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Abstract
This paper examines whether economic links with major corporate customers curb corporate carbon emissions. We show that supplier firms with a concentrated customer base have significantly lower carbon emissions. The baseline results are robust to alternative measures of carbon emissions and customer concentration, and various approaches that mitigate endogeneity concerns due to omitted variables and reverse causality. Moreover, the curbing effect of customer concentration on supplier carbon emissions is more pronounced in firms facing lower customer switching costs, with less (more) supplier (customer) bargaining power, fewer redeployable assets, operating in more carbon-intensive industries, and after the Paris Agreement of 2015. Collectively our evidence suggests that major corporate customers can facilitate the transition to a low-carbon economy through decarbonization along the supply chain.

JEL Classification: G30; G34; M14

Keywords: Customer-supplier relationships; Customer concentration; Carbon emissions

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"Walmart is working with hundreds of their suppliers to reduce carbon emissions and is anticipating cost reductions. IKEA has successfully launched an energy conservation program with its suppliers."

---- *John Maxwell, Global R&C Leader, 2012*

I. Introduction

In recent years, climate change has become an increasingly pressing issue for both policymakers and society as it imposes significant costs on economic activities and social welfare (Hsiang et al., 2017; House, 2021). A fundamental solution to mitigate climate change is the reduction of greenhouse gas (GHG) emissions, especially those of the private sector, a process that is often described as decarbonization. Prior studies have identified several important factors that facilitate or impede the transition to a low-carbon economy, including the structure of a country's financial systems and regulatory policies at the national/regional level, as well as commitment and engagement made by important stakeholders such as banks and institutional investors (De Haas and Popov, 2019; Jouvenot and Krueger, 2021; Azar et al., 2021; Bolton and Kacperczyk, 2021; Kacperczyk and Peydró, 2021; Bartram, Hou, and Kim, 2022).

In this paper, we investigate the role of primary corporate customers in reducing the carbon emissions of their dependent suppliers.[1] Our focus on corporate customers is motivated by a growing literature documenting that the customer-supplier relationship affects various corporate decisions such as capital structure, accounting conservatism, earnings management, cash holdings, innovation, and tax avoidance, etc.[2] Given that major customers play a critical role in shaping corporate policies and are a major determinant of firm value and risk, it is intriguing to investigate whether and how major customers affect supplier firms' carbon emissions. Furthermore, compared

[1] Primary customers are defined as corporate customers that account for at least 10% of suppliers' annual sales.
[2] See, for example, Kale and Shahrur (2007), Banerjee, Dasgupta, and Kim (2008), Hui, Klasa, and Yeung (2012), Raman and Shahrur (2008), Itzkowitz, (2013), Chu, Tian, and Wang (2019), and Cen, Maydew, Zhang, and Zuo (2017). Cen and Dasgupta (2021) provide an excellent review of the literature on economic and financial implications of customer-supplier relationships.

to other stakeholders, corporate customers are uniquely positioned to reduce Scope 3 emissions arising from upstream and downstream activities, which often make up the largest portion of a company's carbon footprint. Further, anecdotal evidence suggests that an increasing number of large firms pledge to cut emissions along the supply chain.[3] However, empirical evidence on whether corporate customers significantly curb carbon emissions of their dependent suppliers is scant in the literature.[4]

Primary corporate customers could be incentivized to engage suppliers on environmental issues for the following reasons[5]: First, major customers typically have better knowledge of the supplier firms' operations and business environments than other stakeholders. They may promote corporate governance structures that make suppliers more responsive to customers and take climate risks seriously.[6] Major customers could push suppliers to reduce carbon emissions to comply with regulations and build their social image. Customers may also threaten to switch to other suppliers that are more carbon efficient, forcing existing suppliers to improve their environmental performance.

Second, as countries around the world commit to carbon neutrality by 2050, many governments have enacted regulations (e.g., carbon taxes or emission trading systems) to curb carbon emissions and to mitigate the potentially catastrophic effect of climate change. Firms with high carbon emissions are particularly vulnerable to a rapid shift away from carbon-intensive

[3] For example, Apple on its website states that it commits to be 100 percent carbon neutral for its supply chain and products by 2030. IKEA offers small-to-medium-sized enterprises in its supply chain support to convert to 100% renewable energy through financing on-site investments and enabling the purchase of renewable electricity. Walmart said it has cut 230 million metric tons of greenhouse gases out of its supply chain in the past three years.

[4] A few exception includes Schiller (2018) and Dai, Liang, and Ng (2021), who find that social responsibility customers promote socially responsible business practices in suppliers. Dai, Duan, Liang, and Ng (2022) show that U.S. corporate customers may outsource carbon emissions to overseas suppliers.

[5] Primary customers are defined as corporate customers that account for at least 10% of supplier's annual sales.

[6] In a similar vein, Azar et al. (2021) find a negative relationship between ownership by large institutional investors and carbon emissions of invested firms.

energy sources and industrial processes, presenting great transition risk (House, 2021). The transition to a low-carbon economy could push major corporate customers into working collaboratively with their suppliers to conserve energy and reduce emissions, giving them a direct stake in how their suppliers source, design, manufacture, and deliver products.

Third, as major customer firms are typically large organizations that are highly visible, they are subject to close regulatory scrutiny and public oversight. The environmental violations of suppliers may have spillover effects on their customers, leading to substantial financial losses and reputational costs.[7] Consequently, customers should have incentives not only to understand how they may be adversely affected by the environmental violations of their suppliers, but also to engage suppliers to adopt environmental-friendly practices.

Employing a sample of 26,786 firm-year observations with 4,052 unique firms, we investigate the relationship between the concentration of a supplier's customer base and its carbon emissions. Following prior studies such as Patatoukas (2012) and Chen, Su, Tian, and Xu (2022a), we measure customer concentration with *CusMax*, which is the fraction of a firm's total sales to its largest major corporate customer, and *CusHHI*, which is a customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales. Using either customer concentration measure, we find that customer concentration significantly curbs suppliers' carbon emissions for all three scopes of greenhouse gas (GHG). These effects are statistically and economically significant. Controlling for a large set of firm characteristics and industry-year fixed effects, we find that a one-standard-deviation increase in *CusMax*, the fraction of a firm's total sales to its largest corporate customer,

[7] For example, Schaeffler Group, a German vehicle parts supplier, faced an estimated economic impact of $43 billion due to the environmental violations of one of its key suppliers in China in 2017 (Sit, 2017). H&M and Zara, two major fashion brands, were criticized for the polluting viscose production of their suppliers located in developing countries in Asia (Hoskins, 2017).

leads to 7.71%, 5.93%, and 5.91% lower Scope 1, 2, and 3 emissions by dependent suppliers, respectively. The baseline results are robust to alternative measures of carbon emissions (e.g., carbon intensities) and alternative customer concentration measures (i.e., the fraction of a supplier's total sales to all major customers; and a major corporate customer indicator). We also find suppliers with a more concentrated customer base are more likely to apply for green patents, suggesting that one way for suppliers to cut emissions is to adopt green technologies in the production process.

The OLS estimates of the relationship between customer concentration and supplier carbon emissions may be biased due to endogeneity issues. Specifically, one may argue that unobservable firm characteristics might determine a firm's customer concentration and carbon emissions simultaneously. For example, firms with a better governance structure may have a more concentrated customer base and adopt environmentally friendly practices. Alternatively, the effect we document could be driven by reverse causality. That is, more carbon efficient suppliers are able to attract larger customers who are environmentally conscious, leading to a more concentrated customer base.

We conduct three tests to mitigate these endogeneity concerns. First, we use the propensity score matching (PSM) approach to identify a matched sample of firm-years without a major customer that are otherwise indistinguishable from those with a major customer. Our diagnostic tests show that our matching procedure removes differences in most observable characteristics other than the difference in the customer concentration. Using the propensity score matched sample, we continue to find a negative effect of customer concentration on supplier carbon emissions.

Second, we employ an instrumental variable approach to address the endogeneity concern due to omitted variables. Following the prior literature (i.e., Campello and Gao, 2017; Chen et al., 2022a), we use M&A intensity and regulatory restrictions in customer industries as two instruments for customer concentration. The rationale of the first instrument is intuitive, as suppliers face higher customer concentration when the number of potential customers decreases significantly following mergers in customer industries. The second instrument is also reasonable, as more stringent industry regulations may introduce entry barriers that benefit incumbents and lead to a small number of sizable firms, increasing customer concentration (Gutiérrez and Philippon, 2017). Our first-stage estimations confirm the relevance of the two instruments. On the other hand, downstream industry M&As and regulations are not likely to affect suppliers' carbon emissions through channels other than the customer-base structure (exclusion restriction). In the second-stage estimations, we continue to find a negative and significant effect of (instrumented) customer concentration on carbon emissions of suppliers, confirming our baseline results.

Third, to mitigate the reverse causality concern, we follow Cen et al. (2017) and Chen et al. (2022a) and use the event study to investigate the impact of newly-established major customer relationships on suppliers' carbon emissions. We find a large and significant reduction in supplier carbon emissions only after the relationship establishment event, and no significant pattern in the years before the event. Overall, all these tests suggest a causal link of customer concentration with carbon emissions of suppliers.

We examine cross-sectional heterogeneity in the effect of customer concentration on corporate carbon emissions, conditional on the characteristics of the customer-supplier relationship, suppliers' and customers' bargaining power, and supplier-specific characteristics. Our first test explores how customers' cost of switching to a different supplier ("customer risk") affects our baseline results. Intuitively, if major customers can switch to different suppliers at a relatively low cost, then suppliers are under great pressure to cut emissions. Following Dhaliwal et al. (2016) and Chen et al. (2022a), we measure customers' costs of switching to other suppliers by the supplier's industry market share. Consistent with our prediction, we find the curbing effect of customer concentration on carbon emissions is more pronounced in suppliers with lower industry market share (i.e., lower customer switching costs). Furthermore, we use government customer concentration as another measure of customer risk. Government customers are typically more stable and maintain longer relationship with suppliers. As a result, government-dependent suppliers face lower risks of customer switching. Consistent with our expectation, we find a negative yet insignificant effect of government customer concentration on supplier carbon emissions.

Our second set of heterogeneity tests explores how the bargaining power of customers and suppliers affect our main results. Following the literature (Fee and Thomas, 2004; Bhattacharyya and Nain, 2011), we use suppliers' industry concentration to proxy for customer bargaining power and suppliers' potential of vertical integration to measure supplier bargaining power. Consistent with our conjectures, we find an attenuated effect of customer concentration on the carbon emissions of suppliers operating in less competitive industries (i.e., lower customer bargaining power) and with greater potential of vertical integration (i.e., greater supplier bargaining power).

Third, we examine how our baseline results vary with the characteristics of suppliers along two dimensions. First, suppliers with high asset redeployability can redeploy their assets for alternative uses after the loss of a major customer and are less likely to be "held up" by major customers. We thus expect the curbing effect of customer concentration on supplier carbon emissions to be weaker when suppliers have more redeployable assets. Second, we conjecture that it is more effective for environmentally conscious customers to target suppliers with higher levels of emissions, as such suppliers have more room to dramatically cut emissions. We find supporting evidence for both predictions.

Finally, we examine how our baseline results vary with changing climate regulatory environment, using the Paris Agreement in 2015 as a quasi-natural experiment of increased climate regulatory environment (Seltzer, Starks, and Zhu, 2022). We find that the negative impact of customer concentration on supplier carbon emissions is more pronounced after the Paris Agreement, supporting the widespread perception of more stringent climate regulations after the Paris Agreement.

Our study primarily contributes to two strands of the literature. First, it adds to the burgeoning literature that identifies factors facilitating or impeding the transition to a low-carbon economy and decarbonization of the business sectors. At a broader level, De Haas and Popov (2019) focus on the structure of a country's financial systems and find that carbon emissions per capita are lower in economies that rely more on equity financing. Jouvenot and Krueger (2021) find that firms in UK reduce emissions after the government mandates publicly listed firms to disclose their GHG emissions in a standardized way in their annual reports. However, some studies show that climate policies without international coordination are not effective in curbing corporate emissions, as firms can relocate or outsource polluting activities to places with less stringent environmental regulations (Bartram, Hou, and Kim, 2022; Dai, Liang, and Ng, 2021). At a micro level, Azar et al. (2021) show that firms with increased ownership by "Big Three" institutional investors subsequently reduce carbon emissions. Bolton and Kacperczyk (2021) show that firms cut carbon emission after making public decarbonization commitments. In contrast, Kacperczyk and Peydró (2021) find limited impacts of bank lending in curbing borrowers' carbon emissions.

These prior studies mostly focus on large firms with high institutional holdings which are subject to close regulatory scrutiny, while they are silent on what may drive carbon emissions of smaller companies. As most dependent suppliers are small or medium sized firms, our study fills the gap by showing the effectiveness of a concentrated customer base on reducing emissions of smaller firms.

Second, we contribute to the growing literature that examines how customer-supplier relationships shape various corporate policies and outcomes. Prior studies show that a firm's customer-base structure is related to its profitability (Patatoukas, 2012), cost of capital (Dhaliwal et al., 2016), financial contracting (Campello and Gao, 2017), capital structure (Kale and Shahrur, 2007), accounting practices (Raman and Shahrur, 2008; Hui et al., 2012), cash holdings (Itzkowitz, 2013), tax strategies (Cen et al., 2017), innovation (Chu et al., 2019), managerial compensation (Chen et al., 2022a), and misconduct (Chen et al., 2022b). Our study adds to this literature by showing that major customers are also instrumental in reducing carbon emissions along the supply chain, which is conducive to achieve global climate goals.

The rest of the paper proceeds as follows. Section 2 describes the data, variable constructions, and empirical methodology. Section 3 discusses the baseline results and robustness tests. Section 4 addresses potential endogeneity issues. Section 5 explores the cross-sectional heterogeneity in the relationship between customer concentration and supplier carbon emissions. Section 6 concludes.

2. Data and Methodology

2.1. Data and the sample

We begin with the customer-supplier data from Compustat North America's Segment Customer files to construct the corporate customer concentration measures. We use fuzzy name matching to identify the potential matched customer firms in Compustat annual files and manually review the matches to remove false positives. For the matched firms, we then collect their suppliers' identification information and the purchase from each supplier over time, based on which we construct measures of corporate customer concentration.

We then obtain firm-level carbon emissions data from the S&P Global Trucost database.[8] Trucost follows the Greenhouse Gas Protocol and classifies firms' carbon emissions into three categories. Scope 1 emissions are directly generated by burning fossil fuels and production processes owned or controlled by a firm. Scope 2 covers indirect emissions produced by a firm's consumption of purchased electricity, heat, or steam. Scope 3 emissions, which are estimated using an input-output model, include indirect emissions produced by the extraction and production of purchased materials and fuels, electricity-related activities not covered in Scope 2, outsourced activities, waste disposal, etc. Trucost provides firm-level annual carbon emissions, measured in tons of CO_2 equivalent, for each category. We merge the customer concentration dataset with the carbon emissions data from S&P Global Trucost database over the period 2002–2019.

In addition, we obtain firm-level financial data from Compustat, stock price information from the Center for Research in Security Prices (CRSP). All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the potential impact of outliers. The observations with missing values are dropped for the variables in the regressions. After combining all the above

[8] Trucost collects firm-level emissions data from various sources including company reports, environmental reports (CSR/ESG reports, the Carbon Disclosure Project, Environmental Protection Agency filings), and data from company websites. If a firm does not disclose emissions data, Trucost uses an input-output model to estimate the firm's carbon emissions.

databases and deleting the observations with missing values, we obtain a final sample of 26,786 firm-year observations with 4,052 unique firms over the sample period of 2002–2019.

2.2 Variable construction

2.2.1 Carbon emissions measures

The literature generally uses two alternative measures of carbon emissions, namely, carbon intensity and levels of carbon emissions. Following Bolton and Kacperczyk (2021) and Azar et al. (2021), we construct firm-level carbon emissions as the natural logarithm of one plus Scope 1, 2, and 3 carbon emission levels (*LnScope1, LnScope2, and LnScope3*). As Bolton and Kacperczyk (2021) point out, while carbon intensity measures are indicative of a firm's carbon footprint improvement, the firm's level of carbon emissions are ultimately what matters for global warming.[9] Nevertheless, we also confirm that our results are robust to using carbon intensity measures of carbon emissions.

2.2.2. Customer concentration measures

We employ Compustat North America Segment Customer database to construct measures of firms' major customer concentration. SFAS No. 14 (before 1997) and FAS No. 131 (after 1997) require firms to report all customers that account for at least 10% of total firm revenues. The Segment Customer database includes both the types and names of major customers. In addition, the database provides the dollar amount of annual revenues from each major customer. Following prior studies (e.g., Cen et al., 2017; Dhaliwal et al., 2016; Chen et al., 2022a), we exclude customers that account for less than 10% of revenues even if the supplier firm voluntarily reports them. On one hand, the presence of non-major customers could be endogenously determined since

[9] For example, from the "Net Zero" perspective, a large firm with 1 million tons of CO_2 is as harmful to the environment as a smaller firm with the same amount of CO_2. Moreover, a scaled measure of carbon intensity is subject to a firm's discretion in choosing an appropriate denominator variable.

suppliers voluntarily report these customers after evaluating the benefits and costs of disclosure. On the other hand, only the loss of major customers has a materially adverse effect on the supplier. In addition, major customers are more likely large and highly visible corporations that are under greater pressure to reduce carbon emissions. Thus, we adhere to the objective 10% cutoff.

We construct two major measures of customer concentration to test the relationship between customer concentration and suppliers' carbon emissions following Chen et al. (2022a) and Patatoukas (2012). Our first measure (*CusMax*) is the highest percentage of sales to a major corporate customer. Our second measure (*CusHHI*) is based on a Herfindahl- Hirschman Index of sales to major corporate customers. Specifically, we compute *CusHHI* in year *t* across supplier *i*'s *J* major customers as:

$$CusHHI_{it} = \sum_{j=1}^{J} \left(\frac{Sales_{ijt}}{Sales_{it}}\right)^2 \tag{1}$$

where $Sales_{ijt}$ is supplier *i*'s sales to major customer *j* in year *t* and $Sales_{it}$ is supplier *i*'s total sales in year *t*. The higher the value of *CusHHI*, the more concentrated the supplier's customer base. The range of this variable is between 0 and 1.

2.2.3 Control variables

Following the literature (e.g., Bolton and Kacperczyk, 2021; Azar et al., 2021), we include a set of firm characteristics that are related to carbon emissions as control variables. More specifically, we include the logarithm of total assets (*Size*) to control for the scale of the firm's business activity and for potential public pressure over its environmental impact. *Tobin's Q* is measured by total assets plus market value of equity minus book value of equity, divided by total assets. We include this variable to control for the firm's growth opportunities. *Leverage* is computed as the sum of long-term debt and current liabilities divided by total assets. *Cash* is measured as the ratio of cash holdings to total assets. We include these two variables to control for the effect of credit constraints and liquidity on the financing of environmentally beneficial investments. We also include the annual stock return over the past year (*Ret*), which captures the firm's past performance. R&D intensity is measured as the ratio of R&D expenditures to total assets (*R&DIntensity*), and capital expenditures is measured by the ratio of capital expenditures to total assets (*Capx)*. These two variables capture the firm's investment activities. Azar et al. (2021) document that institutional shareholders may pressure their portfolio firms to curb carbon emissions, so we include institutional ownership as a control variable in our regression models. Institutional ownership (*IO*) is measured as the proportion of a firm's outstanding shares owned by institutional investors from the 13F filings.

2.3 Descriptive statistics

Table 1 reports the summary statistics of the variables used in the baseline analysis. For the whole sample, the average values of *CusMax* and *CusHHI* are respectively 3.3% and 1.2%; for firms with at least one major customer with sales greater than 10%, the average values of *CusMax* and *CusHHI* are 22.3% and 8.2%, respectively. The average supplier in our sample produces about 2.54 million tons of Scope 1 emissions, 0.38 million tons of Scope 2 emissions, and 2.01 million tons of Scope 3 emissions. We take the natural log of carbon emissions as emissions have right-skewed distribution, and report the summary statistics of these variables in Table 1. An average supplier firm in our sample has total assets of $31.4 million, indicating that suppliers are usually smaller firms compared to customers. These firms have an average leverage of 26% and *Tobin's Q* of 1.92. The average liquidity ratio (cash-to-assets) of suppliers is 14.9% and the average annual stock return is 11.2%. Our sample of suppliers has an average R&D intensity of 3% and capital expenditure ratio of 4.3%. The suppliers in our sample have an average institutional ownership of 70.7%.

[Insert Table 1 here]

2.4 *Empirical specification*

We investigate the relationship between customer concentration and suppliers' carbon emissions at the supplier-year level by estimating the following regression model:

$$Carbon\ Emissions_{i,t} = \alpha + \beta_1 \times Customer\ Concentration_{i,t} + \beta_2 \times Control_{i,t} + Industry \times Year\ FE + \epsilon_{i,t} \quad (2)$$

where *Carbon Emissions* measures the level of suppliers' carbon emissions as discussed in section 2.2.1, including Scopes 1, 2, and 3 carbon emissions (*LnScope1, LnScope2, and LnScope3*). *Customer Concentration* is our main independent variable of interest, including *CusMax* and *CusHHI* as discussed in section 2.2.2. *Controls* include a list of firm characteristics that may affect carbon emissions, including firm size (*Size*), leverage (*Leverage*), Tobin's Q (*Tobin's Q*), stock return (*Ret*), R&D intensity (*R&Dintensity*), capital expenditures (*Capx*), cash ratio (*Cash*), and Institutional ownership (*IO*) discussed in section 2.2.3. We insert *Industry × Year FE*, the industry-year interaction fixed effects, to mitigate concerns about omitted variables that are correlated with a firm's customer concentration and varying within industries and years.[10] Following prior studies (e.g., Dhaliwal et al., 2016; Campello and Gao, 2017; and Cen et al., 2017; Chen et al., 2022a), we do not include firm fixed effects in our regressions, as there is limited within-firm variation in the customer concentration variables. We address potential endogeneity issues in Section 4 of the paper.

[10] Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes.

3. Customer concentration and supplier carbon emissions

3.1 Baseline results

To test whether customer concentration affects suppliers' carbon emissions, we estimate model (4) and present the results in Table 2. We employ *CusMax*, the highest percentage of sales to major corporate customers, and *CusHHI*, the customer sales-based Herfindahl-Hirschman Index, as the two main proxies of customer concentration. The dependent variables are *LnScope1*, *LnScope2*, and *LnScope3*, which proxy for firm-level Scope 1, 2, and 3 carbon emissions, respectively. Columns (1) – (3) show that coefficients on *CusMax* are all negative and significant at the 5% level or better for *LnScope1*, *LnScope2*, and *LnScope3*. The results of using *CusHHI* as the other main measure of customer concentration are qualitatively similar, as shown in Columns (4) – (6). The results indicate that suppliers with higher customer concentration have lower Scope 1, 2, and 3 carbon emissions. In terms of economic magnitude, suppliers' Scope 1, 2, and 3 carbon emissions decline by 7.71%, 5.93%, and 5.91%, respectively, with one-standard-deviation increase in *CusMax*, the fraction of a firm's total sales to its largest corporate customer.[11] For an average firm, this translates to a decrease in Scope 1 emissions of about 195 thousand tons (2.54 million ×7.71%) of CO_2. Suppliers' Scope 1, 2, and 3 carbon emissions decline by 7.59%, 5.76%, and 6.09%, respectively, with one-standard-deviation increase in customer concentration measure *CusHHI*.

Regarding control variables, Table 2 shows that firm size is positively associated with the level of carbon emissions, consistent with the notion that large firms may emit more CO_2. In

[11] The coefficient on *CusMax* in Column (1) of Table 2 is -0.816 and the standard deviation of *CusMax* is 0.091, so the economic magnitude is calculated as (exp(0.816×0.091) - 1)×100 = 7.71% decrease in carbon emissions. The other numbers are calculated similarly.

addition, firms with higher leverage and greater institutional ownership are associated with higher carbon emissions. On the other hand, firms with higher R&D intensity have lower carbon emissions, possibly because firms with advanced technology are more energy efficient. We also observe that firms with poorer past stock performance are associated with higher carbon emissions. In addition, the coefficients on *leverage* are positively significant while those on *Cash* are negatively significant, suggesting that firms with less debt and more liquid assets have lower carbon emissions.

[Insert Table 2 here]

3.2 Robustness checks

To check the validity of the baseline results, we conduct several robustness tests including using alternative measures of carbon emissions and alternative measures of customer concentration. We also provide suggestive evidence to the channel through which firms cut emissions.

3.2.1 Alternative measures of carbon emissions

We construct carbon intensity measures as alternative proxies for carbon emissions, which are defined as the firm-level Scope 1, 2, and 3 carbon emissions divided by total revenues of the firm. We then take the natural logarithm of one plus the carbon intensity measures (*LnInt1, LnInt2, and LnInt3*) as dependent variables. The carbon intensity measures capture firms' emissions per unit of sales, hence are more comparable across firms with different size. We re-estimate model (4) and present the results in Table 3. The coefficients on both *CusMax* and *CusHHI* are still negative and statistically significant for all three carbon intensity measures *LnInt1, LnInt2, and LnInt3*. Our results suggest that suppliers facing major customers' pressure not only reduce the level of CO_2, but also become more efficient with respect to CO_2 emission in the production process.

[Insert Table 3 here]

3.2.2 Alternative measures of customer concentration

Following Chen et al. (2022a), we construct *Frac* and *Major* as two alternative measures of customer concentration. Specifically, *Frac* is the fraction of a supplier's total sales to all major customers that account for at least 10% of its total sales. *Major* is an indicator variable equal to one if a supplier has at least one major corporate customer that accounts for at least 10% of its total sales, and zero otherwise. We re-estimate model (4) and report the results in Table 4. In Columns (1) – (3), the coefficients on *Frac* are negative and significant at the 5% level or better for all three scopes of carbon emissions. The results indicate that the fraction of sales to major customers is negatively associated with suppliers' carbon emissions, supporting our hypothesis that major customers may pressure suppliers to curb carbon emissions. The results using *Major* as an alternative measure of customer concentration are qualitatively similar. In Columns (4) – (6), the coefficients on *Major* are negative and statistically significant for *LnScope1* and *LnScope2*, while insignificant for *LnScope3*.

[Insert Table 4 here]

We use customer concentration measures (*CusMax* and *CusHHI*) measured in the same year as the carbon emissions in the baseline regressions. In Table IA.1 of the Internet Appendix, we repeat the baseline analysis of Table 2 but use lagged measures of customer concentration in the regressions. The negative relationship between customer concentration and carbon emissions remains highly significant and the coefficient estimates are often larger than those in Table 2.

3.2.3 Customer concentration and supplier firm performance

The baseline results raise the question of why a more concentrated customer base is needed to curb suppliers' carbon emissions. One reason could be that emission reduction is costly for the suppliers (at least in the short run), and they may resist such changes in the absence of pressure from major customers. To assess this possibility, we test whether emission reduction leads to poorer operating performance of the suppliers, especially when they have a more concentrated customer base. The dependent variables in this test are two proxies of firm operating performance: return on assets (*ROA)* and asset turnover ratio (*Sales/Assets*). The key independent variable of interest is the interaction between customer concentration measures and the log changes in total carbon emissions of all three scopes (*Chg_Carbon*). Results are shown in Table IA.2 of the Internet Appendix. First, we notice that the coefficients on *CusMax* and *CusHHI* are positive across all specifications and statistically significant when operating performance is measured by *ROA.* The positive association between customer concentration and supplier firm performance is consistent with Patatoukas (2012). More importantly, we find the interactions between customer concentration and log changes in supplier emissions (*CusMax×Chg_Carbon* and *CusHHI×Chg_Carbon*) are positive and significant across all columns. The results support our conjecture that when suppliers are pressured by major customers to cut carbon emissions, they bear the costs of poorer operating performance in the short run. This could explain why major customers are more effective in curbing suppliers' carbon emissions.

3.3 Additional test: customer concentration and green patents

One way for firms to cut emissions is to switch to more carbon-efficient production technologies. Although we do not directly observe the type of technologies firms use in their production process, we can examine whether suppliers with more concentrated customer base are more likely to adopt green technologies using patent data. To that end, we obtain the application of green patents data from OrbisIP database and run a linear probability model of the impact of customer concentration on the suppliers' filing of green patents. The identification of green patents follows the guidelines of OECD using IPC and CPC class (Hascic and Migotto, 2015; Cohen, Gurun, and Nguyen, 2020). According to the classification, patents related to environmental technologies are classified into various broad environmental technology categories.[12] The dependent variable in the regression is *Green Patents*, which is an indicator variable equal to one if the supplier firm files an application for green patent(s) in a given year, and zero otherwise. We use the same set of control variables as in Table 2 and include *Industry* × *Year* fixed effects. Table IA.3 in the Internet Appendix shows that coefficients on both *CusMax* and *CusHHI* are positive and significant at the 10% level. The results lend support to our conjecture that suppliers, facing pressure from major customers, may reduce carbon emissions through adopting green technologies in their production process.

4. Addressing endogeneity concerns

While the results so far are robust and consistent with our hypothesis, the documented relationship between customer concentration and supplier carbon emissions may be subject to endogeneity concerns. For example, some unobservable firm characteristics could affect both the concentration of the supplier's customer base and its carbon emissions ("omitted variable" bias). Alternatively, the negative relationship between customer concentration and carbon emission may be subject to reverse causality. That is, suppliers with lower carbon emissions may attract big

[12] Hascic and Migotto (2015) provide detailed explanations of OCED classification and identification for green patents.

customers more easily, leading to higher customer concentration. In this section, we employ three approaches, including propensity score matching, instrumental variable approach, and the establishment of customer-supplier relationship, to address the above endogeneity concerns.

4.1 Propensity score matching (PSM) approach

The structure of a supplier's customer base is likely endogenous to its characteristics. The decision to establish and maintain customer-supplier relationship is to some extent determined by the customer, who in turn selects suppliers based on their observable characteristics such as size, technology, and profitability, etc. To alleviate this endogeneity concern, the ideal experiment to study the effect of a major customer on the supplier's carbon emission would be to compare the carbon emissions of a supplier with major customers and the same firm without major customers. But since the counterfactual cannot be observed, the best we are able to obtain is the otherwise identical observation. We employ a PSM approach whereby firm-year observations with a major customer are matched with those without a major customer. We proceed in two steps to identify a matched sample of firm-years without a major customer that exhibit no significant differences in other observable characteristics with those with a major customer. We first estimate the probability that a firm has at least one major corporate customer by running a logit regression, with control variables including firm size (*Size*), leverage (*Leverage*), cash holdings (*Cash*), Tobin's Q (*Tobin's Q*), capital expenditures (*Capx*), R&D intensity (*R&DIntensity*), stock return (*Ret*), profitability (*ROA*), and institutional ownership (*IO*). We report the results in Column (1) of Panel A of Table 5. Consistent with Campello and Gao (2017), the results show that, on average, customer-dependent suppliers are smaller, have less growth opportunity, are highly leveraged, have more cash, and have better operating performance, higher institutional ownership, and greater R&D intensity. In the second step, we construct the matched sample using the nearest-neighbor method based on the propensity scores calculated from the first-step logit model. Specifically, each firm-year observation with a major customer (the treatment group) is matched with the firm-year observation without a major customer (the control group) using the nearest neighbor matching method (i.e., the closest propensity score).

After the matching procedure, observations in the treatment and control groups are sufficiently indistinguishable. We conduct two diagnostic tests to verify that firms in the treatment and control groups are truly comparable. We first re-estimate the logit model for the post-match sample. The results are shown in Column (2) of Panel A of Table 5. None of the coefficient estimates is statistically significant, suggesting that firm characteristics are indistinguishable between the two groups. Importantly, the coefficient estimates in Column (2) are much smaller in magnitude than those in Column (1), suggesting that the insignificant results in Column (2) are not simply due to insufficient power with fewer observations. We also compare the differences in firm characteristics used in the logit model between the treated and control groups. We present the results in Panel B of Table 5 and find that none of the differences in observable characteristics between the two groups is statistically significant. Overall, the diagnostic test results suggest that our matching procedure successfully removes almost all the observable differences other than the difference in the concentration of the firm's customer base.

Since our matched sample includes firms with the only main difference that of their customer concentration, it is likely that any difference in carbon emissions between the treated and matched control samples is attributable to a difference in customer concentration. We re-estimate the baseline regression model (2) using the PSM sample and present the results in Panel C of Table 5. The results show that the coefficients on both customer concentration measures, *CusMax* and

CusHHI, are still negative and significant at the 5% level or better, consistent with our baseline findings in Table 2.

[Insert Table 5 here]

4.2 Instrumental variable approach

The PSM approach removes differences in observable firm characteristics in driving the baseline results. However, it is possible that some unobservable or omitted characteristics may affect both a supplier's customer concentration and its carbon emissions. To address this issue, we exploit instrumental variable approach and employ a two-stage least squares (2SLS) framework to estimate the models. Existing studies have shown that mergers of customers with other firms in the same industry leads to stronger combined buyer positions and in turn to a higher customer concentration (e.g., Fee and Thomas, 2004; Bhattacharyya and Nain, 2011). Following Campello and Gao (2017), we use customer industry merger and acquisition (M&A) as the first instrument *(CusM&A)* that exploits the variation in the M&A intensity in customers' industries that could drive changes in customer concentration. Campello and Gao (2017) find that the sales of a supplier to acquirer customers increase rapidly following downstream mergers, with 30% growth in the same year of the merger and 80% growth in the two years after the merger. Therefore, we expect the M&A intensity in customer industries to increase suppliers' customer concentration (instrument relevance). Meanwhile, it is unlikely that downstream M&A activities would affect the supplier firm's carbon emissions other than through the customer concentration channel (exclusion restriction).

We first obtain the firm-level annual costs of M&A activities from Compustat (Item AQC) and compute the average M&A intensity of an industry (two-digit SIC) over the past five years, where industry M&A intensity is computed as the aggregate M&A costs divided by the aggregate sales across all firms within that industry in a given year. For supplier *i* in year *t*, its customer industry M&A ($CusM\&A_{it}$) is the weighted sum of the five-year M&A intensity across the industries to which the firm's major customers belong, weighted by the supplier's percentage sales to each customer:

$$CusM\&A_{it} = \sum_{j=1}^{J} \%Sales_{ijt} \times Industry\ five\ year\ average\left(\frac{M\&A\ costs}{Sales}\right)_{jt} \tag{3}$$

Following Gutiérrez and Philippon (2017) and Chen et al. (2022a), we further employ customer regulation index (*CusReg*) as the second instrument, which exploits plausibly exogenous variation in regulatory restrictions of customers' industries. The rising regulatory stringency introduces barriers that limit entry by actual and potential rivals, which are advantageous to incumbent firms and may ultimately shift market power towards a small number of sizable firms, increasing the concentration of the customer base (Gutiérrez and Philippon, 2017). We thus expect a positive relationship between regulatory restrictions of an industry and customer concentration (instrument relevance). However, the differences in the level of regulation across customers' industries are unlikely directly linked to the supplier firms' carbon emissions (exclusion restriction). The inclusion of supplier industry-year fixed effects in our tests further excludes the possibility that our results are driven by government regulations that could simultaneously affect both the supplier and customer industries.

To construct the second instrument, we obtain the industry-specific regulation data from the RegData database compiled by McLaughlin and Sherouse (2018). The RegData covers all US federal regulations issued by various regulatory agencies. The dataset has two dimensions of regulatory quality: *Restrictiveness*, meaning the occurrence of words/phrases indicating binding constraints in the regulatory text, and *Relevance*, meaning the applicability of each regulation to a specific industry. We construct the industry regulation index for each industry-year as the weighted sum of the number of legally binding words contained in regulatory text across all regulations, weighted by the relevance of each regulation to that industry, by combining the restrictiveness and relevance proxies. For each supplier *i* in year *t*, its customer regulation index ($CusReg_{it}$) is the weighted sum of the industry regulation index across all industries to which the firm's major customers belong, weighted by the supplier's percentage sales to each customer:

$$CusReg_{it} = \sum_{j=1}^{J} \%Sales_{ijt} \times Industry\ Regulation\ Index_{jt} \tag{4}$$

We then estimate the models in a two-stage least squares (2SLS) framework, with the first stage examining how each of the two instruments, *CumM&A* and *CusReg*, affects *CusMax* and *CusHHI*, using the same set of controls as in Model (2). In the second stage, we use the predicted values of instrumented *CusMax* and *CusHHI* ($\widehat{CusMax}$ and $\widehat{CusHHI}$) in the baseline regression of model (2). Results are shown in Table 6. The first-stage results in Panel A show that both *CumM&A* and *CusReg* positively and significantly affect customer concentration *CusMax* and *CusHHI*. In particular, the coefficient estimates on the instruments across all specifications are significant at the 1% level. The reported *F*-statistics are also large for all six regressions, suggesting none of our instruments is weak. The second-stage results, shown in Panel B, indicate that the coefficients on the instrumented *CusMax* and *CusHHI* ($\widehat{CusMax}$ and $\widehat{CusHHI}$) are negative and statistically significant at the 5% level or better for all three scopes of supplier carbon emissions. The results from the instrumental variable approach further support that our baseline findings are not due to unobservable or omitted variables that might affect both customer concentration and supplier carbon emissions.

[Insert Table 6 here]

4.3 Addressing reverse causality

Our results so far support a causal interpretation of customer concentration on supplier carbon emissions. However, one concern is that the relationship could be driven by reverse causality, that is, that suppliers' environmental performance influences their major customers' product market strategy. Although ex-ante this is unlikely a major concern for our setting, we use two approaches to address the potential reverse causality issue.

First, we follow Cen et al. (2017) and Chen et al. (2022a) by using the event study approach to investigate the effect of relationship establishment events on suppliers' carbon emissions. A trend of decreasing carbon emissions before the event would suggest the presence of reverse causality, and vice versa. We construct the following indicators. *Before* is an indicator that equals one if the year is one (t-1) or two (t-2) years before the establishment year (t), and zero otherwise. *Establish* is an indicator that equals one if the year is the establishment year (t), and zero otherwise. *After* is an indicator that equals one if the year is one (t+1) or two (t+2) years after the establishment year (t), and zero otherwise. Relationship establishment is defined as when a firm reports a principal customer in year t for the first time and the relationship lasts for at least three years (i.e., years t, $t + 1$, and $t + 2$).[13] We include *Before*, *Establish*, and *After*, as well as each of their interactions with customer concentration measures *CusMax* and *CusHHI* in Model (2), and report the results in Table 7. We find that none of the interaction terms of *Before* and customer concentration measures, *Before*×*CusMax* and *Before*×*CusHHI*, is significant, suggesting that reduction of carbon emissions does not occur before the establishment of customer-supplier relationship. In contrast, we find that the coefficients on the interaction terms of *Establish* and customer concentration measures, namely *Establish*×*CusMax* and *Establish*×*CusHHI*, are

[13] As mentioned by Cen et al. (2017) and Chen et al. (2022a), one caveat for this test is that the "new" relationship establishment defined here is not necessarily "new". The supplier could start to disclose a particular customer, or a customer could become a major customer as the customer just crosses the 10% disclosure requirement threshold.

negative and significant in all models except in Model (5) where the coefficient is negative yet insignificant. Furthermore, the interaction terms of *After* and customer concentration measures, *After*×*CusMax* and *After*×*CusHHI*, are all negative and significant at the 5% level or better, suggesting that suppliers start to cut emissions only after forming important relationships with major customers.

Second, we restrict our sample to a subset of firm-year observations for which the reverse causality issue is less severe. Specifically, large suppliers are more likely to have the market power to actively influence customers' product markets and hence are subject to greater concern of reverse causality. To rule out such reverse causality, we re-examine the impacts of customer concentration on supplier carbon emissions after excluding the top 5% suppliers in terms of sales and report the results in Table IA.4 of the Internet Appendix. We find that the coefficients on customer concentration measures continue to be negative and significant, with similar economic magnitude in all specifications. Overall, both tests suggest that the negative relationship between customer concentration and supplier carbon emissions is not likely to be driven by reverse causation.

[Insert Table 7 here]

5. Cross-sectional heterogeneity

In this section, we conduct several cross-sectional heterogeneity tests based on the characteristics of customer-supplier relationships, the bargaining power of customers and suppliers, and supplier-specific characteristics. Using the 2015 Paris Agreement as a shock to climate regulation, we also examine whether the impact of customer concentration on supplier carbon emission varies with increased climate regulatory risks.

5.1 Customers' costs of switching suppliers

If major customers can switch to other suppliers at a relatively low cost, then suppliers face high customer risks and are under greater pressure to cut emissions to satisfy their environmentally conscious customers. Following Dhaliwal et al. (2016) and Chen et al. (2022a), we measure customers' switching costs by the supplier's market share, measured as the fraction of a firm's sales relative to the total sales of all firms in the same industry. Lower market share implies lower switching costs as there are many suppliers that customers can purchase from. We construct a *LowMshare* indicator, which equals one if the firm's market share is below the sample median in a year and zero otherwise. We then interact customer concentration measures *CusMax* and *CusHHI* with *LowMshare*. Results are reported in Panel A of Table 8. We find the interaction terms *CusMax×LowMshare* and *CusHHI×LowMshare* are negative and significant at the 5% level or better in all specifications. In contrast, the coefficients of *CusMax* and *CusHHI* become insignificant in the regressions. The results are consistent with our conjecture that suppliers have stronger incentive to cut emissions when their major customers face lower costs of switching suppliers.

Some suppliers have government customers, which are typically more stable and maintain longer relationship with suppliers. As such, government customers constitute a more stable source of revenue for suppliers and are also less likely to switch to other suppliers. We therefore expect the effect of customer concentration on supplier carbon emissions to be attenuated in firms with a concentrated base of government customers. To test this conjecture, we use the same approach to construct *GovMax* and *GovHHI* as two measures of government customer concentration. More specifically, *GovMax* is the highest percentage of sales to major government customers, and *GovHHI* is the sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major government customer sales to the supplier's total sales. We then include *GovMax* and *GovHHI* as the two government customer concentration measures in model (2), and report the results in Panel B of Table 8. We find that the coefficients on both *GovMax* and *GovHHI* are negative yet statistically insignificant. On the other hand, the coefficients on both *CusMax* and *CusHHI* remain negative and significant. The magnitude of the coefficient estimates on both *GovMax* and *GovHHI* is much smaller compared to those of corporate customer concentration measures. The insignificant effect of government customer concentration on supplier carbon emissions is due to the lower risk of losing government customers, which tend to be more stable and maintain longer relationships with suppliers.

[Insert Table 8 here]

5.2 Bargaining power of customers and suppliers

We expect customer concentration to have a more (less) pronounced effect on the carbon emissions of suppliers facing greater customer (supplier) bargaining power. Customers may enjoy greater bargaining power when suppliers operate in more competitive industries. To proxy for supplier industry competition, we construct a sales-based Herfindahl-Hirschman Index (HHI index), which is measured as the sum of squared market shares in sales of all firms in each of the Fama-French 48 industries. Higher HHI index in supplier's industry indicates less competition and lower bargaining power of customers. We define an indicator *SupHHI* that equals one if the supplier industry's HHI index is at or above the sample median in a year, and zero otherwise. We then interact customer concentration measures *CusMax* and *CusHHI* with *SupHHI* and re-estimate model (2). Results are reported in Panel A of Table 9. Consistent with our expectation, we find the coefficients on the interaction terms *CusMax*× *SupHHI and CusHHI*× *SupHHI* are positive and significant at the 5% level or better, suggesting that lower customer bargaining power (i.e., higher supplier industry concentration) significantly weakens the impact of customer concentration on supplier carbon emissions. On the other hand, the coefficient estimates of the standalone customer concentration measures remain negative and highly significant.

Vertical integration acts as a substitute for close customer-supplier relationship (Coase, 1937; Williamson, 1979). We predict that supplier firms with higher potential of vertical integration may have greater bargaining power. To proxy for the potential of vertical integration, we employ the firm-pair vertical relatedness measure constructed by Frésard, Hoberg, and Phillips (2020), which is obtained by linking product vocabularies from input-output tables of the Bureau of Economic Analysis (BEA) to firms' product descriptions in their 10-K report filed with the Securities and Exchange Commission (SEC). We construct a vertical integration indicator *VertIng*, which equals one if a supplier's vertical integration potential is in the top quartile of the sample in a year, and zero otherwise. We then interact customer concentration measures *CusMax* and *CusHHI* with *VertIng* and re-estimate model (2). Results are reported in Panel B of Table 9. The coefficients on the interaction terms *CusMax*× *VertIng* and *CusHHI*× *VertIng* are positive and significant at the 5% level or better, suggesting that stronger supplier bargaining power (i.e., higher potential of vertical acquisitions) significantly undermines the impact of customer concentration on supplier carbon emissions. In contrast, the coefficient estimates of the standalone customer concentration measures remain negative and highly significant. Collectively, these results support the notion that the impact of customer concentration on supplier carbon emissions strengthens with higher (lower) bargaining power of customers (suppliers).

[Insert Table 9 here]

5.3 Suppliers' asset redeployability

We next examine whether the asset redeployability of suppliers influences the effect of customer concentration on carbon emissions. Suppliers with high asset redeployability can redeploy their assets for alternative uses after the loss of a major customer and are less likely to be "held up" and subject to ex-post opportunistic behaviors by customers. Thus, to the extent that suppliers' asset redeployability mitigates customer concentration risk, we conjecture that the negative impacts of customer concentration on supplier carbon emissions should be attenuated when suppliers have more redeployable assets. To proxy for asset redeployability, we employ the firm-level asset redeployability measure constructed by Kim and Kung (2017), which is the value weighted average of industry-level redeployability indices across business segments in which the firm operates. We construct a dummy *Redeploy* that equals one if the supplier firm's asset redeployability is at or above the sample median in a year, and zero otherwise. We then interact customer concentration measures *CusMax* and *CusHHI* with *Redeploy* and re-estimate model (2). Results are reported in Table 10. The coefficients on the interaction terms *CusMax* × *Redeploy* and *CusHHI* × *Redeploy* are positive and significant, suggesting that higher asset redeployability significantly weakens the impact of customer concentration on supplier carbon emissions.

[Insert Table 10 here]

5.4 Carbon intensity of suppliers' industries

A major customer in our sample on average has about 20 dependent suppliers. For customers who are considering decarbonizing their supply chain, it is more effective to target those suppliers with higher prior emissions, as such suppliers have more room to dramatically cut emissions. We thus examine whether the effects of customer concentration on carbon emissions get stronger for suppliers in carbon-intensive industries. We calculate the average CO_2 emission in each of the

Fama-French 12 industries and identify carbon-intensive industries as those with total Scope 1, 2, and 3 emissions above the sample median in each year. Based on this classification, Utilities, Chemicals, Consumer, Manufacturing, Oil, Gas and Coal industries are classified as carbon-intensive industries. We create an indicator *HighCI* that equals one if the supplier firm operates in a carbon-intensive industry, and zero otherwise.[14] We then interact customer concentration measures *CusMax* and *CusHHI* with *HighCI* and report the results in Table 11. We find the coefficients on the interaction terms $CusMax \times HighCI$ and $CusHHI \times HighCI$ are negative and significant at the 1% level in all regression models, consistent with our intuition that major customers focus their decarbonization effort on suppliers from highly polluting industries.

[Insert Table 11 here]

5.5 Paris Agreement of 2015 as a Shock to Climate Regulatory Environment

One important reason that customer firms would want to curb carbon emissions along the supply chain is to comply with stringent regulations, which adversely affect the performance of carbon-intensive firms. The Paris Agreement was adopted by 196 Parties at COP 21 in Paris, on December 12, 2015 and entered into force on November 4, 2016, as a legally binding international treaty to combat climate change.[15] Seltzer, Starks, and Zhu (2022) argue that when the Paris Agreement was announced, a natural implication that firm managers could draw was that governments would tighten their environmental regulations to mitigate the catastrophes related to climate change.

[14] The *HighCI* indicator is subsumed by the $Industry \times Year$ fixed effects.

[15] The goal of the Paris Agreement is to limit global warming to well below 2 °C, preferably to 1.5 °C, compared to pre-industrial levels. Countries also aim to reach global peaking of greenhouse gas emissions as soon as possible and achieve carbon neutrality by 2050.

We thus exploit the Paris Agreement in 2015 as a quasi-natural experiment of increased climate regulatory environment, and expect the curbing effect of customer concentration on supplier carbon emissions to be more pronounced after the Paris Agreement. To test this conjecture, we create an indicator *Paris* that equals one for years after 2015, and zero otherwise. We then interact customer concentration measures *CusMax* and *CusHHI* with *Paris* and re-estimate model (2). Our sample for this test is restricted to the period from 2014 to 2016, a year before and a year after the Paris Agreement.[16] Results are reported in Table 12. The coefficients on *Paris* are significantly negative in all specifications, suggesting a reduction of carbon emissions after the Paris Agreement across firms. More importantly, the coefficient estimates on the interaction terms *CusMax*×*Paris* and *CusHHI*×*Paris* are negative and statistically significant in 5 out of 6 cases. These results are consistent with the view that major customers put greater pressure on their suppliers in reducing carbon emissions when the perception of the climate regulatory environment becomes more stringent.

[Insert Table 12 here]

6. Conclusion

This paper examines whether economic links with major corporate customers curb supplier carbon emissions. We show that supplier firms with a more concentrated customer base have significantly lower carbon emissions. The baseline results are robust to alternative measures of carbon emissions and customer concentration, and to various approaches that mitigate endogeneity concerns due to omitted variables and reverse causality. Moreover, the curbing effect

[16] Since we estimate model (5) over 2014 - 2016, a short period surrounding the 2015 Paris Agreement, we do not include year fixed effects.

of customer concentration on supplier carbon emissions is more pronounced in supplier firms facing lower customer switching costs, with less (more) supplier (customer) bargaining power, fewer redeployable assets, operating in more carbon-intensive industries, and after the Paris Agreement of 2015. Collectively our evidence suggests that major corporate customers can facilitate the transition to a low-carbon economy through decarbonization along the supply chain.

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Table 1 Summary statistics

This table reports the descriptive statistics for the variables used in our baseline analysis. For each variable, we report the number of observations, mean, standard deviation, 25th percentile, median, and 75th percentile. All continuous variables are winsorized at the 1st and 99th percentile. All variables are defined in Appendix A.

	Obs.	Mean	Std.Dev	25th	Median	75th
Carbon emission measures						
LnScope1	26,786	10.497	3.065	8.482	10.357	12.416
LnScope2	26,786	10.480	2.425	9.030	10.627	12.114
LnScope3	26,786	12.243	2.307	10.725	12.406	13.879
LnInt1	26,765	2.842	2.219	1.426	2.686	3.836
LnInt2	26,770	2.822	1.347	2.072	2.879	3.759
LnInt3	26,786	4.576	0.967	3.705	4.536	5.326
CusMax	26,786	0.033	0.091	0.000	0.000	0.000
CusHHI	26,786	0.012	0.045	0.000	0.000	0.000
Customer concentration measures with at least one major customer						
CusMax	4,251	0.223	0.127	0.130	0.177	0.260
CusHHI	4,251	0.082	0.093	0.021	0.041	0.096
Control variables						
Size (Million $)	26,786	31.411	104.673	1.496	4.603	15.644
Leverage	26,786	0.260	0.205	0.092	0.235	0.384
Cash	26,786	0.149	0.182	0.027	0.079	0.197
Tobin's Q	26,786	1.924	1.423	1.090	1.467	2.237
Capx	26,786	0.043	0.050	0.008	0.027	0.059
R&DIntensity	26,786	0.030	0.070	0.000	0.000	0.025
Ret	26,786	0.112	0.455	-0.157	0.074	0.301
IO	26,786	0.707	0.262	0.566	0.764	0.895

Table 2 Customer concentration and carbon emissions

This table reports the results of the impact of customer concentration on suppliers' carbon emissions. The dependent variables are *LnScope1*, *LnScope2*, and *LnScope3*. The main explanatory variables of interest are the two customer concentration measures. *CusMax* is the highest percentage of sales to major corporate customers. *CusHHI* is the customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales. All other variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. All specifications include Industry×Year fixed effects. Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes. Statistical significance based on the heteroscedasticity-robust firm-clustered standard errors is reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	LnScope1	*LnScope2*	*LnScope3*	*LnScope1*	*LnScope2*	*LnScope3*
CusMax	-0.816***	-0.633**	-0.631**			
	(-2.91)	(-2.48)	(-2.47)			
CusHHI				-1.626***	-1.245**	-1.313**
				(-3.16)	(-2.48)	(-2.56)
Size	6.480***	7.818***	6.746***	6.481***	7.819***	6.746***
	(17.09)	(18.87)	(18.95)	(17.09)	(18.87)	(18.95)
Leverage	0.292**	0.259*	0.248*	0.293**	0.260*	0.250**
	(2.04)	(1.79)	(1.95)	(2.05)	(1.79)	(1.96)
Cash	-2.756***	-2.530***	-2.680***	-2.745***	-2.522***	-2.670***
	(-14.17)	(-12.23)	(-14.02)	(-14.14)	(-12.20)	(-14.00)
Tobin's Q	-0.007	0.003	0.027	-0.007	0.003	0.026
	(-0.35)	(0.16)	(1.43)	(-0.37)	(0.15)	(1.41)
Capx	-1.222	-1.268	-2.475***	-1.206	-1.255	-2.461***
	(-1.47)	(-1.50)	(-3.78)	(-1.45)	(-1.48)	(-3.75)
R&Dintensity	-4.833***	-5.334***	-4.704***	-4.853***	-5.351***	-4.715***
	(-10.30)	(-11.33)	(-9.81)	(-10.33)	(-11.33)	(-9.80)
Ret	-0.077***	-0.112***	-0.112***	-0.076***	-0.111***	-0.111***
	(-2.92)	(-4.17)	(-4.60)	(-2.89)	(-4.15)	(-4.58)
IO	0.823***	0.873***	0.811***	0.818***	0.869***	0.808***
	(9.02)	(9.45)	(10.41)	(8.99)	(9.41)	(10.37)
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26,786	26,786	26,786	26,786	26,786	26,786
Adj. R-sq	0.777	0.619	0.700	0.777	0.619	0.700

Table 3 Customer concentration and carbon intensities

This table reports the results of the impact of customer concentration on supplier firms' carbon intensities. The dependent variables are *LnInt1*, *LnInt2*, and *LnInt3*. Carbon intensity is measured as the ratio of carbon emission level to sales. The main explanatory variables of interest are the two customer concentration measures. *CusMax* is the highest percentage of sales to major corporate customers. *CusHHI* is the customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales. All other variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. All specifications include Industry×Year fixed effects. Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes. Statistical significance based on the heteroscedasticity-robust firm-clustered standard errors is reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	LnInt1	*LnInt2*	*LnInt3*	*LnInt1*	*LnInt2*	*LnInt3*
CusMax	-0.345**	-0.211*	-0.117*			
	(-2.09)	(-1.70)	(-1.89)			
CusHHI				-0.652**	-0.387*	-0.268**
				(-2.51)	(-1.66)	(-2.34)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26,765	26,770	26,786	26,765	26,770	26,786
Adj. R-sq	0.840	0.658	0.874	0.840	0.658	0.875

Table 4 Alternative measures of customer concentration

This table reports the results of the impact of customer concentration on supplier firms' carbon emissions using alternative measures of customer concentration. The dependent variable is *LnScope1, LnScope2, and LnScope3*. *Frac* is the fraction of a firm's total sales to all corporate customers that account for at least 10% of its total sales. *Major* is an indicator variable equal to one if a firm has at least one corporate customer that accounts for at least 10% of its total sales, and zero otherwise. All other variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. All specifications include Industry×Year fixed effects. Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes. Statistical significance based on the heteroscedasticity-robust firm-clustered standard errors is reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	LnScope1	*LnScope2*	*LnScope3*	*LnScope1*	*LnScope2*	*LnScope3*
Frac	-0.501***	-0.451**	-0.369**			
	(-2.73)	(-2.55)	(-1.98)			
Major				-0.139*	-0.137**	-0.081
				(-1.86)	(-2.02)	(-1.19)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26,786	26,786	26,786	26,786	26,786	26,786
Adj. R-sq	0.779	0.613	0.691	0.779	0.613	0.691

Table 5 Propensity score matching estimate

This table reports the propensity score matching estimation results. Panel A reports parameter estimates from the logit model used to estimate propensity scores. Industry and year fixed effects are constructed based on 2-digit SIC codes. The dependent variable (*Major*) is an indicator variable equal to one for firms with at least one major customer, and zero otherwise. Panel B reports the univariate comparisons of firm characteristics between firms with and without a major customer. Panel C presents the regression results in the propensity score matched sample. All the control variables in Panel C are the same as the baseline model. All independent variables are defined in Appendix A. All specifications include Industry×Year fixed effects. Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes. Statistical significance based on the heteroskedasticity robust firm-clustered standard errors is reported in parentheses. ∗∗∗, ∗∗ and ∗ indicate significance at the 1%, 5% and 10% level, respectively.

Panel A. Pre-match propensity score regression and post-match diagnostic regression

	(1)	(2)
	Pre-match	Post-match
Assets	-10.844***	-0.071
	(-9.76)	(-0.07)
Leverage	0.427***	-0.003
	(3.86)	(-0.05)
Cash	0.327**	0.013
	(2.28)	(0.16)
Tobin's Q	-0.120***	-0.004
	(-7.00)	(-0.44)
Capx	-0.065	-0.086
	(-0.14)	(-0.31)
R&DIntenstiy	5.529***	0.107
	(14.19)	(0.51)
Ret	-0.030	0.027
	(-0.67)	(1.54)
ROA	1.721***	0.053
	(9.57)	(0.58)
IO	0.629***	0.041
	(8.12)	(0.90)
Industry and year FE	Yes	Yes
N	25,148	7,750
Pseudo R-sq	0.186	0.073

Panel B. Difference in control variables

	With major customer	Without major customers	Differences	t-stat
Assets (Million $)	8.460	8.610	-0.150	-0.39
Leverage	0.263	0.265	-0.002	-0.47
Cash	0.201	0.197	0.004	0.71
Tobin's Q	2.163	2.173	-0.010	-0.32
Capx	0.050	0.050	0.000	0.24
R&DIntensity	0.062	0.061	0.001	0.47
Ret	0.110	0.103	0.007	0.60
ROA	0.007	0.009	-0.001	-0.41
IO	0.742	0.734	0.007	1.30

Panel C. Regression results in the propensity score matched sample

	(1)	(2)	(3)	(4)	(5)	(6)
	LnScope1	*LnScope2*	*LnScope3*	*LnScope1*	*LnScope2*	*LnScope3*
CusMax	-0.769***	-0.512**	-0.432**			
	(-3.38)	(-2.34)	(-2.09)			
CusHHI				-1.461***	-0.965**	-0.941**
				(-3.54)	(-2.47)	(-2.47)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6,687	6,687	6,687	6,687	6,687	6,687
Adj. R-sq	0.787	0.714	0.791	0.787	0.714	0.791

Table 6 Instrumental variable approach results

This table presents estimates using the instrumental variables approach based on two-stage least squares (2SLS) panel regressions. Panel A presents the first-stage regression results in which dependent variables are the measures of customer concentration. The instrumental variables are *CusM&A*, which is a measure of the intensity of merger and acquisition (M&A) activities in customers' industries; and *CusReg*, which is a measure of aggregate regulatory restrictions of customers' industries. Panel B reports the second-stage regression results. The dependent variables are *LnScope1*, *LnScope2*, and *LnScope3*. The main explanatory variables of interest are the two customer concentration measures. *CusMax* is the highest percentage of sales to major corporate customers. *CusHHI* is the customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales. All other variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. All specifications include Industry×Year fixed effects. Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes. Statistical significance based on the heteroscedasticity-robust firm-clustered standard errors is reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. First-stage regression results

	Dependent variable = Customer concentration			
	(1)	(2)	(3)	(4)
	CusMax	*CusHHI*	*CusMax*	*CusHHI*
CusM&A	7.886***	5.330***		
	(19.09)	(17.70)		
CusReg			0.009***	0.006***
			(10.65)	(9.85)
Control variables	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes
N	3,709	2,274	3,709	2,274
F-statistics	55.36	48.32	30.14	24.44

Panel B. Second-stage regression results

	Dependent Variable = *LnScope1*				Dependent Variable = *LnScope2*				Dependent Variable = *LnScope3*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\widehat{CusMax}$	-2.706***		-2.571***		-1.531**		-1.915**		-2.282***		-2.544***	
	(-4.36)		(-3.38)		(-2.43)		(-2.50)		(-3.79)		(-3.50)	
$\widehat{CusHHI}$		-4.004***		-4.020***		-2.265**		-2.994**		-3.376***		-3.978***
		(-4.40)		(-3.39)		(-2.45)		(-2.51)		(-3.78)		(-3.46)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,709	3,709	2,274	2,274	3,709	3,709	2,274	2,274	3,709	3,709	2,274	2,274
Adj. R-sq	0.760	0.760	0.771	0.770	0.658	0.658	0.625	0.624	0.771	0.771	0.745	0.742

Table 7 Supplier carbon emissions around the establishment of customer-supplier relationships

This table presents the result of the impact of customer concentration on supplier firms' carbon emissions around the establishment of customer-supplier relationships. The dependent variables are *LnScope1*, *LnScope2*, and *LnScope3*. The main explanatory variables of interest are the interaction between the two customer concentration measures and dummies indicating the years relative to the relationship establishment year. *CusMax* is the highest percentage of sales to major corporate customers. *CusHHI* is the customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales. *Before* is an indicator equal to one if the year is one (t-1) or two (t-2) years before the establishment year (t), and zero otherwise. *Establish* is an indicator equal to one if the year is the establishment year (t), and zero otherwise. *After* is an indicator equal to one if the year is one (t-1) or two (t-2) years after the establishment year (t), and zero otherwise. Relationship establishment is defined as when a firm reports a principal customer in year t for the first time where the relationship will last for at least three years (i.e., years t, $t + 1$, and $t + 2$). All other variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. All specifications include Industry×Year fixed effects. Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes. Statistical significance based on the heteroscedasticity-robust firm-clustered standard errors is reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	LnScope1	*LnScope2*	*LnScope3*	*LnScope1*	*LnScope2*	*LnScope3*
Before×CusMax	0.640	0.483	1.087			
	(0.20)	(0.16)	(0.40)			
Establish×CusMax	-2.087**	-1.870**	-2.155***			
	(-2.19)	(-2.02)	(-2.65)			
After×CusMax	-1.499***	-1.026**	-1.159***			
	(-3.29)	(-2.28)	(-2.84)			
Before×CusHHI				-2.768	-2.460	-0.838
				(-0.73)	(-0.68)	(-0.24)
Establish×CusHHI				-2.526*	-1.983	-3.007**
				(-1.89)	(-1.56)	(-2.54)
After×CusHHI				-2.395***	-1.592**	-2.043***
				(-3.52)	(-2.27)	(-3.25)
Before	-0.0122	-0.125	-0.220	0.157	0.017	-0.065
	(-0.03)	(-0.36)	(-0.67)	(0.50)	(0.07)	(-0.25)
Establish	0.307	0.091	0.247	0.096	-0.118	0.058
	(1.29)	(0.41)	(1.51)	(0.53)	(-0.70)	(0.48)
After	0.335***	0.115	0.165*	0.236***	0.044	0.100
	(2.97)	(1.12)	(1.81)	(2.67)	(0.54)	(1.40)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,596	4,596	4,596	4,596	4,596	4,596
Adj. R-sq	0.739	0.637	0.750	0.739	0.636	0.750

Table 8 Cross-sectional heterogeneity: Customers' switching costs and government customers

This table examines whether the impact of customer concentration on suppliers' carbon emissions varies with customers' costs of switching to other suppliers (Panel A) and government customers (Panel B). The dependent variables are *LnScope1*, *LnScope2*, and *LnScope3*. The main explanatory variables of interest are the interaction between two customer concentration measures and costs of switching suppliers. *CusMax* is the highest percentage of sales to major corporate customers. *CusHHI* is the customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales. Customer switching costs are measured by *LowMshare,* which is an indicator equal to one if the supplier firm's sales as a fraction of total industry sales is below the sample median in a year, and zero otherwise. *GovMax* is the highest percentage of sales to major government customers. *GovHHI* is the customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major government customer sales to the supplier's total sales. All other variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes. Statistical significance based on the heteroscedasticity-robust firm-clustered standard errors is reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Customers' costs of switching suppliers

	(1)	(2)	(3)	(4)	(5)	(6)
	LnScope1	*LnScope2*	*LnScope3*	*LnScope1*	*LnScope2*	*LnScope3*
CusMax	-0.203	0.040	0.001			
	(-0.72)	(0.15)	(0.00)			
CusMax×*LowMshare*	-1.348**	-1.366***	-1.308***			
	(-2.57)	(-3.00)	(-2.93)			
CusHHI				-0.691	-0.246	-0.386
				(-1.27)	(-0.46)	(-0.71)
CusHHI×*LowMshare*				-2.288**	-2.248***	-2.101**
				(-2.47)	(-2.64)	(-2.50)
LowMshare	-0.960***	-1.173***	-1.075***	-0.987***	-1.199***	-1.100***
	(-11.74)	(-14.14)	(-16.59)	(-12.17)	(-14.79)	(-17.21)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26,786	26,786	26,786	26,786	26,786	26,786
Adj. R-sq	0.786	0.641	0.720	0.786	0.641	0.720

Panel B. Government customer concentration and carbon emissions

	(1)	(2)	(3)	(4)	(5)	(6)
	LnScope1	*LnScope2*	*LnScope3*	*LnScope1*	*LnScope2*	*LnScope3*
GovMax	-0.177	-0.510	-0.185			
	(-0.34)	(-0.94)	(-0.36)			
CusMax	-0.819***	-0.643**	-0.635**			
	(-2.92)	(-2.51)	(-2.48)			
GovHHI				-0.178	-0.999	-0.286
				(-0.16)	(-0.83)	(-0.25)
CusHHI				-1.628***	-1.260**	-1.317**
				(-3.16)	(-2.50)	(-2.56)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26,786	26,786	26,786	26,786	26,786	26,786
Adj. R-sq	0.777	0.619	0.700	0.777	0.619	0.700

Table 9 Cross-sectional heterogeneity: bargaining power of customers and suppliers

This table examines whether the relationship between customer concentration and suppliers' carbon emission varies with customer (Panel A) and supplier bargaining power (Panel B). The dependent variables are *LnScope1*, *LnScope2*, and *LnScope3*. The main explanatory variables of interest are the interaction between two customer concentration measures and customer/supplier bargaining power. *CusMax* is the highest percentage of sales to major corporate customers. *CusHHI* is the customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales. Customer bargaining power is proxied by supplier industry concentration *SupHHI*. *SupHHI* is an indicator equal to one if the supplier industry's concentration is at or above the sample median in a year, and zero otherwise. Industry concentration is measured as the sum of squared market shares in sales of all firms in each of the Fama-French 48 industries. Supplier bargaining power is proxied by the potential of vertical integration *VertIng*. *VertIng* is an indicator equal to one if the supplier firm's vertical integration is in the top quartile of the sample in a year, and zero otherwise. The vertical integration is constructed by Fresard, Hoberg, and Phillips (2020). All other variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes. Statistical significance based on the heteroscedasticity-robust firm-clustered standard errors is reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Customer bargaining power proxied by supplier industry competition

	(1)	(2)	(3)	(4)	(5)	(6)
	LnScope1	*LnScope2*	*LnScope3*	*LnScope1*	*LnScope2*	*LnScope3*
CusMax	-1.551***	-1.326***	-1.307***			
	(-3.18)	(-3.36)	(-3.30)			
CusMax× *SupHHI*	1.348**	1.366**	1.308***			
	(2.57)	(3.00)	(2.93)			
CusHHI				-2.979***	-2.494***	-2.487***
				(-3.77)	(-3.55)	(-3.56)
CusHHI× *SupHHI*				2.288**	2.248***	2.101**
				(2.47)	(2.64)	(2.50)
SupHHI	0.960***	1.173***	1.075***	0.987***	1.199***	1.100***
	(11.74)	(14.14)	(16.59)	(12.17)	(14.79)	(17.21)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26,786	26,786	26,786	26,786	26,786	26,786
Adj. R-sq	0.786	0.641	0.720	0.786	0.641	0.720

Panel B. Supplier bargaining power proxied by the potential of vertical integration

	(1)	(2)	(3)	(4)	(5)	(6)
	LnScope1	*LnScope2*	*LnScope3*	*LnScope1*	*LnScope2*	*LnScope3*
CusMax	-1.528***	-1.428***	-1.229***			
	(-2.86)	(-2.96)	(-2.60)			
CusMax×VertIng	1.101**	1.220**	0.928**			
	(2.05)	(2.49)	(2.00)			
CusHHI				-2.938***	-2.873***	-2.336**
				(-2.97)	(-2.84)	(-2.38)
CusHHI×VertIng				1.971**	2.416**	1.546*
				(2.02)	(2.46)	(1.69)
VertIng	0.170**	0.159*	0.152**	0.191**	0.179**	0.170**
	(1.97)	(1.84)	(2.02)	(2.26)	(2.13)	(2.31)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26,786	26,786	26,786	26,786	26,786	26,786
Adj. R-sq	0.777	0.620	0.701	0.777	0.620	0.701

Table 10 Cross-sectional heterogeneity: Supplier firms' asset redeployability

This table examines whether the relationship between customer concentration and suppliers' carbon emission varies with suppliers' asset redeployability. The dependent variables are *LnScope1*, *LnScope2*, and *LnScope3*. The main explanatory variables of interest are the interaction between two customer concentration measures and suppliers' asset redeployability. *CusMax* is the highest percentage of sales to major corporate customers. *CusHHI* is the customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales. *Redeploy* is an indicator equal to one if the supplier firm's asset redeployability is at or above the sample median in a year, and zero otherwise. Firm-level asset redeployability measures are constructed by Kim and Kung (2017). All other variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes. Statistical significance based on the heteroscedasticity-robust firm-clustered standard errors is reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) *LnScope1*	(2) *LnScope2*	(3) *LnScope3*	(4) *LnScope1*	(5) *LnScope2*	(6) *LnScope3*
CusMax	-2.074***	-1.493***	-1.559***			
	(-3.22)	(-3.00)	(-3.13)			
CusMax×Redeploy	1.642**	1.152**	1.222**			
	(2.47)	(2.10)	(2.23)			
CusHHI				-4.012***	-3.127***	-3.008***
				(-3.78)	(-3.51)	(-3.34)
CusHHI×Redeploy				2.940**	2.340**	2.097**
				(2.54)	(2.29)	(2.04)
Redeploy	0.134	0.273**	0.163*	0.171	0.296***	0.192**
	(1.16)	(2.36)	(1.68)	(1.48)	(2.59)	(1.98)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26,786	26,786	26,786	26,786	26,786	26,786
Adj. R-sq	0.777	0.621	0.701	0.777	0.621	0.701

Table 11 Cross-sectional heterogeneity: Carbon intensity of suppliers' industries

This table examines whether the relationship between customer concentration and suppliers' carbon emission varies with the carbon intensity of suppliers' industries. The dependent variables are *LnScope1*, *LnScope2*, and *LnScope3*. The main explanatory variables of interest are the two customer concentration measures. *CusMax* is the highest percentage of sales to major corporate customers. *CusHHI* is the customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales. *HighCI* is an indicator equal to one if the supplier firm is in an industry with total scope 1, 2, and 3 carbon emissions at or above the median of all the Fama-French 12 industries in a year, and zero otherwise. This indicator is subsumed by the Industry×Year fixed effects. All other variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes. Statistical significance based on the heteroscedasticity-robust firm-clustered standard errors is reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	LnScope1	*LnScope2*	*LnScope3*	*LnScope1*	*LnScope2*	*LnScope3*
CusMax	-0.147	-0.141	-0.093			
	(-0.47)	(-0.46)	(-0.31)			
CusMax×HighCI	-2.282***	-1.678***	-1.835***			
	(-3.72)	(-3.26)	(-3.52)			
CusHHI				-0.587	-0.363	-0.387
				(-1.03)	(-0.63)	(-0.66)
CusHHI× HighCI				-4.382***	-3.723***	-3.907***
				(-3.85)	(-3.66)	(-3.72)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26,786	26,786	26,786	26,786	26,786	26,786
Adj. R-sq	0.777	0.620	0.701	0.777	0.620	0.701

Table 12 The impacts of the 2015 Paris Agreement

This table examines whether the relationship between customer concentration and supplier carbon emission varies with changing climate regulatory environment. We use the 2015 Paris Agreement as the quasi-natural setting of increased climate regulatory risks. The Paris Agreement test is restricted to firms with and without a concentrated customer base from 2014 to 2016. The dependent variables are *LnScope1*, *LnScope2*, and *LnScope3*. The main explanatory variables of interest are the interaction between two customer concentration measures and the announcement of the Paris Agreement. *CusMax* is the highest percentage of sales to major corporate customers. *CusHHI* is the customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales. *Paris* is an indicator equal to one if the year is 2016, and zero otherwise. All other variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. Industries are defined based on the two-digit Standard Industrial Classification (SIC) codes. Statistical significance based on the heteroscedasticity-robust firm-clustered standard errors is reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) *LnScope1*	(2) *LnScope2*	(3) *LnScope3*	(4) *LnScope1*	(5) *LnScope2*	(6) *LnScope3*
Paris	-0.349***	-0.447***	-0.374***	-0.357***	-0.458***	-0.388***
	(-17.25)	(-22.41)	(-21.29)	(-18.44)	(-23.92)	(-23.17)
CusMax	-0.525	0.391	0.614			
	(-1.30)	(1.06)	(1.57)			
CusMax×Paris	-0.650**	-1.009***	-1.520***			
	(-2.02)	(-3.34)	(-4.73)			
CusHHI				-1.783**	-0.240	0.086
				(-2.28)	(-0.34)	(0.10)
CusHHI×Paris				-0.883	-1.402**	-2.391***
				(-1.35)	(-2.27)	(-3.32)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	8,607	8,607	8,607	8,607	8,607	8,607
Adj. R-sq	0.691	0.559	0.622	0.692	0.559	0.622

Appendix A. Variable definitions

Variable	Definition
Carbon emission measures	
LnScope1	Natural logarithm of one plus the Scope 1 carbon emissions.
LnScope2	Natural logarithm of one plus the Scope 2 carbon emissions.
LnScope3	Natural logarithm of one plus the Scope 3 carbon emissions.
LnInt1	Natural logarithm of one plus the Scope 1 carbon emission intensity (intensity= the ratio of total emissions to sales).
LnInt2	Natural logarithm of one plus the Scope 2 carbon emission intensity.
LnInt3	Natural logarithm of one plus the Scope 3 carbon emission intensity.
Customer concentration measures	
CusMax	The highest percentage of sales to major corporate customers.
CusHHI	The customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales.
Frac	The fraction of a firm's total sales to all corporate customers which have at least 10% of total sales.
Major	An indicator variable equal to one if a firm has at least one corporate customer that accounts for at least 10% of its total sales, and zero otherwise.
Other variables	
Size	Total book assets (billion $).
Leverage	The sum of long-term debt and debt in current liabilities divided by total assets.
Cash	The ratio of cash to total assets.
Tobin's Q	The sum of total assets plus the market value of equity minus the book value of equity, and divided by total assets.
Capx	The ratio of capital expenditure to total assets.
R&Dintensity	The ratio of annual R&D expenses to total assets.
Ret	The annual stock return over the past year.
ROA	The ratio of net income to total assets.
IO	The proportion of institutional ownership from 13F.
Sales	Total sales.
GreenPatent	An indicator variable equal to one if the company files application for green patent(s) in a given year, and zero otherwise. The identification of green patent is following the guidelines of OECD using IPC and CPC class (Hascic and Migotto, 2015; Cohen, Gurun, and Nguyen, 2020).
Mktshare	The percentage a firm's sales relative to the total sales of? firms in the same industry.
LowMshare	An indicator equal to one if the firm's market share is below the median of the sample in a year and zero otherwise.
VertIng	An indicator equal to one if the firm's vertical integration is in the top quartile of the sample in a year and zero otherwise. The vertical integration measure is constructed by Fresard, Hoberg, and Phillips (2020).
Redeploy	An indicator equal to one if the firm-level redeployability is at or above the sample median in a year and zero otherwise. The firm-level redeployability measures are constructed by Kim and Kung (2017).
HighCI	An indicator equal to one if the supplier firm is in an industry with total Scope 1, 2, and 3 carbon emissions at or above the median of all the industries in a year and zero otherwise

Internet Appendix to "Customer Concentration and Corporate Carbon Emissions"

Table IA.1 Customer concentration and carbon emissions: using lagged customer concentration measures

This table reports the results on the impact of customer concentration on suppliers' carbon emissions using lag one-year of customer concentration measures. The dependent variables are *LnScope1*, *LnScope2*, and *LnScope3*. The main explanatory variables of interest are lag one-year of two customer concentration measures. *Lag_CusMax* is the lag one-year of highest percentage of sales to major corporate customers. *Lag_CusHHI* is the lag one-year of customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales. All other variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. All specifications include Industry×Year fixed effects. Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes. Statistical significance is based on the heteroscedasticity-robust firm-clustered standard errors reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) *LnScope1*	(2) *LnScope2*	(3) *LnScope3*	(4) *LnScope1*	(5) *LnScope2*	(6) *LnScope3*
Lag_CusMax	-1.020***	-0.827***	-0.760***			
	(-3.25)	(-2.96)	(-2.71)			
Lag_CusHHI				-2.025***	-1.648***	-1.607***
				(-3.53)	(-2.96)	(-2.80)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	23,466	23,466	23,466	23,466	23,466	23,466
Adj. R-sq	0.775	0.605	0.694	0.775	0.605	0.694

Table IA.2 Customer concentration and suppliers' operating performance

This table examines the impact of customer concentration on supplier firms' performance. The dependent variables are *ROA* and *Sales/Assets*. The main explanatory variables of interest are the two customer concentration measures. *CusMax* is the highest percentage of sales to major corporate customers. *CusHHI* is the customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales. *Chg_Carbon* is the log changes in total carbon emissions of Scope 1, 2 and 3. All other variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. All specifications include Industry×Year fixed effects. Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes. Statistical significance based on the heteroscedasticity-robust firm-clustered standard errors is reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	ROA	*Sales/Assets*	*ROA*	*Sales/Assets*
CusMax	0.096***	0.050		
	(3.99)	(0.80)		
CusMax×Chg_Carbon	0.081**	0.120***		
	(2.19)	(2.63)		
CusHHI			0.166***	0.021
			(3.45)	(0.21)
CusHHI×Chg_Carbon			0.135**	0.249***
			(2.23)	(3.64)
Chg_Carbon	0.017**	-0.011	0.018**	-0.011
	(2.21)	(-1.11)	(2.47)	(-1.18)
Control variables	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes
N	23,466	22,657	23,466	22,657
Adj. R-sq	0.368	0.680	0.368	0.680

Table IA.3 Customer concentration and green patents

This table reports the linear probability regression results on the impact of customer concentration on the probability of suppliers' filing of green patents. The dependent variable is *GreenPatent*, which is an indicator variable equal to one if the company files application for green patent(s) in a given year, and zero otherwise. Green patent classification is constructed following Hascic and Migotto (2015) and Cohen, Gurun, and Nguyen (2020). The main explanatory variables of interest are the two customer concentration measures. *CusMax* is the highest percentage of sales to major corporate customers. *CusHHI* is the customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales. Control variables are the same as Table 2. All other variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. All specifications include Industry×Year fixed effects. Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes. Statistical significance based on the heteroscedasticity-robust firm-clustered standard errors is reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) GreenPatent	(2) GreenPatent
CusMax	0.080*	
	(1.83)	
CusHHI		0.157*
		(1.87)
Control variables	Yes	Yes
Industry×Year FE	Yes	Yes
N	26,786	26,786
Adj. R-sq	0.001	0.001

Table IA.4 Customer concentration and supplier carbon emissions: removing the largest suppliers

This table examines the impact of customer concentration on a supplier's carbon emissions by removing suppliers in the top 5% sales group. The dependent variables are *LnScope1*, *LnScope2*, and *LnScope3*. The main explanatory variables of interest are the two customer concentration measures. *CusMax* is the highest percentage of sales to major corporate customers. *CusHHI* is the customer sales-based Herfindahl-Hirschman Index computed by summing the squares of the ratios of major corporate customer sales to the supplier's total sales. All other variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. All specifications include Industry×Year fixed effects. Industries are defined based on the four-digit Standard Industrial Classification (SIC) codes. Statistical significance based on the heteroscedasticity-robust firm-clustered standard errors is reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	LnScope1	*LnScope2*	*LnScope3*	*LnScope1*	*LnScope2*	*LnScope3*
CusMax	-0.707**	-0.485*	-0.494**			
	(-2.56)	(-1.94)	(-2.02)			
CusHHI				-1.356***	-0.960*	-1.035**
				(-2.68)	(-1.94)	(-2.08)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	24,568	24,568	24,568	24,568	24,568	24,568
Adj. R-sq	0.772	0.600	0.690	0.772	0.600	0.690