The Carbon Cost of Competitive Pressure*

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Abstract

Higher exposure to competition – measured by product fluidity – is associated with higher carbon emission intensity, via both higher absolute emissions and lower revenues. This result is robust to using instrumental variables to obtain exogenous variation in fluidity and holds when using only reported emission data, excluding estimated emissions. Higher emissions in the short-term are not followed by medium-term improvements, suggesting that competition does not pressure companies to become greener. The relationship between competition and carbon emissions is stronger in areas less concerned about climate change and areas with weaker social norms, as well as for less profitable firms.

JEL classification: D40, G30, M14, Q50

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1 Introduction

Climate change presents a profound challenge to society, making carbon emissions reduction a critical global priority. Policymakers and regulators seek to align financial incentives with environmental objectives through carbon pricing, green financing, disclosure mandates, and many other policies.[1] Assessing and pricing the risks related to climate change and carbon emissions is a challenge for the financial markets. Most finance scholars, professionals, and policymakers argue that markets are more likely to underestimate than to overestimate climate risks.[2] At the same time, competition is crucial in driving efficiency, innovation, and consumer welfare. The public discourse about the importance of competition has become increasingly urgent as industries have grown more concentrated and profitable in recent decades, prompting calls for regulatory action to ensure competitive markets.[3]

However, it is possible the policy goals of carbon reduction and increasing competition might be in conflict. Carbon abatement is costly, and unless such costs are fully compensated by competitive advantages resulting from perceived sustainability, firms face a trade-off between profitability and investing in carbon emission reduction. Several studies argue that competition may spur green innovation and hence have positive long-term effects on carbon abatement.[4] Some of these same studies acknowledge that in the short-term, competition might result in higher carbon emissions, but there is no prior empirical evidence. None of these studies directly look at the relationship between carbon emissions and competition in the longer-term either. Instead, they focus on various measures of green innovation and green investment.

In this paper, we study the role of competitive pressure in corporate carbon emissions. Our main measure of carbon intensity is the scope 1 GHG intensity, converted into CO_2 equivalent, based on Trucost data. As alternative sources of carbon emissions data, we use

[1] For discussions of carbon reduction policies, see, e.g., Gillingham and Stock (2018).

[2] See Stroebel and Wurgler (2021).

[3] For U.S. industry concentration, see Covarrubias et al. (2019) and Grullon et al. (2019). For global evidence, see De Loecker and Eeckhout (2018), Bae et al. (2021), and Frésard (2010).

[4] See, e.g., Aghion et al. (2023), Dai et al. (2025), Schinkel and Treuren (2020), and Cenci et al. (2025).

the self-reported carbon emissions from the Carbon Disclosure Project (CDP) as well as U.S. facility emissions data from the Environmental Protection Agency (EPA). To measure domestic competitive pressure, we use the product fluidity index of Hoberg et al. (2014). This index is based on textual analysis of the mandatory product descriptions in 10-K filings, capturing the similarity between a firm's products and the overall changes in the rivals' products. A greater product fluidity index means more overlap with competitors in product space, implying higher levels of competitive pressure.[5] We construct a comprehensive sample of U.S. listed firms for the years 2002-2023.

We find that higher competitive pressure is associated with higher carbon emissions per unit of revenue. This finding is both statistically and economically significant and robust to controlling for a large number of firm characteristics as well as firm, industry-time and state-time fixed effects. A one-standard-deviation increase in product fluidity is associated with a 4-5% increase in carbon intensity, depending on the model specification. The results remain very similar when using the self-reported carbon emissions data from the CDP, suggesting that the findings are not driven by the Trucost methodology to estimate emissions.

Since carbon intensity is calculated as total carbon emissions divided by revenue, a higher intensity can result from either higher emissions or lower revenue. To understand the contribution of each of these alternative mechanisms, we perform regression analyses of both total carbon emissions as well as revenue conditional on fluidity. We find that the higher carbon intensity associated with higher fluidity results from both higher absolute emissions as well as lower revenue.

Our findings suggest that higher competitive pressure is associated with higher carbon emissions in the short-term. However, it is possible that competition might also spur companies to innovate and become greener in the longer-term. This would be consistent with the arguments made by, e.g., Aghion et al. (2023), Dai et al. (2025), Schinkel and Treuren (2020), and Cenci et al. (2025). To explore this, we perform a regression analysis incorpo-

[5] *Fluidity* is used by a number of recent studies to measure competitive threats in the product market (e.g., Li and Zhan (2019), Mattei and Platikanova (2017), Hoberg et al. (2014)).

rating lagged fluidity for different periods. If higher emissions in the short-term are offset by improvements in the medium-term, we should see the coefficient estimates for fluidity become negative for further lagged fluidity values. This is not the case. Our estimates show a significant positive short-term relationship between fluidity and carbon emissions, but no reversal in the medium-term. Hence, our results do not suggest that competition pushes firms to become greener in the longer-term.

To further confirm our results with different data, as well as to explore the channels, we obtain data on individual facility-level carbon emissions in the U.S. from the EPA. We match these facilities to publicly listed parent companies and calculate the firm-level yearly aggregate carbon emissions in this dataset. We also calculate the implied carbon intensity based on the reported revenue and total (U.S.) carbon emissions. The firm-level results using the EPA data are consistent with our earlier results using Trucost or CDP data, with higher fluidity being associated with higher carbon emission intensity. We also perform a regression analysis of facility-level emissions on firm-level fluidity and find no statistically nor economically significant relationship at the facility-level. This suggests that the firm-level relationship between competitive pressure and carbon emissions is largely driven by changes in the facility composition, with higher-carbon facilities used relatively more when facing more competitive pressure.

Next, we explore the role of local climate attitudes and political views in moderating the effect of competitive pressure on carbon emissions.[6] We use county-level data on climate opinions from the Yale Climate Maps and find that the effect of fluidity on carbon emissions is significantly larger for firms headquartered in areas that consider climate action by corporations less important. The estimated relationship between fluidity and carbon emissions is also somewhat stronger for firms in Republican-voting areas, but the difference along political lines is not statistically significant. We also use corporate lobbying data from Leippold

[6]For example, Ramadorai and Zeni (2024) find that firms' beliefs about climate regulation strongly affect abatement. Several studies suggest that political views are correlated with preferences on sustainability, also in investments (Hong and Kostovetsky (2012), Gormley et al. (2024), Kempf and Tsoutsoura (2024)).

et al. (2024) and find that firms that spend more on lobbying Democrats (Republicans) exhibit a weaker (stronger) link between fluidity and carbon emissions.

Investing in carbon abatement may be partly driven by considerations of stakeholders other than shareholders. Hence, we might expect such investment to depend on the strength of social norms in the communities where the firm operates. To test this, we use three proxies for the strength of social norms. First, we use the *Social capital* index of Lin and Pursiainen (2022) to measure the strength of local social norms. Second, we use the local volunteering rate (Chetty et al. (2022a), Chetty et al. (2022b)), defined as the percentage of Facebook users who are members of a group which is predicted to be about "volunteering" or "activism" based on group title and other group characteristics in the county. Third, we use *Civic org.*, measured by the share of users participating in Facebook groups associated with public good provision. With all of these proxies for social norms, we find that the positive relationship between product fluidity and carbon emissions is stronger when social norms are weaker.

If firms face a trade-off between carbon abatement and profitability, we might expect the emissinos of less profitable firms to be more sensitive to competitive pressure. To examine this, we partition our sample based on various measures of profitability and return on capital. Across all these measures, the relationship between fluidity and carbon emissions is significantly stronger for less profitable firms. These results are consistent with firms protecting their profit margins at the expense of higher emissions.

To better establish causality between competition and carbon emissions, we use two instrumental variables to capture exogenous variation in product fluidity: changes in state-level trade-weighted foreign exchange rates (Li and Zhan (2019), Loncan (2023), Loncan and Valta (2024)) and the staggered introduction of Paid Sick Leave (PSL) laws (Loncan and Valta (2024), Maclean et al. (2024)). An appreciation in the state-level FX rate reduces the relative costs of imports, thus increasing local competition from foreign products. The passage of a PSL increases firm costs, presumably with a stronger effect for firms with less market power, and hence reduces competitive pressure. Similar to Loncan and Valta (2024), we confirm that both of these instruments strongly predict firm-level fluidity. Using either one of them or both simultaneously as instruments for fluidity, we confirm that increases in fluidity are associated with significant increases in carbon emissions. The economic magnitude of the IV estimates is substantially larger than our baseline OLS estimates.

Many commentators (see, e.g., Paulson (2015), van Lierop (2024)) and some academic studies (e.g., Maeckle (2024), Wiersema et al. (2025)) have suggested that short-termism is a key obstacle to tackling carbon emissions. To explore whether short-termism plays a role in our findings, we use three proxies for investor short-termism: the churn ratio of Gaspar et al. (2005), the adjusted churn ratio of Yan and Zhang (2009), and the share of transient ownership by Bushee (1998).[7] Across all these measures, we find that the estimated positive relationship between product fluidity and carbon emissions is actually stronger for firms with longer-horizon shareholders, although this difference is not statistically significant. This contrasts with the results of Starks et al. (2023), who find that long-term institutional investors tilt their portfolios towards firms with better ESG profiles.

On the other hand, the estimated relationship between fluidity and carbon emissions is stronger for firms with lower institutional ownership in general, although this difference is also not statistically significant. This seems consistent with Azar et al. (2021), who find a negative association between Big Three ownership and subsequent carbon emissions among MSCI index constituents. Taken together, our results on ownership suggest that institutional ownership matters, but that the sensitivity of carbon emissions to competitive pressure is not driven by short-term owners.

To assess the importance of our findings for the aggregate carbon emissions in the economy, we perform further subsample analyses dividing our sample by firm size, age, and total

[7] Churn ratio is an indicator of investor turnover for the firm, measured by a weighted average of the total portfolio churn rate of all institutional shareholders over the four quarters of the year. The transient investor defined by Bushee (1998) is based on factor analysis and cluster analysis of past investment behavior. Transient institutions have high portfolio turnover and engage in momentum trading strategies.

carbon emissions.[8] We find that the results are broadly similar for firms regardless of their size, age, or total carbon footprint. This suggests that the relationship we document between competitive pressure and carbon emissions may be important for the total carbon emissions, as it also applies to the large emitters.

We make several contributions. First, we contribute to the rapidly growing literature on corporate carbon emissions and the role of markets in moderating them. A number of studies argue that competition may spur green innovation and hence have positive long-term effects on carbon abatement (Aghion et al. (2023), Dai et al. (2025), Schinkel and Treuren (2020), Cenci et al. (2025)). Our evidence suggests that in the short-term, competitive pressure is associated with higher emissions, and our analysis does not indicate that this gets reversed in the medium-term either. Hence, our findings contrast the arguments made in these prior studies. More broadly, a large literature focuses on the pricing of climate risk and carbon and other emission risk in equity (Choi et al. (2020), Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2023), Aswani et al. (2024), Zhang (2025), Hsu et al. (2023)), debt (Duan et al. (2023b), Ginglinger and Moreau (2023), Ivanov et al. (2024)), and other financial markets (e.g., Ilhan et al. (2021), Giglio et al. (2021)). Some recent studies use earnings call transcripts to quantify firms' climate risk exposures (e.g., Li et al. (2024), Sautner et al. (2023)).

A related literature focuses on the effects of carbon abatement policies. Hong et al. (2023) model the welfare consequences of mandates that restrict investors to hold firms with net-zero carbon emissions. Martinsson et al. (2024) and Andersson (2019) estimate that the Swedish carbon tax substantially reduced carbon emissions. A large literature discusses the social cost of carbon (e.g., Barnett et al. (2020), van den Bremer and van der Ploeg (2021)). Akey and Appel (2021) find that limitations in parent company environmental liability result in lower investment in abatement technologies. Shapiro and Walker (2018) show that air pollution emissions from U.S. manufacturing have fallen substantially over time

[8]For example, Fang et al. (2024) argue that under financial constraints, smaller and younger firms invest more in capital and engage less in pollution abatement.

despite a large increase in manufacturing output, primarily driven by within-product changes in emissions intensity. Our study is also related to the literature documenting unintended consequences of carbon reduction policies. Several studies focus on emissions leakage amid local restrictions (e.g., Fowlie (2009), Fowlie et al. (2016), Bartram et al. (2022)). Shapiro (2016) finds that the benefits of international trade exceed trade's environmental costs due to CO_2 emissions. Cruz and Rossi-Hansberg (2024) study the geographic variation in the effects of climate change.

We add to the broader literature on the effects of competition. There are many studies suggesting that more competition is associated with lower prices (Dafny et al. (2012), Borenstein and Rose (1994), Brown and Goolsbee (2002)), better product quality Matsa (2011), and reduced governance problems (Lie and Yang (2023), Giroud and Mueller (2010, 2011)), as well as other broadly positive outcomes. von Meyerinck et al. (2024) show that competition is important for consumers' ability to discipline firms. Our findings suggest that competition may also have negative societal impacts in reducing firms' commitment to sustainability. Other studies finding negative societal as well as firm-level effects from competition include Autor et al. (2013), Autor et al. (2020), Pierce and Schott (2016), Frésard and Valta (2016), Valta (2012). Hombert and Matray (2018) find that innovative firms are less exposed to import competition. Frésard (2010), on the other hand, finds that financial strength can lead to market share gains. The discussion about the effects of competition is increasingly important as industries have grown more concentrated and profitable in recent decades, both in the U.S. (Covarrubias et al. (2019), Grullon et al. (2019)) and globally (De Loecker and Eeckhout (2018), Bae et al. (2021), Frésard (2010)).

There is some prior work on the relationship between competition and different measures of sustainability. Flammer (2015) finds that tariff reductions are associated with increases in CSR, while Ding et al. (2022) provide international evidence that intensifying competition laws are associated with an increase in CSR. Duanmu et al. (2018) find that a reduction in protective tariffs at WTO entry is associated with worsening of environmental performance of Chinese manufacturing firms. Some related recent studies look at consumer responses to negative ESG incidents (Houston et al. (2023), Duan et al. (2023a)).

We also contribute to the literature on the role of ownership in corporate emissions (e.g., Shive and Forster (2020)). Our finding that firms with longer-term owners exhibit a stronger relationship between competitive pressure and carbon emissions is in contrast to Starks et al. (2023), who find that short-term owners are associated with poorer ESG profiles, and to Pursiainen et al. (2024), who show that the relationship between competition and ESG performance is more negative for firms with shorter-term shareholders. On the other hand, our result that institutional ownership is associated with a weaker link between competition and emissions appears consistent with prior studies suggesting that institutional ownership is associated with more investment in sustainability and more climate risk disclosures (Azar et al. (2021), Ilhan et al. (2023), Cohen et al. (2023)).

Finally, our study is related to the literature on the interaction between morals and markets. Falk and Szech (2013) present experimental evidence that market interaction erodes moral values. Similarly, Bartling et al. (2015) find that consumers in markets exhibit less social concern than subjects in a comparable individual choice context. In a more recent paper, Bartling et al. (2023) argue that it may not be markets per se, but rather playing repeatedly that leads to the erosion of moral values. Dewatripont and Tirole (2024) show that intense market competition does not crowd out consequentialist ethics. Our findings provide nuance to this discussion, as the carbon emissions of firms that might be expected to be more "moral" indeed seem to be less sensitive to competitive pressure – but react nevertheless.

2 Data and methodology

2.1 Sample construction

To construct our sample, we start with all public U.S. firms over the period of 2002 to 2023. Our sample starts from 2002, as it is the beginning of carbon intensity data coverage in S&P Global Trucost. Other carbon emission data sources include disclosed carbon intensity data from Carbon Disclosure Project (CDP) and facility-level emissions from the Environmental Protection Agency (EPA). Product fluidity data are from the Hoberg and Phillips Data Library. Corporate financial and accounting data are from Compustat. Climate opinion data are from Yale Climate Opinion Maps. Presidential election voting data are from MIT Election Lab. Lobbying data are from Leippold et al. (2024). Social capital data are from Lin and Pursiainen (2022) and Meta. State-level exchange rate data from the Federal Reserve at Dallas. Institutional ownership data are from Thomson Reuters Institutional (13f) Holdings. After dropping firms from the financial sector (SIC codes between 6000 and 6999) and deleting observations with missing data, we obtain a sample with 28,721 firm-year observations for 3,725 U.S. firms.

2.2 Measuring carbon intensity

We measure corporate carbon intensity using data provided by S&P Global Trucost, a database prevalent in recent studies (e.g., Azar et al. (2021), Bolton and Kacperczyk (2023), Cohen et al. (2023)). Trucost compiles emission data from publicly available sources, such as financial reports, CSR reports, CDP filings, and EPA filings. It categorizes carbon emissions related to corporate activities into different scopes. For each scope, Trucost quantifies carbon emissions in absolute tonnes of CO2 equivalent, as well as calculates emission intensity as the ratio of absolute tonnes to a firm's revenue in millions of U.S. dollars. Among them, emission intensity, i.e., carbon efficiency, reflects corporate operational scale and indicates its dependency on carbon emissions in generating revenue.

As an alternative source of carbon emissions data, we use the self-reported carbon emissions from the Carbon Disclosure Project (CDP). CDP annually distributes a questionnaire to firms and asks them to report their greenhouse gas emissions in accordance with the Greenhouse Gas Protocol. This database is one of the most widely used sources for reported firm-level climate data (e.g., Cohen et al. (2023)).

We focus on Scope 1 carbon emissions – emissions that come from direct emitting sources a firm owns or controls – because they are more directly controlled by firms, and they are more accurately quantified. We logarithmically transform the Scope 1 carbon intensity. Specifically, we define *ln(Scope 1 intensity)* as the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. Higher values indicate greater levels of carbon emissions.

2.3 Measuring competitive pressure

As the main measure for competitive pressure, we use the product fluidity index of Hoberg et al. (2014). This index (*Fluidity*) is based on textual analysis of the mandatory product descriptions in 10-K filings, capturing the similarity between a focal firm's products and the overall changes in the rivals' products. A higher product fluidity index means more overlap with opponents in product space, implying higher levels of competitive pressure. Fluidity is used by a number of recent studies to measure competitive threats in the product market (e.g., Li and Zhan (2019), Mattei and Platikanova (2017), Hoberg et al. (2014), Loncan (2023), Loncan and Valta (2024)).

The product fluidity index has four benefits. First, company-level product fluidity data contain firm-specific information that is not available in other competition dimensions, such as national competition laws. The index reflects the actual competitive pressure that each company faces in the product market from both public companies and potential private firms. Second, product fluidity reflects the instability caused by the action of rivals rather than the diversification in self-products of the focal company. The launch of comparable products from opponents could intensify product market competition for firms with stationary product structures. Third, a potential endogeneity problem in investigating the association between competition and carbon emission intensity is that the CEO who formulates environmental policies also sets the competition strategies. Since product fluidity captures moves by rival firms competing in a focal company's product field, this measurement is more likely to be exogenous from a single firm's perspective (Hoberg et al. (2014)). Last, the fluidity data have comprehensive coverage for U.S. public companies across various industries, providing the same scope as the Compustat database and the CRSP database.

2.4 Control variables

Following previous literature, we control for a wide range of firm characteristics that might influence corporate carbon intensity(e.g., Azar et al. (2021), Bolton and Kacperczyk (2023), Cohen et al. (2023)).

The control variables include *ln(Total assets)*, measured by the natural logarithm of total assets; *Leverage*, measured by the ratio of book value of debt to total assets; *Cash*, measured by the ratio of cash and short-term investments to total assets; *Tangibility*, measured by the ratio of net property, plant and equipment to total assets; *Tobin's Q*, measured by the ratio of the market value of a firm plus total liability to total assets; *EBIT margin*, measured by the ratio of earnings before interest and taxes to total sales; and *ln(Firm age)*, measured by the natural logarithm of the number of years since a firm first appeared in the CRSP monthly stock return files. Detailed definitions of variables can be found in Appendix A. To avoid the effects of outliers, we winsorize all continuous variables at the 1% level.

2.5 Description of the data

Table 1 provides summary statistics for the key variables used in the analysis. The average Scope 1 carbon emission intensity (*Scope 1 intensity*) is 221.763 tonnes of CO2 equivalent per million dollars of revenue, with a standard deviation of 812.769. When log-transformed, the mean carbon intensity (*ln(Scope 1 intensity)*) is 3.288. Using CDP data as an alternative source, the mean Scope 1 intensity(*Scope 1 intensity (CDP)*) is 341.072, with a higher standard deviation of 1031.049, and a mean logged value of 3.090. It is worth noting that the number of observations with CDP data drop to 4,532. Product fluidity (*Fluidity*), the primary measure of competition, has an average value of 6.220 with a standard deviation of 3.659.

Firm size, measured by the logarithm of total assets, has a mean of 7.702. On average, firms finance 28.2% of their assets with debt, while cash holdings constitute approximately 19.8% of total assets. Net property, plant and equipment accounts for 27.1% of total assets. Tobin's Q has a mean of 2.348. The mean *EBIT margin* is -0.064, and the average firm age after log-transformed is 2.968.

3 Main results

3.1 Product fluidity and carbon emissions

To examine the relationship between competitive pressure and corporate carbon emissions, we perform a regression analysis of the following form:

$$\textit{ln(Scope 1 intensity)}_{i,t} = \alpha + \beta Fluidity_{i,t-1} + \gamma X_{i,t-1} + \epsilon_{i,t-1} \tag{1}$$

where i and t denote the firm and year, respectively. The dependent variable, *ln(Scope 1 intensity)*, is the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). X is a vector of controls. We include firm and year fixed effects throughout the paper, but also include alternative sets of fixed effects for robustness. All right-hand-side variables are lagged by one year. Standard errors are clustered by firm.

Table 2 presents the main results. Across all model specifications, the coefficients of *Flu-*

idity are positive and statistically significant at the 1% level, indicating a positive relationship between product fluidity and carbon emissions. This relationship is also economically meaningful: based on the specification with firm and year fixed effects, a one-standard-deviation increase in fluidity is associated with a 4.32% increase in carbon emissions per unit of revenue. This positive relationship remains robust even after controlling for firm characteristics, including size, leverage, cash holdings, and tangibility, as well as incorporating alternative sets of fixed effects including the industry-year, state-year, or state-industry-year levels.

To address concerns that the results might be driven by the methodology used by Trucost to estimate emissions (e.g., Aswani et al. (2024)), we replicate the analysis using self-reported carbon emissions from the Carbon Disclosure Project (CDP) as an alternative data source. The results, reported in Table 3, are highly similar. Despite the substantially smaller sample size, the estimated coefficients on *Fluidity* remain positive, statistically significant, and of comparable economic magnitude. These findings suggest that the observed relationship is not an artifact of the Trucost estimation methodology.

The baseline regressions document a positive association between product fluidity and carbon emissions. To explore this relationship further, we examine the covariation between changes in emissions intensity and changes in fluidity using binscatter plots in Figure 1. Panel A uses Trucost data, while Panel B relies on self-reported CDP data. Each panel presents a scatterplot based on 10 quantile bins of lagged annual changes in product fluidity, with fitted linear trends. The y-axis measures the annual change in *ln(Scope 1 intensity)*, defined as the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue (in millions of USD). The x-axis measures the annual change in *Fluidity*, the text-based product fluidity index of Hoberg et al. (2014).

In both panels, the average Δ *ln(Scope 1 intensity)* is negative, reflecting a general trend of declining carbon intensity across firms. However, the upward slope of the fitted line suggests that firms with larger increases in fluidity tend to exhibit smaller reductions in emissions intensity compared to those with smaller changes in fluidity. This pattern is consistent with the idea that heightened competitive pressure may coincide with slower progress in carbon abatement, though the relationship could also reflect other unobserved factors. The results align with the interpretation that competition—rather than directly increasing emissions—might delay investments in emissions-reducing technologies or practices.

3.2 Decomposition of carbon intensity

To better understand the channels through which competition affects carbon intensity, we decompose it into its two components: total Scope 1 emissions and firm revenue. Table 4 presents regression results for both Trucost and CDP samples using *ln(S1 intensity)*, *ln(S1 emissions)*, and *ln(Revenue)* as dependent variables. *ln(S1 emissions)*, the natural logarithm of absolute Scope 1 emissions, captures absolute emissions, while *ln(Revenue)*, the natural logarithm of net sales, reflects firm scale.

The results show that product fluidity is positively associated with *ln(S1 emissions)* and negatively associated with *ln(Revenue)*, with the former effect being economically larger. This implies that increases in carbon intensity under heightened competition are primarily driven by rising emissions rather than declining revenue. These findings suggest that firms facing greater product market pressure emit more, rather than becoming more carbon-intensive simply due to shrinking scale.

This decomposition supports the interpretation that competitive pressure leads to reduced investment in abatement or weaker environmental controls, rather than mechanical changes in output levels alone.

3.3 Lagged fluidity and carbon emissions

We further examine the dynamic relationship between product fluidity and carbon intensity by incorporating contemporaneous and multiple lagged measures of fluidity into our regression model. This approach allows us to test not only the short-term but also potential medium-term effects of competitive pressure on firm emissions behavior. The results, shown in Table 5, indicate that higher product fluidity is significantly associated with increased carbon intensity in the short term, with the strongest effect observed for the one-year lag. When multiple lags are included jointly, the one-year lag remains the most predictive of emissions intensity.

To assess whether competition might ultimately lead firms to innovate and reduce emissions in the longer term—consistent with the theoretical arguments of Aghion et al. (2023), Dai et al. (2025), Schinkel and Treuren (2020), and Cenci et al. (2025)—we examine whether coefficients on more distant lags turn negative. We find no such reversal. The estimated effects beyond the first year are statistically insignificant and do not indicate a downward trend. These results suggest that, while competitive pressure is associated with increased emissions in the short term, we find no evidence that it prompts firms to become greener over the medium term.

3.4 Facility-level emissions

To validate our firm-level results using an alternative data source that directly captures operational emissions, we turn to facility-level data from the U.S. Environmental Protection Agency (EPA). Unlike Trucost or CDP, which rely in part on estimates or self-reports, the EPA database collects emissions reported by firms at the facility level for regulatory purposes. This allows us to test whether the link between competition and emissions holds in a setting that is less susceptible to disclosure biases or estimation assumptions.

Table 6 presents regression results of the relationship between product fluidity and U.S. facility-level carbon emissions. In columns (1) and (2), the dependent variable is *ln(Carbon emissions - firm)*, defined as the natural logarithm of one plus the total carbon emissions of all facilities associated with the firm. Columns (3) and (4) use *ln(Carbon intensity - firm)*, measured as the natural logarithm of one plus the ratio of total facility emissions to firm revenue. Column (5) shifts the unit of analysis to the facility level, where the dependent variable is *ln(Facility emissions)*, the natural logarithm of one plus the carbon emissions of a single facility. The main independent variable in all regressions is *Fluidity*.

The coefficients on fluidity are positive across all specifications but only statistically significant in some. In particular, the association is stronger and statistically significant when using aggregated emission intensity as the dependent variable, while the estimates for individual facility emissions are smaller in magnitude and not statistically significant. These patterns suggest that while competitive pressure is associated with an overall increase in reported emissions at the firm level, its effect at the facility level is more muted or heterogeneous. Specifically, the facility-level results suggest that the firm-level relationship between competitive pressure and carbon emissions is largely driven by changes in the facility composition, with higher-carbon facilities used relatively more when facing more competitive pressure.

3.5 Climate opinions, political views, and lobbying

Firms operate within broader societal and political contexts that influence their environmental decisions. Prior research suggests that corporate expectations regarding future climate regulation shape emissions strategies (Ramadorai and Zeni (2024)), while political ideology correlates with sustainability preferences, including in investment behavior (Hong and Kostovetsky (2012), Gormley et al. (2024), Kempf and Tsoutsoura (2024)).

Public climate opinions reflect societal expectations for corporate environmental responsibility and may moderate firms' ability to increase emissions in response to competitive pressure. Greater climate concern may generate stronger pressure from consumers, investors, and regulators, whereas weaker concern may allow firms to prioritize cost-cutting over sustainability efforts. Similarly, political ideology shapes regulatory environments: conservative-leaning regions typically impose less stringent environmental policies, providing firms with greater flexibility to raise emissions under competition, whereas progressive-leaning areas are associated with stricter oversight and higher reputational risks.

Panel A of Table 7 examines how public climate opinions and local political views moderate the relationship between product fluidity and carbon intensity. We first partition the sample based on local climate concern, measured using the Yale Climate Opinion Maps (Howe et al. (2015); Baldauf et al. (2020)). *Climate concern* is defined as the share of county residents who believe corporations and industry should be doing more or much more to address global warming. Firms headquartered in counties with climate concern above the sample median are classified as *High*, and others as *Low*. The results show that the positive association between product fluidity and carbon intensity is significantly weaker in regions with higher climate concern, suggesting that stronger societal expectations may constrain firms' emissions responses to competition.

We next partition the sample based on county-level political ideology, proxied by the Republican vote share in the most recent Presidential election (MIT Election Lab). *Republican* is measured by a dummy variable that equals one if a county has a majority of voters voting Republican party in the Presidential election. Firms in counties with *Republican* majority are classified as *Yes*, otherwise as *No*. The results indicate that firms in more conservative areas exhibit a somewhat stronger positive relationship between competition and carbon emissions, consistent with weaker regulatory or social constraints. However, the economic magnitude of the difference is small and not statistically significant.

Panel B of Table 7 examines whether firm-level lobbying expenditures moderate the relationship between product fluidity and carbon intensity. *Democratic* is measured by the Democratic-leaning lobbying expenses of Leippold et al. (2024). *Republican* is measured by the Republican-leaning lobbying expenses of Leippold et al. (2024). Firms with *Democratic* or *Republican* above sample medians each year are classified as *High*, otherwise as *Low*.

The results show that firms that lobby Democrats more heavily exhibit a weaker relationship between competition and carbon intensity. Although it is not statistically significant, the results suggest that engagement with Democratic policymakers, who generally support stronger environmental regulations, may constrain firms from increasing emissions even under competitive pressure. In contrast, firms that lobby Republicans more heavily exhibit a stronger positive relationship between competition and carbon intensity, implying that lobbying efforts directed toward Republican policymakers, who typically advocate for deregulation, allow firms greater flexibility to increase emissions in response to competitive pressures.

3.6 Social norms

Firms' carbon abatement decisions are also by social norms, which reflect community expectations regarding corporate responsibility. In regions with stronger pro-environmental norms, firms may face greater public pressure to maintain sustainability efforts, limiting their ability to increase emissions in response to competition. By contrast, firms operating in areas with weaker social norms may experience less stakeholder scrutiny, allowing them to prioritize cost-cutting over environmental considerations when competitive pressures intensify.

Table 8 presents the results examining how social norms moderate the relationship between product fluidity and carbon intensity. Firms are partitioned based on three proxies for local social norms. First, we use the *Social capital* index of Lin and Pursiainen (2022), which measures the strength of community relationships and trust networks that impose behavioral norms. Higher levels of social capital imply stronger informal governance structures. Second, we use *Volunteering*, measured by the share of Facebook users in a county who belong to groups associated with volunteering or activism, based on group titles and other group characteristics (Chetty et al. (2022a), Chetty et al. (2022b)). Third, we include *Civic org.*, measured by the share of users participating in Facebook groups associated with public good provision. For each measure, firms are classified as *High* or *Low* based on whether their values exceed the sample median in a given year.

The results show that the positive relationship between product fluidity and carbon intensity is weaker for firms in regions with higher social capital, greater volunteering activity, or stronger civic engagement. This suggests that local social norms serve as informal constraints on firms' emissions responses to competitive pressure. In contrast, firms in low-norm regions exhibit a stronger sensitivity of emissions intensity to competition. These findings support the view that community-level norms play a moderating role in how firms adjust environmental practices in the face of heightened product market pressure.

3.7 Profitability

If firms face a trade-off between carbon abatement and profitability, we might expect the emissinos of less profitable firms to be more sensitive to competitive pressure. To examine whether firms' profitability influences the relationship between competitive pressure and carbon emissions, we partition our sample based on several measures of profitability: *EBIT margin*, *EBITDA margin*, *Tobin's Q*, *EBIT to assets*, *RoA*, and *RoE*. Firms are classified as *High* or *Low* based on whether their profitability measures are above or below the sample median in a given year.

Panel A of Table 9 reports results for operating margin measures. We find that the positive association between product fluidity and carbon intensity is statistically significant for firms with lower profitability margins, while the effect is insignificant for high-margin firms. The difference between groups is not statistically significant. A similar pattern emerges for cash flow-based profitability measures, where the effect of competition on emissions appears stronger for less profitable firms, though the difference remains insignificant. For market-based valuation measures, the relationship holds for both high and low valuation firms, with slightly stronger effects for the latter group.

Panel B examines asset-based profitability measures. Firms with lower profitability ratios exhibit a stronger positive relationship between competition and emissions compared to high-ratio firms, and this difference is statistically significant. For accounting-based profitability measures, the effect is significant for both high- and low-profitability firms, with no meaningful difference between groups. The results are most pronounced for return-based profitability measures, where less profitable firms show a substantially stronger link between competition and emissions.

Overall, these results demonstrates that profitability meaningfully moderates the relationship between competition and carbon emissions, with less profitable firms exhibiting greater sensitivity to competitive pressures. These results are consistent with firms protecting their profit margins at the expense of higher emissions.

4 Additional analysis

4.1 Instrumenting product fluidity

To better address potential endogeneity concerns in the relationship between competitive pressure and carbon emissions, we employ two instrumental variables (IVs) to generate plausibly exogenous variation in product fluidity: changes in state-level trade-weighted foreign exchange rates (Li and Zhan (2019), Loncan (2023), Loncan and Valta (2024)) and the staggered adoption of Paid Sick Leave (PSL) mandates (Loncan and Valta (2024), Maclean et al. (2024)).

The first instrument, Δ *ln(FX)*, is defined as the growth rate of the real trade-weighted exchange rate at the state level. An appreciation of the state-level U.S. dollar is plausibly associated with increased local competition, as a stronger dollar reduces the relative price of imports and thereby intensifies competition faced by domestic firms. Since exchange rates are determined by aggregated, decentralized market transactions, the actions of individual firms are unlikely to materially influence state-level exchange rates. This supports the plausibility of the exclusion restriction, whereby the residual of the structural equation is uncorrelated with the exchange rate fluctuations.

The second instrument, *PSL*, is a dummy variable equal to one if a firm's headquarter state has implemented a Paid Sick Leave mandate.[9] The implementation of PSL laws raises firms' labor costs by mandating paid compensation for employee sick leave, thus reducing profit margins. Firms with greater market power may be better positioned to absorb these

[9] See Internet Appendix Section IA.12 for details on the staggered implementation of these policies.

higher costs, while firms with weaker market positions are likely to be disproportionately affected. As a result, PSL mandates may erode the competitive strength of less powerful firms, thereby reducing overall market competition. Since PSL mandates are policy decisions made at the state level, independent of firm-level competitive actions, it is plausible that the exclusion restriction holds, and that the policy shocks are exogenous with respect to firms' carbon emission behaviors.

By using the two instrumental variables, we assume that changes in state-level trade-weighted exchange rates (Δ *ln(FX)*) and the introduction of Paid Sick Leave mandates (*PSL*) are correlated with product market fluidity but do not directly affect firms' carbon emissions except through their impact on competition.

Table 10 presents the results of the instrumental variables (IV) estimation, using Δ *ln(FX)* and *PSL* as instruments for product fluidity. The table is organized into three panels: Panel A reports the ordinary least squares (OLS) estimates of the relationship between the instruments and carbon intensity; Panel B presents the first-stage regression results; and Panel C reports the second-stage IV estimates.

Panel A shows that a stronger U.S. dollar (Δ *ln(FX)*) is associated with higher carbon emissions, consistent with the notion that increased competitive pressure from cheaper imports may raise firms' emissions. Conversely, Paid Sick Leave mandates (*PSL*) are negatively associated with carbon intensity, suggesting that stricter labor regulations may reduce emissions, possibly by raising firms' operational costs and dampening competitive intensity.

Panel B confirms that both instruments are strongly correlated with product fluidity. A stronger U.S. dollar significantly increases fluidity, indicating that exchange rate appreciations intensify product market competition by lowering the cost of imported goods. In contrast, the introduction of PSL mandates significantly reduces fluidity, consistent with higher labor costs deterring entry or expansion, particularly among smaller or less competitive firms (Loncan and Valta (2024)). The high first-stage F-statistics mitigate concerns about weak instruments and confirm the relevance of the instruments.

Panel C shows that instrumented product fluidity remains positively and significantly associated with carbon intensity. The magnitude of the IV estimates is larger than the corresponding OLS estimates, suggesting that OLS specifications may underestimate the true effect of competitive pressure on firms' emissions. Overall, the IV results reinforce the interpretation that greater competition is associated with higher carbon emissions.

4.2 Ownership and investor horizon

Many commentators (see, e.g., Paulson (2015), van Lierop (2024)) and academic studies (e.g., Maeckle (2024), Wiersema et al. (2025)) have suggested that short-termism is a major barrier to corporate carbon reduction efforts. Short-term-oriented investors, who frequently trade stocks and prioritize immediate financial returns, may pressure firms to focus on cost-cutting and short-term profitability at the expense of long-term sustainability goals. In contrast, long-term investors, such as pension funds and large institutional shareholders, often advocate for corporate policies that enhance long-term value, including environmental responsibility. In this case, we would expect firms with longer-term shareholders to be less likely to increase carbon emissions in response to competitive pressure.

To test this conjecture, we perform subsample analyses using a number of proxies for investor short-termism: *Churn ratio* is measured by the weighted average portfolio churn rate of institutional shareholders over four quarters (Gaspar et al. (2005)); *Adjusted churn ratio* is the refined measure of *Churn ratio*(Yan and Zhang (2009)); and *Transient ownership* is calculated as the share of transient institutional owners relative to total institutional ownership(Bushee (1998)). Shareholders of firms with higher *Churn ratio*, *Adjusted churn ratio* and *Transient ownership* are more likely to have shorter investment horizons. We also include a subsample analysis based on overall institutional ownership.

Table 11 presents the regression results for subsamples by investor horizon. Firms are categorized into high and low groups based on the sample median for each measure each year. Across all measures, the positive relationship between product fluidity and carbon emissions is, if anything, slightly stronger for firms with longer-horizon shareholders. This pattern contrasts somewhat with the findings of Starks et al. (2023), who document that long-term institutional investors are more likely to allocate capital toward firms with stronger ESG profiles.

We also find that the relationship between product fluidity and carbon emissions is more pronounced for firms with lower institutional ownership. Institutional ownership, defined as the share of outstanding equity held by institutional investors, appears to attenuate firms' emissions responses to competitive pressure. This result is consistent with Azar et al. (2021), who document that Big Three ownership is associated with lower subsequent carbon emissions among MSCI index constituents.

Taken together, the results suggest that institutional ownership may play a moderating role in firms' environmental responses to competition. However, they provide limited support for the view that short-term investor pressure drives the sensitivity of carbon emissions to competitive pressure. If anything, the emissions-competition link appears at least as strong among firms with longer-term-oriented shareholders, suggesting that short-termism is unlikely to be the primary explanation for the observed patterns.

4.3 Firm size, age, and total carbon emissions

We also examine how firm characteristics—specifically size, age, and total carbon emissions—moderate the relationship between product fluidity and carbon intensity. Prior research suggests that smaller and younger firms, particularly those facing financial constraints, may prioritize capital investment over pollution abatement (Fang et al. (2024)). By analyzing firms across different size and age groups, we assess whether competition-induced increases in emissions are concentrated among certain types of firms or represent a broader trend across the corporate sector. In addition, examining heterogeneity based on total carbon emissions allows us to evaluate whether competitive pressure disproportionately affects high-emission firms, which contribute most to aggregate carbon output, or whether the effects are more uniformly distributed.

Table 12 presents the subsample regression results. Firms are categorized into high and low groups each year based on the sample median for three variables: *Total assets* (as a proxy for firm size), *Firm age* (measured as the number of years since first appearance in the CRSP monthly return files), and *Total Scope 1 emissions* (capturing absolute emissions rather than emissions intensity). This categorization allows us to assess whether larger, older, or high-emitting firms exhibit different sensitivities to competitive pressure with respect to carbon intensity.

The results show that product fluidity is positively associated with carbon intensity across all subsamples. However, the differences between the high and low groups are economically small and statistically insignificant. This suggests that firm size, firm age, and total emissions do not materially alter the relationship between competition and emissions intensity. Overall, the findings indicate that competitive pressure is associated with increased carbon emissions across a broad range of firms, rather than being driven by particular types of firms.

4.4 Additional results and robustness checks

Our Internet Appendix contains several additional analyses that support and extend our main findings:

(i) *Comparison of carbon emissions data across sources.* Table IA.1 and Table IA.2 present firm-year observations and correlation matrices comparing carbon intensity and absolute emissions measures from Trucost, CDP, and the EPA.

(ii) *Alternative emissions data: CDP self-reported data.* Table IA.3 and Table IA.4 replicate the regressions in Table 5 and Table 7 using CDP self-reported Scope 1 emissions instead of Trucost estimates.

(iii) *Different emission scopes.* Table IA.5 examines whether the effect of product fluidity on carbon outcomes holds across different scopes of emissions. The analysis includes location-based Scope 2, market-based Scope 2, upstream Scope 3, and downstream Scope 3 carbon intensity.

(iv) *Alternative measures of competition.* Table IA.6 tests the robustness of the main results using alternative proxies for competition. These include Herfindahl–Hirschman indices (HHIs) based on 2-, 3-, and 4-digit SIC codes, 2- and 4-digit NAICS codes, and the TNIC text-based industry classification.

(v) *Fluidity and financial performance.* Table IA.7 investigates the relationship between product fluidity and firm financial performance, including EBIT margin, EBITDA margin, Tobin's Q, EBIT to assets, return on assets (RoA), and return on equity (RoE).

(vi) *Industry heterogeneity.* Table IA.8 examines whether the effect of product fluidity on carbon intensity differs across industries with varying environmental risk profiles. Firms are classified using four industry-level indicators: GHG-sensitive industries, environmentally sensitive industries (SASB), environmentally sensitive industries (AOS), and sin industries.

(vii) *The role of financial constraints.* Table IA.9 explores whether the effect of product fluidity on carbon intensity is moderated by financial constraints, using the Whited–Wu index, SA index, and text-based measures of equity and debt constraints as proxies.

(viii) *Distress risk subsample analysis.* Table IA.10 examines whether financially distressed firms respond differently to competition, using the KZ index, Z-score, and ZM-score as proxies.

(ix) *Climate concern and emissions change.* Figure IA.1 plots the change in Scope 1 carbon intensity against local climate concern. Firms located in regions with greater public climate concern exhibit larger emissions reductions, consistent with social pressure acting as a constraint on carbon behavior.

(x) *Revenue and emissions response to fluidity.* Figure IA.2 shows binscatter plots of changes in revenue (Panel A) and absolute emissions (Panel B) against changes in product fluidity. Competition is associated with output decline and higher emissions.

5 Conclusion

This paper examines how competitive pressure, measured by product fluidity, influences firms' carbon emission intensity. Across a range of specifications, we find that greater competition is consistently associated with higher carbon emissions relative to firm revenue. The results are robust to addressing endogeneity with instrumental variables and to using alternative emissions data from the Carbon Disclosure Project (CDP).

Our findings suggest that competitive pressure may create incentives for firms to deprioritize carbon abatement, highlighting an underexplored tension between market competition and environmental sustainability. Although public climate concern and social norms modestly attenuate this relationship, and institutional ownership exerts some moderating effect, these forces are insufficient to fully offset the pressures competition imposes on corporate environmental behavior. Political ideology and firm-level lobbying orientation show directional patterns consistent with expectations but have limited economic and statistical significance.

Importantly, we find no evidence that short-term investor pressure explains the link between competition and emissions; in fact, firms with longer-term investors exhibit at least as strong a sensitivity to competition. Moreover, the positive association between competition and emissions holds across firms of different sizes, ages, and baseline emissions levels, indicating that the effect is broad-based rather than confined to specific firm types.

Overall, these results offer a nuanced perspective on the drivers of corporate carbon behavior. Policies promoting competition may inadvertently undermine climate objectives unless accompanied by complementary regulatory or market-based mechanisms that realign firms' environmental incentives. Future efforts to design effective climate policies must therefore account for how competitive dynamics interact with firms' sustainability decisions.

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Appendix A: Definitions of variables

Variable	Definition
Scope 1 intensity	The ratio of Scope 1 carbon emissions to revenue in millions of dollars.
ln(Scope 1 intensity)	The natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars.
Scope 1 intensity (CDP)	The ratio of disclosed Scope 1 carbon emissions to revenue in millions of dollars.
ln(Scope 1 intensity (CDP))	The natural logarithm of one plus the ratio of disclosed Scope 1 carbon emissions to revenue in millions of dollars.
Fluidity	The product fluidity index of Hoberg et al. (2014).
ln(Total assets)	The natural logarithm of total assets.
Leverage	The ratio of book value of debt to total assets.
Cash	The ratio of cash and short-term investments to total assets.
Tangibility	The ratio of net property, plant and equipment to total assets.
Tobin's Q	The ratio of the market value of a firm plus total liability to total assets.
EBIT margin	The ratio of earnings before interest and taxes to total sales.
ln(Firm age)	The natural logarithm of the number of years since a firm first appeared in the CRSP monthly stock return files.
ln(S1 intensity)	The natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars.
ln(S1 emissions)	The natural logarithm of one plus the absolute Scope 1 carbon emissions.
ln(Revenue)	The natural logarithm of net sales.
ln(Carbon emissions - firm)	The natural logarithm of one plus the total carbon emissions of all facilities of the firm.
ln(Carbon intensity - firm)	The natural logarithm of one plus the ratio of the total carbon emissions of all facilities of the firm to revenue.
ln(Facility emissions)	The natural logarithm of one plus the carbon emissions of the facility.
Climate concern	The ratio of population who think corporations and industry should be doing more or much more to address global warming.
Republican	A dummy variable that equals one if a county has a majority of voters voting Republican party in the Presidential election.
Democratic	The Democratic-leaning lobbying expenses of Leippold et al. (2024).
Republican	The Republican-leaning lobbying expenses of Leippold et al. (2024).
Social capital	The social capital index of Lin and Pursiainen (2022).
Volunteering	The ratio of Facebook users who are members of a group which is predicted to be about volunteering or activism based on group title and other group characteristics.
Civic org.	The ratio of Facebook users who are members of a group which is predicted to be public good based on group title and other group characteristics.
EBITDA margin	The ratio of earnings before interest, taxes, depreciation, and amortization to total sales.
EBIT to assets	The ratio of earnings before interest and taxes to total assets.

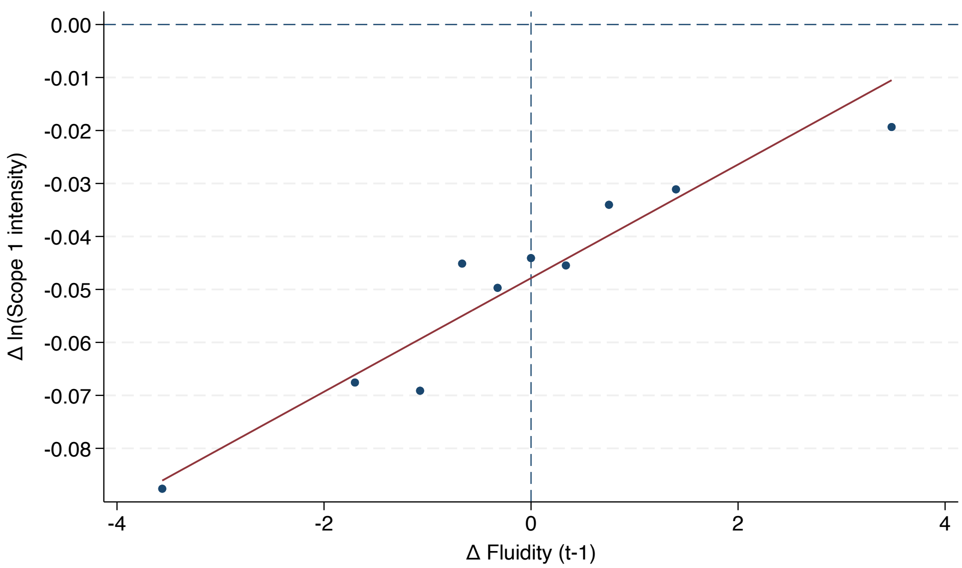
RoA	The ratio of net income to total assets.
RoE	The ratio of net income to firm equity.
Δ ln(FX)	The growth rate of real trade-weighted state-level exchange rates.
PSL	A dummy variable that equals one if a state adopts Paid Sick Leave mandates.
Inst. ownership	The ratio of shareholdings by all institutional investors to total shares outstanding.
Churn ratio	The weighted average churn ratio of Gaspar et al. (2005).
Adj. churn ratio	The adjusted weighted average churn ratio of Yan and Zhang (2009).
Transient ownership	The ratio of shareholdings of transient institutional investors to the total institutional ownership.
Total assets	The number of total assets.
Firm age	The number of years since a firm first appeared in the CRSP monthly stock return files.
Total scope 1 emissions	Firm-level yearly emissions capturing absolute carbon output.
ln(S2 (loc.) intensity)	The natural logarithm of one plus the ratio of location-based Scope 2 carbon emissions to revenue in millions of dollars.
ln(S2 (mkt.) intensity)	The natural logarithm of one plus the ratio of market-based Scope 2 carbon emissions to revenue in millions of dollars.
ln(S3 (up) intensity)	The natural logarithm of one plus the ratio of upstream Scope 3 carbon emissions to revenue in millions of dollars.
ln(S3 (down) intensity)	The natural logarithm of one plus the ratio of downstream Scope 3 carbon emissions to revenue in millions of dollars.
SIC2 HHI	The Herfindahl–Hirschman index based on the 2-digit SIC code. Herfindahl–Hirschman index is calculated as the sum of the squared market shares based on firm sales.
SIC3 HHI	The Herfindahl–Hirschman index based on the 3-digit SIC code. Herfindahl–Hirschman index is calculated as the sum of the squared market shares based on firm sales.
SIC4 HHI	The Herfindahl–Hirschman index based on the 4-digit SIC code. Herfindahl–Hirschman index is calculated as the sum of the squared market shares based on firm sales.
NAICS2 HHI	The Herfindahl–Hirschman index based on the 2-digit NAICS code. Herfindahl–Hirschman index is calculated as the sum of the squared market shares based on firm sales.
NAICS4 HHI	The Herfindahl–Hirschman index based on the 4-digit NAICS code. Herfindahl–Hirschman index is calculated as the sum of the squared market shares based on firm sales.
TNIC HHI	The Herfindahl-Hirschman index based on the 10-K text-based network industry classification.
GHG sensitive	A dummy variable that equals one if GHG emissions are a material sustainability issue for the industry, as idenfied by the Sustainability Accounting Standards Board (SASB) Materiality Map.
Env. sensitive SASB	A dummy variable that equals one if environment is a material sustainability issue for the industry, as idenfied by the Sustainability Accounting Standards Board (SASB) Materiality Map.

Env. sensitive AOS	A dummy variable that equals one if a firm operates primarily in environmentally sensitive industries (2-digit SIC codes: 10, 13, 26, 28, 29, 33, 49), as idenfied by Cho and Patten (2007).
Sin industry	A dummy variable that equals one if a firm is sin industries (SIC codes: 2100-2199, 2080-2085; NAICS codes: 7132, 71312, 713210, 71329, 713290, 72112, and 721120).
WW index	The WW index of Whited and Wu (2006).
SA index	The SA index of Hadlock and Pierce (2010).
Equity constr. (f)	The equity constraints index using the full model of Hoberg and Maksimovic (2015) and Linn and Weagley (2024).
Equity constr. (p)	The equity constraints index using the prime model of Hoberg and Maksimovic (2015) and Linn and Weagley (2024).
Debt constr. (f)	The debt constraints index using the full model of Hoberg and Maksimovic (2015) and Linn and Weagley (2024).
Debt constr. (p)	The debt constraints index using the prime model of Hoberg and Maksimovic (2015) and Linn and Weagley (2024).
KZ index	The KZ index of Kaplan and Zingales (1997).
Z score	The Z score of Altman (1968).
ZM score	The ZM score of Zmijewski (1984).

Figure 1: Binscatter of changes in carbon intensity vs. changes in product fluidity

This figure shows the relationship between changes in product market fluidity and changes in carbon intensity. Panel A uses Trucost data; Panel B uses CDP self-reported data. Each panel presents a scatterplot based on 10 quantile bins of lagged annual changes in product fluidity, with fitted linear trends. The y-axis measures the annual change in *ln(Scope 1 intensity)*, defined as the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue (in millions of USD). The x-axis measures the annual change in *Fluidity*, the text-based product fluidity index of Hoberg et al. (2014).

Panel A. Trucost data



Panel B. CDP data

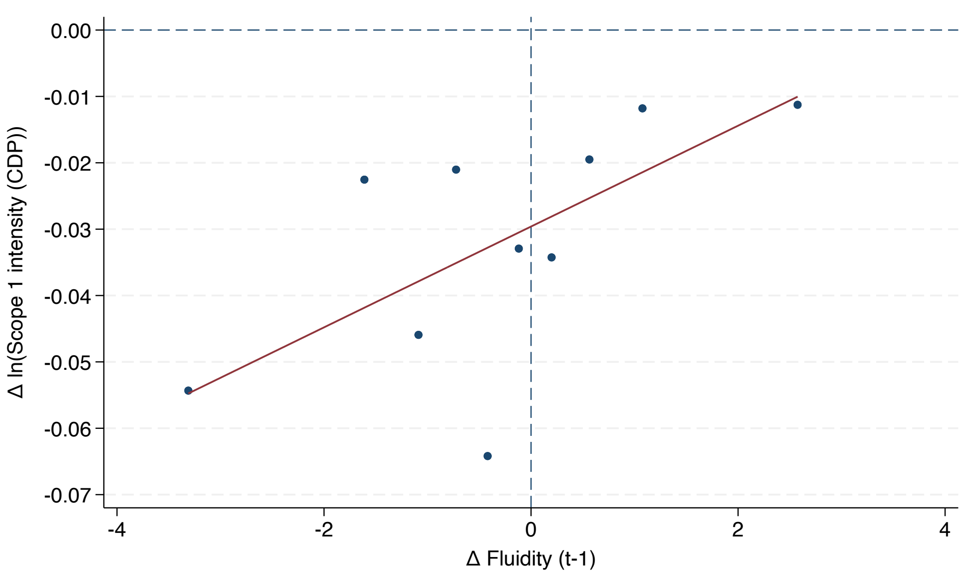


Table 1
Summary statistics

This table presents the descriptive statistics for the main variables used in our analyses. All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level.

	Mean	Std	p25	p50	p75	N
Carbon emissions						
Scope 1 intensity	221.763	812.769	8.464	17.501	46.906	28,721
ln(Scope 1 intensity)	3.288	1.740	2.248	2.918	3.869	28,721
Δ ln(Scope 1 intensity)	-0.049	0.307	-0.072	-0.021	0.016	25,339
Scope 1 intensity (CDP)	341.072	1031.049	2.466	12.633	91.607	4,532
ln(Scope 1 intensity (CDP))	3.090	2.294	1.243	2.612	4.528	4,532
Δ ln(Scope 1 intensity (CDP))	-0.032	0.241	-0.120	-0.032	0.049	3,718
Competition						
Fluidity	6.220	3.659	3.482	5.303	8.028	28,721
Δ Fluidity	-0.089	1.912	-1.025	-0.118	0.810	27,392
Controls						
ln(Total assets)	7.702	1.801	6.492	7.771	8.934	28,694
Leverage	0.282	0.221	0.109	0.261	0.402	28,582
Cash	0.198	0.229	0.036	0.105	0.265	28,692
Tangibility	0.271	0.244	0.081	0.181	0.408	28,680
Tobin's Q	2.348	1.870	1.253	1.719	2.698	28,661
EBIT margin	-0.064	0.571	0.020	0.091	0.165	28,478
ln(Firm age)	2.968	0.932	2.303	3.135	3.689	28,007
N	28,721					

Table 2
Carbon intensity and product fluidity

This table presents regression results of the relationship between product fluidity and carbon intensity. The dependent variable is *ln(Scope 1 intensity)*, measured by the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Fluidity	0.0613***	0.0629***	0.0118***	0.0109***	0.0123***
	(0.0081)	(0.0074)	(0.0032)	(0.0034)	(0.0038)
ln(Total assets)		-0.0231	-0.0909***	-0.0542***	-0.0681***
		(0.0179)	(0.0166)	(0.0170)	(0.0198)
Leverage		-0.3864***	0.0158	-0.0094	0.0175
		(0.0919)	(0.0457)	(0.0461)	(0.0515)
Cash		-0.5468***	0.1210**	0.0640	0.0408
		(0.1190)	(0.0603)	(0.0615)	(0.0695)
Tangibility		4.0766***	0.1859	0.2163*	0.1140
		(0.1309)	(0.1220)	(0.1206)	(0.1575)
Tobin's Q		-0.0682***	-0.0091*	-0.0032	-0.0110**
		(0.0088)	(0.0051)	(0.0050)	(0.0054)
EBIT margin		-0.1019***	-0.0547***	-0.0212	-0.0197
		(0.0339)	(0.0151)	(0.0149)	(0.0164)
ln(Firm age)		0.2329***	0.0457	0.0308	-0.0051
		(0.0291)	(0.0387)	(0.0384)	(0.0487)
Year FE	No	No	Yes	No	No
Industry-Year FE	No	No	No	Yes	No
State-Year FE	No	No	No	Yes	No
State-Industry-Year FE	No	No	No	No	Yes
Firm FE	No	No	Yes	Yes	Yes
N	28,721	27,664	27,423	26,184	19,834
R^2	0.017	0.426	0.931	0.942	0.954

Table 3
CDP reported carbon emissions and product fluidity

This table presents regression results of the relationship between product fluidity and disclosed carbon intensity, using data from the Carbon Disclosure Project (CDP). The dependent variable is *ln(Scope 1 intensity (CDP))*, measured by the natural logarithm of one plus the ratio of disclosed Scope 1 carbon emissions to revenue in millions of dollars from CDP. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Fluidity	0.1965***	0.0860***	0.0173***
	(0.0323)	(0.0215)	(0.0061)
Controls	No	Yes	Yes
Year FE	No	No	Yes
Firm FE	No	No	Yes
N	4,532	4,508	4,393
R^2	0.064	0.604	0.980

Table 4
Decomposition of carbon intensity

This table presents regression results of the relationship between product fluidity and carbon intensity components. *ln(S1 intensity)* is measured by the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. *ln(S1 emissions)* is measured by the natural logarithm of one plus the absolute Scope 1 carbon emissions. *ln(Revenue)* is measured by the natural logarithm of net sales. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Trucost sample			CDP sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	ln(S1 intensity)	ln(S1 emissions)	ln(Revenue)	ln(S1 intensity)	ln(S1 emissions)	ln(Revenue)
Fluidity	0.0118***	0.0090**	-0.0056**	0.0173***	0.0173*	-0.0018
	(0.0032)	(0.0044)	(0.0024)	(0.0061)	(0.0091)	(0.0024)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	27,423	27,423	27,055	4,393	4,399	4,393
R^2	0.931	0.948	0.973	0.980	0.965	0.982

Table 5
Carbon intensity and lagged product fluidity

This table presents regression results of the relationship between product fluidity in different periods and carbon intensity. The dependent variable is *ln(Scope 1 intensity)*, measured by the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Fluidity(t)	0.0065**					0.0027
	(0.0031)					(0.0028)
Fluidity		0.0118***				0.0096***
		(0.0032)				(0.0022)
Fluidity(t-2)			0.0099***			0.0046**
			(0.0032)			(0.0022)
Fluidity(t-3)				0.0074**		0.0028
				(0.0035)		(0.0023)
Fluidity(t-4)					0.0053	0.0023
					(0.0038)	(0.0031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	26,817	27,423	26,497	25,381	24,362	23,671
R^2	0.931	0.931	0.931	0.931	0.932	0.932

Table 6
EPA data on U.S. facility emissions

This table presents regression results of the relationship between product fluidity and U.S. facility emissions, using data from the Environmental Protection Agency (EPA). In columns (1) and (2), the dependent variable is *ln(Carbon emissions - firm)*, measured by the natural logarithm of one plus the total carbon emissions of all facilities of the firm. In columns (3) and (4), the dependent variable is *ln(Carbon intensity - firm)*, measured by the natural logarithm of one plus the ratio of the total carbon emissions of all facilities of the firm to revenue. In column (5), the dependent variable is *ln(Facility emissions)*, measured by the natural logarithm of one plus the carbon emissions of the facility. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	ln(Carbon emissions - firm)		ln(Carbon intensity - firm)		ln(Facility emissions)
	(1)	(2)	(3)	(4)	(5)
Fluidity	0.1339***	0.0159	0.1628***	0.0259**	0.0015
	(0.0271)	(0.0121)	(0.0269)	(0.0123)	(0.0031)
Controls	No	Yes	No	Yes	No
Year FE	No	Yes	No	Yes	Yes
Firm FE	No	Yes	No	Yes	No
Facility FE	No	No	No	No	Yes
N	3,727	3,666	3,630	3,570	35,193
R^2	0.041	0.920	0.066	0.923	0.883

Table 7
Climate opinions, political views, and lobbying

This table presents subsample regression results by local climate opinions and political views, as well as firm political lobbying. The dependent variable is *ln(Scope 1 intensity)*, measured by the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). Panel A reports the regression results of the effect of product fluidity on carbon intensity by local climate opinions and political views. *Climate concern* is measured by the ratio of population who think corporations and industry should be doing more or much more to address global warming. Firms in counties with *Climate concern* above sample medians are classified as *High*, otherwise as *Low*. *Republican* is measured by a dummy variable that equals one if a county has a majority of voters voting Republican party in the Presidential election. Firms in counties with *Republican* majority are classified as *Yes*, otherwise as *No*. Panel B reports the regression results of the effect of product fluidity on carbon intensity by firm political lobbying. *Democratic* is measured by the Democratic-leaning lobbying expenses of Leippold et al. (2024). *Republican* is measured by the Republican-leaning lobbying expenses of Leippold et al. (2024). Firms with *Democratic* or *Republican* above sample medians each year are classified as *High*, otherwise as *Low*. All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Local climate opinions and political views

	Climate concern		Republican	
	(1)	(2)	(3)	(4)
	High	Low	Yes	No
Fluidity	0.0022	0.0166***	0.0155**	0.0098***
	(0.0050)	(0.0045)	(0.0071)	(0.0037)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	12,379	12,719	5,149	19,916
R^2	0.921	0.933	0.943	0.929
Diff. high-low	-0.0143	.	0.0056	.
p-value	0.0040	.	0.1920	.

Panel B: Firm political lobbying

	Democratic		Republican	
	(1)	(2)	(3)	(4)
	High	Low	High	Low
Fluidity	0.0083	0.0168**	0.0178**	0.0058
	(0.0079)	(0.0078)	(0.0081)	(0.0074)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	3,078	3,920	3,448	3,562
R^2	0.959	0.953	0.956	0.959
Diff. high-low	-0.0085	.	0.0120	.
p-value	0.1640	.	0.1100	.

Table 8
Social norms

This table presents subsample regression results by social norms. The dependent variable is *ln(Scope 1 intensity)*, measured by the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). *Social capital* is measured by the social capital index of Lin and Pursiainen (2022). *Volunteering* is measured by the ratio of Facebook users who are members of a group which is predicted to be about volunteering or activism based on group title and other group characteristics. *Civic org.* is measured by the ratio of Facebook users who are members of a group which is predicted to be public good based on group title and other group characteristics. Firms with *Social capital*, *Volunteering*, *Civic org.* above sample medians each year are classified as *High*, otherwise as *Low*. All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Social capital		Volunteering		Civic org.	
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Low	High	Low	High	Low
Fluidity	0.0077	0.0162***	0.0074	0.0168***	0.0059	0.0173***
	(0.0048)	(0.0046)	(0.0050)	(0.0046)	(0.0048)	(0.0046)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12,886	12,002	12,535	12,628	12,487	12,670
R^2	0.931	0.931	0.930	0.929	0.934	0.927
Diff. high-low	-0.0085	.	-0.0094	.	-0.0114	.
p-value	0.0360	.	0.0240	.	0.0120	.

Table 9
Profitability

This table presents subsample regression results by profitability. The dependent variable is *ln(Scope 1 intensity)*, measured by the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). In Panel A, *EBIT margin* is measured by the ratio of earnings before interest and taxes to total sales. *EBITDA margin* is measured by the ratio of earnings before interest, taxes, depreciation, and amortization to total sales. *Tobin's Q* is measured by the ratio of the market value of a firm plus total liability to total assets. In Panel B, *EBIT to assets* is measured by the ratio of earnings before interest and taxes to total assets. *RoA* is measured by the ratio of net income to total assets. *RoE* is measured by the ratio of net income to firm equity. Firms with *EBIT margin*, *EBITDA margin*, *Tobin's Q*, *EBIT to assets*, *RoA*, or *RoE* above sample medians each year are classified as *High*, otherwise as *Low*. All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: EBIT margin, EBITDA margin, and Tobin's Q

	EBIT margin		EBITDA margin		Tobin's Q	
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Low	High	Low	High	Low
Fluidity	0.0073	0.0118***	0.0078	0.0129***	0.0094**	0.0119**
	(0.0047)	(0.0036)	(0.0048)	(0.0035)	(0.0042)	(0.0047)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	13,837	13,648	13,845	13,660	13,654	13,716
R^2	0.946	0.931	0.948	0.921	0.901	0.945
Diff. high-low	-0.0045	.	-0.0051	.	-0.0024	.
p-value	0.1760	.	0.1720	.	0.2980	.

Panel B: EBIT to assets, RoA, and RoE

	EBIT to assets		RoA		RoE	
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Low	High	Low	High	Low
Fluidity	0.0056	0.0146***	0.0096**	0.0118***	0.0056	0.0147***
	(0.0045)	(0.0037)	(0.0046)	(0.0036)	(0.0046)	(0.0037)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	13,942	13,714	13,839	13,644	13,770	13,646
R^2	0.918	0.954	0.924	0.951	0.932	0.948
Diff. high-low	-0.0089	.	-0.0022	.	-0.0091	.
p-value	0.0320	.	0.3460	.	0.0300	.

Table 10
Instrumenting product fluidity with FX and PSL

This table presents the IV regression results of the relationship between product fluidity and carbon intensity. *ln(Scope 1 intensity)* is the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. Δ *ln(FX)* is the growth rate of real trade-weighted state-level exchange rates. *PSL* is a dummy variable that equals one if a state adopts Paid Sick Leave mandates. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). Panel A is the regressions estimated with OLS. Panel B and Panel C are estimated with 2SLS and we instrument for *Fluidity* with Δ *ln(FX)* and *PSL*. All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: FX and PSL – OLS regression

	ln(Scope 1 intensity)		
	(1)	(2)	(3)
Δ ln(FX) (t-2)	0.1512**		0.1454**
	(0.0664)		(0.0662)
PSL (t-2)		-0.1142***	-0.1074***
		(0.0356)	(0.0355)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	26,132	26,483	26,132
R^2	0.931	0.931	0.931

Panel B: First stage – FX and PSL

	Fluidity		
	(1)	(2)	(3)
Δ ln(FX) (t-2)	1.7360***		1.7159***
	(0.2573)		(0.2566)
PSL (t-2)		-0.3501***	-0.3718***
		(0.0903)	(0.0903)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	26,132	26,483	26,132
R^2	0.820	0.819	0.820

Panel C: Second stage – instrumented fluidity

	ln(Scope 1 intensity)		
	(1)	(2)	(3)
Fluidity	0.0871**	0.3261**	0.2121***
	(0.0401)	(0.1313)	(0.0703)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	26,132	26,483	26,132
R^2	-0.049	-1.040	-0.416
F-stat	45.525	15.036	29.404

Table 11
Ownership and investor horizon

This table presents subsample regression results by ownership and investor horizon. The dependent variable is *ln(Scope 1 intensity)*, measured by the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). *Inst. ownership* is measured by the ratio of shareholdings by all institutional investors to total shares outstanding. *Churn ratio* is measured by the weighted average churn ratio of Gaspar et al. (2005). *Adj. churn ratio* is measured by the adjusted weighted average churn ratio of Yan and Zhang (2009). *Transient ownership* is measured by the ratio of shareholdings of transient institutional investors to the total institutional ownership. Firms with *Inst. ownership*, *Churn ratio*, *Adj. churn ratio* or *Transient ownership* above sample medians each year are classified as *High*, otherwise as *Low*. All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Inst. ownership		Churn ratio		Adj. churn ratio		Transient ownership	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High	Low	High	Low	High	Low	High	Low
Fluidity	0.0107**	0.0127***	0.0103**	0.0136***	0.0097**	0.0134***	0.0063	0.0148***
	(0.0049)	(0.0040)	(0.0044)	(0.0046)	(0.0046)	(0.0047)	(0.0046)	(0.0046)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13,639	12,996	11,339	11,483	11,377	11,420	11,485	11,344
R^2	0.917	0.953	0.938	0.939	0.935	0.942	0.935	0.943
Diff. high-low	-0.0020	.	-0.0033	.	-0.0036	.	-0.0085	.
p-value	0.3620	.	0.2800	.	0.2460	.	0.0600	.

Table 12
Firm size, age, and total carbon emissions

This table presents subsample regression results by firm size, age, and total scope 1 emissions. The dependent variable is *ln(Scope 1 intensity)*, measured by the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). *Total assets* are the number of total assets. *Firm age* is the number of years since a firm first appeared in the CRSP monthly stock return files. *Total scope 1 emissions* are firm-level yearly emissions capturing absolute carbon output. All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Total assets		Firm age		Total scope 1 emissions	
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Low	High	Low	High	Low
Fluidity	0.0094*	0.0075**	0.0104**	0.0081*	0.0120**	0.0104***
	(0.0048)	(0.0031)	(0.0046)	(0.0042)	(0.0053)	(0.0036)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	13,940	13,221	13,525	13,718	12,363	11,975
R^2	0.946	0.930	0.941	0.932	0.937	0.858
Diff. high-low	0.0019	.	0.0023	.	0.0016	.
p-value	0.3440	.	0.3220	.	0.4040	.

Internet appendix

IA.1 Number of observations by year

This table reports the number of firm-year observations in our sample by year. The sample spans 2002-2023 and includes all U.S. public firms with available data on carbon emissions and fluidity measures.

Table IA.1
Number of observations by year

Year	Trucost sample	CDP sample	EPA sample
2002	379		
2003	518		
2004	607	1	
2005	749	2	
2006	761	7	
2007	755	15	
2008	770	48	
2009	789	210	10
2010	786	225	234
2011	784	241	282
2012	784	252	288
2013	853	263	295
2014	841	270	298
2015	845	275	282
2016	2,127	312	280
2017	2,133	309	269
2018	2,215	346	263
2019	2,243	377	261
2020	2,355	434	257
2021	2,409	470	241
2022	2,610	481	239
2023	2,408	2	228
Total	28,721	4,540	3,727

IA.2 Correlation matrix

To assess the consistency of carbon emissions data across different sources, Table IA.2 presents correlation matrices for carbon intensity and emissions levels using data from Trucost, CDP, and the EPA.

Panel A reports pairwise correlations for carbon intensity measures. Panel B reports correlations for absolute carbon emissions. In both panels,we find strong and positive correlations among Trucost, CDP, and EPA emissions data, indicating that emissions estimates across providers are broadly aligned at the firm level.

These results provide reassurance that our findings are not driven by the choice of emissions data source and that the measures used across different sections of the paper reflect a consistent underlying signal of firms' carbon footprints.

Table IA.2
Correlation matrix

This table presents the correlation matrix of carbon data from different data providers. In Panel A, *Trucost ln(Scope 1 intensity)* is measured by the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars, using data from the Trucost. *CDP ln(Scope 1 intensity)* is measured by the natural logarithm of one plus the ratio of disclosed Scope 1 carbon emissions to revenue in millions of dollars, using data from the Carbon Disclosure Project (CDP). *EPA ln(Carbon intensity - firm)* is measured by the natural logarithm of one plus the ratio of the total carbon emissions of all facilities of the firm to revenue, using data from the Environmental Protection Agency (EPA). In Panel B, *Trucost ln(Scope 1 emissions)* is measured by the natural logarithm of one plus the Scope 1 carbon emissions, using data from the Trucost. *CDP ln(Scope 1 emissions)* is measured by the natural logarithm of one plus the disclosed Scope 1 carbon emissions, using data from the CDP. *EPA ln(Carbon intensity - firm)* is measured by the natural logarithm of one plus the total carbon emissions of all facilities of the firm, using data from the EPA.

Panel A: Carbon intensity

	Trucost ln(Scope 1 intensity)	CDP ln(Scope 1 intensity)	EPA ln(Carbon intensity - firm)
Trucost ln(Scope 1 intensity)	1		
CDP ln(Scope 1 intensity)	0.995	1	
EPA ln(Carbon intensity - firm)	0.886	0.888	1

Panel B: Carbon emissions

	Trucost ln(Scope 1 emissions)	CDP ln(Scope 1 emissions)	EPA ln(Carbon emissions - firm)
Trucost ln(Scope 1 emissions)	1		
CDP ln(Scope 1 emissions)	0.994	1	
EPA ln(Carbon emissions - firm)	0.851	0.855	1

IA.3 CDP reported emissions and lagged product fluidity

Table IA.3 examines the relationship between product fluidity in different periods and carbon intensity using self-reported emissions data from the Carbon Disclosure Project (CDP), rather than the Trucost-based carbon intensity measures used in the main analyses. Specifically, we incorporate contemporaneous and multiple lagged measures of product fluidity to assess how competition in different periods relates to firms' current carbon emissions.

The results are broadly consistent with those presented in our main analysis as in Table 5. Across specifications, higher product fluidity is positively associated with greater carbon intensity, and the relationship remains robust when fluidity measures are lagged by one or more years. The one-year lagged fluidity exhibits the strongest positive association with carbon intensity, suggesting that firms' emissions responses to increased competition may materialize with a short delay. These findings reinforce the evidence of a persistent link between competitive pressure and corporate carbon emissions, and demonstrate that the results are not driven by the specific emissions data source.

Table IA.3
CDP reported emissions and lagged product fluidity

This table presents regression results of the relationship between product fluidity in different periods and carbon intensity, using data from the Carbon Disclosure Project (CDP). The dependent variable is *ln(Scope 1 intensity (CDP))*, measured by the natural logarithm of one plus the ratio of disclosed Scope 1 carbon emissions to revenue in millions of dollars. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Fluidity(t)	0.0109**					0.0065
	(0.0054)					(0.0050)
Fluidity		0.0173***				0.0132***
		(0.0062)				(0.0049)
Fluidity(t-2)			0.0111*			0.0028
			(0.0061)			(0.0045)
Fluidity(t-3)				0.0099*		0.0026
				(0.0056)		(0.0045)
Fluidity(t-4)					0.0139***	0.0116***
					(0.0053)	(0.0045)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,603	4,633	4,572	4,517	4,453	4,400
R^2	0.978	0.978	0.978	0.978	0.978	0.978

IA.4 CDP reported emissions, climate opinions, and political views

Table IA.4 presents an analysis of how local sociopolitical factors moderate the relationship between fluidity and carbon emissions using self-reported emissions data from the Carbon Disclosure Project (CDP). This alternative data source allows us to verify the robustness of our main findings while addressing potential concerns about measurement approaches. The analysis focuses on two key moderators: county-level climate concern and political ideology.

Notably, these patterns remain robust despite differences between CDP-reported emissions and our primary Trucost-based measures. We find that the positive relationship between competition and emissions is significantly attenuated in areas with stronger public concern about climate change. Also,firms located in more politically conservative areas exhibit a stronger positive relationship between competition and emissions.The consistency across alternative data sources strengthens our confidence in the findings and suggests that the moderating effects reflect fundamental rather than measurement artifacts.

Table IA.4
CDP reported emissions, climate opinions, and political views

This table presents subsample regression results by local climate opinions and political views, using data from the Carbon Disclosure Project (CDP). The dependent variable is *ln(Scope 1 intensity (CDP))*, measured by the natural logarithm of one plus the ratio of disclosed Scope 1 carbon emissions to revenue in millions of dollars. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). *Climate concern* is measured by the ratio of population who think corporations and industry should be doing more or much more to address global warming. Firms in counties with *Climate concern* above sample medians are classified as *High*, otherwise as *Low*. *Republican* is measured by a dummy variable that equals one if a county has a majority of voters voting Republican party in the Presidential election. Firms in counties with *Republican* majority are classified as *Yes*, otherwise as *No*. All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Climate concern		Republican	
	(1)	(2)	(3)	(4)
	High	Low	Yes	No
Fluidity	-0.0073	0.0303***	0.0466*	0.0086
	(0.0057)	(0.0104)	(0.0274)	(0.0061)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	2,004	2,075	605	3,494
R^2	0.979	0.975	0.966	0.980
Diff. high-low	-0.0376	.	0.0380	.
p-value	0.0000	.	0.0260	.

IA.5 Different emission scopes

In this section, we examine whether the positive relationship between product market competition and emissions holds across different scopes of greenhouse gas emissions. While our main analysis focuses on Scope 1 emissions—those directly controlled by the firm—firms also contribute to carbon emissions indirectly through electricity consumption (Scope 2) and supply chain or product use activities (Scope 3).

Table IA.5 reports regression results using four alternative dependent variables: *ln(S2 (loc.) intensity)* and *ln(S2 (mkt.) intensity)* for location-based and market-based Scope 2 emission intensities, respectively, and *ln(S3 (up) intensity)* and *ln(S3 (down) intensity)* for upstream and downstream Scope 3 emission intensities. All variables are defined as the natural logarithm of one plus the ratio of emissions to revenue, consistent with our Scope 1 analysis.

The relationship between product fluidity and carbon emissions appears to be scope-dependent. While there is little evidence of an effect on Scope 2 or upstream Scope 3 emissions, the significant and positive effect on downstream Scope 3 emissions suggests that competitive pressure may lead firms to externalize emissions to later stages of the value chain, such as distribution or product usage.

Table IA.5
Different emission scopes

This table presents regression results of the relationship between product fluidity and different emission scopes. *ln(S2 (loc.) intensity)* is measured by the natural logarithm of one plus the ratio of location-based Scope 2 carbon emissions to revenue in millions of dollars. *ln(S2 (mkt.) intensity)* is measured by the natural logarithm of one plus the ratio of market-based Scope 2 carbon emissions to revenue in millions of dollars. *ln(S3 (up) intensity)* is measured by the natural logarithm of one plus the ratio of upstream Scope 3 carbon emissions to revenue in millions of dollars. *ln(S3 (down) intensity)* is measured by the natural logarithm of one plus the ratio of downstream Scope 3 carbon emissions to revenue in millions of dollars. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	ln(S2 (loc.) intensity)	ln(S2 (mkt.) intensity)	ln(S3 (up) intensity)	ln(S3 (down) intensity)
Fluidity	-0.0023	0.0060	-0.0002	0.0203***
	(0.0035)	(0.0126)	(0.0012)	(0.0063)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	27,423	1,287	27,423	14,816
R^2	0.819	0.968	0.960	0.893

IA.6 Alternative measures of competition

To ensure that our main results are not driven by the specific choice of the product fluidity index, we repeat the baseline analysis using several alternative measures of product market competition. Table IA.6 presents regression results using Herfindahl–Hirschman indices (HHIs) constructed from different industry classification systems.

We consider HHIs based on both SIC and NAICS industry codes at varying levels of granularity. Specifically, *SIC2 HHI*, *SIC3 HHI*, and *SIC4 HHI* are constructed using market shares within industries defined at the 2-digit, 3-digit, and 4-digit levels of the Standard Industrial Classification (SIC) system. Similarly, *NAICS2 HHI* and *NAICS4 HHI* are constructed using the North American Industry Classification System (NAICS). We also include *TNIC HHI*, a text-based Herfindahl index derived from the network industry classification in Hoberg and Phillips' 10-K-based taxonomy.

Across all specifications, the results are broadly consistent with those using product fluidity. Higher market concentration—corresponding to lower competition—is generally associated with lower carbon intensity, implying that greater competition (i.e., lower HHI) is linked to higher emissions. Although the magnitudes and levels of statistical significance vary, the direction of the relationship aligns with our main findings using the fluidity measure.

These findings support the interpretation that competitive pressure, however measured, tends to increase firms' carbon intensity. At the same time, the product fluidity index remains a more granular and dynamic proxy for competition, capturing firm-specific exposure to rival product changes that traditional industry-level HHIs may miss.

Table IA.6
Alternative measures of competition

This table presents baseline regression results using alternative measures of competition. The dependent variable is *ln(Scope 1 intensity)*, measured by the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. *SIC2 HHI* is the Herfindahl–Hirschman index based on the 2-digit SIC code. *SIC3 HHI* is the Herfindahl–Hirschman index based on the 3-digit SIC code. *SIC4 HHI* is the Herfindahl–Hirschman index based on the 4-digit SIC code. *NAICS2 HHI* is the Herfindahl–Hirschman index based on the 2-digit NAICS code. *NAICS4 HHI* is the Herfindahl–Hirschman index based on the 4-digit NAICS code. Herfindahl–Hirschman index is calculated as the sum of the squared market shares based on firm sales. *TNIC HHI* is the Herfindahl-Hirschman index based on the 10-K text-based network industry classification. All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
SIC2 HHI	-1.0600***					
	(0.3481)					
SIC3 HHI		-0.0144				
		(0.1778)				
SIC4 HHI			0.0314			
			(0.1140)			
NAICS2 HHI				-1.7767**		
				(0.6927)		
NAICS4 HHI					-0.3926**	
					(0.1820)	
TNIC HHI						-0.0130
						(0.0354)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	27,423	27,423	27,423	27,423	26,960	27,418
R^2	0.931	0.930	0.930	0.931	0.931	0.930

IA.7 Fluidity and financial performance

To understand how competitive pressure relates to firms' financial performance, we examine the association between product fluidity and various measures of financial performance. TableIA.7 presents regression results using six commonly used profitability and valuation metrics as dependent variables.

We include two margin-based measures: *EBIT margin* and *EBITDA margin*, both scaled by total sales. We also consider asset-based profitability ratios: *EBIT to assets* and *Return on Assets (RoA)*, as well as the equity-based *Return on Equity (RoE)*. Lastly, we include *Tobin's Q* as a forward-looking valuation measure, capturing market expectations of future profitability.

The coefficients on fluidity are generally negative across these specifications.This aligns with that competitive pressure reduces firms' profitability, reinforcing the interpretation that increased emissions under competition may partly stem from cost-cutting behavior in response to reduced margins.

Table IA.7
Fluidity and financial performance

This table presents regression results of the relationship between product fluidity and financial performance. *EBIT margin* is measured by the ratio of earnings before interest and taxes to total sales. *EBITDA margin* is measured by the ratio of earnings before interest, taxes, depreciation, and amortization to total sales. *Tobin's Q* is measured by the ratio of the market value of a firm plus total liability to total assets. *EBIT to assets* is measured by the ratio of earnings before interest and taxes to total assets. *RoA* is measured by the ratio of net income to total assets. *RoE* is measured by the ratio of net income to firm equity. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) EBIT margin	(2) EBITDA margin	(3) Tobins'Q	(4) EBIT to assets	(5) RoA	(6) RoE
Fluidity	-0.0059***	-0.0041***	-0.0116**	-0.0039***	-0.0031***	-0.0077***
	(0.0015)	(0.0014)	(0.0059)	(0.0006)	(0.0004)	(0.0014)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	27,787	27,783	27,760	27,797	27,797	27,775
R^2	0.868	0.877	0.720	0.802	0.745	0.465

IA.7.1 Industry heterogeneity

To examine whether the relationship between fluidity and carbon intensity varies across industries with different environmental risk profiles, we conduct subsample analyses based on industry sensitivity to greenhouse gas (GHG) emissions and environmental issues.

We consider four industry-level classifications. First, *GHG sensitive* is measured by a dummy variable that equals one if GHG emissions are a material sustainability issue for the industry, as idenfied by the Sustainability Accounting Standards Board (SASB) Materiality Map. Second,*Env. sensitive SASB* is measured by a dummy variable that equals one if environment is a material sustainability issue for the industry, as idenfied by the SASB Materiality Map. Third,*Env. sensitive AOS* is measured by a dummy variable that equals one if a firm operates primarily in environmentally sensitive industries (2-digit SIC codes: 10, 13, 26, 28, 29, 33, 49), as idenfied by Cho and Patten (2007). Fourth,*Sin industry* is measured by a dummy variable that equals one if a firm is sin industries (SIC codes: 2100-2199, 2080-2085; NAICS codes: 7132, 71312, 713210, 71329, 713290, 72112, and 721120). Firms in the *GHG sensitive*, *Env. sensitive SASB*, *Env. sensitive AOS*, or *Sin industry* are classified as *Yes*, otherwise as *No*.

Table IA.8 reports regression results with industry heterogeneity. The positive association between product fluidity and carbon intensity is generally present across both environmentally sensitive and non-sensitive industries. However, the magnitude of the coefficient is typically larger for firms in GHG-sensitive or environmentally sensitive industries, suggesting that competition-induced emissions responses are particularly pronounced where environmental performance is already a material concern. Firms in sin industries also exhibit a somewhat stronger link between fluidity and emissions intensity, consistent with lower stakeholder pressure and weaker reputational constraints in those sectors.

Table IA.8
Industry heterogeneity

This table presents subsample regression results by industry heterogeneity. The dependent variable is *ln(Scope 1 intensity)*, measured by the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). *GHG sensitive* is measured by a dummy variable that equals one if GHG emissions are a material sustainability issue for the industry, as idenfied by the Sustainability Accounting Standards Board (SASB) Materiality Map. *Env. sensitive SASB* is measured by a dummy variable that equals one if environment is a material sustainability issue for the industry, as idenfied by the SASB Materiality Map. *Env. sensitive AOS* is measured by a dummy variable that equals one if a firm operates primarily in environmentally sensitive industries (2-digit SIC codes: 10, 13, 26, 28, 29, 33, 49), as idenfied by Cho and Patten (2007). *Sin industry* is measured by a dummy variable that equals one if a firm is sin industries (SIC codes: 2100-2199, 2080-2085; NAICS codes: 7132, 71312, 713210, 71329, 713290, 72112, and 721120). Firms in the *GHG sensitive*, *Env. sensitive SASB*, *Env. sensitive AOS*, or *Sin industry* are classified as *Yes*, otherwise as *No*. All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	GHG sensitive		Env. sensitive SASB		Env. sensitive AOS		Sin industry	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Yes	No	Yes	No	Yes	No	Yes	No
Fluidity	0.0218***	0.0049	0.0117***	0.0065	0.0215***	0.0064	0.0178**	0.0058
	(0.0079)	(0.0034)	(0.0043)	(0.0047)	(0.0055)	(0.0040)	(0.0081)	(0.0074)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,795	19,628	18,013	9,410	7,683	19,740	3,448	3,562
R^2	0.909	0.888	0.933	0.900	0.944	0.885	0.956	0.959
Diff. high-low	0.0170	.	0.0052	.	0.0150	.	0.0120	.
p-value	0.0000	.	0.1460	.	0.0080	.	0.1100	.

IA.8 Financial constraints

Table IA.9 examines whether financial constraints moderate the competition-emissions relationship. Financial constraints are measured by the *WW index* of Whited and Wu (2006), *SA index* of Hadlock and Pierce (2010),and*Equity constr. (f)*, *Equity constr. (p)*, *Debt constr. (f)*, and *Debt constr. (p)* of Hoberg and Maksimovic (2015) and Linn and Weagley (2024).

The results reveal two key patterns. First, ompetition consistently predicts higher carbon intensity across all subsamples (all fluidity coefficients positive). Second, none of the constraint measures show statistically significant moderation effects. The non-significant differences between groups imply that the competition-emissions relationship operates through channels that are largely independent of firms' financial constraints and competitive pressures may overwhelm financial considerations in firms' environmental decision-making.

Table IA.9
Financial constraints

This table presents subsample regression results by financial constraints. The dependent variable is *ln(Scope 1 intensity)*, measured by the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). In Panel A, financial constraints are measured by the *WW index* of Whited and Wu (2006) and *SA index* of Hadlock and Pierce (2010). In Panel B, financial constraints are measured by the *Equity constr. (f)*, *Equity constr. (p)*, *Debt constr. (f)*, and *Debt constr. (p)* of Hoberg and Maksimovic (2015) and Linn and Weagley (2024). Firms with *WW index*, *SA index*, *Equity constr. (f)*, *Equity constr. (p)*, *Debt constr. (f)*, or *Debt constr. (p)* above sample medians each year are classified as *High*, otherwise as *Low*. All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: WW index and SA index

	WW index		SA index	
	(1)	(2)	(3)	(4)
	High	Low	High	Low
Fluidity	0.0107***	0.0058	0.0057	0.0090*
	(0.0034)	(0.0049)	(0.0035)	(0.0050)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	13,153	13,476	13,369	13,828
R^2	0.927	0.945	0.931	0.944
Diff. high-low	0.0049	.	-0.0033	.
p-value	0.1360	.	0.2760	.

Panel B: Hoberg financial constraints index

	Equity constr. (f)		Equity constr. (p)		Debt constr. (f)		Debt constr. (p)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High	Low	High	Low	High	Low	High	Low
Fluidity	0.0147***	0.0115**	0.0164***	0.0103*	0.0093*	0.0151***	0.0095*	0.0135***
	(0.0046)	(0.0052)	(0.0047)	(0.0053)	(0.0055)	(0.0046)	(0.0051)	(0.0042)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10,302	10,737	10,273	10,677	10,698	10,369	10,562	10,291
R^2	0.933	0.920	0.930	0.922	0.922	0.924	0.926	0.926
Diff. high-low	0.0032	.	0.0061	.	-0.0057	.	-0.0040	.
p-value	0.2680	.	0.1380	.	0.1440	.	0.2360	.

IA.9 Financial distress risk

Table IA.10 examines whether financial distress risk alters how firms adjust their carbon emissions in response to competitive pressures. We employ three well-established measures of financial distress: the Kaplan-Zingales (KZ) index, Altman's Z-score, and Zmijewski's (ZM) score.

The analysis reveals two key patterns. First, we observe a consistently positive relationship between fluidity and carbon emissions across all distress risk categories. This main effect remains statistically significant regardless of how we measure financial distress. Second, and more importantly, we find no evidence that financial distress risk meaningfully moderates this relationship. The differences between high-distress and low-distress firms are statistically insignificant for all three measures. While the point estimates suggest slightly stronger competition effects for low-distress firms when using the ZM-score, this difference does not reach conventional significance levels. The consistent results across distress measures suggest that the mechanism linking competition to higher emissions operates independently of firms' financial health.

Table IA.10
Financial distress risk

This table presents subsample regression results by financial distress risk. The dependent variable is *ln(Scope 1 intensity)*, measured by the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue in millions of dollars. *Fluidity* is the text-based product fluidity index of Hoberg et al. (2014). Financial distress risk is measured by the *KZ index* of Kaplan and Zingales (1997), *Z score* of Altman (1968), and *ZM score* of Zmijewski (1984). Firms with *KZ index*, *Z score*, or *ZM score* above sample medians each year are classified as *High*, otherwise as *Low*. All variables are defined in Appendix A. All continuous variables are winsorized at the 1% level. Standard errors shown in parentheses are clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	KZ index		Z score		ZM score	
	(1) High	(2) Low	(3) High	(4) Low	(5) High	(6) Low
Fluidity	0.0103**	0.0123***	0.0110**	0.0130***	0.0102**	0.0145***
	(0.0042)	(0.0045)	(0.0049)	(0.0042)	(0.0041)	(0.0049)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	13,135	13,007	13,007	12,949	13,039	13,081
R^2	0.943	0.934	0.881	0.956	0.953	0.913
Diff. high-low	-0.0020	.	-0.0019	.	-0.0043	.
p-value	0.3600	.	0.3720	.	0.2040	.

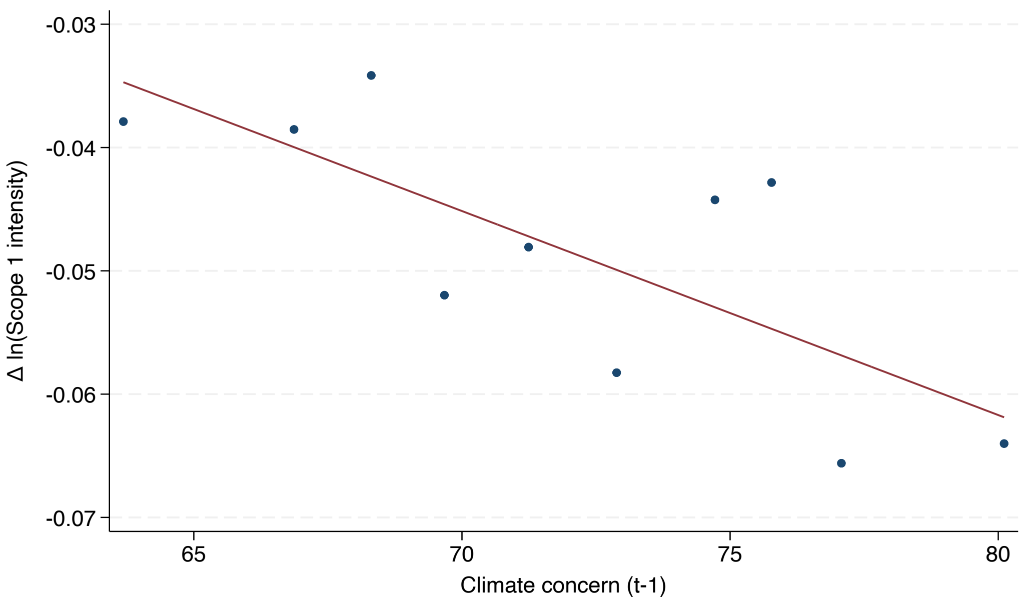
IA.10 Binscatter of changes in carbon intensity vs. climate concern

Figure IA.1 visualizes the relationship between public climate concern and changes in firm-level carbon intensity. The plot is constructed using 10 quantile bins of lagged climate concern.

The fitted trend shows a clear negative slope: firms located in regions with greater climate concern tend to reduce their carbon intensity more over time. This pattern suggests that stronger societal expectations regarding climate responsibility may incentivize or pressure firms to accelerate emissions reduction efforts, independent of other firm-specific characteristics.These results complement our regression evidence in Table 7, supporting the view that local climate norms serve as informal constraints on emissions behavior.

Figure IA.1: Binscatter of changes in carbon intensity vs. climate concern

This figure shows the relationship between climate concern and changes in carbon intensity. It presents a scatterplot based on 10 quantile bins of lagged climate concern, with fitted linear trends. The y-axis measures the annual change in *ln(Scope 1 intensity)*, defined as the natural logarithm of one plus the ratio of Scope 1 carbon emissions to revenue (in millions of USD). The x-axis measures *Climate concern*, the ratio of population who think corporations and industry should be doing more or much more to address global warming.



IA.11 Binscatter of changes in revenue and carbon emissions (absolute) vs. changes in product fluidity

Figure IA.2 illustrates the relationship between annual changes in product fluidity and changes in revenue and absolute Scope 1 carbon emissions separately.

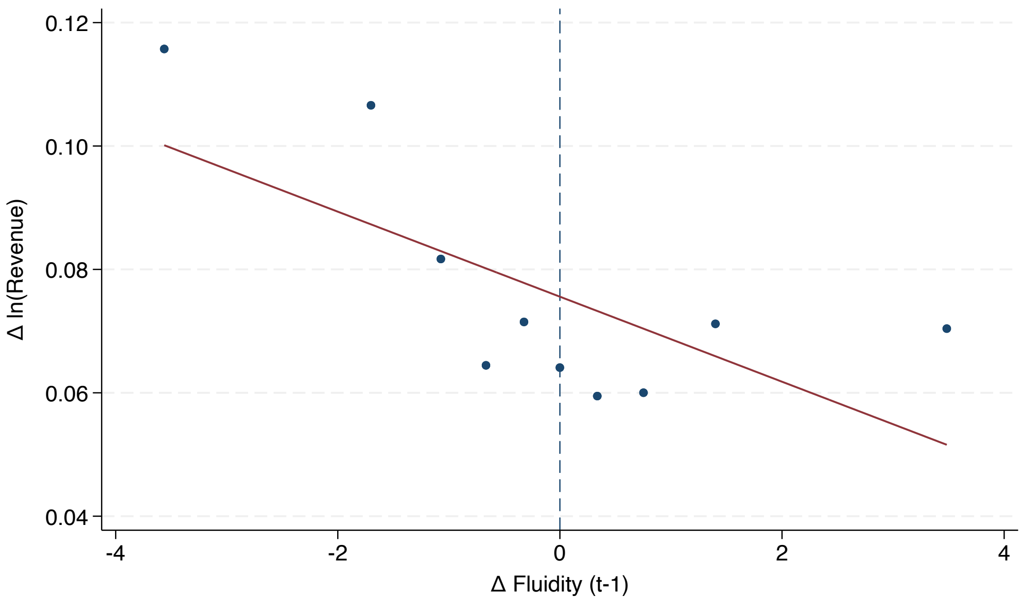
Panel A plots changes in *ln(Revenue)* against decile bins of lagged changes in product fluidity. The fitted trend suggests that firms experiencing larger increases in competitive pressure tend to see revenue reduction.

Panel B shows the corresponding relationship for *ln(Scope 1 emissions)*. The trend is positive, indicating that increased competition is associated with growth in absolute emissions. This aligns with our main findings, suggesting that firms may prioritize scale and cost efficiency over environmental considerations when competitive pressure intensifies.

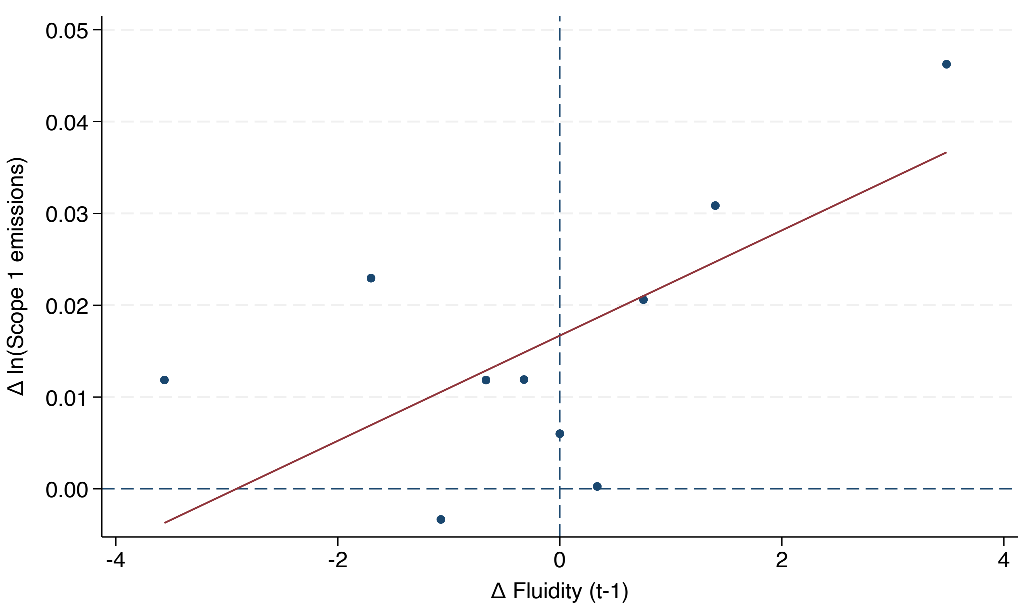
Figure IA.2: Binscatter of changes in revenue and carbon emissions (absolute) vs. changes in product fluidity

This figure shows the relationship between changes in product market fluidity and changes in revenue as well as carbon emissions (absolute). It presents a scatterplot based on 10 quantile bins of lagged annual changes in product fluidity, with fitted linear trends. In Panel A, the y-axis measures the annual change in *ln(Revenue)*, defined as the natural logarithm of net sales. In Panel B, the y-axis measures the annual change in *ln(Scope 1 emissions)*, defined as the natural logarithm of one plus the absolute Scope 1 carbon emissions. The x-axis in both panels measures the annual change in *Fluidity*, the text-based product fluidity index of Hoberg et al. (2014).

Panel A. Revenue



Panel B. Carbon emissions (absolute)



IA.12 List of PSL mandates

This table lists U.S. states and jurisdictions that implemented Paid Sick Leave (PSL) mandates during our sample period (2002-2023), along with their respective effective years. The staggered adoption across states provides variation for identification.

Table IA.11
List of PSL mandates

State	Effective year
District of Columbia	2008
Connecticut	2012
California	2015
Massachusetts	2015
Oregon	2016
Rhode Island	2016
Arizona	2017
Vermont	2017
Maryland	2018
New Jersey	2018
Washington	2018
Colorado	2021
New York	2021
New Mexico	2022
Minnesota	2024