible with the general typologies of CPA by Oliver and Holzinger (2008) and Grover and Dresner (2022) to further the understanding of influence-oriented engagement, which is the focus of this study. Among the variety of typologies of corporate political actions, Oliver and Holzinger's (2008) model builds on the dynamic capabilities perspective, which is a crucial theory in OSCM research, to explain the motives of engagement strategies. Specifically, firms will take the perspective of value maintenance if protecting the established value base delivers more benefits to them than adapting to policy changes. In contrast, they will adopt the perspective of value creation if they can promote regulatory advancements to raise the value of their resources. The influence actions under the perspectives of value maintenance and value creation follow a defensive and a proactive strategy, respectively. Grover and Dresner (2022) extend Oliver and Holzinger's (2008) model specifying a competitive dynamics perspective and developing an integrated model of political actions and supply chain strategies. In this typology, firms that seek to defend their competitive position embrace a defensive influence strategy while firms aiming at improving their competitive position choose a proactive influence strategy. Although elaborating on a different theoretical concept, the essence of obtaining positive distributive effects and achieving a favorable competitive position is to obtain more output than input by engaging in policymaking processes. Therefore, I conclude that Meckling (2015) shares the theoretical emphasis on the value of engagements with Oliver and Holzinger (2008), with Grover and Dresner (2022) providing additional insights on the regulatory conditions.

The compatibility between the typologies of Meckling (2015), Oliver and Holzinger (2008), and Grover and Dresner (2022) allows me to integrate them to develop a taxonomy for EICCP. Building on these typologies, I further propose to consider firms' resources as criteria to classify influence-oriented engagement strategies in the context of climate change following the resource-based view. The resulting taxonomy for EICCP is based on three factors: firms' value perspective and engagement level, the level of participation, and resources devoted to EICCP, as shown in Figure 2.1.

Figure 2.1 Taxonomy of EICCP



I select these factors as the classification criteria because the engagement strategies I identify through this taxonomy have different implications on firms' performance and competitive advantage, which is relevant to OSCM research. Although the examination of performance outcomes of EICCP strategies is beyond the scope of this study, I will briefly discuss those implications to inspire future research.

First, EICCP can be motivated by different value perspectives and subsequently classified into different engagement levels. The value perspective depicts firms' motives for influencing policy processes. Following Oliver and Holzinger (2008) and Grover and Dresner (2022), I differentiate the value maintenance perspective from the value creation perspective. The value maintenance perspective reflects firms' intention to maintain the status quo to protect their value base when they currently occupy an advantageous competitive position. In contrast, the value creation perspective consists of firms' motives for changing the status quo to create value by confronting or anticipating climate policy changes that undermine the firms' competitive advantage. Further, I propose to divide EICCP strategies under each value perspective into two engagement levels. I derive the factor of the engagement level from Meckling's (2015) typology that considers firms' perceived regulatory pressures. Specifically, I posit that firms' engagement level reflects firms' willingness to engage considering external conditions that include regulatory pressures. A high engagement level is associated with a higher level of scrutiny that firms perceive, while a low engagement level is related to a lower level of scrutiny.

Combining value perspectives and engagement levels, I classify EICCP strategies into four categories: opposition, hedging, support, and promotion strategies. The value maintenance perspective with a low engagement level leads to an opposition strategy, with which firms negate the eligibility of certain climate change policies or regulatory initiatives and seek to veto them. The value maintenance perspective with a high engagement level leads to the hedging strategy, with which firms seek to level the pressure of policy development and compliance across a global industry by challenging the application scope of certain climate change policies or regulatory initiatives. The engagement level in the hedging strategy is relatively higher than in the opposition strategy because the hedging strategy includes a mixture of defensive and proactive actions to strategically accommodate the political demand for climate change and make a self-interested contribution to climate change policies at the same time. In addition, the opposition strategy usually concentrates on a single or a small set of policies while the hedging strategy focuses on regulatory changes that influence the competitive dynamics of the international market. Serving as an example is the utility companies' advocacy to establish a comprehensive renewable energy policy that applies equally to all energy sectors worldwide. Instead of directly opposing the climate policies that affect their business, these utility companies propose a more complicated regulatory option, which will prolong the policymaking process. At the same time, this regulatory option allows them to maintain competitive advantages by advocating the same or even more stringent regulations on their global competitors (Meckling, 2015).

The value creation perspective with a low engagement level results in the support strategy, with which firms participate in climate change policymaking to promote policy compliance without pursuing radical changes in the policy. Common practices of support strategies include participation in climate change-related workshops, voluntary disclosure, communication, and information sharing with other entities about the reduction of carbon emissions and other climate change impacts. The value creation perspective with a high engagement level yields the promotion strategy, with which firms seek to advance climate change policymaking by proposing more stringent policy schemes, setting standards or measures for further policy development, enhancing incentives, or using specific technologies to expand their regulatory influence. The core of the promotion strategy is that firms attempt to redefine the current policies or their legitimacy (Oliver and Holzinger, 2008).

The four engagement strategies described above have different implications for the sustainability of firms' competitive advantage. Specific to the criterion of value perspectives, firms with a value maintenance motive are more defensive to environmental changes. However, such changes cannot be avoided in the long run. Therefore, the competitive advantage of those firms will be undermined over time. In comparison, firms with a value creation motive are proactively shaping external environments to leverage the firm's strengths and interests. Therefore, firms employing the promotion and support strategies have more potential in developing sustainable competitive advantage than firms relying on opposition and hedging strategies, since the perspective of value creation reflects firms' intention and capabilities to develop new competencies that accommodate new environmental conditions. Within the value creation strategies, the promotion strategy leads to more sustainable competitive advantages than the support strategy. This is because firms adopting the promotion strategy, through reshaping climate change policies, develop superior capabilities to combat climate change, when compared to firms that adopt a support strategy, and can thus obtain more favorable regulatory conditions that fit the firms' strengths. In comparison, firms with a support strategy need to obtain competitive advantages by outperforming their competitors and creating a first mover advantage.

While the value perspective and the engagement levels capture firms' strategic decisions based on external conditions, I propose other criteria to categorize EICCP strategies considering firms' internal resources. Prior literature has indicated the critical role of firms' internal resources in promoting their environmental strategies (Menguc et al., 2010; Paulraj, 2011). As such, the extent to which firms pursue environmental strategies depends on the availability of firm-specific resources (Lee et al., 2018). Specific to the climate change issue and extending firms' efforts from adaptation-oriented strategies to influence-oriented strategies, I argue that the heterogeneity in firms' internal resources can also lead to different EICCP strategies. In my taxonomy, I consider two aspects of internal resources: resource availability, which is reflected by firms' level of participation in EICCP, and the types of resources firms devote to EICCP, following Hillman and Hitt (1999), who incorporate resources into their framework of proactive corporate political strategy as decision variables.

Specifically, first, capturing resource availability, firms' EICCP can fall into two levels of participation, the individual level, and the collective level. EICCP at the individual level means that a firm directly interacts with climate change policymakers on behalf of itself, while engaging at the collective level indicates that a firm participates in groups, such as climate change coalitions and associations, with the group performing activities that are integral to influencing policymaking. Hillman and Hitt (1999) argue that firms may or may not possess requisite resources for independent actions and the ones with resource constraints tend to engage in collective actions to consolidate resources. Building on this logic, the level of participation implies firms' resource availability. Specifically, firms adopting the strategy of individual engagement are likely to be industrial leaders and possess more political resources than firms relying on collective engagement.

Extending Hillman and Hitt's (1999) arguments from an OSCM perspective, I posit that different levels of participation have different implications on firms' reputational risks and environmental performance. On the one hand, firms involved in collective engagement have a better chance to shape climate policies in favor of their businesses without exposing themselves to a higher level of scrutiny (Brulle, 2014; Cory et al., 2021). On the other hand, collective engagement can potentially lead to better environmental performance. This is because collective engagement fosters inter-organizational information sharing and allows firms to benchmark against other members. Many climate change-related coalitions also help members set ambitious goals of reducing carbon emissions while serving as a platform for the promotion of best practices. With several analyses showing that trade associations have become the dominant sources of lobbying expenditures in the U.S. (Brulle, 2018; Drutman, 2015), I believe empirically examining performance outcomes of different levels of participation can be valuable for future research.

And second, EICCP can rely on different types of resources that firms devote to engagement activities. Specifically, Hillman and Hitt (1999) identified information, financial incentives, and constituency-building as three different resources firms can use to influence policymaking, among which information and financial incentives apply to direct policy engagement, while constituency-building work in indirect policy engagement. Since this study focuses on direct policy engagement in climate change, I elaborate on information and financial incentives and identify knowledge resources and financial resources as resources firms can devote to EICCP. I argue that in the climate change context, firms use not only information, which is defined as "firms' preferences for policy or policy positions" (Hillman and Hitt, 1999, pp. 834), but also the expertise in mitigating climate impact as resources to influence the decisions of policymakers. Such expertise can take the form of technological know-how needed for implementing or developing carbon reduction techniques. I refer to them as knowledge resources. The use of knowledge resources is relevant to OSCM research given that it is tacit and accumulates through firms' sustainable practices. Firms that rely on knowledge resources in EICCP are likely to be leading firms in sustainable operations and are thus expected to have good environmental performance (Schmidt et al., 2017). Financial resources refer to political action funds firms spend to influence climate change policymaking, as per Hillman and Hitt's (1999) definition. Prior literature on CPA indicates that the expenditure on policy engagement is negatively associated with firms' environmental performance, especially for industries that are under great environmental scrutiny (Cho et al., 2006).

Identifying the different types of resources devoted to EICCP helps to further understand the different performance implications of different EICCP strategies. I argue that knowledge resources and financial resources, although both are related to firms' environmental performance, may yield different performance outcomes since they have different levels of transferability. Specifically, knowledge resources that a firm devotes to EICCP are not consumed but strengthened through consistent engagement activities, while the political action funds devoted to an engagement activity, or a specific climate-related issue, cannot be spent elsewhere. Following the resource-based view, firms devoting knowledge resources to EICCP should be able to develop a greater ability to reshape climate change policy in favor of their businesses than firms relying on financial resources in the long run. As such, firms can take advantage of favorable policy conditions to make their emission figures look better without reducing carbon emissions. Consequently, using knowledge resources for EICCP allows firms to achieve better environmental performance.

3.3. Measuring EICCP strategies

To validate the taxonomy that I propose for EICCP strategies, I seek to investigate distinct EICCP strategies firms adopt. However, identifying firms' EICCP strategies is challenging given the scarcity of information and the lack of established measures for EICCP. Investigations by non-profit organizations have shown that large firms and trade associations resist political disclosure (Levinthal, 2016), and thus, the mandatory disclosure of CPA, which can be a stable source of information, cannot be established (Werner, 2017). To solve this problem, I follow the literature on voluntary CPA disclosure (e.g., Goh et al., 2020; Lei et al., 2019) to analyze firm-level self-disclosed data from the Carbon Disclosure Project's (CDP) Climate Change (CC) dataset. The data is unstructured text, which includes firms' descriptions of their direct and indirect policy engagement. To extract information from the texts to measure EICCP strategies, I employ the method of text analytics. Specifically, I use Natural Language Processing (NLP) with random forest classification, a supervised learning approach, to automate the text mining processes. While text analytics has been extensively applied in OSCM research, the machine learning approach for text analysis is relatively novel (Bansal et al., 2020). Recent research has shown that the machine learning approach performs better than other text analysis approaches, such as the dictionary method. Therefore, I adopt the machine learning approach in this study. Below, I describe the data and the method I use.

3.3.1. Data

The CDP CC dataset collects firms' public responses to an information request sent by CDP CC on behalf of their signatory investors. Since 2013, CDP CC has included in the questionnaire a series of questions about firms' engagement in climate change policies. For this study, I use the responses to the open-ended question: "On what issues have you been engaging directly with policymakers?" The text data for analysis combine firms' statements on details of engagement and proposed legislative solutions to form a complete response to an issue. Firms can submit multiple answers if they engage in more than one issue, which results in multiple data entries for a firm year. I construct panel data using responses from 2013 to 2019 from the CDP CC datasets, which include 1,309 firms and 8,529 firm-year responses.

3.3.2 Text Analytics Using Natural Language Processing with Random Forest Classification

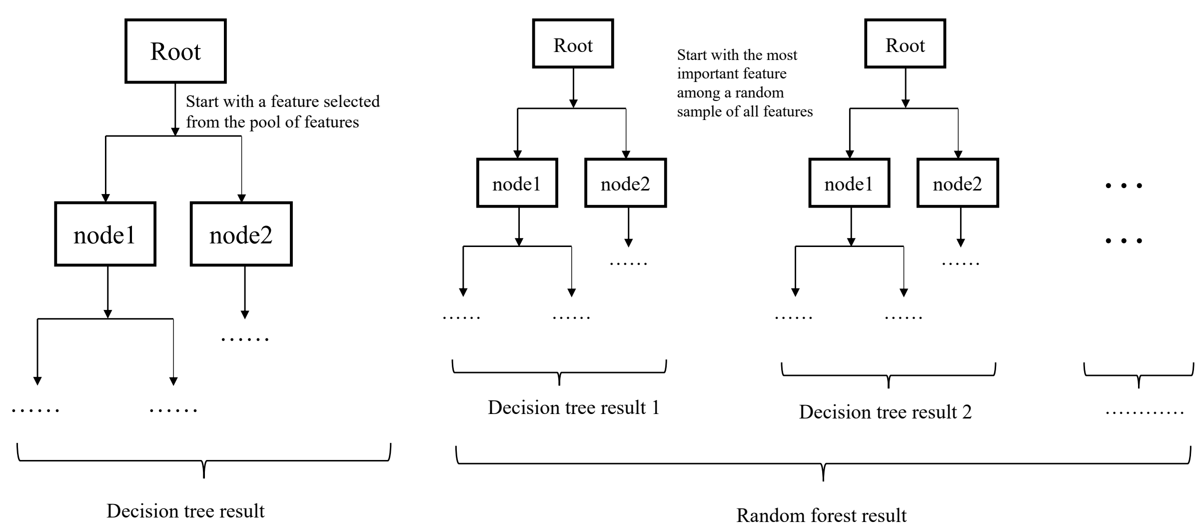
To validate the typology of EICCP strategies I proposed, I apply Natural Language Processing (NLP) techniques to the policy engagement disclosure data from the CDP CC dataset. Specifically, I follow the supervised learning approach to employ the random forest model as the major classifier to train the classification model and use it to automatically identify and classify different engagement strategies. The application of automated learning for text analysis has substantially progressed over the last decades in business research due to the empirical evidence that the well-designed algorithms are gradually closing the gap between automated classification and manual classification in precision, and that automated classification outperforms the manual classification in efficiency, objectivity, statistical power and replicability (e.g., Donovan et al., 2021; Frankel et al., 2016; Huang et al., 2018). Among different classification models for supervised learning, I choose to use the random forest model due to the recent evidence that the assessment of text disclosures using the random forest method yields "the least measurement error relative to measures based on alternative machine-learning methods such as support vector regression and supervised-latent-Dirichlet allocation" (Frankel et al., 2021, p. 16).

A random forest is an ensemble of a predefined number of individual decision trees. It relies on the decision tree that yields the best prediction results to do the classification. Therefore, the random forest model inherits the merits of the decision tree model but possesses additional advantages. First, the outcome of the random forest model is less sensitive to the selection of training data and is more accurate than the output of a single decision tree (Ali et al., 2012). In each decision tree in a random forest model, the analysis follows a hierarchical framework to divide the training data consecutively by a set of word features. The model training starts from identifying and using the most important word feature among all the selected features to divide the training data into two parts, then, advances to the next hierarchy in which each part is further divided by another word feature that ranks in the second place in terms of importance. The model training continues until all the training data are properly classified. Since the analysis involves word features in the order of importance, I need to first evaluate the importance of each word feature using metrics such as entropy, information gain, gain ratio, and Gini index. This evaluation captures the relative importance of words in a specific text and is not robust to changes in the training data. The random forest model overcomes this deficiency by introducing a voting mechanism to train the best model. Instead of using the original training data, it draws random samples of a predefined size from training data with replacement and trains decision tree models separately on each random sample. When incorporating several decision trees for the analysis and using the most voted decision tree results for classification, the random tree model considers a larger set of word features and generates a better training model. The iterative approach also increases the robustness of the prediction.

Second, model overfitting is less likely for the random forest model than for the decision tree model. Besides the calculation of the importance of word features, the decision tree model training relies on decisions including how to set a threshold for importance level to select word features and how many end nodes should be in the final decision tree. Those arbitrary decisions can be decisive for the training outcomes – a model with more word features and more end nodes yields more accurate results but might be overfitted and affected by the noise in the data. In comparison, the random forest model depends less on parameter settings. With running decision tree models iteratively, the random forest model allows using word features with a relatively lower level of importance, as well as a flexible number of features and end nodes, without jeopardizing the accuracy of the final prediction. Figure 2.2 provides illustrations of the presumptive results of the decision tree model and random forest model.

I detail my application of the NLP techniques with random forest classification below.

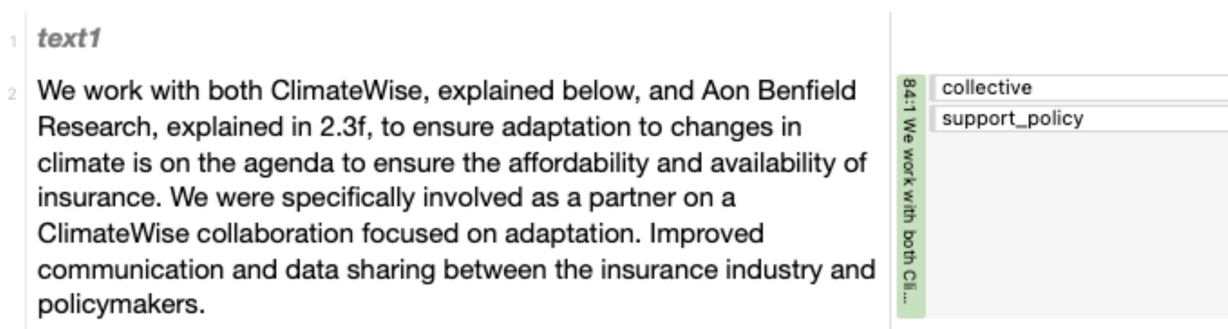
Figure 2.2 Presumptive results of decision tree model and random forest models



3.3.3 Manual Labelling

The data inputs for the text analytics are unstructured and usually comprise a set of sentences and paragraphs. Before training the data to develop a prediction model, I need to construct labels and conduct feature engineering to identify features that have the highest predictive power of the label. Since the concept and the typology of EICCP are novel, there is no established data that I can use to label different strategies. Therefore, I perform manual labeling to prepare the training data for further analysis. First, I randomly pick 10% of firm responses, which equals 850 texts, to form the training sample. Second, I import the training sample into Atlas.ti, qualitative data analysis, and research software, and assign labels to texts (see Figure 2.3 for the interface of Atlas.ti). Labeling is a manual process and relies on researchers' judgment. I read and manually assign labels to each text if I believe it falls in a category of an engagement strategy. One text can have multiple labels if it presents more than one engagement strategy. Although the process is subjective, I endeavor to achieve consistency by developing standards for labeling and engaging other raters for validation. In Table 2.1 I briefly discuss the standards for labeling for each strategy and provide examples.

Figure 2.3 The interface of Atlas.ti



Note. I can access the original text on Atlas.ti and assign self-defined labels to the text.

Table 2.1 Illustrations of manual labeling standards and text examples for each strategy

Strategy	Standards	Text example
Opposition strategy	The appearance of only dissenting views on a specific policy	On May 27, 2015, Apple voiced objections to the energy policy language of North Carolina bill H332, which we believed, if passed, would have had a significant negative impact on the availability of a clean and diversified energy supply in the state. We partnered with other technology companies to jointly write to the North Carolina legislature. The bill was thereafter defeated. Enabling a clean and diversified energy supply.
Hedging strategy	The appearance of concerns on a specific policy, or the coexistence of favorable and dissenting views on a specific policy, followed by justifications that the opposition originates from the concerns over unfair competition, profit loss, and instability of the market; usually mentions an alternative policy	In France, the environmental legislation Grenelle II and the Decree 2011-1336 request the implementation of mandatory carbon reporting on shipment level by October 2011. We generally support this approach but have been actively engaged through consultations, talks, and presentations at relevant meetings to request that not an isolated national approach is taken, but also international methodologies will be considered valid. With the publication of the EN 16258 standard, the transport sector has its first official standard for carbon calculations on a product level. This standard and the tools and methods proposed therein should be recognized as a valid methodology within the French legislation.

Table 2.1 (cont'd)

Strategy	Standards	Text example
Support strategy	The appearance of only favorable views on a specific policy; no evidence of proactively advancing the policy or guiding the policymaking into a new direction	Pendal is a signatory and investor participant in the global Climate Action 100+ initiative. It has directly supported engagement with an Australian oil and gas company. Through Regnan, Pendal has supported submissions to the Australian Stock Exchange (ASX) consultation on the latest edition of its Principles and Recommendations, a framework for listed company reporting. We encouraged more detailed guidance relating to the consideration of climate change as a material business risk. Further, that companies should disclose material climate-related risks in their main corporate filings.
Promotion strategy	The appearance of only favorable views on a specific policy, with proactive practices in policymaking such as proposing new policies	Consumers Energy participated in the Midwest Collaborative to develop a regional influence on EPA's effort to craft GHG regulations via Section 111 of the Clean Air Act (CAA). The Midwest Collaborative is a voluntary group effort, consisting of industry, state regulatory, and environmental advocacy representatives. One of the group's primary goals is to develop stakeholder consensus on a policy framework for any upcoming regulations implemented under Section 111 of the CAA. Participation is based on periodic conference calls with some face-to-face meetings. The primary work product is to develop a straw man proposal to present to EPA before its completion of draft regulations. Consumers Energy supports a representative stakeholder process developing consensus-driven guidance for submittal to EPA to influence rulemaking processes.

Table 2.1 (cont'd)

Strategy	Standards	Text example
Collective strategy	Statements on firms' affiliation or membership of one or multiple groups, followed by the descriptions of how the group(s) engage in climate change policymaking	Same as above
Individual strategy	A firm instead of a group is the subject of the policy engagement; no evidence of engagement through groups or affiliations	Cabot engaged with the United States Environmental Protection Agency to better understand the application of the clean power program to a proposed cogeneration project at its Franklin, Louisiana vacuity. Cabot routinely communicated with staff at the Agency's Research Triangle Park offices. Cabot will continue to advocate for clarification of the applicability of the Clean Power program to ensure it encourages the capture of conversion of waste energy.

Table 2.1 (cont'd)

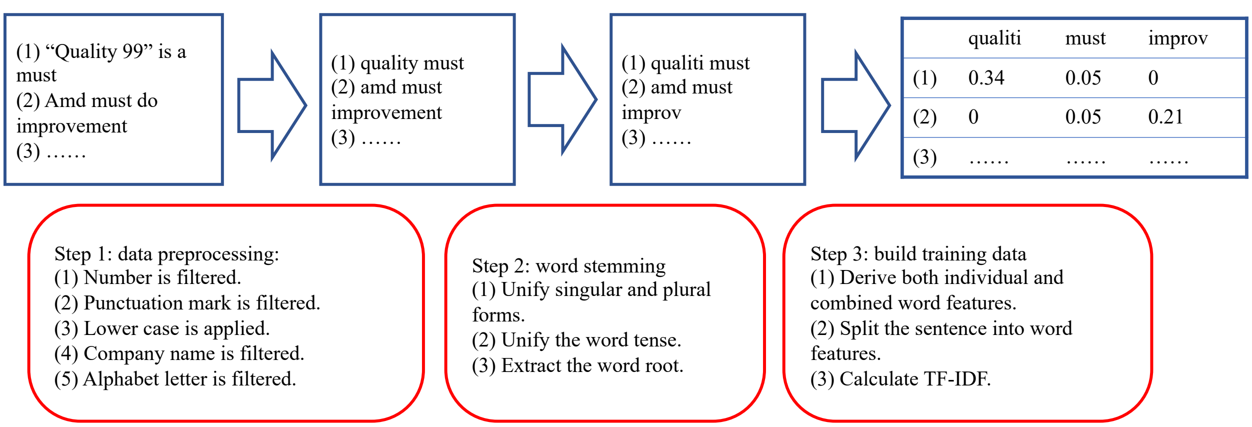
Strategy	Standards	Text example
Use of knowledge resources	The use of the information such as policy recommendations, understanding of the technologies, etc., are mentioned	As one of the largest insurance and asset management companies in the world, AXA engages in a set of policy and regulatory issues that may affect the Group's strategy over the short and long term. On top of key prudential, consumer protection-related, and digital economy-related topics, the Group engages in the various policy and regulatory initiatives related to the long-term financing of the economy (EU or French projects) in connection also to sustainability issues and climate change. AXA contributed to the EU High-Level Expert Group on Sustainable Finance, which developed recommendations on how sustainability could be placed in the European Union's core financial processes, how different participants in the financial system could act on it, and how to mobilize capital more effectively for a sustainable economy. Sustainable finance offers Europe a powerful tool for achieving its goals of economic prosperity, social inclusion, and environmental regeneration.

Note. I removed the label for the use of financial resources due to limited observations. This table does not present a text sample for the strategy "Use of financial resources" because I did not find any disclosure about this strategy in the training data. Since the use of financial resources is theoretically justified, failing to find relevant descriptions may attribute to two reasons. First, the current training data does not successfully capture the description of this strategy. Second, firms choose not to report their use of financial resources. It is a limitation of the current study that I have not expanded the size of the training data to test those assumptions. I will consider investigating this strategy in future research.

3.3.4 Feature Engineering

In this step, I identify and evaluate word features using the labeled training data. Feature engineering is the process of deriving useful features from unstructured data using the manual label as a reference. In text analytics, word features that are useful for the prediction meet the following standards. First, they should significantly correlate with the manual labels either in a positive or negative relationship. Second, they should not have a high correlation with all manual labels. This criterion rules out stop words or other common vocabularies that exist in nearly all text responses but do not deliver meaningful information to guide classification. Third, useful word features should not be redundant and duplicated. This criterion requires the stemming of words to unify inflected or derived words to the same word root by eliminating the suffixes and prefixes of words. To prepare word features that meet those requirements, I follow the standard data processing procedure for text analysis specified in the three steps in Figure 2.4, similar to prior text analytics research (e.g., Frankel et al., 2016, 2021).

Figure 2.4 Data pre-processing for feature engineering



In Step 1, I first eliminate the 13 non-English responses. Then, I pre-process each sentence of the remaining responses by deleting the numbers, punctuations, company names, alphabet letters, and a list of common stop words used in the English language. Also, I changed all capital letters into lower cases since it reduces the inconsistency among words without affecting the meaning of the documents. In Step 2, I perform word stemming using the Porter Stemming Algorithm (Porter, 1980) to unify different word forms including the singular and plural forms, and distinct word tense and part of speech. In Step 3, I further derive the individual and combined word features. Individual word features refer to only a single stemmed word, while combined word features refer to a combination of two consecutive stemmed words. The combined word feature is more informative than the individual word feature because it can capture the coexistence features of words in the sentence and further differentiate the word used for the development of a better classification model. For instance, the stemmed word "qualiti" is neutral in sentiment but the combined stemmed word "high qualiti" expresses a positive sentiment. In this study, I use both individual and combined word features as candidate features for each text response. After constructing the word features, I remove the sentence boundary and eliminate duplicate stemmed words or stemmed word groups. This sub-step results in a set of unique word features derived from all text responses. The final sub-step is to evaluate and quantify the importance of each word feature. To do so, I use the term frequency-inverse document frequency (TF-IDF) measure. The TF-IDF measure is the multiplication of the term frequency, which is captured by the count of a specific word feature over the total number of word features in a text response, and the inverse document frequency, which is the log of the count of a specific word feature in all the text responses over the count of this word feature in the present text response. TF-IDF is an established measure widely used in NLP since it not only captures the importance of the word features in one text response but also offsets the effects of the useless high-frequency word feature that nearly all text responses share (Gentzkow et al., 2019). The data pre-processing procedure converts unstructured data to structured data, which supports further feature identifications.

While the structured data generated by the previous procedure provides interpretable information for machine learning, it is highly dimensional, with tens of thousands of word features in the data, making it difficult to incorporate into statistical analyses and to train a predictive model. When the number of word features exceeds the number of text responses, the training model will face the overfitting problem. Therefore, I need to conduct feature selection to extract word features that have the highest predictive power. In this step, I use the biserial correlation metric to measure the association between manual labels and word features, following the text mining literature. A high correlation coefficient between a word feature and a manual label indicates that the word feature is qualified for model training. In this study, I use the words that rank in the 75% quantile in the correlation coefficient to ensure that the number of overall word features does not exceed the number of observations in the training data and thus, avoid the overfitting problem. I used the 70% quantile and 80% quantile for sensitivity tests and found consistent prediction results. Table 2.2 shows the top-ranked word features in the biserial correlation metric for the manual label "promotion strategy" as an illustration.

Table 2.2 Word features with the highest biserial correlation coefficients by manual label

Word features	Original words	Biserial correlation with the manual label
benefit	benefits, benefit, benefitting	0.32926985
condit	conditions	0.31306848
include + carbon	included + carbon, including + carbon	0.30337897
infrastructur	infrastructure, infrastructures	0.28793145
car	car, cars	0.28597564
germani	germany	0.28348094
german + govern	german + government	0.28313922
million +electror	million + electric	0.26013577
damag	damage	0.26011967
reduct	reduction, reductions	0.25823276

3.3.5 Model Training

I use the structured training data from previous steps to train random forest models. A random forest model can iterate the training process by including many decision trees, a predefined number of randomly selected word features in each decision tree, and a predefined condition to stop partition. In my analysis, I use 500 decision trees for each random forest iteration. The more decision trees are included in a random forest model, the more stable the training model will be, but the less efficient the computation. I use 300 and 400 decision trees for the robustness check and find that changing the setting does not significantly influence model accuracy. Then, I set the range of 1 to 50 as the number of word features used in a decision tree, which determines the number of word features each partition will consider. For example, if I set 50 as the number of word features applied, in each partition, the model will randomly select 50 word features and choose the word feature with the highest biserial correlation coefficient as the decision node, then move on to the next partition to identify another most relevant word feature among the 50 random selected word features. While literature suggests that a lower number of word features used decreases the correlations among decisions trees and yields more stable predictions (Probst et al., 2019), I choose to start from a relatively large range of word features and rely on the prediction accuracy to empirically define the optimal number of word features for model training. The partition in each decision tree will end as no more partitions are needed. The common conditions for stopping partition include a threshold of least improved entropy and the number of partitions, whose values are automatically chosen by the algorithm. Besides those stopping criteria, the model usually requires another threshold for the minimum sample size in the terminal node. This threshold applies to prevent overfitting when the stopping criteria are not met (Segal, 2004). I arbitrarily predefined the number equivalent to 5% of the training texts as the minimal size of a terminal node. However, I found the actual partition in our data all stopped when there was at least more than 10% of the training texts. That means the decision trees met the stopping criteria before triggering the threshold of the minimum sample size in the terminal node. That is to say, the model training does not rely on the arbitrary number we defined.

3.4. Evaluation and Results of EICCP Measures

The evaluation of the random forest model is different from other classification models in which an n-fold cross-validation approach is applied to get an unbiased estimate of the model accuracy (Segal, 2004). Since each decision tree in the random forests randomly selects a predefined number of word features to train the model, I can configure the maximum number of selected word features to construct an important metric for the selected word features. The validation process for this metric is similar to a three-fold cross-validation approach. Specifically, each iteration in the random forest model employs a different bootstrapped sample from the training data, in which about one-third of the training data is left out and is not used in the construction of the decision trees. Once all decision tree models are trained using the remaining two-thirds of the training data, the majority vote of those models can be generated. The accuracy of the random forest model is then evaluated by applying this majority-vote model to the one-third of training data that has been left out and calculating the accuracy of label classifications. The model accuracy metric will stabilize as the number of decision trees in the random forest model increase but usually will not improve significantly when the number of decision trees passes a certain threshold (Probst et al., 2019). Therefore, I used a different number of trees for the robustness check.

Table 2.3 shows the accuracy, the optimal number of the word features for the random forest model training, and the total number of labeled text responses in the training data. I was not able to model the strategy featured by the use of financial resources because of too few numbers of labeled texts for this strategy. The accuracy of random forest models for all other models is over 80%, with the prediction of hedging strategies having the highest accuracy and the use of knowledge resources in EICCP ranking second in terms of accuracy. The optimal number of word features needed for random forest model training captures the efficiency of this predictive model. The best models use as few as eight word features to identify the hedging strategy or to differentiate individual engagements from collective engagements. In general, incorporating more word features will stabilize the model's accuracy. Figure 2.5 illustrates the relationship between the number of word features used for model training and the resulting model accuracy for the promotion strategy. The reported number of manually labeled texts shows that the distribution of EICCP strategies is not balanced. The least adopted strategy is the opposition strategy. The label classification of the opposition strategy requires more word features and is likely to be more sensitive to the changes in the training data.

Table 2.4 presents a list of ten top-ranked word features for the training of random forest models for each strategy. The importance value is scaled to a range of 1 to 100 for illustrative purposes. The higher the importance value, the more useful a word feature for the label prediction.

Although I include the combined word features into the pool of word features, the results show that the importance of the single-word features outweighs the importance of the combined word features. I also observe that some single-word features rank top in importance for more than one label. This is normal in random forest classifications since the model not only considers the information delivered by the individual word feature but also the interrelations among word features for the prediction.

Table 2.3 Results of the random forest models by manual labeling

	Promotion strategy	Support strategy	Hedging strategy	Opposition strategy	Individual vs. Collective engagement	Use of knowledge resources
Accuracy	83.52%	88.06%	95.53%	85.83%	88.14%	91.76%
The optimal number of word features for random forest model training	15	18	8	24	8	12
Total number of labeled texts in the training data	279	461	129	42	447	461

Table 2.4 Top-ranked word features with their importance value in the random forest model by manual labeling

Label	Stemmed word	Original word	Importance value
Promotion strategy	benefit	benefits, benefit, benefitting	100
	deliv	delivering, deliver, delivered	95.76604651
	car	car, cars	85.82345359
	reduct	reduction, reductions	82.30050453
	refer	reference	81.1160511
	recycl	recyclable, recycling	80.11132255
	damag	damage	54.16039484
	german	german	39.51177473
	germani	germany	38.53420378
	prior	prior	26.90623168

Table 2.4 (cont'd)

Label	Stemmed word	Original word	Importance value
Support strategy	like	like, likely	100
	support	support, supporting, supports, supported, supportive	87.35595215
	carbon	carbon	76.4263096
	effici	efficiency, efficient, efficiently, efficiencies	69.73425017
	avoid	avoid	65.67096615
	reduct	reduction, reductions	60.99042573
	see	see, seeing, sees	60.07590989
	tax	taxes, tax, taxing	53.22218388
	report	report, reporting, reports, reported	52.34498386
	commit	commitment, committed, commitments, committed, commit, committing, commits	50.30464546

Label	Stemmed word	Original word	Importance value
Hedging strategy	base	based, base	100
	tax	taxes, tax, taxing	95.26947338
	price	price, pricing, prices	94.91548668
	competit	competition, competitive, competitiveness	88.85893806
	adjust	adjusted, adjust	85.85833515
	avoid	avoid	81.19206705
	carbon	carbon	60.82896735
	equal	equal, equally, equality	51.1678536
	leakag	leakage	41.26519366
	view	view, views	40.99033926

Table 2.4 (cont'd)

Label	Stemmed word	Original word	Importance value
Opposition strategy	reject	reject, rejecting	100
	notic	noticeable	22.42896593
	seem	seems	18.65198389
	shortcom	shortcomings	17.0592976
	situat	situation	15.25507852
	shortag	shortage	15.1787334
	unlik	unlike	13.87098634

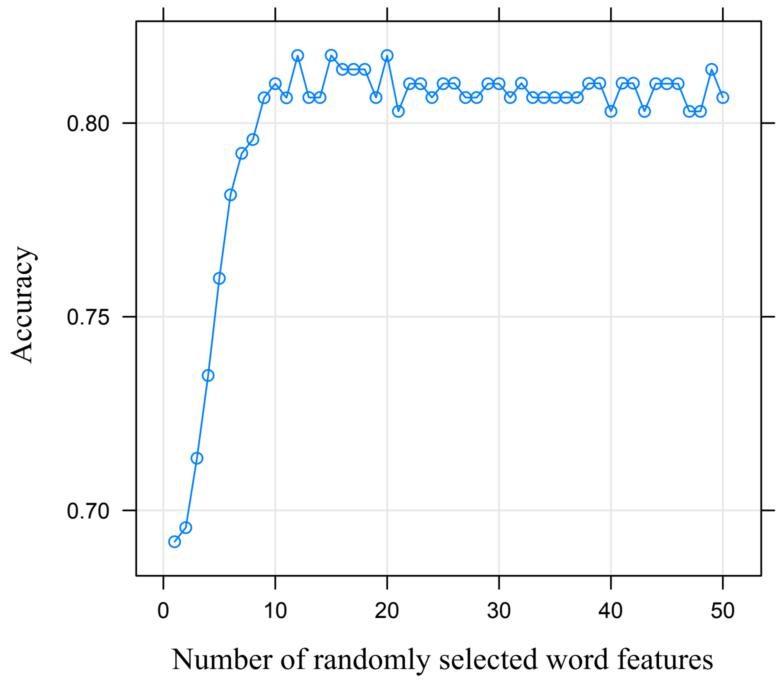
Label	Stemmed word	Original word	Importance value
Individual vs. Collective engagement	insur	insurance, insurer, insurers	100
	fight	fight	73.81066551
	issu	issued, issues, issue	72.22356913
	economi	economy	68.47477488
	council	council	66.79671497
	coordin	coordinates, coordinated, coordination, coordinate	64.96486061
	aim	aims, aiming, aim, aimed	64.3818241
	associ	associated, association, associations	63.61627332
	industri	industrial, industry, industry's, industries	47.4586111
	research	research	42.19198728

Table 2.4 (cont'd)

Label	Stemmed word	Original word	Importance value
Use of knowledge resources	team	teams, team	100
	calcul	calculation, calculator, calculate	72.28758843
	guidanc	guidance	69.32843009
	rail	rail	67.11812223
	lead	lead, leading	55.9354086
	urbanis	urbanization	53.56842282
	rapid	rapid	49.64596555
	locki	lockie	41.55400531
	profil	profile	26.72260299
	scarciti	scarcities	13.66049445

Note. The tables show only the ten top-ranked word features based on the importance of each strategy. For label prediction, I included more word features in the analysis. The original words for each word stem share the same word root but have different forms of tense and form. I extract them from the original documents and reassign them to each word stem after the model training.

Figure 2.5 The relationship between the accuracy and the number of randomly selected word features for the model training for the promotion strategy



3.5. Discussion

In this study, I propose a taxonomy for EICCP strategies based on firms' value perspectives and engagement levels, levels of participation, and resources devoted to EICCP. Examining EICCP strategies using firms' self-disclosed data, I found that there is an unbalanced application of different strategies and provide an overview of the real-world EICCP below.

3.5.1. Overview of EICCP

The adoption of EICCP strategies has clear trends as shown in Figure 2.6. Focusing on the four strategies classified by value perspective and engagement level, the implementation of the support strategy has declined while the usage of the promotion, hedging, and opposition strategies has increased from 2013 to 2019. However, the support strategy remains the most adopted strategy among these four strategies (see Figure 2.7). There are very few firms that take the opposition strategy. The application of the promotion strategy is slightly more than that of the hedging strategy, but both have a significantly lower level of implementation than the support strategy. These observations are consistent with the notion that when the climate change policy process advances and provokes a higher level of public pressure, firms tend to enhance their engagement (Hillman and Hitt, 1999; Meckling, 2015) – moving from low engagement levels to high engagement levels, such as moving toward the promotion or the hedging strategies. The only exception here is the opposition strategy, which is a strategy with a low engagement level according to the taxonomy I propose, but which has been implemented increasingly over time. A potential interpretation is that many nations have only started the policy process recently and are thus expected to stay on the agenda-setting stage for a long time. At this stage, the opposition strategy is efficient in reducing compliance costs for them, so it experienced an increase in adoptions.

In addition, the level of individual engagement was lower in 2019 than it was in 2013, suggesting that firms increasingly adopt collective engagements over time. This also meets the political notion that firms increasingly engage through coalitions, associations, or other groups to consolidate resources and make a greater impact on policymaking without exposing themselves to a higher level of reputational risks and scrutiny (Cory et al., 2021; Hillman and Hitt, 1999). Finally, the use of knowledge resources in EICCP is substantially less in 2019 than in 2013. This might be attributed to the larger knowledge base about climate change and research on climate change that policymakers can access through enhanced intergovernmental collaborations (IPCC, 2022). Consequently, the business sector provides less input.

Figure 2.6 Implementation trends for different EICCP strategies

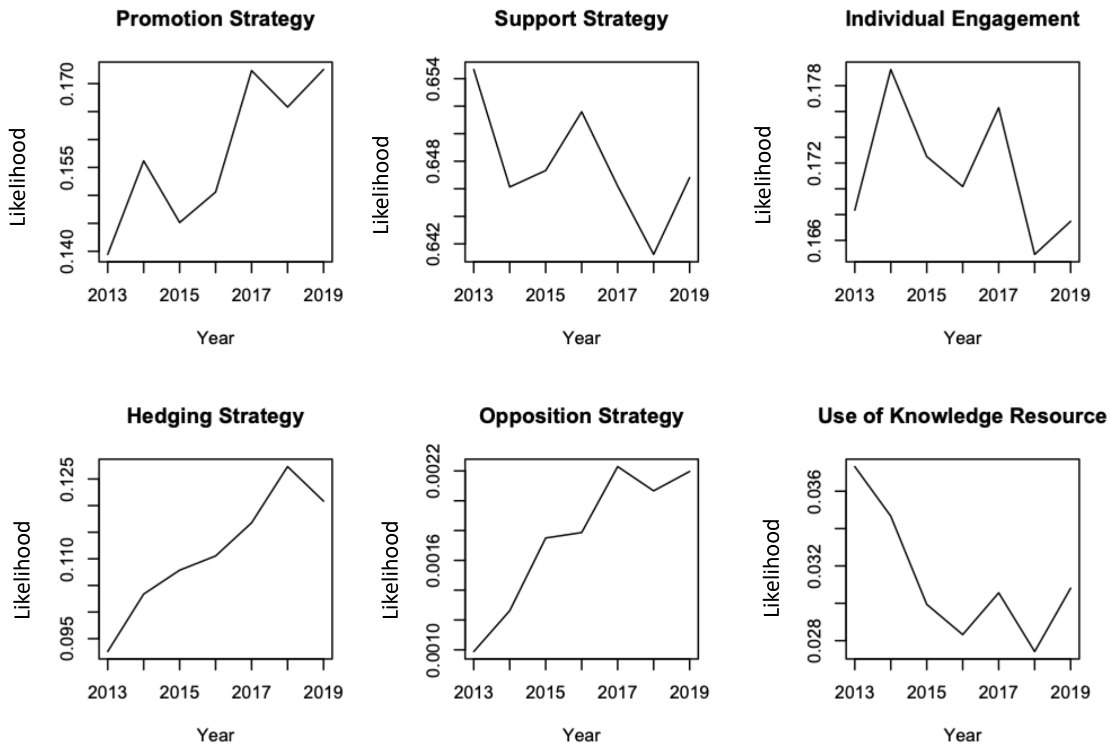
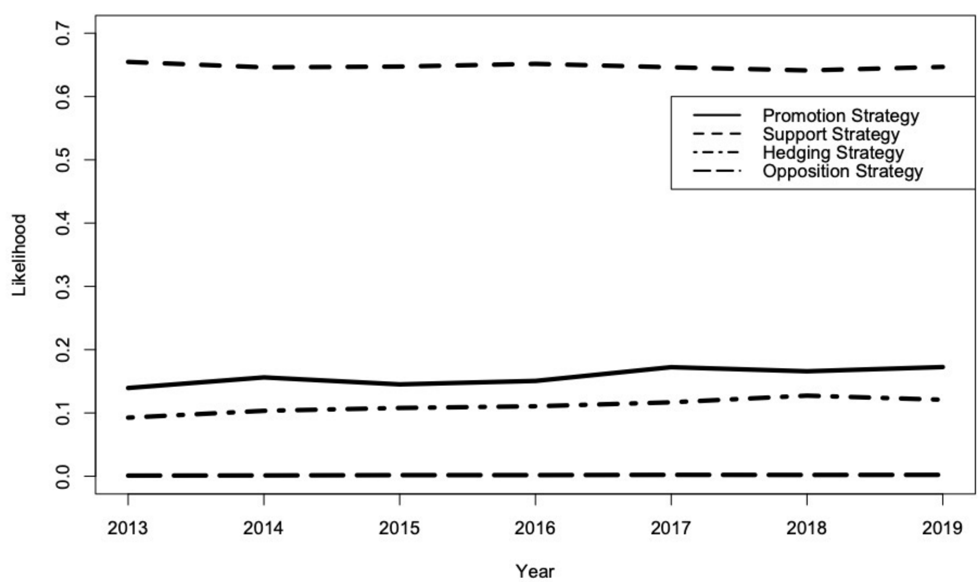


Figure 2.7 Longitudinal comparison of four EICCP strategies classified by value perspectives and engagement levels



3.5.2. Contributions

My research is positioned at the interface between public policy and OSCM. Heeding the calls for OSCM research that "consider regulatory policy uncertainty as a driver of decisions and business performance, and how it shapes exchange" (Tokar and Swink, 2019, pp. 76), I sought to investigate firms' responses to climate change policies. Prior literature has identified firms' various approaches to obtain organizational legitimacy under regulatory scrutiny but also indicated that academic attention to firms' influence-oriented actions, which refers to firms' political activities aiming at shaping governmental policy or process, is still scarce (Grover and Dresner, 2022). The lack of consideration for business factors in influencing policymaking processes leads to an unrealistic assumption that the policy and regulatory environment is an objective and uncontrollable context that is external to firms' strategic decisions, operations, and activities. Consequently, extant research on climate change focuses mainly on policy compliance and adaptation, with very few studies exploring business efforts in reshaping the policies in favor of firms' interests (Cory et al., 2021; Greiner and Kim, 2021).

To further the disciplinary understanding of firms' influence-oriented actions in climate change, I proposed the concept of EICCP, investigated firms' various strategies of EICCP, and proposed a typology for engagement strategies. Validating my typology using firms' self-disclosure on direct or indirect engagement with policymakers in climate change issues from CDP data, I empirically demonstrated that firms adopt various approaches to influence policy and regulatory environments for climate change issues. This study provided insights into the multiplicity of the firms' influence-oriented responses to climate change policies. I further discussed the implications of performance and competitive advantage for different engagement strategies, setting a foundation for future research on the outcomes of the complex decision-making in EICCP.

My research also adds to prior research methodologically. While recent research suggests that the machine learning method performs better than a dictionary-based method in accuracy and robustness for text analytics, machine learning approaches have not been sufficiently implemented in business literature (Frankel et al., 2021; F. Li, 2010). I followed machine learning methods to convert unstructured and qualitative disclosure data into structured word features via feature engineering. Then, I performed text analytics on the converted and structured data using the random forest model, a supervised learning method that overperformed other methods in sentiment analysis (Frankel et al., 2021), to identify firms' engagement strategies.

This study yielded measures of EICCP engagement strategies that can be used for future research. Using firms' self-disclosed information, my measures captured the extent to which firms engage in each type of strategy. They are available for 1,309 global firms spanning from 2013 to 2019. Future studies can use the measures developed for empirical investigations on antecedents and outcomes of EICCP.

REFERENCES

REFERENCES

Ali, J., Khan, R., Ahmad, N., and Maqsood, I. (2012). Random Forests and Decision Trees. *IJCSI International Journal of Computer Science Issues*, *9*(5), 272–278.

Aragón-Correa, J. A., Marcus, A. A., and Vogel, D. (2020). The Effects of Mandatory and Voluntary Regulatory Pressures on Firms' Environmental Strategies: A Review and Recommendations for Future Research. *Academy of Management Annals*, *14*(1), 339–365.

Automotive World. (2020). *Growing momentum: Global overview of government targets for phasing out sales of new internal combustion engine vehicles*. https://www.automotiveworld.com/news-releases/growing-momentum-global-overview-of-government-targets-for-phasing-out-sales-of-new-internal-combustion-engine-vehicles/.

Bansal, P., Gualandris, J., and Kim, N. (2020). Theorizing Supply Chains with Qualitative Big Data and Topic Modeling. *Journal of Supply Chain Management*, *56*(2), 7–18.

Barnett, M., and Duvall, R. (2004). Power in Global Governance. In *Power in Global Governance*. Cambridge University Press.

Blumentritt, T. P. (2003). Foreign Subsidiaries' Government Affairs Activities: The Influence of Managers and Resources. *Business & Society*, *42*(2), 202–233.

Bonardi, J. P., Hillman, A. J., and Keim, G. D. (2005). The Attractiveness of Political Markets: Implications for Firm Strategy. *Academy of Management Review*, *30*(2), 397–413.

Boudette, N. E., and Davenport, C. (2021, January 28). G.M. Will Sell Only Zero-Emission Vehicles by 2035. *The New York Times*, 28–30. https://www.nytimes.com/2021/01/28/business/gm-zero-emission-vehicles.html.

Brulle, R. J. (2014). Institutionalizing Delay: Foundation Funding and the Creation of U.S. Climate Change Counter-Movement Organizations. *Climatic Change*, *122*(4), 681–694.

Brulle, R. J. (2018). The Climate Lobby: A Sectoral Analysis of Lobbying Spending on Climate Change in the USA, 2000 to 2016. *Climatic Change*, *149*(3–4), 289–303.

Bumpus, A. G. (2015). Firm Responses to a Carbon Price: Corporate Decision Making under British Columbia's Carbon Tax. *Climate Policy*, *15*(4), 475–493.

Chen, C.-M. (2017). Supply Chain Strategies and Carbon Intensity: The Roles of Process Leanness, Diversification Strategy, and Outsourcing. *Journal of Business Ethics*, *143*(3), 603–620.

Cho, C. H., Patten, D. M., and Roberts, R. W. (2006). Corporate Political Strategy: An Examination of the Relation between Political Expenditures, Environmental Performance, and Environmental Disclosure. *Journal of Business Ethics*, *67*(2), 139–154.

Clapp, J., and Meckling, J. (2013). Business as a Global Actor. In *The Handbook of Global Climate and Environment Policy* (pp. 286–303). John Wiley & Sons Ltd.

Cory, J., Lerner, M., and Osgood, I. (2021). Supply Chain Linkages and the Extended Carbon Coalition. *American Journal of Political Science*, *65*(1), 69–87.

Dadhich, P., Genovese, A., Kumar, N., and Acquaye, A. (2015). Developing Sustainable Supply Chains in the UK Construction Industry: A Case Study. *International Journal of Production Economics*, *164*, 271–284.

Dahan, N. (2005). A Contribution to the Conceptualization of Political Resources Utilized in Corporate Political Action. *Journal of Public Affairs*, *5*(1), 43–54.

Doherty, C., Kiley, J., Asheer, N., and Jordan, C. (2020). *Election 2020: Voters Are Highly Engaged, but Nearly Half Expect To Have Difficulties Voting*. https://www.pewresearch.org/politics/2020/08/13/important-issues-in-the-2020-election/.

Domonoske, C. (2021). Big Oil (Probably) Isn't Going Away Anytime Soon. But It's Definitely Changing. *Npr*.

Donovan, J., Jennings, J., Koharki, K., and Lee, J. (2021). Measuring Credit Risk Using Qualitative Disclosure. *Review of Accounting Studies*, *26*(2), 815–863.

Drutman, L. (2015). The Business of America Is Lobbying: How Corporations Became Politicized and Politics Became More Corporate. *Oxford Scholarship Online*, *15*(1), 583–605.

Eberlein, B., and Matten, D. (2009). Business Responses to Climate Change Regulation in Canada and Germany: Lessons for MNCs from Emerging Economies. *Journal of Business Ethics*, *86*(S2), 241–255.

EEU. (2018). *Renewable energy targets 2020 and 2030*. https://eeueuropa.eu/renewable-energy-targets-2020-2030/.

Frankel, R., Jennings, J., and Lee, J. (2016). Using Unstructured and Qualitative Disclosures to Explain Accruals. *Journal of Accounting and Economics*, *62*(2–3), 209–227.

Frankel, R., Jennings, J., and Lee, J. (2021). Disclosure Sentiment: Machine Learning vs. Dictionary Methods. *Management Science*.

Gentzkow, M., Kelly, B., and Taddy, M. (2019). Text as Data. *Journal of Economic Literature*, *57*(3), 535–574.

Ghadge, A., Wurtmann, H., and Seuring, S. (2020). Managing Climate Change Risks in Global Supply Chains: A Review and Research Agenda. *International Journal of Production Research*, *58*(1), 44–64.

Goh, L., Liu, X., and Tsang, A. (2020). Voluntary Disclosure of Corporate Political Spending.

Journal of Corporate Finance, *61*, 101403.

Greiner, M., and Kim, J. (2021). Corporate Political Activity and Greenwashing: Can <scp>CPA</Scp> Clarify Which Firm Communications on Social & Environmental Events Are Genuine? *Corporate Social Responsibility and Environmental Management*, *28*(1), 1–10.

Grover, A. K., and Dresner, M. (2022). A Theoretical Model on How Firms Can Leverage Political Resources To Align With Supply Chain Strategy for Competitive Advantage. *Journal of Supply Chain Management*, *58*(2), 48–65.

Hardy, C., Bhakoo, V., and Maguire, S. (2020). A New Methodology for Supply Chain Management: Discourse Analysis and Its Potential for Theoretical Advancement. *Journal of Supply Chain Management*, *56*(2), 19–35.

Hetzner, C. (2021). Automakers Blast Europe's Proposed Ban on New Combustion Engine Cars by 2035. *Fortune.Com*, N.PAG.

Hillman, A. J., and Hitt, M. A. (1999). Corporate Political Strategy Formulation: A Model of Approach, Participation, and Strategy Decisions. *Academy of Management Review*, *24*(4), 825–842.

Hillman, A. J., Keim, G. D., and Schuler, D. (2004). Corporate Political Activity: A Review and Research Agenda. *Journal of Management*, *30*(6), 837–857.

Huang, A. H., Lehavy, R., Zang, A. Y., and Zheng, R. (2018). Analyst Information Discovery and Interpretation Roles: A Topic Modeling Approach. *Management Science*, *64*(6), 2833–2855.

IEA. (2022). *IEA's Policies and Measures Database*. https://www.iea.org/policies.

IPCC. (2022). *Special Report: Global Warming of 1.5 C- Summary for Policymakers*. In *Global Warming of 1.5°C*. Cambridge University Press. https://www.cambridge.org/core/product/identifier/9781009157940%23prf2/type/book_part . https://doi.org/10.1017/9781009157940.001

Ji, G., Gunasekaran, A., and Yang, G. (2014). Constructing Sustainable Supply Chain under Double Environmental Medium Regulations. *International Journal of Production Economics*, *147*, 211–219.

Jin, M., Granda-Marulanda, N. A., and Down, I. (2014). The Impact of Carbon Policies on Supply Chain Design and Logistics of a Major Retailer. *Journal of Cleaner Production*, *85*, 453–461.

Jira, C. (Fern), and Toffel, M. W. (2013). Engaging Supply Chains in Climate Change. *Manufacturing & Service Operations Management*, *15*(4), 559–577.

Keim, G. D., and Bonardi, J. P. (2005). Corporate Political Strategies for Widely Salient Issues.

The Academy of Management Review, *30*(3), 555–576.

Keim, G. D., and Zeithaml, C. P. (1986). Corporate Political Strategy and Legislative Decision Making: A Review and Contingency Approach. *The Academy of Management Review*, *11*(4), 828.

Lawton, T., McGuire, S., and Rajwani, T. (2013). Corporate Political Activity: A Literature Review and Research Agenda. *International Journal of Management Reviews*, *15*(1), 86–105.

Lee, J. W., Kim, Y. M., and Kim, Y. E. (2018). Antecedents of Adopting Corporate Environmental Responsibility and Green Practices. *Journal of Business Ethics*, *148*(2), 397–409.

Lee, K.-H. (2011). Integrating Carbon Footprint into Supply Chain Management: The Case of Hyundai Motor Company (HMC) in the Automobile Industry. *Journal of Cleaner Production*, *19*(11), 1216–1223.

Lei, L. (Gillian), Li, Y., and Luo, Y. (2019). Social Media and Voluntary Nonfinancial Disclosure: Evidence from Twitter Presence and Corporate Political Disclosure. *Journal of Information Systems*, *33*(2), 99–128.

Levinthal, D. (2016). *Trade Groups to Top Corporations: Resist Political Disclosure*. https://publicintegrity.org/politics/trade-groups-to-top-corporations-resist-political-disclosure/.

Li, F. (2010). The Information Content of Forward-Looking Statements in Corporate Filings-A Naïve Bayesian Machine Learning Approach. *Journal of Accounting Research*, *48*(5), 1049–1102.

Mahon, J. F. (1983). Corporate Political Strategies: An Empirical Study of Chemical Firm Responses to Superfund Legislation. *Research in Corporate Social Performance and Policy*, *5*, 143–182.

McCarthy, N. (2019). *Oil And Gas Giants Spend Millions Lobbying To Block Climate Change Policies*. Forbes. https://www.forbes.com/sites/niallmccarthy/2019/03/25/oil-and-gas-giants-spend-millions-lobbying-to-block-climate-change-policies-infographic/?sh=6797aac87c4f.

Meckling, J. (2015). Oppose, Support, or Hedge? Distributional Effects, Regulatory Pressure, and Business Strategy in Environmental Politics. *Global Environmental Politics*, *15*(2), 19–37.

Menguc, B., Auh, S., and Ozanne, L. (2010). The Interactive Effect of Internal and External Factors on a Proactive Environmental Strategy and Its Influence on a Firm's Performance. *Journal of Business Ethics*, *94*(2), 279–298.

Meznar, M. B., and Nigh, D. (1995). Buffer or Bridge? Environmental and Organizational

Determinants of Public Affairs Activities in American Firms. *Academy of Management Journal*, *38*(4), 975–996.

Moniz, P., and Wlezien, C. (2020). Issue Salience and Political Decisions. In *Oxford Research Encyclopedia of Politics*. Oxford University Press.

Oglethorpe, D., and Heron, G. (2010). Sensible Operational Choices for the Climate Change Agenda. *The International Journal of Logistics Management*, *21*(3), 538–557.

Okereke, C., and Russel, D. (2010). Regulatory Pressure and Competitive Dynamics: Carbon Management Strategies of UK Energy-Intensive Companies. *California Management Review*, *52*(4), 100–124.

Oliver, C., and Holzinger, I. (2008). The Effectiveness of Strategic Political Management: A Dynamic Capabilities Framework. *Academy of Management Review*, *33*(2), 496–520.

Pagell, M., and Shevchenko, A. (2014). Why Research in Sustainable Supply Chain Management Should Have No Future. *Journal of Supply Chain Management*, *50*(1), 44–55.

Paulraj, A. (2011). Understanding the Relationships Between Internal Resources and Capabilities, Sustainable Supply Management and Organizational Sustainability. *Journal of Supply Chain Management*, *47*(1), 19–37.

Pee, A. de, Pinner, D., Roelofsen, O., Somers, K., Speelman, E., and Witteveen, M. (2018). *Decarbonization of industrial sectors: the next frontier*. In *McKinsey & Company* (Issue June). https://www.mckinsey.com/~/media/McKinsey/Business Functions/Sustainability and Resource Productivity/Our Insights/How industry can move toward a low carbon future/Decarbonization-of-industrial-sectors-The-next-frontier.ashx.

Porter, M. F. (1980). An Algorithm for Suffix Stripping. *Program*, *14*(3), 130−137.

Probst, P., Wright, M. N., and Boulesteix, A. L. (2019). Hyperparameters and Tuning Strategies for Random Forest. In *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* (Vol. 9, Issue 3).

Rizet, C., Browne, M., Cornelis, E., and Leonardi, J. (2012). Assessing Carbon Footprint and Energy Efficiency in Competing Supply Chains: Review – Case Studies and Benchmarking. *Transportation Research Part D: Transport and Environment*, *17*(4), 293–300.

RSP. (2021). *State Renewable Portfolio Standards and Goals*. https://www.ncsl.org/research/energy/renewable-portfolio-standards.aspx.

Schmidt, C. G., Foerstl, K., and Schaltenbrand, B. (2017). The Supply Chain Position Paradox: Green Practices and Firm Performance. *Journal of Supply Chain Management*, *53*(1), 3–25.

Segal, M. R. (2004). Machine Learning Benchmarks and Random Forest Regression. In *Biostatistics*.

Shaffer, B. (1995). Firm-Level Responses to Government Regulation: Theoretical and Research Approaches. *Journal of Management*, *21*(3), 495–514.

The World Bank. (2022). *Carbon Pricing Dashboard*. https://carbonpricingdashboard.worldbank.org/.

Theißen, S., Spinler, S., and Huchzermeier, A. (2014). Reducing the Carbon Footprint within Fast-Moving Consumer Goods Supply Chains through Collaboration: The Manufacturers' Perspective. *Journal of Supply Chain Management*, *50*(4), 44–61.

Tidy, M., Wang, X., and Hall, M. (2016). The Role of Supplier Relationship Management in Reducing Greenhouse Gas Emissions from Food Supply Chains: Supplier Engagement in the UK Supermarket Sector. *Journal of Cleaner Production*, *112*, 3294–3305.

Tienhaara, K. (2013). Corporations: Business and Industrial Influence. In P. G. Harris (Ed.), *Routledge Handbook of Global Environmental Politics* (pp. 164–175). Taylor & Francis Group.

Tokar, T., and Swink, M. (2019). Public Policy and Supply Chain Management: Using Shared Foundational Principles to Improve Formulation, Implementation, and Evaluation. *Journal of Supply Chain Management*, *55*(2), 68–79.

Villena, V. H., and Dhanorkar, S. (2020). How Institutional Pressures and Managerial Incentives Elicit Carbon Transparency in Global Supply Chains. *Journal of Operations Management*, *66*(6), 697–734.

Werner, T. (2017). Investor Reaction to Covert Corporate Political Activity. *Strategic Management Journal*, *38*(12), 2424–2443.

CHAPTER 4 – Supply Network Complexity, Regulatory Risks, and Firms' Engagement in Influencing Climate Change Policies

4.1. Introduction

Firms' climate impact is facing unprecedentedly increasing scrutiny by stakeholders, investors, and regulators, with the annual world carbon emission hitting a record in 2019, and the setting of the goal in the 2020 Paris Agreement to limit global warming to well below 2°C (ideally to 1.5°C) in the following 10 years. Such scrutiny not only exposes firms to climate risks (Engel et al., 2015) but also makes it challenging for firms to assert leadership on climate change. As such, adapting to existing climate policies is not enough to distinguish firms as climate leaders; more proactive efforts are required (Reichart, 2019). To enhance organizational legitimacy and competitive advantage, many firms have strived to go beyond policy compliance and engage in influencing climate change policies. As examples serve more than 1,600 businesses that have committed to ambitious emission reduction targets through the Science Based Targets initiative (SBTi) (*Ambitious Corporate Climate Action - Science Based Targets*, 2022), and around 360 corporates that have committed to 100% renewable electricity through RE100 initiatives to advocate the world's transition to a zero-carbon economy (*RE100*, 2022). These endeavors demonstrate firms' more active advocacy of climate policies. Other examples include oil firms spending millions of dollars per year on lobbying against climate-motivated policies that impose carbon taxes or prices on carbon emissions, which reflect those firms' opposition to regulatory restrictions (McCarthy, 2019).

As firms' engagement in influencing climate change policies (EICCP) becomes frequent and potentially impactful, it attracts the attention of different stakeholders in climate change policies to keep track of or even monitor firms' engagements. On the one hand, non-governmental organizations (NGOs) have started to track big corporates' deployment of political capital on climate change to examine the impact of their engagement (InfluenceMap, 2021). On the other hand, investors have urged firms to establish governance and disclosure procedures for their engagement (Veena Ramani, 2020). However, firms' EICCP has not received much academic attention. Existing research mainly deals with climate change policies as external conditions to which firms need to adapt, rather than regulatory environments that firms can shape or manipulate in favor of their business (Greiner and Kim, 2021; Grover and Dresner, 2022). In Chapter 3, I discussed the importance of investigating EICCP in understanding firms' overall environmental strategies and proposed and validated different strategies of EICCP. In this chapter, I continue furthering the understanding of EICCP by investigating the antecedents of EICCP from a supply chain perspective.

Prior literature has studied the antecedents of firms' general political engagement (e.g., Clapp and Meckling, 2013; Hillman et al., 2004; Sadrich and Annavarjulia, 2002). However, those discussions are not specifically concentrating on firms' engagement in climate change policies. In different regulatory contexts, firms' engagement decisions can be heterogeneous (e.g., firms may or may not engage, or may engage at different levels), considering the varying regulatory risks to which they are exposed and the difficulties of exerting influences on policymaking. Therefore, discussions on the antecedents of CPA need to be context specific. In addition, extant studies focus on the impact of firm-level, industry-level, and country-level factors on the degree of firms' engagement (Lux et al., 2011), while attention on the influence of supply chain-level factors is scarce. From a network perspective, I argue that firms' engagement in climate change policies under regulatory risks is contingent upon the features of their supply network, given that the characteristics of firms' network ties have implications on the extent to which the network members can benefit from the focal firms' strategic decisions (Ojala and Hallikas, 2006; Tachizawa and Wong, 2015).

In this study, I investigate the moderating effects of supply network complexity on the relationship between firms' regulatory risks and EICCP. Extant literature has identified regulatory risks as key drivers of corporate political activities (CPA) (Clapp and Meckling, 2013; Lux et al., 2011). However, some empirical studies have not found evidence for such a link between regulatory risks and CPA (e.g., Lenway and Rehbein, 1991; Martin, 1995). I suggest that these inconsistent results can be attributed to firms' different perceptions of CPA's efficacy. While CPA has the potential to reshape the regulatory environment in favor of firms (Greiner and Kim, 2021; Hillman et al., 2004), it requires substantial financial inputs and ultimately an investment decision for engaging firms (Mitchell et al., 1997). As firms perceive the high level of uncertainty and difficulty in influencing climate change policies, they may not choose to engage due to the potentially low return on investments. I argue that supply network complexity constrains firms' capabilities of engaging in climate change-related policymaking and increases the uncertainty of the engagement outcomes. Therefore, examining regulatory risks and firms' network complexity as interrelated factors is critical for the understanding of firms' engagement decisions. Following this logic, I seek to answer the following research questions: 1) Does a higher level of regulatory risks lead to a higher level of EICCP? 2) Does supply network complexity serve as a contingent factor for the relationship between regulatory risks and EICCP? Specifically, does supply network complexity negatively moderate the regulatory risks-EICCP link, such that this relationship becomes weaker when supply network complexity is higher?

To address these questions, I adopt the measures of EICCP generated in Chapter 3 and compile a panel spanning from 2013 to 2019 for firm-level regulatory risks and firms' supply networks. I find that regulatory risks have different impacts on firms' EICCP under different levels of supply network complexity. Further, distinct dimensions of supply network complexity have different moderating effects on the regulatory risk-EICCP link.

4.2. Literature Review

4.2.1 Theoretical Underpinnings for EICCP Studies

Following the conceptualization of EICCP in Chapter 3, I define EICCP as strategic actions firms perform to influence climate change policymaking processes, aiming at shaping policies or promoting policy changes in favor of their interests. While no literature exists that has studied the antecedents of EICCP, CPA research can provide some theoretical foundations for my study, since EICCP is a special type of CPA applied to climate change issues. Literature on CPA adopts several theoretical underpinnings to study the antecedents of firms' policy engagement, which I summarize below.

One theory used to understand CPA is legitimacy theory, which builds on the idea that firms always attempt to obtain legitimacy from different reference groups in society and that CPA provides firms with opportunities to be increasingly legitimate (R. Gray et al., 1995). Research on CPA contends that engaging in CPA gives firms opportunities to communicate with and convince policymakers that they are willing to comply, as well as to create a positive reputation when pursuing constituency building through advertising campaigns and strategic public relations (Banerjee and Venaik, 2018). Due to these potentials, prior literature contends that the intention of enhancing organizational legitimacy motivates firms to engage in CPA (Lux et al., 2011).

A further theory that has been used is the institutional theory, which contends that institutional forces push firms toward isomorphism (DiMaggio and Powell, 1983). Specific to the adoption of CPA, institutional theory suggests that firms may be forced to engage in CPA because the industry leaders or their competitors do so (e.g., Kim, 2008; Schuler et al., 2002).

Yet a third theory that justifies firms' engagement in CPA is the resource dependence theory, which is based on the tenet that business depends on public policy (Pfeffer and Salancik, 1978). Specifically, firms should engage more in CPA as the magnitude of their dependence on public policy increases. That is to say, firms confronting an increased level of regulatory scrutiny or more constraining and costly regulations are more motivated to manage such dependency through CPA (Hart, 2001; Mitchell et al., 1997).

This literature review suggests that firms' CPA engagement is a complicated strategic decision and can be explained from different theoretical perspectives. To strengthen the understanding of a particular type of CPA such as EICCP, incorporating several theories and integrating different theoretical underpinnings are helpful.

4.2.2 Supply Chain Complexity Research

Supply chain complexity research has thrived over the last two decades with the popularity of network research in the supply chain field. My literature review yields numerous empirical, analytical, and conceptual pieces that investigate complexity as the main construct. I summarize those studies in Table 3.3 of the Appendices. Since the present study is an empirical study, I primarily focus on prior empirical and conceptual works to briefly discuss the concept, the metrics, and the application of supply chain complexity in sustainability literature below.

First, the earliest conceptualization of supply chain complexity traces back to the seminal work of Choi and Hong (2002), which defines it as the load on the network system that requires coordination – "the higher the differentiation and the loose coupling among the elements in the system, the higher the load required to coordinate the system" (Choi and Hong, 2002, p. 471).

Building on this, Skilton and Robinson (2009) specify supply network complexity as "a function of the number of participants in the whole chain of relationships that ultimately connect consumers to the means of production for specific goods and services, the level of differentiation between participants, and the level and types of interrelationships that exist between participants" (Skilton and Robinson, 2009, p. 42). Although later studies further differentiate structural complexity, which refers to the "number and variety of elements defining the system" (Bode and Wagner, 2015, p. 216), and dynamic complexity, which refers to the interactions among those elements (Bode and Wagner, 2015), their conceptualization of supply network complexity is consistent with Skilton and Robinson (2009). We, therefore, follow Skilton and Robinson's (2009) conceptualization in this study.

Second, although prior literature has consensus on the concept of supply chain complexity, there is no agreement about its dimensions. A popular multi-faceted metric that has been applied is the one by Choi and Hong (2002), who consider horizontal, vertical, and spatial complexity as the three dimensions of supply chain complexity (Adhikary et al., 2020; Bode and Wagner, 2015). The other metrics that prior literature has used include a single-facet metric focusing on the number of nodes in the supply chain or the network size (Blackhurst et al., 2011; Kim et al., 2011; Wiedmer et al., 2021), a two-dimensional metric addressing the number of nodes together with the number of flows (Craighead et al., 2007), and a multi-dimensional metric capturing a series of characteristics of upstream and downstream operations that include the number of nodes, the differentiation among nodes, and the dispersion of nodes, among others (Bozarth et al., 2009; Brandon-Jones et al., 2015). Bode and Wagner (2015) attribute those differences to the different scopes of the studies, suggesting that some studies focus on the entire supply chain while others are only interested in certain parts or segments of the supply chain. In this study, we focus on the supply network, which is upstream of the supply chain. With this emphasis, we measure the three dimensions with the prevalent metrics that consider the number, the types, and the differentiations of relational ties between buyers and suppliers.

Third, most studies focus on the structural aspect of complexity (Adhikary et al., 2020; Lu and Shang, 2017; Sharma et al., 2020). Lu and Shang (2017) justify this decision by contending that structural complexity provides explicit measures, while dynamic complexity can possess many different dimensions as the variety of interactions increases with the number and type of elements in the supply chain. Further, Lu and Shang (2017) propose a characteristic to extend the dimensions of structural complexity, which is the visibility of structural links. The authors argue that horizontal, vertical, and spatial complexity are visible structural dimensions, while eliminative and cooperative complexity, which measure the level of connections between the first-tier suppliers and the focal buyer's customers, and the level of connections among first-tier suppliers, respectively, are not-so-visible dimensions. Given that this study focuses only on the relationship ties between buyers and suppliers, such dynamic complexity is beyond the scope of our discussion. I specifically investigate how firms' EICCP is contingent on structural complexity of their supply networks.

Fourth, empirical research on supply chain complexity covers a variety of topics, with significant attention being paid to risks and disruptions. While several studies explore how supply chain complexity is associated with plant- or firm-level operational, financial, environmental and innovation performance (Adhikary et al., 2020; Bozarth et al., 2009; Lu and Shang, 2017; Sharma et al., 2020), over half of the studies reviewed investigate the influence of supply chain complexity on supply chain disruptions and resiliency, including the severity, frequency, impact and recovery from disruptions (Blackhurst et al., 2011; Bode and Wagner, 2015; Brandon-Jones et al., 2015;

Craighead et al., 2007; Handley and Benton, 2013; Wiedmer et al., 2021). However, most of these studies specifically focus on disruptions, without attending to other types of risks. To extend this stream of research, I investigate the associations between supply network complexity and regulatory risks.

A further stream of research, on which I rely primarily in this essay, studies sustainability and environmental issues from the perspective of complexity. However, Adhikary et al. (2020) is the only empirical piece that falls into this category, which focuses on structural complexity as well as network embeddedness as antecedents to a focal firm's greenhouse gas emissions. Another relevant study is conceptual (Tachizawa and Wong, 2015), in which the authors discuss how supply network complexity, specifically the number of suppliers, the number of interactions, and the level of the interrelationship among suppliers, affect focal firms' environmental performance.

Overall, the literature view shows that supply chain complexity has not been sufficiently considered in sustainability research. Although a few studies examine supply network complexity as antecedents of firms' performance outcomes (Adhikary et al., 2020; Tachizawa and Wong, 2015), how supply network complexity influences firms' overall sustainability strategy has not been investigated. Given that EICCP constitutes a critical decision in sustainable operations, I seek to understand, in this exploratory study, how supply network complexity serves as a contextual factor for firms' policy engagement when firms confront regulatory risks. This study not only extends sustainability literature by clarifying the boundary conditions in which firms engage in influence-oriented responses instead of adaptation-oriented responses to climate change policies but also contributes to complexity literature by investigating the association between supply network complexity to risks beyond disruptions.

4.3. Hypothesis Development

4.3.1 Regulatory Risks and EICCP

Regulatory risks, in the context of this essay, refer to risks to which firms are exposed due to the development of climate change-related regulations and policies. These risks can originate from regulatory uncertainty that is intrinsic to policy formulation as well as the high level of regulatory stringency resulting from established and strict policies (Söderholm et al., 2015).

High levels of regulatory uncertainty motivate firms to take actions that either reduce the uncertainty or protect them from the uncertainty, following the tenet of resource dependence theory (Drees and Heugens, 2013). EICCP can be considered to be such actions. Prior literature suggests that engaging in climate change policymaking at the early stage of the political process not only offers firms opportunities to shape the policies but also grants these firms first-mover advantages that facilitate policy compliance (Banerjee and Venaik, 2018). When the climate change policies in development align with the interests of a firm, the firm can advocate the policies to facilitate the strengthening of organizational legitimacy and obtain competitive advantages. In contrast, when the current climate policy is not conducive to promoting the firm's competitive advantage, the firm can attempt to reshape it through lobbying or constituency building. Given that firms are able to reduce regulatory uncertainty in the long run through EICCP, EICCP can be positively associated with regulatory risks triggered by a high level of policy uncertainty.

High levels of regulatory stringency, however, may discourage firms to engage in influencing policymaking. While regulatory uncertainty is higher in the agenda-setting stage, which is an early stage of the political process, regulatory stringency rises as the political process advances to the policy formulation stage. At this stage, the opportunities to change the established policy instrument through EICCP are limited and require more investments (Meckling, 2015).

Prior literature has indicated that CPA does not lead to favorable outcomes when firms' influence on policies and the impact of the ultimately established policies are uncertain (Hadani et al., 2017). Therefore, regulatory risks triggered by a high level of policy stringency should be negatively related to EICCP.

In the context of climate change, recent research on policy processes has indicated that the stages of agenda setting and policy formulation for climate change policies are intertwined (Leppänen and Liefferink, 2022). The back-and-forth climate change policymaking signifies the advancement from agenda setting to policy formulation (Bromley-Trujillo and Holman, 2020). Therefore, I argue that regulatory risks associated with climate change policies originate from regulatory stringency rather than from regulatory uncertainty. Since the high level of regulatory stringency is negatively related to firms' policy engagement, I theorize the following:

H1: Regulatory risks are negatively related to firms' EICCP.

4.3.2 Moderating Effects of Supply Network Complexity on the Regulatory Risks-EICCP Link

The relationship between regulatory risks and EICCP is not only constrained by the essence of regulatory risks, but also by firms' capabilities of implementing firm-level political actions. The lack of capabilities can nullify firms' decision to engage in policymaking even when the regulatory risks are high. In this study, I take a network perspective and investigate how supply network complexity constrains firms' EICCP capabilities. I examine three structural complexity dimensions—horizontal complexity, vertical complexity, and spatial complexity—following prior literature on supply chain complexity (Adhikary et al., 2020; Bode and Wagner, 2015; Lu and Shang, 2017). According to the conceptualization of Lu and Shang (2017), horizontal complexity measures the number of first-tier suppliers a firm has, which captures the width of the supply base; vertical complexity measures the average number of second-tier suppliers each first-tier supplier has, which reveals the depth of the supply base; and spatial complexity measures the number of countries in which the firms' supplier are located, which reflects the geographical spread of the supply base. High supply network complexity in those dimensions indicates that focal firms should consider numerous stakeholders that are experiencing different stages of the policymaking process and residing in different regulatory contexts, and thus, are very likely to require a variety of changes in climate change policies. On the one hand, the divergent demand requires greater investment in EICCP, which makes the engagement decision less favorable for the focal firm. On the other hand, the high level of supply network complexity makes the outcomes of EICCP unpredictable. Engagement efforts that favor some suppliers may further increase the regulatory pressure on others. Therefore, a highly complex supply network drains firms' capabilities of political engagement and thus demotivates firms' EICCP, even when the regulatory risks are high. Therefore, I propose the following hypotheses:

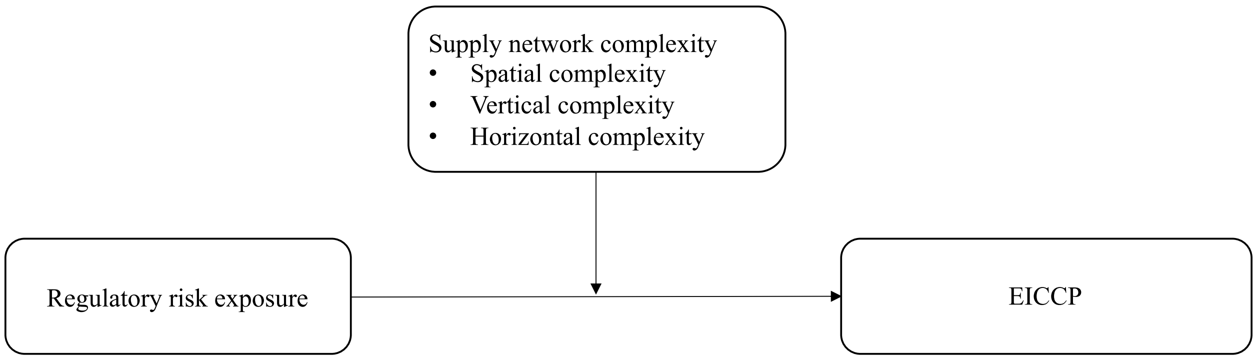
H2a. Horizontal complexity negatively moderates the regulatory risks-EICCP relationship such that the higher the horizontal complexity, the more negative the regulatory risks-EICCP relationship.

H2b. Vertical complexity negatively moderates the regulatory risks-EICCP relationship such that the higher the vertical complexity, the more negative the regulatory risks-EICCP relationship.

H2c. Spatial complexity negatively moderates the regulatory risks-EICCP relationship such that the higher the vertical complexity, the more negative the regulatory risks-EICCP relationship.

Figure 3.1 presents the theoretical model of this study.

Figure 3.1 Theoretical model



4.4. Methodology

4.4.1. Data

To test my hypotheses, I compile the following datasets to construct a panel:

CDP Climate Change Dataset. As introduced in Chapter 3, this dataset collects firms' public responses to an information request sent by CDP on behalf of their signatory investors regarding climate change issues. For this study, I continue to use firms' responses to the open-ended question— "On what issues have you been engaging directly with policymakers?" as the main data source of firm-level engagements in influencing climate change policies. Firms can provide more than one response to detail different types of engagement. Therefore, I aggregate responses at the firm level for each year of observation. Each firm-year response includes firms' descriptions of their engagement and their proposed legislative solutions.

FactSet Revere-Supply Chain Relationship Dataset. This dataset offers a detailed mapping of a firm's various relationships with other stakeholders in the supply chain, including customers, suppliers, partners, and competitors. I focus on firms' direct suppliers and their suppliers' suppliers to construct a multi-tier supply network for each firm in the dataset. To do so, I take the following steps to process the data: 1) I extract all the relationships tagged as supplier to obtain a list of firms' first-tier suppliers. 2) I then extract all the relationships tagged as customer to complement and cross-validate the list I obtained in step (1). Specifically, I reverse all these relationships to obtain another list of the first-tier suppliers for the listed customers. 3) I then merge the two lists and keep the unique data entries to construct a complete list of uniquely defined buyer-supplier relationships. Treating buyers as focal firms, I count the number of first-tier suppliers for each focal firm. 4) I identify the second-tier suppliers by searching for the suppliers of each first-tier supplier I found in step (3). Then I aggregate the number of second-tier suppliers at the level of focal firms. 5) I identify the country in which each first and second-tier supplier is located and count the total number of countries existing for the focal firm level. Through these five steps, I obtain the number of first-tier suppliers, the number of second-tier suppliers, and the number of countries in which the suppliers in the first two tiers of a focal firm are located. I will detail how I construct the variables of the supply network complexity in the next section.

Firm-Level Climate Change Exposure Dataset. This data was created by Sautner et al. (2022) to quantify firm-level risk exposure related to opportunity and physical and regulatory shocks of climate change. In this study, I use the metrics that capture firms' exposure to regulatory risks in climate change. To construct this risk variable, Sautner et al. (2022) conduct text analytics on firms' earnings conference calls using a machine learning approach with the keyword discovery algorithm. This method starts with predefining a short list of climate change bigrams as a training library. The training library then serves as the input to the algorithm that calculates the probability of classifying a certain sentence into the climate change-related category. Using 80% of the probability as a threshold, Sautner et al. (2022) obtained over 700,000 sentences that potentially mention climate change content and about 70 million sentences that do not. At this point, they expand the initial list of climate change bigrams by discovering bigrams that appear frequently and only in climate change-related sentences. They further classify climate change-related bigrams into different categories based on two criteria. The first criterion focuses on whether a bigram indicates opportunities or risks. The second criterion concentrates on topics including technologies, regulations, and physical climate aspects. Combining the two criteria yields several lists of bigrams including the one that the authors use to further calculate the regulatory risks. Specifically, the authors divide the total number of potential bigrams in a text by the number of bigrams related to a regulatory risk to construct a measure of regulatory risks.

Compustat Fundamental Dataset. This dataset offers information about firms' profiles and financial status, which serve as controls in this study.

The data compilation started with the CDP dataset, which yielded a panel that includes 1,309 firms and 8,529 firm-year responses spanning from 2013 to 2019. We then merged the panel with the FactSet, Firm-Level Climate Change Exposure, and Compustat datasets to obtain network, regulatory risk, and financial information, respectively, for firms in the panel. The associated variables are discussed in the next section.

4.4.2. Variables

Dependent Variable. My dependent variable is EICCP, which is a count variable that uses the number of strategies a firm pursues out of four basic EICCP strategies (promotion, support, hedging, and opposition) in a given year as a proxy of the firm's level of engagement. This measurement is consistent with prior sustainability studies that use the count of sustainability strategies to measure firms' engagement in green practices (e.g., Chen and Ho, 2019; Peters et al., 2019). I construct this variable based on the machine learning predictions obtained in Chapter 3. Specifically, I conduct the text analysis on firms' self-disclosure of EICCP using the random forest approach, following the recent empirical finding that the random forest approach outperforms the dictionary-based approach in text classification (Frankel et al., 2021). The prediction models yield the probabilities that firms pursue one of the four basic EICCP strategies. I use 50% of the probability as a threshold to identify the strategies a firm took. For example, if the machine learning prediction outcomes show that in the year 2019, the probability that firm A pursued a promotion strategy is 75%, the probability of pursuing a support strategy is 55%, a hedging strategy is 35%, and an opposition strategy is 1%; this scenario would suggest that firm A engaged through promotion and support strategies, but not through hedging or opposition strategies. The value of firm A's EICCP strategies in 2019 is therefore 2. Among the 22,314 firm-year observations spanning from 2013 to 2019 in my sample, 4,720 firm-year observations feature one engagement strategy, 642 are characterized by two strategies, and 7 by three strategies. The number of observations for each case vary when I used a different probability as a threshold. I report those numbers and present the results of the sensitivity analysis in Table 3.4 of the Appendices. To briefly summarize the results here, applying a higher probability as the threshold (60% or 70%) yields consistent regression results.

Independent variables. All independent variables were lagged by one year for my econometric modeling and estimation (i.e., using observations from 2012 to 2018), considering that firms' current strategies of EICCP depend on firms' past perceptions of risks and resources. This is consistent with extant CPA literature (Lux et al., 2011).

I follow prior literature to measure supply network complexity using three variables (Bode and Wagner, 2015; Lu and Shang, 2017): horizontal complexity, which is measured by the number of firms' first-tier suppliers; vertical complexity, which is measured by the average number of the second-tier suppliers per firms' first-tier supplier; and spatial complexity, which is measured by the total number of countries the first and second-tier suppliers come from.

To capture firms' regulatory risks in climate change, I use a measure established by Sautner et al. (2022), which accounts for the "relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls" by "counting the number of such bigrams and divide by the total number of bigrams in a transcript" (Sautner et al., 2022; p. 35).

Control variables. I include several time-varying variables in my model to control for potential heterogeneity in firms' EICCP strategies, consistent with CPA literature. These control variables include: 1) firms' annual sales and 2) the number of employees, which both capture firm size; these are included since prior literature suggests that larger firms are more likely to engage intensively in influencing policymaking (Kim, 2008; Schuler and Rehbein, 1997). 3) Firms' sales growth, 4) net income, 5) return on assets, and 6) market share, which all capture firms' economic opportunity; these are included since extant research posits that economic factors, including firms' revenue growth and profitability, can also lead to higher levels of policy engagement (Kim, 2008; Taylor, 1997; Zardkoohi, 1985). 6) Firms' slack, measured by using firms' current ratio, which captures the availability of firms' financial resources and provides financial support for CPA (Lenway and Rehbein, 1991; Schuler and Rehbein, 1997); and 7) firms' sector, which is a categorical variable that controls for sector level differences in policy engagement. I also controlled for firm and year fixed effects. Table 3.1 provides details of the variables I use in this study.

4.4.3. Econometric Models

Due to the count nature of the dependent variable, I fit a Poisson regression with panel data to investigate the effects of supply network complexity and regulatory risks, as well as their interactions on firms' EICCP. In comparison to negative binomial regression analysis, which is another model applicable to count variables, Poisson regression analysis relies on fewer assumptions for the correct specification of the dispersion and has robust properties for the estimation (Wooldridge, 2010). Specifically, while negative binomial regression requires the occurrence of overdispersion as a function of the mean to produce consistent results, Poisson regression makes no assumptions on the dispersion and can be robust to scenarios of both underdispersion and overdispersion. Therefore, I apply Poisson regression to our dependent variable EICCP. The regression model is as follows:

$$\begin{aligned} EICCP_{it} = {} & \beta_1 Horizontal\ Complexity_{i,t-1} + \beta_2 Vertical\ Complexity_{i,t-1} + \\ & \beta_3 Spatial\ Complexity_{i,t-1} + \beta_4 Regulatory\ Risk\ Exposure_{i,t-1} + \\ & \beta_5 Horizontal\ Complexity_{i,t-1} \times Regulatory\ Risk\ Exposure_{i,t-1} + \\ & \beta_6 Vertical\ Complexity_{i,t-1} \times Regulatory\ Risk\ Exposure_{i,t-1} + \\ & \beta_7 Spatial\ Complexity_{i,t-1} \times Regulatory\ Risk\ Exposure_{i,t-1} + \\ & \beta_8 Controls_{i,t-1} + \beta_9 Sector_i + \beta_{10} Year_{it} + \varepsilon_{it}, \end{aligned}$$

in which $Controls_{i,t-1}$ is a vector of all the time-varying control variables.

For model estimation, I first apply the random-effects approach. The likelihood-ratio test, which compares the panel estimator with the pooled estimator, indicates that the random-effects model is significantly different from the pooled model. In this case, the fixed-effects specification can provide a better model fit (StataCorp, 2019). Therefore, I adopt the fixed-effect approach for model estimation. To account for the potential overdispersion and heteroskedasticity, I also use robust standard errors.

Table 3.1 Summary statistics and data sources

Variables	Description	Mean	SD	Data Source
EICCP	Categorical, number of four basic strategies of EICCP (promotion, support, hedging, and opposition) a firm take	0.270	0.506	CDP Climate Change Dataset
Supply Network Complexity				
Horizontal Complexity	Number of tier-1 suppliers	20.706	31.609	FactSet Revere Buyer-Supplier Relationship Dataset
Vertical Complexity	Number of tier-2 suppliers per tier-1 supplier	18.554	22.124	
Spatial Complexity	Number of countries in which tier-1 and tier-2 suppliers locate	9.947	10.770	
Firms' Regulatory Risk Exposure	Number of such bigrams representing the regulatory risk of climate change divided by the total number of bigrams in the text	8.43 × 10-5	3.218 × 10-4	Firm-level Climate Change Exposure Dataset
Controls				
Sales	Log transformation of firms' annual sales (in millions)	8.679	1.397	Compustat Fundamental Dataset
Employees	Log transformation of the number of employees	2.933	1.296	
Sales Growth	Percentage change of the sales of the current year compared to the sales of the previous year	0.275	19.785	
Net Income	Log transformation of firms' annual net income (in millions)	10.051	0.143	
ROA	The ratio of firms' net income and the average total assets	0.122	0.071	
Market Share	Firms' annual sales divided by the total sales of the industry over the same period	0.216	0.285	
Slack	Firms' current ratio, which is their current assets divided by their current liabilities	1.666	1.414	

4.5. Results

I report the regression results in Table 3.2. Model 1 examines the main effects of regulatory risk exposure on EICCP. I found no statistical evidence that regulatory risk exposure and EICCP are significantly associated. H1 was therefore not supported. In Model 2, I added the interaction terms between regulatory risk exposure and supply network complexity. The results show a negative interaction between horizontal complexity and regulatory risk exposure ($\beta = -0.060$, $p < 0.05$), supporting H2a. The absence of the main effect and the significant interaction indicate crossover moderating effects of horizontal complexity, such that when the level of horizontal complexity is high, regulatory risk exposure is negatively related to EICCP; however, when the level of horizontal complexity is low, the association is positive. Similarly, the negative interactions between vertical complexity and regulatory risk exposure ($\beta = -0.078$, $p < 0.05$) suggest that the regulatory risk exposure is negatively related to EICCP when the level of vertical complexity is high, and vice versa when the level of vertical complexity is low. H2b is therefore supported. An examination of the interaction of spatial complexity and regulatory risk exposure yields different results, suggesting that regulatory risk exposure and EICCP are positively related when the level of spatial complexity is high ($\beta = 0.209$, $p < 0.01$). Therefore, H2c was rejected.

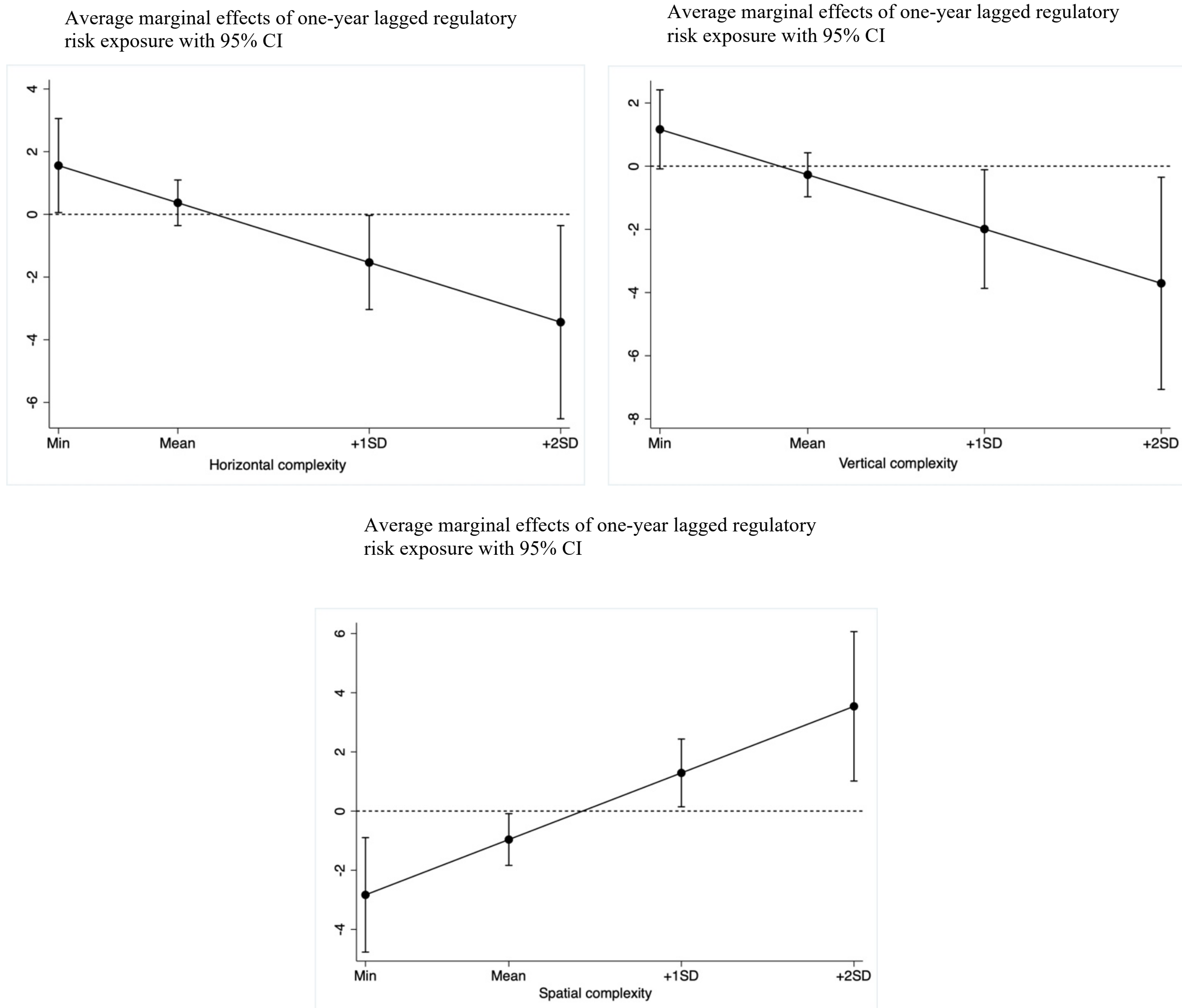
I plot the marginal effects of regulatory risk exposure on EICCP at different values of the three supply network complexity aspects in Figure 3.2. The plots show that with the value of horizontal complexity one standard deviation above the mean, regulatory risk exposure is negatively related to EICCP ($\beta = -1.535$, $p < 0.05$); with the value of vertical complexity one standard deviation above the mean, regulatory risk exposure is also negatively related to EICCP ($\beta = -1.990$, $p < 0.05$); in contrast, with the value of spatial complexity one standard deviation above the mean, regulatory risk exposure is positively related to EICCP ($\beta = 1.289$, $p < 0.05$).

Table 3.2 Results of the Poisson regression

	Model 1		Model 2	
	coef	se	coef	se
Independent Variables (one-year lagged)				
Horizontal Complexity	-0.000	(0.002)	0.000	(0.002)
Vertical Complexity	-0.000	(0.002)	0.001	(0.002)
Spatial Complexity	-0.004	(0.005)	-0.007	(0.005)
Regulatory Risks	-0.150	(0.344)	-0.044	(0.479)
Horizontal Complexity × Regulatory Risks			-0.060*	(0.027)
Vertical Complexity × Regulatory Risks			-0.078*	(0.035)
Spatial Complexity × Regulatory Risks			0.209**	(0.071)
Control Variables (one-year lagged)				
Sales	-0.077	(0.181)	-0.099	(0.181)
Employees	-0.034	(0.159)	-0.021	(0.155)
Sales Growth	0.057	(0.041)	0.060	(0.038)
Net Income	-0.077	(0.258)	-0.088	(0.258)
ROA	-0.254	(0.755)	-0.174	(0.739)
Market Share	-0.488*	(0.202)	-0.494*	(0.195)
Slack	-0.066	(0.049)	-0.066	(0.048)
Observations	1,624		1,624	
Number of Firms	402		402	
Log Pseudolikelihood	-1012.2267		-1011.089	

Note. Robust standard errors in parentheses. ** p<0.01, * p<0.05

Figure 3.2 Effects of regulatory risks on EICCP at different values of supply network complexity



4.6. Discussion and Conclusion

In this study, I show that regulatory risks, supply network complexity, and their interactions influence firms' EICCP. I found neither the main effects of regulatory risks on EICCP nor the main effects of supply network complexity on EICCP, suggesting that those factors do not individually influence EICCP. However, I found the interactions between two dimensions of supply network complexity, horizontal and vertical complexity, and regulatory risks are negatively related to EICCP. This provides empirical evidence that considering more suppliers, or a bigger extended supply chain, reduces firms' propensity to engage in policymaking under regulatory pressures. The interaction between spatial complexity and regulatory risks, in contrast, is positively related to EICCP, contradicting my hypothesis. One potential interpretation is that a high level of spatial complexity, reflected by a greater number of countries in which suppliers reside, increases the regulatory risks firms perceive and thus, leads to a higher level of EICCP. Another interpretation is that firms' that have a higher level of complexity are likely to be large and multinational companies that have more resources or capabilities to influence climate change policymaking.

My research makes several contributions. First, this study builds on Chapter 3 to econometrically assess EICCP, which provides face validity to the concept of EICCP. Although I did not find any main effects of regulatory risks on EICCP, I found a negative sign for the coefficient, indicating that regulatory risks are potentially negatively related to EICCP.

Second, as the first study in the supply chain field that empirically investigates the antecedents of political engagement in a specific context, I explore supply network complexity dimensions as contingency factors for firms' EICCP under regulatory risks. The main effects of the three dimensions of supply network complexity were missing, while the signs of the coefficient of horizontal and vertical complexity are positive and the sign of the coefficient of spatial complexity is negative. Despite the absent direct link, supply network complexity has significant moderating effects on the regulatory risks-EICCP link. Integrating resource dependency theory and network perspectives, I argue that network complexity constrains firms' capabilities in political engagement. My endeavor responds to the call for more policy-related studies in our field from a supply chain perspective (Tokar and Swink, 2019).

This paper also extends the supply chain complexity literature by demonstrating the relevance of supply network complexity for firms' sustainability-related strategic decisions. While prior literature on supply chain complexity focuses on the risk of supply chain disruptions, this essay extends this stream of study by discussing the synergy between supply network complexity and the regulatory risks that firms confront on EICCP. My work contributes to the risk management literature contending that supply chain complexity causes more than one type of risk.

My research also has limitations. First, this study is exploratory in nature and only focuses on one set of network-level factors when investigating the antecedents of EICCP. Future research can integrate firm-level, industry-level, and country-level factors to construct a more comprehensive framework. Interesting questions to ask include whether EICCP varies in different industries or countries; and whether industrial factors and supply network factors constitute three-way moderating effects on the link between supply network risks and EICCP. Second, while I focus on the intensity of engagement in this study, the types of engagement strategies are also worthwhile to study. For example, further studies can be conducted to examine whether different risk perceptions and network characteristics lead to different types of EICCP engagement strategies. Cluster analysis can be applied for this purpose.

APPENDICES

Table 3.3 Summary of Existing Research on Supply Chain Complexity

Study	Research settings: Risk	Research settings: Green	Metrics of network complexity	Method	Data Source	Dependent variables	Independent variables
Empirical							
Choi and Hong, 2002	No	No	Horizontal, vertical, and spatial complexity measures, which refer to, respectively, the average number of entities across all tiers, the average number of entities in all possible vertical supply chains, and the average geographical distance between companies in the top two tiers in the network	Multi-case study	Interview of firm managers, firm documents and observations of plant visits	Formalization, centralization and complexity of supply network	Antecedents of supply network structure, including: Formulized rules, norms and policies; Cost consideration; Centralized approach; Expensive product lines; Use of core supplier list; etc.

Table 3.3 (cont'd)

Study	Research settings		Metrics of network complexity	Method	Data Source	Dependent variables	Independent variables
	Risk	Green					
Craighead et al., 2007	Yes	No	Total number of nodes within a supply chain; Total number of forward, backward, and within-tier materials flows in a supply chain	Multi-case study	Interview of executives and supply chain professionals of multiple supply chain entities of a U.S.-based automobile manufacturer	Severity of supply chain disruptions	Supply chain density, supply chain complexity, node criticality; Supply chain mitigation capabilities: recovery capability and warning capability (moderators)
Bozarth et al., 2008	No	No	Upstream complexity, including number of suppliers, long supplier lead times, supplier delivery unreliability, and percentage of purchases imported; Downstream complexity, including number of customers, customer heterogeneity, short product life cycle, and demand variability	Structrual equation modeling	Survey data of seven developed countries	Plant-level performance	Supply chain upstream complexity, internal manufacturing complexity, and downstream complexity

Table 3.3 (cont'd)

Study	Research settings		Metrics of network complexity	Method	Data Source	Dependent variables	Independent variables
	Risk	Green					
Kim et al., 2011	No	No	Network size; Network density, including network density, core size, core density, core to periphery (CTP) density, and periphery to core (PTC) density	Case study with social network analysis	Interview of firm managers, firm documents and observations of plant visits	Node-level network characteristics including five centrality measures; network level characteristics including centralization and complexity measures	Material flow or contractual relationship network type
Blackhurst, Dunn and Craighead, 2011	Yes	No	Number of nodes in supply chain	Multi-case study	Interview of executives and supply chain professionals of multiple supply chain entities of a U.S.-based automobile manufacturer	Supply chain resiliency	Resiliency enhancers including human capital, organizational and interorganizational capital, and physical capital; Resiliency reducers including flow activities (e.g. number of nodes in supply chain), flow units, and source of flow units

Table 3.3 (cont'd)

Study	Research settings		Metrics of network complexity	Method	Data Source	Dependent variables	Independent variables
	Risk	Green					
Hadley and Benton, 2013	Yes	No	Location-specific complexity including geographic dispersion, geographic distance, and cultural distance	OLS regression	Survey data of U.S. public companies	Inter-organizational management costs including control costs and coordination costs	Task-specific complexity including scale of service, breadth of tasks, and service customization; Location-specific complexity including geographic dispersion, geographic distance, and cultural distance
Bode and Wager, 2015	Yes	No	Supply network horizontal, vertical and spatial complexity	Negative multinomial regression	Survey data of firms in German, Austria and Switzerland, and archival data	Frequency of supply chain disruptions	Supply network horizontal, vertical and spatial complexity

Table 3.3 (cont'd)

Study	Research settings		Metrics of network complexity	Method	Data Source	Dependent variables	Independent variables
	Risk	Green					
Brandon-Jones et al., 2015	Yes	No	Scale as the number of suppliers; Differentiation as the degree of difference in size and technical capability between suppliers; Delivery reliability by on-time performance and lead-time; Geographic dispersion as an index developed by Stock, Greis, and Kasarda (2000).	OLS regression	Survey data of manufacturing firms in the United Kindom	Frequency of supply chain disruptions; Plant performance	Scale complexity, differentiation complexity, delivery complexity, and geographic dispersion complexity; Production capacity, safety stock at suppliers and at plant, and visibility (moderators)
Lu and Shang, 2017	No	No	Supply network horizontal, vertical, spatial, eliminative and cooperative complexity	OLS regression	Archival data	Focal firm's financial performance	Supply network horizontal, vertical, spatial, eliminative and cooperative complexity

Table 3.3 (cont'd)

Study	Research settings: Risk	Research settings: Green	Metrics of network complexity	Method	Data Source	Dependent variables	Independent variables
Sharma et al., 2020	No	No	Supply network horizontal, vertical and spatial complexity	Control function instrumental variable panel regression	Archival data	Focal firm's innovation	Focal firm's supply network horizontal, vertical and spatial complexity; focal firm's strategic emphasis and influence over the network
Adhikary et al., 2020	No	Yes	Supply network horizontal, vertical and spatial complexity	Control function instrumental variable panel regression	Archival data (Bloomberg SPLC, FA and ESG, GRI, and CDP database)	Focal firm's green house gas emissions	Focal firm's supply network horizontal, vertical and spatial complexity; focal firm's betweenness centrality and reach
Wiedmer et al., 2021	Yes	No	Supply complexity as nodes in the network	Difference-in-differences models	Archival data (Panjiva, import and export data of automotive industry)	Supply network resilience including disruption impact and disruption recovery	Supply complexity (nodes in the network), logistics complexity (arcs in the network), and product complexity

Table 3.3 (cont'd)

Study	Research settings		Metrics of network complexity	Method	Data Source	Dependent variables	Independent variables
	Risk	Green					
Simulation and Modeling							
Basole and Bellamy, 2014	Yes	No	Network topology: Random; Small-world; Scale-free	Simulation with OLS regression	N/A	Risk propogation and recovery in supply network	Supply network structure (small-world vs. scale-free); network structural visibility; initial level of healthy entities in supply network
Giannoccaro, Nair and Choi, 2017	No	No	Number of nodes in supply network; Supply interactions	Simulation	N/A	Supply network adaptive performance	Focal firm's scope of control; supply network complexity, including supply interactions and number of firms
Demirel et al., 2019	Yes	No	Horizontal complexity; Vertical complexity; Degree heterogeneity; Interrelatedness between suppliers	Analytical study (generalized modeling method) and case study	Archival data of selected firms for case study	Stability of supply networks	Dynamics of material flows and inventory level

Table 3.3 (cont'd)

Study	Research settings		Metrics of network complexity	Method	Data Source	Dependent variables	Independent variables
	Risk	Green					
				Conceptual			
Vachon and Klassen, 2002	No	No	Network level: Technological dimension of the supply chain; Information processing dimension of complexity	Conceptual study	N/A	Defining supply chain complexity from technological and information processing dimensions at network level	
Choi and Krause, 2006	Yes	No	Supply base level: Number of suppliers; Degree of differentiation among these suppliers; Level of inter-relationships among the suppliers	Conceptual study	N/A	Number of suppliers, Degree of differentiation, Level of interrelationships	
Skilton and Robinson, 2009	No	No	Number of suppliers; Differentiation of suppliers; Level of interrelationship between suppliers	Conceptual study	N/A	Traceability of adverse events	Supply network complexity, degree of tight coupling and transparency

Table 3.3 (cont'd)

Study	Research settings		Metrics of network complexity	Method	Data Source	Dependent variables	Independent variables
	Risk	Green					
Pathak, Wu and Johnston, 2014	No	No	Network level: Community supply network; Federal supply network; Consortium supply network Hierarchical supply network	Conceptual study	N/A	Co-opetitive dynamics in four network archetypes, including community, federation, consortium and hierarchy supply networks	
Yan et al., 2015	No	No	Network level: Operational nexus supplier; Monopolistic nexus supplier; Informational nexus supplier	Conceptual study	N/A	Conceptualizing and identifying three types nexus suppliers, which influence focal firms' operational performance differently	
Tachizawa and Wong, 2015	No	Yes	Number of suppliers; Number of interactions among suppliers; Level of interrelationship between suppliers	Conceptual study	N/A	Focal firm's environmental performance	Green SCM formal/ informal governance mechanism; supply network complexity; centralization; density

Table 3.4 Sensitivity Tests

	Model 1		Model 2	
	coef	se	coef	se
Independent Variables (one-year lagged)				
Horizontal Complexity	-0.000	(0.002)	0.001	(0.002)
Vertical Complexity	0.000	(0.002)	0.003	(0.002)
Spatial Complexity	-0.007	(0.005)	-0.004	(0.007)
Regulatory Risks	-0.299	(0.571)	0.229	(0.749)
Horizontal Complexity × Regulatory Risks	-0.128**	(0.040)	-0.094+	(0.054)
Vertical Complexity × Regulatory Risks	-0.145*	(0.067)	-0.162+	(0.086)
Spatial Complexity × Regulatory Risks	0.451***	(0.128)	0.368*	(0.187)
Control Variables (one-year lagged)				
Sales	0.094	(0.227)	-0.314	(0.275)
Employees	-0.324	(0.210)	-0.260	(0.265)
Sales Growth	0.082*	(0.039)	0.117**	(0.041)
Net Income	0.161	(0.343)	-0.162	(0.428)
ROA	-1.099	(0.826)	0.096	(1.209)
Market Share	-0.216	(0.313)	-0.095	(0.437)
Slack	-0.065	(0.061)	0.024	(0.070)
Observations	1,487		1,487	
Number of Firms	365		310	
Log Pseudolikelihood	-865.612		-685.966	

Note. Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1. Model 1 refer to the case that I use 60% of the probability, instead of 50% used in the main analysis, as a threshold to identify the strategies a firm took. With this threshold, among the 22,314 firm-year observations spanning from 2013 to 2019 in my sample, 4,195 firm-year observations feature one engagement strategy, and 358 are characterized by two strategies. Model 2 refer to the case that I use 70% of the probability as a threshold to identify the strategies a firm took. With this threshold, 3,386 firm-year observations feature one engagement strategy, and 174 are characterized by two strategies. The results of both Model 1 and Model 2 are consistent with the results of the main analysis reported in Table 3.2.

REFERENCES

REFERENCES

Adhikary, A., Sharma, A., Diatha, K. S., and Jayaram, J. (2020). Impact of Buyer-Supplier Network Complexity on Firms' Greenhouse Gas (GHG) Emissions: An Empirical Investigation. *International Journal of Production Economics*, *230*(July), 107864.

Ambitious Corporate Climate action - Science Based Targets. (2022). https://sciencebasedtargets.org/.

Banerjee, S., and Venaik, S. (2018). The Effect of Corporate Political Activity on MNC Subsidiary Legitimacy: An Institutional Perspective. *Management International Review*, *58*(5), 813–844.

Blackhurst, J., Dunn, K. S., and Craighead, C. W. (2011). An Empirically Derived Framework of Global Supply Resiliency. *Journal of Business Logistics*, *32*(4), 374–391.

Bode, C., and Wagner, S. M. (2015). Structural Drivers of Upstream Supply Chain Complexity and the Frequency of Supply Chain Disruptions. *Journal of Operations Management*, *36*(1), 215–228.

Bozarth, C. C., Warsing, D. P., Flynn, B. B., and Flynn, E. J. (2009). The Impact of Supply Chain Complexity on Manufacturing Plant Performance. *Journal of Operations Management*, *27*(1), 78–93.

Brandon-Jones, E., Squire, B., and Van Rossenberg, Y. G. T. (2015). The Impact of Supply Base Complexity on Disruptions and Performance: The Moderating Effects of Slack and Visibility. *International Journal of Production Research*, *53*(22), 6903–6918.

Bromley-Trujillo, R., and Holman, M. R. (2020). Climate Change Policymaking in the States: A View at 2020. *Publius: The Journal of Federalism*, *50*(3), 446–472.

Chen, C. M., and Ho, H. (2019). Who Pays You To Be Green? How Customers' Environmental Practices Affect the Sales Benefits of Suppliers' Environmental Practices. *Journal of Operations Management*, *65*(4), 333–352.

Choi, T. Y., and Hong, Y. (2002). Unveiling the Structure of Supply Networks: Case Studies in Honda, Acura, and DaimlerChrysler. *Journal of Operations Management*, *20*(5), 469–493.

Clapp, J., and Meckling, J. (2013). Business as a Global Actor. In *The Handbook of Global Climate and Environment Policy* (pp. 286–303). John Wiley & Sons Ltd.

Craighead, C. W., Blackhurst, J., Rungtusanatham, M. J., and Handfield, R. B. (2007). The Severity of Supply Chain Disruptions: Design Characteristics and Mitigation Capabilities. *Decision Sciences*, *38*(1), 131–156.

DiMaggio, P. J., and Powell, W. W. (1983). The Iron Cage Revisited Institutional Isomorphism and Collective Rationality in Organizational Fields. *American Sociological Review*, *48*(2), 147–160.

Drees, J. M., and Heugens, P. P. M. A. R. (2013). Synthesizing and Extending Resource Dependence Theory. *Journal of Management*, *39*(6), 1666–1698.

Engel, H., Enkvist, P.-A., and Henderson, K. (2015). *How companies can adapt to climate change*. https://www.mckinsey.com/~/media/McKinsey/Business Functions/Sustainability/Our Insights/How companies can adapt to climate change/How companies can adapt to climate change.pdf?shouldIndex=false.

Frankel, R., Jennings, J., and Lee, J. (2021). Disclosure Sentiment: Machine Learning vs. Dictionary Methods. *Management Science*.

Gray, R., Kouhy, R., and Lavers, S. (1995). Corporate Social and Environmental Reporting A Review of the Literature and a Longitudinal Study of UK Disclosure. *Accounting, Auditing & Accountability Journal*, *8*(2), 47–77.

Greiner, M., and Kim, J. (2021). Corporate Political Activity and Greenwashing: Can <scp>CPA</Scp> Clarify Which Firm Communications on Social & Environmental Events Are Genuine? *Corporate Social Responsibility and Environmental Management*, *28*(1), 1–10.

Grover, A. K., and Dresner, M. (2022). A Theoretical Model on How Firms Can Leverage Political Resources To Align With Supply Chain Strategy for Competitive Advantage. *Journal of Supply Chain Management*, *58*(2), 48–65.

Hadani, M., Bonardi, J.-P., and Dahan, N. M. (2017). Corporate Political Activity, Public Policy Uncertainty, and Firm Outcomes: A Meta-Analysis. *Strategic Organization*, *15*(3), 338–366.

Handley, S. M., and Benton, W. C. (2013). The Influence of Task- and Location-Specific Complexity on the Control and Coordination Costs in Global Outsourcing Relationships. *Journal of Operations Management*, *31*(3), 109–128.

Hart, D. M. (2001). Why Do Some Firms Give? Why Do Some Give a Lot? High-Tech PACs, 1977-1996. *Journal of Politics*, *63*, 1230–1249.

Hillman, A. J., Keim, G. D., and Schuler, D. (2004). Corporate Political Activity: A Review and Research Agenda. *Journal of Management*, *30*(6), 837–857.

InfluenceMap. (2021). *Big Tech and Climate Policy*. https://influencemap.org/report/Big-Tech-and-Climate-Policy-afb476c56f217ea0ab351d79096df04a.

Kim, J.-H. (2008). *Business and Politics Corporate Lobbying Revisited Corporate Lobbying Revisited **.

Kim, Y., Choi, T. Y., Yan, T., and Dooley, K. (2011). Structural Investigation of Supply Networks: A Social Network Analysis Approach. *Journal of Operations Management*, *29*(3), 194–211.

Lenway, S. A., and Rehbein, K. (1991). Leaders, Followers, and Free Riders: An Empirical Test of Variation in Corporate Political Involvement. *Academy of Management Journal*, *34*(4), 893–905.

Leppänen, T., and Liefferink, D. (2022). Agenda-Setting, Policy Formulation, and the EU Institutional Context: The Case of the Just Transition Fund. *European Policy Analysis*, *8*(1), 51–67.

Lu, G., and Shang, G. (2017). Impact of Supply Base Structural Complexity on Financial Performance: Roles of Visible and Not-so-Visible Characteristics. *Journal of Operations Management*, *53–56*(March 2016), 23–44.

Lux, S., Crook, T. R., and Woehr, D. J. (2011). Mixing Business With Politics: A Meta-Analysis of the Antecedents and Outcomes of Corporate Political Activity. *Journal of Management*, *37*(1), 223–247.

Martin, C. J. (1995). Nature or Nurture? Sources of Firm Preference for National Health Reform. *American Political Science Review*, *89*(4), 898–913.

McCarthy, N. (2019). *Oil And Gas Giants Spend Millions Lobbying To Block Climate Change Policies*. Forbes. https://www.forbes.com/sites/niallmccarthy/2019/03/25/oil-and-gas-giants-spend-millions-lobbying-to-block-climate-change-policies-infographic/?sh=6797aac87c4f.

Meckling, J. (2015). Oppose, Support, or Hedge? Distributional Effects, Regulatory Pressure, and Business Strategy in Environmental Politics. *Global Environmental Politics*, *15*(2), 19–37.

Mitchell, N. J., Hansen, W. L., and Jepsen, E. M. (1997). The Determinants of Domestic and Foreign Corporate Political Activity. *Journal of Politics*, *59*(4), 1096–1113.

Ojala, M., and Hallikas, J. (2006). Investment Decision-Making in Supplier Networks: Management of Risk. *International Journal of Production Economics*, *104*(1), 201–213.

Peters, G. F., Romi, A. M., and Sanchez, J. M. (2019). The Influence of Corporate Sustainability Officers on Performance. *Journal of Business Ethics*, *159*(4), 1065–1087.

Pfeffer, J., and Salancik, G. (1978). The External Control of Organizations: A Resource Dependence Perspective. In *Harper & Row*.

RE100. (2022). https://www.there100.org/.

Reichart, E. (2019). *3 Ways Business Must Use Political Influence to Champion Climate Ambition*. World Resources Institute. https://www.wri.org/blog/2019/04/3-ways-business-must-use-political-influence-champion-climate-ambition.

Sadrich, F., and Annavarjulia, M. (2002). Antecedents of Corporate Lobbying Participation and Intensity: A Review of the Literature. *Public Administration Quarterly*, *26*(3/4), 465–502.

Sautner, Z., van Lent, L., Vilkov, G., and Zhang, R. (2022). *Firm-level Climate Change Exposure*.

Schuler, D. A., and Rehbein, K. (1997). The Filtering Role of the Firm in Corporate Political Involvement. *Business & Society*, *36*(2), 116–139.

Schuler, D. A., Rehbein, K., and Cramer, R. D. (2002). Pursuing Strategic Advantage Through Political Means: A Multivariate Approach. *Academy of Management Journal*, *45*(4), 659–672.

Sharma, A., Pathak, S., Borah, S. B., and Adhikary, A. (2020). Is It Too Complex? The Curious Case of Supply Network Complexity and Focal Firm Innovation. *Journal of Operations Management*, *66*(7–8), 839–865.

Skilton, P. F., and Robinson, J. L. (2009). Traceability and Normal Accident Theory: How Does Supply Network Complexity Influence the Traceability of Adverse Events? *Journal of Supply Chain Management*, *45*(3), 40–53.

Söderholm, K., Söderholm, P., Helenius, H., Pettersson, M., Viklund, R., Masloboev, V., Mingaleva, T., and Petrov, V. (2015). Environmental Regulation and Competitiveness in the Mining Industry: Permitting Processes With Special Focus on Finland, Sweden and Russia. *Resources Policy*, *43*, 130–142.

StataCorp. (2019). Xtpoisson. In *Stata 16 Base Reference Manual*. TX: Stata Press.

Tachizawa, E. M., and Wong, C. Y. (2015). The Performance of Green Supply Chain Management Governance Mechanisms: A Supply Network and Complexity Perspective. *Journal of Supply Chain Management*, *51*(3), 18–32.

Taylor, D. F. (1997). The Relationship between Firm Investments in Technological Innovation and Political Action. *Southern Economic Journal*, *63*(4), 888.

Tokar, T., and Swink, M. (2019). Public Policy and Supply Chain Management: Using Shared Foundational Principles to Improve Formulation, Implementation, and Evaluation. *Journal of Supply Chain Management*, *55*(2), 68–79.

Veena Ramani, C. (2020). *Blueprint for Responsible Policy Engagement on Climate Change*. The Harvard Law School Forum on Corporate Governance. https://corpgov.law.harvard.edu/2020/08/03/blueprint-for-responsible-policy-engagement-on-climate-change/.

Wiedmer, R., Rogers, Z. S., Polyviou, M., Mena, C., and Chae, S. (2021). The Dark and Bright Sides of Complexity: A Dual Perspective on Supply Network Resilience. *Journal of Business Logistics*, 1–24.

Wooldridge, J. M. (2010). Econometric Analysis of Cross Section and Panel Data. In *MIT Press*.

Zardkoohi, A. (1985). On the Political Participation of the Firm in the Electoral Process. *Southern Economic Journal*, *51*(3), 804.