Does climate policy uncertainty affect a firm's lease versus buy decision?

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Abstract

We examine whether firms prefer to lease or buy to finance corporate investment when exposed to elevated climate policy uncertainty (CPU). Using a sample of 83,666 panel data observations from 2000 to 2017, we uncover that CPU and operating lease intensity have a significant and positive association. The findings are robust to alternative lease and economic policy uncertainty proxies. We also mitigate endogeneity concerns by applying propensity score matching (PSM) and entropy balancing. Additionally, we find that financially constrained and environmentally exposed firms tend to increase their operating lease intensity during periods of tighter CPU. Consistent with the hedging property of leasing described by Smith (1979), leasing dependence allows firms to effectively form an ideal hedge against asset ownership risk during the more significant risk exposures induced by CPU. The findings are also consistent with financial contracting motivation (Smith & Wakeman, 1985), guiding firms to depend on leasing to avoid the higher cost of debt financing.

Keywords: climate policy uncertainty, operating leases, debt capacity

JEL Codes: G32, G38, D81

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1.0 Introduction

The significant economic impact of environmental risks and natural calamities brought on by climate change has long been acknowledged (Huynh & Xia, 2021; Dell et al., 2014). For example, Stern (2007) estimated that the yearly cost of climate change will be at least 5% of world GDP. However, climate change consequences have become considerably more severe in recent years, showing that globally, weather-related insurance losses surpassed 65 billion USD in 2010, up from an annual average of 10 billion USD in the 1980s (Benfield, 2018). It is also stated that over 10% of Moody's rated debt, or almost 7.2 trillion USD, is extremely susceptible to physical climate-related risks that might disrupt fixed-income markets (Bloomberg, 2021). Climate change has, therefore, become a prominent risk factor (Sautner et al., 2023; Hong et al., 2019) for businesses and governments (Boulange et al., 2021).

In addition to physical risk, a regulatory risk has also arisen from governments' targets to achieve net zero emissions, referred to in the United Nations Climate Change Conference in 2021 (COP26). Such commitments have triggered environment-related policy shifts worldwide (Azimli, 2023), which alter the settings in which firms operate (Engau & Hoffmann, 2011). Hence, policies that address climate change also experience substantial uncertainty around their implementation, such as the U.S. withdrawal from the Paris Accord in 2017 and rejoining again under the Biden administration (Gavriilidis, 2021). In such conditions, firms are exposed to policy uncertainty sourced through climate policy shifting and implementation. These policy uncertainties have profound consequences for the firm's financial actions (Zhang et al., 2015). For example, the economic outcomes of this occurrence alter the regular actions of firms and investors. It raises the risk that firms and investors would postpone spending and investing owing to market uncertainty (Bloom, 2009).

Similarly, motivated by the well-recognized evident influences of climate change on economic events in earlier studies (e.g., Burke et al., 2015; Dell et al., 2014; and Hsiang, 2010), financial economists are increasingly interested in understanding how climate policy uncertainty (CPU) exacerbates market frictions, creating a shift in the behaviours of corporate executives and investors and thus influencing capital structure and its adjustments (Engle et al., 2020). However, the need for a valid and accepted measure of CPU limits such interest among financial economists. In this context, Gavriilidis (2021) develops a unique news-based uncertainty index linked to climate policy of that kind. We utilize this paper as the first empirical evidence that the news-based uncertainty index related to climate policy (Gavriilidis, 2021) affects firm-level lease-versus-buying decisions as a financing hedging strategy. To contribute to the existing corporate finance literature, we investigate whether and to what extent CPU influences firms' lease decisions.

In this paper, we consider the lease financing perspective of CPU to examine firms' responses to elevated CPU levels. Most U.S. firms extensively depend on leasing as one of the most reliable external financing sources (Eisfeldt & Rampini, 2009; Rampini & Viswanathan, 2013; Liu & Zhang, 2020; Li & Tsou, 20). From 1981 through 2020, 72% of US corporations utilized operating leases, according to Wang (2023). Approximately 20% of the total physical productive assets, among publicly traded U.S. companies have been arranged through lease arrangements. However, for smaller and financially restricted firms, the number is more than double (40%) (Li & Tsou, 2019). Firms hinge on operating leases for up to 36% of their overall debt and up to 12% of their assets on average (Wang, 2023). Despite leasing comprising a growing element of corporate capital structure, empirical findings of leasing are limited (Eisfeldt & Rampini, 2009) and deserve more attention in the finance literature for several reasons. First, leasing has a higher magnitude in the capital structure of U.S. firms (Chu, 2020). Second, the leased capital ratio among U.S. firms over business cycles demonstrates a significant countercyclical pattern and a positive association with the volatility of cross-sectional idiosyncratic uncertainty (Li & Tsou, 2022). As evidenced by the insights of Hassan et al. (2017) and Baker et al. (2016), we explore how firms' idiosyncratic characteristics affect the CPU-leasing nexus. Although leasing appears to be a crucial risk management tool for lowering firm-level vulnerability brought on by CPU, the present literature mysteriously ignores them. This study makes the case that CPU may positively correlate with operating lease intensity. We predict that firms have a higher propensity to depend on leased capital during in bad states triggered by CPU. This research aims to contribute to the leasing literature by emphasizing that the crucial function of CPUs in leasing is likely to affect leasing decisions for several reasons. First, the corporate lease-versus-buy choice may be impacted by leasing as a strategy that combines an asset with a hedging arrangement in the event of uncertainty (Smith, 1979). Firms can effectively form an ideal hedge against asset ownership through leasing It separates ownership from usage, with the lessee obtaining the advantages of use and the lessor receiving lease payments while carrying the risk of obsolescence and a decline in asset residual value (Devos & Li, 2021). Second, Smith and Wakeman's (1985) "financial contracting" theories propose that firms lease to avoid losing money on more expensive external borrowing (Rahman & Chowdhury, 2023). The motivations can also be explained in the following manner. First, an operating lease is an alternative to debt financing, specifically for financially constrained firms (Modigliani & Miller, 1958) and firms with collateral constraints (Wang, 2023). The failure of lenders to correctly price the increased risk of bankruptcy driven by policy uncertainties often results in tighter borrowing contracts. It thus limits the debt capacity of financially constrained firms (Kim et al., 1978). For these firms, leasing is an alternative financing strategy. Sharpe and Nguyen (1995) support this idea by explaining the greater leasing propensity of lower-rated and cash-poor firms. Second, according to studies (Gulen & Ion, 2016; Zhang et al., 2015), increased policy uncertainty has a detrimental influence on future cash flows and a firm's financial stability, reducing the quantity of assets available as collateral for borrowing. In the context of climate change-driven accelerated calamities, Wang (2023) finds that natural catastrophes wreak havoc on enterprises' prospective pledgeable assets, resulting in collateral limits, even though collateral controls firms' access to external finance (Rajan & Zingales, 1995; Rampini & Viswanathan, 2013).

These arguments contend that a reduction in a firm's capacity to secure external credit because of collateral requirements reduces a firm's ability to generate external financing in the face of tighter policy uncertainty. However, leasing is self-collateralized. Leases can be obtained without committing additional assets. As a result, under collateral constraints with greater CPU, leasing might be an appealing financing option. Third, CPU is coupled with higher information asymmetry challenges, as firms are supplemented by high ambiguity about government plans, which can affect the firm's competitiveness and projected cash flow (Ben-Nasr et al., 2020). Hence, information asymmetry raises capital rationing and inhibits the firm's capacity to obtain capital in public debt markets (Cao et al., 2013). Therefore, firms are exposed to higher debt financing costs, as evidenced by Chava (2014). However, leasing can cope with external financing friction, and therefore, lease intensity should be high for firms exposed to higher CPU.

Using data from a large sample, we empirically assess the link between CPU and leasing. Our sample includes 83,666 panel observations of 9,391 firms across 18 years from 2000 to 2017 compiled from the Wharton Research Data Services (WRDS) database and Compustat. Our main proxy for operating lease intensity[2] (LEASE) measurement is consistent with earlier research (e.g., Devos & Rahman, 2014; Robicheaux et al., 2008; Lim et al., 2003 and Graham et al., 1998). We use the Climate Policy Uncertainty Index developed by Gavriilidis (2021) as a proxy for CPU, which is consistent with prior studies (e.g., Karim et al., 2023; Bouri et al., 2022).

We find that CPU positively affects leasing even after firm-level controls. Consistent with the hedging property of leasing, the likely explanation for this result is that leasing allows firms to effectively form an ideal hedge against asset ownership during the more significant risk exposures induced by elevated CPU. Similarly, we can extend the explanation with "financial contracting" motivations. Since the risk accumulation induced by more CPU could create an information

[2] The value of operating leases is divided by the total worth of property, plant, and equipment (PPE) to calculate operating lease intensity. We measure operating leases as the sum of the current rental expense, discounted future rental commitments for up to five years, and discounted future rental obligations beyond five years up to ten years, under Devos and Rahman (2014), Graham et al. (1998), Lim et al. (2003), and Robicheaux et al. (2008). We choose a discount rate of 10%.

asymmetry problem between financiers and borrowers and reduce the number of assets available as collateral to borrow, firms face a higher borrowing cost. Therefore, firms exposed to financing friction will prefer to lease to avoid the higher cost of debt financing. The findings have statistical significance and are economically meaningful. For example, our findings suggest that all else being equal, a 1.8 percent increase in *LEASE* is associated with a one-standard-deviation increase in *CPU*, centred around the mean. As part of the robustness test, we include two additional operating lease intensity proxies and the monthly WSJ Climate Change News Index of Engle et al. (2020) produced for the CPU proxy. However, irrespective of the proxies, CPU increases operating lease intensity. Furthermore, the impact of CPU on lease intensity remains significant even after controlling for economic policy uncertainty developed by Baker et al. (2016) and other firm-level and macroeconomic uncertainties. Like the lease-verses-buy decision, we also explore whether firms substitute other financing instruments, such as debt, for operating leases because of higher CPU. Although our findings acknowledge that a lease is not a perfect substitute for debt, all else being equal, CPU increases leasing more than other financing instruments, thus supporting the hedging property of leasing. In other additional tests, we show that the impact of CPU on leasing is more prominent for financially constrained firms, firms that are highly exposed to the risk of climate disasters, and firms operating in more emissions-intensive industries. Our results suggest that firms only change leasing behaviour in response to direct GHG emissions once exposed to CPU, which has a significant policy impact.

Although the CPU Index developed by Gavriilidis (2021) is considered exogenous and beyond the control of individual firms, one might still be concerned that the editorial slant could influence climate change news coverage. Therefore, we remain cautious with our empirical results: CPU and leasing could be endogenously determined. We mitigate endogeneity concerns by utilizing the impact of regulatory intervention (state-level climate adaptation plans, SCAPs) on leasing and applying propensity score matching (PSM) and entropy balancing. The results from regulatory intervention show that the positive impact of CPU on lease intensity is mitigated for firms headquartered in states that have adopted SCAPs. This strengthens our baseline findings that the impact of CPU on leasing intensity is causal. Additionally, to address any systematic differences in the sample, we use PSM and find that our results remain substantially unchanged. We perform entropy balancing to examine the robustness of the main results and find that the results are unaltered to guarantee that the distributions of the variables are not substantially different between impacted and unaffected firms. Overall, these endogeneity tests bolster our confidence in our baseline results, i.e., a positive correlation between CPU and firms' preference for operating leases as a financing choice.

This study comprehends several streams of the existing financial economics literature. First, it contributes to the expanding corpus of research on the effects of policy uncertainty on a firm's financing decisions and outcomes (e.g., Tran, 2021; Bajaj et al., 2021; Li & Qiu, 2018; Liu & Zhang, 2020 and D'Mello & Toscano, 2020). To the best of our knowledge, this study is the first to investigate the relationship between CPU and a different financing instrument, leasing. Our paper also contributes to the considerable literature related to understanding the economic motivation for leasing intensity among U.S. firms (e.g., Sharpe & Nguyen, 1995; Kang & Long, 2001; Eisfeldt & Rampini, 2009; Devos et al., 2012; Lim et al., 2017; Devos & Li, 2020; Rahman & Chowdhury, 2023). Our findings provide a comprehensive narrative about the economic rationality of depending on leasing to economize on costly debt financing alternatives during risky business operations triggered by CPU.

Our final contribution applies to the managerial and policy implications of lease financing. As one of the most crucial alternative financing mechanisms, we expect sufficient corporate disclosure about the lease financing arrangement to avoid potential agency conflict. As a matter of policy intervention, this paper calls for a consistent climate policy framework for the financial and environmental sustainability of the economy.

The remainder of the paper is organized as follows: Section 2 follows the introduction and develops the hypotheses. The data and technique are described in Section 3. Section 4 presents empirical findings, and Section 5 concludes the study.

2.0 Literature Review and Hypothesis Development

2.1 Climate Policy Uncertainty

All economic agents, including both firms and governments, face challenges in addressing climate change, mitigating climate risks, and pursuing a climate-resilient development path (Dai & Zhang, 2023). Specifically, government-led regulatory strategies associated with the prevention of climate change pose considerable risk (and uncertainty) for firms operating in both developed and developing economies (Engle et al., 2020). The uncertainty in policy formulation and implementation and the potential policy ramifications of this process should be considered when examining how climate change may affect the economy (Battiston et al., 2021; Semieniuk et al., 2021). Financial economists utilize the CPU of Gavriilidis (2021), a novel text-based climate regulatory uncertainty index developed using major U.S. newspaper articles, to examine the financial dimensions of climate regulations. The CPU index of Gavriilidis (2021) is an extension of the Climate Change News Index developed by Engle et al. (2020) based solely on the Wall Street Journal. These indices better represent the regulatory implications of climate legislation for business enterprises since the relationship between climate risk and financial markets strengthens with economic integration (Fahmy, 2022; Ren et al., 2022). In such aspects of financial markets, Bouri et al. (2022) highlight the CPU's predictive capacity in explaining the price changing aspects wherein green energy stocks perform better, especially during crisis periods. Other studies (Chan & Malik, 2022; Agliardi & Agliardi, 2021; Ilhan et al., 2021) have reported similar conclusions. CPU also impacts corporate financialization trends (Ren et al., 2022) since financing arrangements offer both storage liquidity and investment profitability, as well as a hedging property, and may thus be accommodated by business firms for various reasons when market circumstances change (Demir & Ersan, 2017; Gulen & Ion, 2016; Nguyen & Phan, 2017). However, this paper examines the impact of CPU on leasing, an alternative financing source yet to be examined.

2.2 Lease Financing

A firm should rationally choose the type of asset and the form of acquisition that accommodate the wealth-maximization principle of corporate finance (Lasfer, 2005). With this alignment, the corporate finance literature regards leasing as an essential form of asset acquisition (Li & Tsou, 2022). However, researchers consistently seek to understand the growing importance of lease financing among U.S. firms[3]. There is substantial literature in finance exploring corporate choices regarding leases, but it focuses primarily on tax considerations. With no consideration of transaction costs or information asymmetries, the Miller-Modigliani model is often used to examine corporate lease vs. buy decision. Firms with higher tax rates prefer leasing to buying; otherwise, they remain indifferent about choosing between leasing and purchasing (e.g., Miller & Upton (1976), Myers et al. (1976)). However, Smith and Wakeman (1985) first provide an integrated analysis of the various nontax incentives influencing the lease-versus-buy decision using exercisable contractual provisions. Following the "financial contracting" motivations of the leasing decision as proposed by Smith and Wakeman (1985), Krishnan and Moyer (1994) find that leasing is typical among firms with less retained earnings, excellent growth rates, lower coverage ratios, higher debt ratios, more operating hazards, and a higher chance of bankruptcy. Empirically, Sharpe and Nguyen (1995) demonstrate that lower-rated, non-dividend-paying, cash-poor enterprises that are more inclined to pay relatively large premiums for outside funding, have more outstanding lease shares. Using data from the commercial aviation sector, Gavazza (2010) discovers that liquid assets are more likely to be leased, have shorter operating leases, longer capital leases, and lower operational lease rate markups. Eisfeldt and Rampini (2009) and Gavazza (2010) offered a related

[3] From 1981 through 2020, 72% of US corporations utilized operating leases, according to Wang (2023). Approximately 20% of the total physical productive assets among the publicly traded companies in the United States have been arranged through lease arrangements. However, for smaller and financially restricted firms, the number is more than double (40%) (Li & Tsou, 2019). Firms depend operating leases for up to 36% of their overall debt and up to 12% of their assets on average (Wang, 2023).

conclusion. This paper is not the first to investigate the link between leasing and financial constraints. Financial constraints are considered in Eisfeldt and Rampini's (2009) model of selecting between leasing and secured loans. Their model also implies that financially constrained firms have higher lease intensity than their non-constrained counterparts. The summary of this earlier literature, which mainly reflects financial constraints directly or indirectly, can be reinvestigated ex post through the findings of Wang (2023). Wang (2023) argues that firms increase operating leases since natural disasters deepen firms' collateral constraints, which leads to external financing frictions. In addition, the impact is more potent in highly leveraged firms before natural disasters and in financially constrained firms ex ante. Studies in this space have identified several other bases for leasing, including ownership structure (Flath, 1980; Mehran et al., 1999), agency conflict and governance factors (Devos & Rahman, 2014; Robicheaux et al., 2008), and tournament-based incentives (Rahman & Chowdhury, 2023). However, this paper further considers uncertainty driven by climate regulation, which may be a critical factor in firms' leasing decisions.

2.3 Climate Policy Uncertainty and Operating Lease Intensity

Policy actions towards climate mitigation and adaptation are paramount (Pachauri & Reisinger, 2007). Any policy uncertainty sourced through the economic risks resulting from policy regulation (Al-Thaqeb & Algharabali, 2019) has always become an essential cause of business operational risk (Tchankova, 2002). With such regulatory targets, Busch and Hoffmann (2009) expect that firms better address their exposures to climate uncertainty by (1) risk reduction, (2) risk transfer, and (3) risk avoidance-related strategies in their business and financial operations. In this literature, we explain the economic rationality of leasing during the period of elevated uncertainty, which is CPU in this paper.

First, the theoretical findings of the leasing literature relate to the hedging attributes of lease agreements. Accordingly, Devos and Li (2020) prove that firms recognize the hedging features of leases when considering leasing decisions. Apart from using financial derivatives-driven hedging instruments (e.g., Brown, 2001; Guay, 1999), Weiss and Maher (2009) identify how leasing serves as a hedge for firms facing uncertain adverse settings in their operations, where leasing is similar to a financial hedge by "mitigating risk by counter-balancing actions" (Van Mieghem, 2003). Prior studies (e.g., Gulen & Ion, 2015) argue that policy uncertainty damages enterprises' production investment. Acknowledging that economic policy is crucial to public policy. Pástor and Veronesi (2012; 2013) conclude that uncertainty affects enterprises' business behaviour. CPU, as an added source of external risk for enterprises, will have significant implications for enterprises' operational and financial choices (Ren et al., 2022). During the period of tighter CPU, leasing can be a good hedge against operational damages of a firm's physical asset portfolio, as leasing comes with a hedging position on that asset in the event of uncertainty (Smith, 1979). Firms here can effectively form an ideal hedge against asset ownership through leasing. It separates ownership from use, while accepting the risk of obsolescence and declining asset residual value, the lessor obtains lease payments (Devos & Li, 2021). Consequently, we hypothesize that CPU and operating lease intensity are positively associated.

Second, the economic rationale of lease financing can also be explained using Smith and Wakeman's (1985) "financial contracting" hypothesis, which proposes that firms lease to avoid losing money on more expensive external borrowing (Rahman & Chowdhury, 2023). Following the 'financial contracting' motivation, Sharpe and Nguyen (1995) articulate that firms exposed to high external funding costs are capable of avoiding costlier external debts by leasing. Studies show that lease financing may lower the risk premiums on external finances that arise from severe agency conflicts and subsequent costly loan monitoring (Smith, 1979) or underinvestment (Myers, 1977; Stulz & Johnson, 1985). Therefore, an operating lease is an alternative to debt financing, specifically for financially constrained firms and firms with higher agency problems.

Third, policy uncertainty weakens the financial stability of firms through the increasing risk of bankruptcy risk and thus often results in tighter borrowing contracts and thus limits the debt capacity of financially constrained firms (Kim et al., 1978). For these firms, leasing is an alternative financing strategy that explains the greater leasing propensity of lower-rated and cash-poor firms. Firms with limited cash flows (Gulen & Ion, 2016; Zhang et al., 2015) suffer from collateral constraints during periods of higher policy uncertainty since the assets accessible as collateral to borrow become less valuable (Wang, 2023). However, the value of collateral assets determines firms' eligibility for external financing (Rajan & Zingales, 1995; Rampini & Viswanathan, 2013). These claims suggest that a drop in a firm's ability to obtain external credit due to collateral restrictions weakens a firm's ability to obtain external financing under tighter policy uncertainty. However, leasing is self-collateralized. Firms can acquire leases without covenanting additional assets. Hence, leasing may be an alternate financing preference under collateral constraints for higher CPU. Last, CPU is associated with higher information asymmetry problems (Myers & Majluf, 1984), as firms are supplemented by high uncertainty regarding government policies, which can affect the firm's competitiveness and usual cash flow (Ben-Nasr et al., 2020). Hence, information asymmetry increases capital rationing and confines the capital raising ability of a firm in public debt markets (Cao et al., 2013). Therefore, firms are exposed to higher debt financing costs (Chava, 2014; Correa et al., 2023). However, leasing can cope with external financing friction, and therefore, lease intensity should be highly pronounced for firms exposed to higher CPU.

In conclusion, we can summarize the above literature in the following manner. The hedging principle of leasing provides operational flexibility to firms in adapting to technological and capacity-related changes because the relocation of leased capital is more straightforward than that of owned capital (Zhang, 2011). This flexibility is valuable during tightened CPU when profits and cash flows are uncertain. Moreover, from the perspective of lessors, it is much simpler for a lessor to reclaim an asset than it is for a secured creditor (Benston & Smith, 1976). Therefore, the risks of ownership of an asset and the complexity of collateral requirements related to the debt arrangement and consequent higher debt financing cost substantiate that leases are more accessible to finance than buying an asset. Hence, we conjecture that firms with high CPU prefer to lease an asset instead of buy, which leads us to our central testable hypothesis.

H1: Climate policy uncertainty (CPU) is positively associated with operating lease intensity.

3.0 Data and Methodology

3.1 Data and Sample

We utilize firm-specific lease data from the Wharton Research Data Services (WRDS) database and financial data from Compustat to construct the operating lease intensity and other needed control variables. To measure the variable of interest, CPU, we use the publicly available CPU Index developed by Gavriilidis (2021)[4]. We also require other CPUs and natural disaster-related data to construct other alternative variables of interest. Accordingly, we utilize the Emergency Events Database (EM-DAT) established by the Centre for Research on the Epidemiology of Disasters (CRED)[5] for natural disaster data collection and Green House Gas (GHG) emissions data from S&P Global's Trucost database[6]. Furthermore, we merge these data with Compustat. Moreover, we utilize a few macroeconomic indicators from Federal Reserve Economic Data (FRED). Our sample period covers 2000 to 2017 and is restricted to 2017 to represent recent trends in operating lease intensity and exclude tax changes made in 2018. Accordingly, due to regulatory changes, operating leases are required to be capitalized on the statement of financial positions, which may offset incentives for firms to alter their lease decisions. Our data represent 24,982 firms and 224,985 firm-year observations during the sample period. However, we exclude firm-year observations with negative asset and year values and any other missing information. After applying filters, our final dataset comprises 83,666 panel data observations from 9,391 firms. The sample omits utility firms (SIC: 4900–4999) and financial institutions (SIC: 6000–6999) because they are subject to different regulations due to the nature of their operations[7], which can impact

[4] Climate policy uncertainty data can be found here. https://www.policyuncertainty.com.
[5] The database is publicly available here: https://public.emdat.be/.
[6] The database is accessible here: https://www.spglobal.com/esg/trucost.
[7] For example, retail banks capitalize loans as an asset instead of most nonfinancial firms that would record a loan as a liability on the balance sheet. Banks are subject to holding regulatory capital to prevent default and disruption to the flow of funds in the economy. Utilities tend to be government-owned monopolists due to the high fixed costs of developing the utility. As with banks, these firms are subject to an inflated regulated asset base.

their leasing choices in a different way from those of nonfinancial and nonutility companies (Rahman & Chowdhury, 2023; Devos & Rahman, 2014). Finally, we winsorize all continuous variables at their 1st and 99th percentiles to limit the influence of outliers.

3.2 Measures of Climate Policy Uncertainty

The measurement of our variable of interest (CPU) is the climate change news index *(CPU)* developed by Gavriilidis (2021), a market-wide index indicating climate change risk. The index uses text-based analysis to proxy for climate policy changes, such as quantifying the frequency of words including "uncertainty" in eight U.S. newspapers. The idea is that climate change receives extensive media coverage mostly during periods of elevated concerns about climate change risk. The climate change news-based index captures the intensity of climate change conversations in critical newspapers (Huynh & Xia, 2021). Gavriilidis (2021) conducts various validation checks and shows that this index realistically captures the combined negative interpretation among investors regarding climate change risk at a particular period. For example, Gavriilidis (2021) employs the index to study the association between CPU and CO2 emissions, and the findings suggest that shocks to CPU are associated with lower emissions, both at the aggregate level and in most sectors examined. The availability of this index allows financial economists (e.g., Azimli, 2023; Treepongkaruna et al., 2023; Bouri et al., 2022) to examine the impacts of climate policy-driven uncertainty in the scope of climate finance. We take caution before directly using the CPU data. For example, we measure the annual mean before taking the natural logarithm of the index to standardize the value and extract meaning through percentage change analysis.

3.3 Measures of Leasing Intensity

The proxy for the firm-level lease intensity (*LEASE*) is the operating lease ratio. Following the prior literature (e.g., Rahman & Chowdhury, 2023; Devos & Rahman (2014)), *LEASE* indicates the proportion of net property, plant, and equipment a firm leases instead of purchasing. In accordance with prior research (e.g., Devos & Rahman (2014), Graham et al. (1998), Lim et al.

(2003), Robicheaux et al. (2008), and Sharpe and Nguyen (1995)), we calculate the value of operating leases by adding rental expenses to the discounted values of upcoming rental obligations since leasing is an off-balance-sheet item and the capitalized operating lease value is unavailable. Our process includes a series of steps. First, we accumulate lease information from Compustat and use a 10% discount rate to determine the present values of rental agreements for the following five years and beyond. The next step is to calculate LEASE by dividing the total rental expenditures and rental commitment present values by the total rental expenses, rental commitment present values, and net property, plant, and equipment.

3.4 Empirical Model

Our baseline model for examining the impact of CPU on lease financing decisions is

consistent with those from earlier investigations (e.g., Devos and Rahman (2014), Beatty et al. (2010) and Sharpe and Nguyen (1995)) and uses the following OLS regression models.

$$
\begin{aligned}
LEASE_{i,t} = \beta_0 &+ \beta_1 CPU_{i,t} + \beta_2 NODIV_{i,t} + \beta_3 OIBDP/SALE_{i,t} + \beta_4 STLCF_{i,t} \\
&+ \beta_5 LTLCF_{i,t} + \beta_6 SIZE_{i,t} + \beta_7 LOSS_{i,t} + \beta_8 TAX\ RATE_{i,t} \\
&+ \beta_{9-12} S\&P\ RATING_{r,i,t} + \beta_{13} AGE_{i,t} + \beta_{14} Q_{i,t} + \beta_{15} CAPEX_{i,t} \\
&+ Firm\ Fixed\ Effects + \varepsilon_{i,t}
\end{aligned}
$$

where *i* denotes the firm and *t* denotes the year. The dependent variable, *LEASE,* measures the operating lease intensity. The variable of interest, *CPU*, is the newspaper-based textual index developed by Gavriilidis (2021). In all regressions, we incorporate firm fixed effects to account for omitted time-invariant firm attributes. We also use industry fixed effects as a robustness check to control for time-invariant industry-specific variables and extend our findings to all industries. We do not incorporate year fixed effects, as CPU inherently contains year-specific effects that affect *LEASE*, which is consistent with Ren et al. (2022). We also include an intercept (β_0) to ensure that the model is unbiased. The term yields no economic significance, as it quantifies a firm's operating lease intensity when all regressors equal zero. Heteroscedasticity and robust standard errors are used in the estimation process, and they are clustered at the firm level. Based on prior literature, we introduce a list of control variables to account for their potential influence on lease intensity. Our regression model also includes 11 firm-specific factors as control variables, primarily representing proxies for financial constraints and firm-level uncertainty. For instance, we expect that financially constrained companies will take out more operating leases to expand debt capacity (Beatty et al. (2010), Sharpe and Nguyen (1995)). Therefore, we construct the dummy variable *NODIV*.[8] It is expected to have a positive coefficient. We proxy for firm *OIBDP/SALE,* as the operating income ratio before depreciation over total sales is expected to be positively associated with leasing intensity. We anticipate that the coefficient on *Size* will be negative since larger enterprises are less likely to be financially restricted (Beatty et al., 2010). The rating dummies are anticipated to have negative coefficients compared to unrated status[9]. We also include controls that explain operating lease intensity through tax incentives. Following the studies of Devos and Rahman (2014), Graham et al. (1998), and Sharpe and Nguyen (1995), we expect that *TAX RATE* is negatively correlated with *LEASE,* as firms with a lower corporate tax rate prefer not to lease as much because they cannot capture the benefit from reducing their depreciation expense relative to a firm with a higher corporate tax rate. Finally, we assume a positive coefficient on *Loss* because loss-making firms rarely capitalize on the tax advantage of asset ownership (Sharpe & Nguyen, 1995; Beatty et al., 2010). *AGE* may have a negative coefficient since more mature firms allocate

[8] We assume that financially constrained firms are limited to dividend declaration following Beatty et al. (2010) and Sharpe and Nguyen (1995). Here, the dummy indicates whether a corporation is financially restricted and is equal to one if it does not pay a dividend every year t over the sample period and to zero otherwise.

[9] Four dummy variables are created for each firm-year observation, ranging from the most significant to the lowest rating. If the company has an AAA-A.A. rating, the first dummy variable is one; otherwise, it is zero. If the company has an A+ to A- rating, the second dummy variable equals one; otherwise, it equals zero. If the company has a BBB+ to BBB- rating, the third dummy variable equals one; otherwise, it equals zero. The fourth dummy variable equals zero if the company has a BB+-D rating. The variable UNRATED is similarly defined as one in the absence of any credit ratings for the company and zero otherwise. We include everything but UNRATED in the regression model. This method compares the coefficients on each dummy to those on the UNRATED dummy.

higher levels of capital towards debt and less towards leasing (Robicheaux et al., 2008). Following Chu (2020) and Graham et al. (1998), we include *Q* or Tobin's Q, which assesses a firm's market value relative to book value, and expect a positive coefficient. The correlation between *CAPEX* and *LEASE* is predicted to have negative effects, as firms with more significant capital investment as a portion of PPE are less financially constrained. We provide complete explanations of all these used variables in the Appendix.

3.5 Descriptive Statistics

[Insert Table 1 here]

Table 1 presents descriptive statistics of all the variables shown in this study to establish a causal relationship between CPU and operating lease intensity. The dependent variable, lease intensity *(LEASE)*, has a mean value of 0.397 with a standard deviation of.331. Similar to this study, Rahman and Chowdhury (2023) report a nearer *LEASE* value with a mean and standard deviation. We observe substantial variation of *CPU* measures across the sample period consistent with Treepongkaruna et al. (2023) and Bouri et al. (2022). Our *CPU* index has a mean value of 4.23 and a standard deviation of.592. All control variables are within usual, predicted, and appropriate ranges as captured in the literature (Devos & Rahman, 2014). We winsorize all continuous variables at the 1st and 99th percentiles to lessen the impact of outliers. The description of these variables provides preliminary evidence in favour of our motivation to conjecture whether CPU affects lease intensity.

4.0 Results and Discussion

4.1 Baseline Regression Results

Table 2 presents the baseline regression results of our empirical investigation. This investigation uses the OLS regression model to study the connection between CPU and operating lease intensity. We identify clear evidence in support of the hypothesis. In a volatile state driven by CPU, firms prefer increasing operating lease dependency to buying. Column 1 only includes the main variables of interest, showing that all else being equal, a 1% change in *CPU* increases *LEASE* by 1.8%. The finding ensures statistical significance and is economically meaningful. For a one-standard-deviation increase in CPU, the operating lease intensity increases by 2.68% [0.018/.397*0.592]. Overall, our baseline results are consistent with the conjecture that CPU usage positively impacts operating lease intensity. The result is also robust to firm fixed effects and is unchanged when we add control variables in Column (2). The coefficient, however, weakens to 1.1% in Column (3) when we include industry fixed effects in lieu of firm fixed effects. We attribute this to unobservable time-invariant industry fixed effects, consistent with Wang (2023), who shows that operating lease intensity decreases significantly with industry-times-year fixed effects.

[Insert Table 2 here]

Most of our other explanatory control variables in Models (2) and (3) have their predicted coefficient, which aligns with related literature (e.g., Devos and Rahman (2014), Robicheaux et al. (2008) and Sharpe and Nguyen (1995)). For example, *NODIV, STLCF*, *LTLCF, AGE,* and *Q* positively affect *LEASE*, whereas *OIBDP/Sales*, *SIZE*, *TAX RATE, and CAPEX* are negatively correlated with *LEASE*. Note that with industry fixed effects, lower-rated firms do not necessarily lease more. From Column (2), lower credit-rated firms decrease *LEASE*. The constant terms in all models are significant (at the 1% level). Ultimately, the regression shows that financially constrained firms significantly lease more.

4.2 Climate Policy Uncertainty and Lease-Debt Substitutability

Prior studies show the unfavourable credit terms displayed by creditors towards firms in areas of elevated policy uncertainty (Bloom, 2009; Julio & Yook, 2012; Gulen & Ion, 2016), leaving these firms stressed with severe financial restrictions. Consequently, it is interesting to explain how firms exposed to higher policy uncertainty acquire adequate capital support to pass through such challenging times. One of the possible answers is that firms substitute the lease for debt during elevated CPU as a part of economization on costly external finances. The motivation originates from the existing corporate finance literature where leases can substitute for debt. However, Ang and Peterson (1984), along with later studies (e.g., Lewis and Schallheim (1992) and Eisfeldt and

Rampini (2009)), attempt to confirm this prediction in their seminal empirical study and instead report a complementary relationship. On the other hand, Bayliss and Diltz (1986), Marston and Harris (1988), Beattie et al. (2000), and Yan (2006) all find that debt and leases are substitutes, with changing degrees of substitutability. In an interesting further investigation, Schallheim et al. (2013) propose that both theoretically and empirically, debt and leases are both substitutes and complements. In this part, we explore the substitutability of operating leases with capital leases and debt to comprehend the explanatory power of CPU on lease intensity.

[Insert Table 3 here]

As a part of this exploration, Column (1) in Table 3 reports that a 1% change in *CPU* increases *LEASE SUB* by 0.8%. The coefficient is statistically significant and economically meaningful. When we compare these results to those obtained in Table 2, Columns (1) and (2), all else being equal, *CPU* increases *LEASE* more than other financing instruments. The results corroborate prior studies (e.g., Yan, 2006). The extant literature (e.g., Lewis and Schallheim (1992) and Sharpe and Nguyen (1995)) supports this position, wherein operating leases allow a firm to expand debt capacity without increasing the cost of borrowing. Nevertheless, the implications of these results are significant, as consistent climate policy may provide additional support to the substitutability of debt and leases.

4.3 Endogeneity Checks

In most cases, since a textual-based index, such as that developed by Gavriilidis (2021), is based on the media coverage of climate-related news among eight U.S. newspapers, our variable of interest, *CPU*, is considered exogenous and beyond the control of individual firms (Cao et al., 2021). Therefore, there is little reason to believe that a firm's fundamentals may affect climate change uncertainty (Engle et al., 2020; Huynh & Xia, 2021). However, one might still be concerned that climate change news coverage could be influenced by the editorial slant (e.g., the specific preferences, agenda, priorities, and personal beliefs) of a particular news outlet (Druckman & Parkin, 2005). Thus, to alleviate concerns about media bias and further establish the causal relationship between CPU and lease intensity, we employ SCAPs as an exogenous policy shock to climate regulation and sample matching techniques to mitigate endogeneity concerns.

4.3.1 State-level Climate Adaptation Plans and Lease Intensity

Thus far, higher policy uncertainty has led to higher operating lease intensity. However, we hypothesize that firms that face higher climate regulatory pressure are less likely to increase their lease intensity in the presence of higher climate uncertainty (Cao et al., 2021). We therefore explore the impact of CPU on operating lease intensity in a state of numerous regulatory interventions. Here, we examine the moderating effect of SCAPs on operating lease intensity. Several U.S. states have proactively developed and implemented SCAPs to moderate the harm caused by or to exploit beneficial opportunities related to climate change (Ray & Grannis, 2015). Between 2008 and 2020, 19 states finalized their SCAPs. Florida, Maryland, and Virginia were the first to finalize their SCAPs in 2008, while North Carolina and Montana were the latest. Significant states such as California and New York finalized their SCAPs in 2009 and 2010, respectively. A list of states that approved SCAP legislation has been added in Appendix Section C. Finalization of the SCAP in a state signals to local firms and their investors that the state government is serious about climate change and is determined to take future climate-related action, including legislative action, if necessary, to reduce greenhouse gas emissions and combat climate change (He et al., 2020). Climate policy-related uncertainty is expected to be partially mitigated and materially lower in states with SCAPs dedicated to alleviating the climate-induced negative economic impact. Therefore, the impact of CPU on lease intensity should be eased in firms located in SCAP states relative to firms in non-SCAP states (Ray & Grannis, 2015).

[Insert Table 4 Here]

To empirically examine how environmental legislation moderates the impact of CPU on lease intensity, we incorporate SCAPs in our regression models explained in Table 4. The CPU impact is less pronounced for firms in states that have adopted SCAPs. We present our results in

Table 4. The significant and positive coefficients of *SCAP* and *CPU* suggest that increased *SCAP (CPU)* is associated with higher operating lease intensity. The results are also economically meaningful. The coefficient is similar to our baseline results on the average positive impact of *CPU* on *LEASE*. Importantly, the interaction term, *SCAP*CPU*, has a significant negative coefficient, indicating that the positive impact of CPU on lease intensity is mitigated for firms headquartered in states that have adopted SCAP. The table shows that a 1% change in the *SCAP*CPU* interaction term decreases *LEASE* by 1.43%, which is also statistically significant and economically meaningful. The coefficients of all control variables that have predicted signs are aligned with the extant literature (e.g., Devos and Rahman (2014), Robicheaux et al. (2008), and Sharpe and Nguyen (1995)). The results indicate that firms respond positively to climate regulations in SCAP states, where the future risk of climate damage is perceived to be lower. This finding also offers important implications by showing that environmental regulations reduce CPU, consistent with other studies (Cao et al., 2021). This narrative explains that the impact of CPU on leasing intensity is causal.

4.3.2 Propensity Score Matching and Entropy Balancing

PSM is a tool used in the economics and finance literature as an attempt to reduce functional form misspecification (FFM) when differences between treatment and control groups cannot be adequately accounted for using multiple regression analysis with a linear functional form (Shipman et al., 2017). Consistent with Rahman and Chowdhury (2023), our model could induce identification concerns arising from FFM if firms with high CPU could systematically differ from firms with low CPU and there is any nonlinearity in leasing. We employ PSM to solve this FFM-related problem. Table 5 presents these findings. Following Hasan et al. (2022) regarding the effect of firm-level political risk, we define the '*TREATED*' group as those with *CPU* values above the sample median and the '*CONTROL*' group as those with below-median values. We use all the firm-level controls in our baseline regression model and apply nearest-neighbour PSM with a 0.01

calliper without replacement. Panels A and B in Appendix C show the ex ante summary statistics of 39,862 and 43,804 firm-level observations for the *TREATED* and *CONTROL* groups before and after covariate matching. We find that the matching variables between the *TREATED* and *CONTROL* groups are significantly different, which implies a good match in our sample (Rahman et al., 2023). Table 5, Column 1 reports the matched regression results, where we run our baseline model on this matched sample. We find that the estimated coefficient of *CPU* remains positively significant. Overall, these results support that our baseline findings of higher lease intensity for higher CPU are less likely driven by any FFM.

[Insert Table 5 Here]

Next, to achieve covariate balancing through "equal percent bias reduction" (Gaver & Utke, 2019), as opposed to "random matching" in PSM (King & Nielsen, 2019)), recent studies (Gaver & Utke, 2019; Hainmueller, 2017; McMullin & Schonberger, 2020) have focused on the entropy balancing tactic, which can improve covariate imbalances after matching. Similarly, we also employ such entropy balancing to more effectively minimize the variations in observable variables across the treatment and control groups, following Kyaw et al. (2022). Panels C and D in Appendix C report the mean, median, and skewness variables of *the* *TREATED* and *CONTROL* groups before and after weighting. Panels C and D are comparable. According to regression results in Column (2) in Table 5, the coefficient of CPU is positive and significant, strengthening once again the positive influence of CPU on lease intensity. The results mirror those seen in Wang (2023), who adopts entropy balancing to mitigate endogeneity concerns between natural disasters and operating lease intensity.

4.4 Effects of Natural Disasters

Existing studies (e.g., Wang, 2023) report that disaster-affected firms struggle with external financing friction induced by natural disaster-related collateral constraints and therefore have a higher dependency on leasing financing. Therefore, there is a concern that the firms included in our sample respond to leasing after natural disasters since climate risk and natural disasters impose substantial costs on credit contracts (e.g., Correa et al., 2023). Being critical and concerned with the effect of natural disasters on leasing, we feel motivated to explore and explain the explanatory power of CPU on operating lease intensity during an extreme frequency of natural disasters. We hypothesize that the effect of CPU on leasing is more prominent for firms that are more exposed to the risk of climate disasters, following Manu et al. (2022).

We utilize the EM-DAT database to develop natural disaster proxies. In line with Malik et al. (2019), we use geophysical (volcanic activity, mass movement, or earthquake), meteorological (extreme temperature, fog, or storm), hydrological (wave action, landslide, or flood), and climatological (wildfire, glacial lake outburst, or drought) disasters. We also restrict our sample to only climatological disasters to determine whether climate-related disasters have a more concentrated effect on *LEASE*. We measure the effect of natural disasters through total financial loss and total insured loss. While total financial loss includes "all damages and economic losses directly or indirectly related to the disaster," total insured loss includes "economic damages covered by insurance companies." We construct *SALIENT LOSS* as a dummy variable equal to 1 if the firm has a current year's total financial loss exceeding 1 billion USD. We construct *SALIENT INSURED LOSS*, a dummy variable set to 1, if the firm has a current-year total insured loss exceeding 1 billion USD, following Dessaint and Matray (2017) and Huang et al. (2020). Apart from third-party insurers, we also acknowledge that firms may prefer to "self-insure by accumulating cash reserves" and that the natural disaster insurance market is "imperfect" and "may not cover a variety of indirect losses" (Wang, 2023). Table 6 presents the results of our OLS regression with a firm-fixed effects model to analyse how natural disasters moderate the relationship between CPU and lease intensity.

[Insert Table 6 Here]

Both Columns (1) and (3) report that firms featuring a salient total financial loss reduce operating lease intensity by 2.1% and 3.6%, respectively, which is consistent with Dessaint and

Matray (2017). Prior studies (e.g., Duong et al. (2020), Froot (2001), and Ren et al. (2022)) have made similar causal inferences that firms take precautions against natural disasters and amass cash to cease leasing altogether. However, insurance seems to be an effective risk-shifting tool in this case. As shown in Column (2), a firm with salient insured loss increases its operating lease intensity by 6.6%. This coefficient is statistically significant and economically meaningful. However, operating lease intensity decreases by 4.6% if we only include climatological disasters in Column (4). Overall, we find that firms insure against different disaster types and that lease intensity increases with geophysical, meteorological, and hydrological disasters as opposed to decreasing with climatological disasters. This finding is consistent with Wang (2023), who articulates that insurance contracts do not cover the economic losses sourced from natural disasters. This articulation could be a possible reason for the negative coefficient in Column (3).

Furthermore, the interaction terms have significant coefficients for all disasters but are of low significance (10% significance level in Column 4) or insignificant only for climate-related disasters. The negative coefficient of the interaction term, *CPU*SALIENT INSURED LOSS* in Column (2), indicates that firms exposed to both higher CPU and salient loss potential prefer to "self-insure" and amass cash, which is consistent with Dessaint and Matrav (2017) and Froot (2001) as opposed to Column (1). On the other hand, the coefficient of the interaction term, *CPU*SALIENT INSURED LOSS,* becomes significantly positive when considering only climatological disasters. Except for *CPU*SALIENT INSURED LOSS*, these results support Manu et al. (2022), in which CPU is exacerbated by natural disaster risk. Instead of insuring against future loss, firms prefer to "self-insure" and amass cash, following Dessaint and Matrav (2017) and Froot (2001). Moreover, the explanatory power of CPU and the constant term are highly significant in all columns. However, our concerns about the low reliability of the findings in Models (3) and (4) due to data unavailability for climatological disasters cannot be ruled out. Most control variables that significantly determine *LEASE* are aligned with the extant literature (e.g., Devos and Rahman (2014), Robicheaux et al. (2008), and Sharpe and Nguyen (1995)).

4.5 Effects of Emissions

We are concerned about whether the explanatory power of CPU includes upward bias due to any major unobservable factors, such as greenhouse gas emissions. The amount of direct carbon emission intensity increases regulatory policy uncertainty, damages a company's ability to finance its debt, and raises credit risk (Zhang & Zhao, 2022) and, thus, lowers credit ratings. Moreover, investors expect more rigorous climate policies in the extended period. Under such conditions, firms substitute financing instruments that increase leverage for operating leases, and we hypothesize that firms operating in more emissions-intensive industries lower corporate leverage when exposed to CPU.

[Insert Table 7 Here]

Panel A in Table 7 reports the impact of raw GHG emissions on lease intensity. Unlike *HIGH GHG DIRECT,* both *HIGH GHG* and *HIGH GHG INDIRECT* have a 3.3% and 3.7% negative relationship with leases, respectively. However, the interaction terms *(CPU*GHG)* in all three models have a significant positive association. The interpretation is consistent with Eisfeldt and Rampini's (2009) hypothesis, which shows that leasing has a higher debt capacity and that financially constrained firms prefer borrowing. As mentioned at the beginning of this section, firms emitting high carbon emissions face higher cash flow uncertainty, resulting in lower credit market access.

Panel B in Table 7 reports the leasing dependency of firms with high total greenhouse gas emissions. Like Panel A in the table, all GHG intensities significantly negatively impact leasing decisions except *HIGH INTENSITY DIRECT*. However, the interaction effects between CPU and *HIGH GHG* and *CPU* and *HIGH GHG INDIRECT* emissions are significantly positive, except for the interaction term between *CPU* and *HIGH GHG DIRECT*. Such a conclusion is aligned with Manu et al. (2022), who indicate that high-emitting firms exacerbate the effect of CPU. Interestingly, our results suggest that firms only change leasing behaviour in response to direct GHG emissions once exposed to CPU. However, we acknowledge that firms may misrepresent direct emissions data as indirect to remove accountability and protect their market value from divestment, as mentioned by Konar and Cohen (2001). Importantly, firms are not mandated to report emissions data by the SEC. In addition, taxonomies such as the EU Taxonomy for Sustainable Activities were introduced after the sample period of 2020.

Moreover, the explanatory power of CPU through the six columns in both panels is highly significant (at the 5% level). However, the lower coefficients of CPU imply that GHG absorbs explanatory power from *CPU* relative to the baseline results. All control variables that significantly determine *LEASE* are consistent with the extant literature (e.g., Devos and Rahman (2014), Robicheaux et al. (2008), and Sharpe and Nguyen (1995)). We are further concerned about the reliability restriction of the findings due to the lower number of firm-year observations.

4.6 Additional Robustness Tests

We also conduct two additional robustness tests to enhance the validity of our results. We replicate our primary regression using two lease intensity measures to ensure that our results resist the choice of lease intensity measurements. Similarly, we apply another climate change risk index to our regression findings to increase their external viability. Last, we control for unobserved impacts of other firm-level and macrolevel uncertainties in the regression.

4.6.1 Alternative Lease Intensity Measure

We construct two alternative lease measures to further increase robustness. One is *LEASE 2,* as used by Eisfeldt and Rampini (2009) and Sharpe and Nguyen (1995). *LEASE 2* is modelled as a perpetuity using lagged capitalized lease expenditure and a 10% discount rate as the payment proxy. We then divided this product by the summation of net property, plant, and equipment (PPE) and capitalized lease expenses. The measure overcomes the limitation where fixed capital would otherwise understate the PPE stock used in production. The second alternative lease measure is *LEASE 3,* constructed based on Devos and Li (2020) and Graham et al. (1998). *LEASE* is the sum of current rental expenses and the present value of operating lease commitments for up to five years, discounted at 10% divided by long-term debt, including capital leases and the total present value of operating leases. Apart from the lease measures, we also restrict our sample to manufacturing firms in line with Beatty et al. (2010).

[Insert Table 8 Here]

Panel A in Table 8 shows the regression outcomes of alternative operating lease intensity measures. Irrespective of proxy measure used, CPU increases operating lease intensity. The results corroborate Chu (2020), who adopted *LEASE 2,* and Devos and Rahman (2014), who adopted *LEASE 3*. Column (3), dedicated to manufacturing firms, also reports that CPU positively affects *LEASE*. Beatty et al. (2010) describe these firms as asset-intensive, going against the traditional wait-and-see approach per real options theory. The findings correspond with Devos and Rahman (20) and Beatty et al. (2010). Most control variables have predicted coefficients aligned with the extant literature (e.g., Devos and Rahman (2014), Robicheaux et al. (2008), and Sharpe and Nguyen (1995)). The constant term remains significant (at the 1% level) in all models.

We further acknowledge the findings raised by Yan (2006) regarding our alternative lease measures. According to Yan (2006), *LEASE 2* is considered oversimplified by assuming that lease payments stay the same year-on-year. Furthermore, *LEASE 3* contains a downward bias, as it does not consider leases beyond year five, and intensity is scaled by total debt instead of investment capital.

4.6.2 Alternative Climate Policy Uncertainty Measures

The WSJ Climate Change News Index produced by Engle et al. (2020) is our alternate CPU scale. This index calculates the proportion of the Wall Street Journal (WSJ) allocated to the issue of climate change each day to determine the extent to which climate change is discussed. Because this WSJ index's story and composition pattern are similar to the CPU Index of Gavriilidis (2021), we consider that adopting the WSJ Index as an alternate proxy for CPU is desirable. Furthermore, the articles in the Wall Street Journal cover a wide variety of climate-related concerns (Engle et al., 2020), including physical damage and disruptions caused by climatic occurrences and new innovations and legislations of climate laws and policies. Panel B in Table 8 shows the regression results concerning the WSJ Index (CPU_{WSJ}). All columns reflect that the WSJ index significantly impacts operating lease intensity. All the controls have the predicted signs.

4.6.3 Additional Controls

We also examine the impact of CPU on leasing in conditions of possible upward bias due to the presence of economic policy uncertainty (EPU), firm-level uncertainty, and macroeconomic uncertainty.

Table 9 Panel A controls for EPU utilizing the policy uncertainty index established by Baker et al. (2016). The results in Column (1) report that a 1% change in *BBD* increases *LEASE* by 1.1%, which is statistically significant. However, Column (2) shows a negative coefficient of *EPU NEWS* on *LEASE*. The highly significant negative effect of *EPU NEWS* and the highly significant positive effect of *CPU* suggest that *CPU* and *EPU*, constructed by text-based analysis, may have potentially offsetting effects on *LEASE*. Although ΔTAX and *LEASE* are positively associated in Column (3), Column (4) shows that a 1% increase in *DISAGREE* increases *LEASE* by 1.4%. All results are highly significant. However, *EPU NEWS* and ΔTAX in Columns (2) and (3) lower the lease intensity during the period of higher CPU, which is aligned with Duong et al. (2020), in which firms retreat from leasing to insuring against policy uncertainty. In all cases, the explanatory power of CPU is highly significant (at the 1% level).

Most control variables have predicted coefficients aligned with the literature (e.g., Devos and Rahman (2014), Robicheaux et al. (2008), and Sharpe and Nguyen (1995)).

[Insert Table 9 Here]

We further investigate whether firms with greater firm-level volatility increase operating lease intensity to substitute for financial instruments that increase leverage, as consistent with prior studies (Sharpe and Nguyen (1995) and Beatty et al. (2010)). Panel B from Table 9 shows that more significant firm-level uncertainty impacts a firm's capability to secure external financing, increasing operating lease intensity. All such explanatory variables, namely, *σ(RETURN), σ(SALES*), *σ(CASH),* and *σ(PROFIT),* have a significantly positive impact on leasing. These results are aligned with Coles et al. (2006), Duong et al. (2020), and Kini and Williams (2012), in which more significant firm-level uncertainty causes higher operating lease intensity. In all these cases, the coefficient of *CPU* remains significantly positive and almost similar across the diverse levels of firm-level uncertainties. The controls also have the predicted coefficients.

Finally, we examine the impact of CPU on leasing after controlling for macroeconomic impacts, as presented in Table 9, Panel C. According to the results, Δ*GDP, INFLATION*, and Δ*FFR* positively affect *LEASE*, and *UNEMPLOY* and *CC* impact negatively. The coefficient on *UNEMPLOY* is consistent with the Phillips curve.[10] All results are significant. The results corroborate the findings of Duong et al. (2020) and are consistent with the natural business cycle. Namely, increases in real and nominal GDP and lower unemployment are controlled with contractionary monetary policy, which is implemented through increasing interest rates (*FFR*). High interest rates lower consumer confidence as the general cost of living increases. The explanatory power of *CPU* is highly significant, and most control variables have predicted coefficients aligned with the extant literature (e.g., Devos and Rahman (2014), Robicheaux et al. (2008), and Sharpe and Nguyen (1995). The constant term remains significant (at the 1% level) in all columns.

5.0 Conclusion

The literature shows that firms are exposed to climate policy uncertainty (CPU) sourced through climate policy shifting and implementation, which have a significant influence on a firm's regular

[10] Phillips (1958) found that a 1% increase in wage inflation led to an approximate 1% decrease in unemployment and vice versa. Empirical data are from the Bureau of Labour Statistics.

actions and financial structure. This thought leads financial economists to explore how CPU provokes frictions in financial markets and influences capital structure and its adjustments. However, despite leasing being one of the dominant financing alternatives among U.S. firms, the impact of CPU on a firm's operating lease intensity has attracted limited attention. The financing size and relevance of leasing motivate us to explore the association between CPU and operating lease intensity. We hypothesize that firms should have a higher propensity to depend on leased capital during bad states triggered by CPU since leasing can combine an asset with a hedging feature in the event of policy uncertainty and cope with external financing friction. We empirically test this conjecture between CPU and leasing using the news-based uncertainty index of Gavriilidis (2021) and a large sample of 83,666 panel observations of 9,391 firm-year observations across 18 years from 2000 to 2017. We find a significant positive relationship between CPU and lease intensity. Our findings are consistent with prior and relevant literature. The findings emphasize that CPU increases the cost of borrowing, which triggers the substitution from financing instruments that increase leverage to operating leasing, which is consistent with our hypothesis. The finding is also robust after controlling for other firm-level and macroeconomic uncertainty.

Our results make several critical contributions to the growing corporate finance literature. First, we establish that CPU is an essential determinant for operating lease intensity. We comprehend the economic rationality of depending on leasing to economize on costly debt financing alternatives during risky business operations triggered by CPU. However, we do not find that a lease is a perfect substitute for debt. However, the study faces a series of limitations. First, determining the true lease obligation of a firm is very challenging, which limits our findings' external validity. Additionally, we should include evidence of whether firms substitute operating leases when capitalized on the balance sheet following the change in lease accounting standards in 2018. We leave these topics for future research. Nevertheless, we conclude that firms place greater emphasis on the hedging property of leasing during the period of tightened CPU.

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Table 1
Descriptive Statistics

This table presents the summary statistics of our baseline regression variables. *CPU* measures climate-related policy uncertainty as the mean of the natural logarithm of the Climate Policy Uncertainty (CPU) index constructed by Gavriilidis (2021). *LEASE* is the sum of the current rental expense (*XRENT*) and the discounted future rental commitments for up to five years (*MRC1–MMRC5*) and discounted rental commitments beyond five years up to ten years (MRCTA) divided by the denominator, which is property, plant, and equipment (*PPE*) plus the numerator. We specifically report the mean, standard deviation (STDEV), 25th percentile (P25), 50th percentile (P50), and 75th percentile (P75) values. All continuous variables have been winsorized at the 1st and 99th percentiles.

Variable	Mean	STDEV	P25	P50	P75
LEASE	0.397	0.331	0.051	0.359	0.711
CPU	4.230	0.592	3.581	4.253	4.781
NODIV	0.615	0.487	0.000	1.000	1.000
OIBDP/SALE	– 0.993	8.393	0.031	0.122	0.248
STLCF	0.188	0.391	0.000	0.000	0.000
LTLCF	0.274	0.446	0.000	0.000	1.000
SIZE	6.361	2.229	4.772	6.314	7.827
LOSS	0.339	0.473	0.000	0.000	1.000
TAX RATE	0.181	0.401	0.000	0.260	0.364
AAA – AA-	0.012	0.109	0.000	0.000	0.000
A+ – A-	0.052	0.221	0.000	0.000	0.000
BBB+ – BBB-	0.093	0.290	0.000	0.000	0.000
BB+ – D	0.140	0.347	0.000	0.000	0.000
AGE	2.334	0.978	1.792	2.485	3.045
Q	1.933	1.580	1.050	1.390	2.146
CAPEX	0.046	0.058	0.010	0.027	0.058

Table 2
Climate Policy Uncertainty and Operating Lease Intensity: Baseline Regression

This table presents the baseline regression results where the dependent variable is operating lease intensity (*LEASE)* and the key explanatory variable is climate policy uncertainty *(CPU).* Column (1) reports regression results of climate policy uncertainty (*CPU*) with *LEASE* with firm fixed effects. Column (2) considers additional control variables with firm fixed effects. Column (3) includes controls and industry fixed effects as opposed to firm fixed effects. All variables are defined in the Appendix. The *t* values in the parentheses are calculated based on robust standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: *LEASE*		
	(1)	(2)	(3)
CPU	0.018***	0.018***	0.011***
	(0.00)	(0.00)	(0.00)
NODIV		– 0.001	0.061***
		(0.79)	(0.00)
OIBDP/SALE		0.000	– 0.001***
		(0.89)	(0.00)
STLCF		0.010***	0.036***
		(0.00)	(0.00)
LTLCF		0.018***	0.056***
		(0.00)	(0.00)
SIZE		– 0.052***	– 0.031***
		(0.00)	(0.00)
LOSS		0.003	0.027***
		(0.11)	(0.00)
TAX RATE		– 0.003***	0.000
		(0.01)	0.98)
AAA – AA-		– 0.026**	0.0138
		(0.03)	(0.57)
A+ – A-		– 0.013**	0.053***
		(0.02)	(0.00)
BBB+ – BBB-		0.003	0.050***
		(0.43)	(0.00)
BB+ – D		0.008*	0.007
		(0.06)	(0.27)
AGE		0.036***	0.0041*
		(0.00)	(0.07)
Q		– 0.002***	0.011***
		(0.01)	(0.00)
CAPEX		– 0.470***	– 1.266***
		(0.00)	(0.00)
Constant	0.319***	0.591***	0.495***
	(0.00)	(0.00)	(0.00)
N	83,666	83,666	83,666
Adj. R^2	0.8665	0.8769	0.4974
Firm FE	Yes	Yes	No
Industry FE	No	No	Yes

Table 3
Climate Policy Uncertainty and Lease-Debt Substitutability

This table investigates the substitutability of operating leases and other financing instruments through OLS regression with a firm fixed effects model. We investigate the effect of climate policy uncertainty (*CPU*) on lease substitutes. We shift the dependent variable from operating lease intensity (*LEASE*) to *LEASE SUB,* which represents total leases. All variables are defined in the Appendix. We include p values in parentheses based on robust standard errors clustered at the firm level. We use *, ** and *** to denote findings that are significant at the 1%, 5% and 10% levels, respectively.

	Dependent Variable: LEASE SUB
	(1)
CPU	0.008***
	(0.00)
NODIV	– 0.03***
	(0.00)
OIBDP/SALE	– 0.000
	(0.16)
STLCF	– 0.010**
	(0.03)
LTLCF	– 0.014***
	(0.01)
SIZE	– 0.064***
	(0.00)
LOSS	– 0.031***
	(0.00)
TAX RATE	0.003
	(0.16)
AAA – AA-	– 0.063***
	(0.01)
A+ – A-	– 0.079***
	(0.00)
BBB+ – BBB-	– 0.074***
	(0.00)
BB+ – D	– 0.108***
	(0.00)
AGE	– 0.013***
	(0.00)
Q	0.009***
	(0.00)
CAPEX	– 0.005
	(0.88)
Constant	0.870***
	(0.00)
N	69,033
Adj. R^2	0.7357
Firm FE	Yes

Table 4
State-Level Climate Adaptation Plans and Operating Lease Intensity

This table reports how adoptions of state-level climate adaptation plans (SCAPs) moderate the effect of CPU on firms' operating lease intensity. SCAP is an indicator variable equal to one if the firm is in a state that has adopted the SCAP, zero otherwise. All variables are defined in the Appendix. We include p values in parentheses based on robust standard errors clustered at the firm level. We use *, ** and *** to denote findings that are significant at the 1%, 5% and 10% levels, respectively.

	Dependent Variable: LEASE
	(1)
SCAP	0.068***
	(0.163)
CPU	0.018***
	(0.001)
SCAP × CPU	-0.143***
	(0.004)
NODIV	– 0.000
	(0.003)
OIBDP/SALE	–0.000
	(0.000)
STLCF	0.009**
	(0.003)
LTLCF	0.016***
	(0.004)
SIZE	– 0.055***
	(0.003)
LOSS	0.003*
	(0.002)
TAX RATE	-0.003***
	(0.002)
AAA – AA-	-0.035**
	(0.015)
A+ – A-	– 0.184***
	(0.007)
BBB+ – BBB-	0.000
	(0.005)
BB+ – D	0.007
	(0.005)
AGE	0.0331***
	(0.003)
Q	-0.002*
	(0.001)
CAPEX	– 0.549***
	(0.025)
Constant	0.626***
	(0.167)
N	67,316
Adj. R^2	0.8831
Firm FE	Yes

Table 5
Propensity Score Matching and Entropy Balancing

This table presents the results of sample matching techniques used to mitigate endogeneity bias. For both PSM and entropy-balanced matched techniques, we construct high climate policy uncertainty (*HIGH CPU*) if the firm-year *CPU* observation is greater than the sample median. We then include the results of our matched sample in model (1) using *LEASE* as the dependent variable. Model (2) then includes the matched sample with entropy-balanced covariates and *LEASE* as the dependent variable. The control variables are similar to those in the baseline model. All variables are defined in the Appendix. We include p values in parentheses based on robust standard errors clustered at the firm level. We use *, ** and *** to denote findings that are significant at the 1%, 5% and 10% levels, respectively.

	Propensity Score Matching	Entropy Matching
	Dependent Variable: *LEASE*	Dependent Variable: *LEASE*
CPU	0.018***	0.017***
	(0.00)	(0.00)
NODIV	0.000	0.000
	(0.98)	(0.88)
OIBDP/SALE	0.000	0.000
	(0.54)	(0.83)
STLCF	0.009***	0.009***
	(0.00)	(0.00)
LTLCF	0.018***	0.019***
	(0.00)	(0.00)
SIZE	– 0.053***	– 0.052***
	(0.00)	(0.00)
LOSS	0.001	0.002
	(0.47)	(0.24)
TAX RATE	– 0.003**	– 0.004***
	(0.01)	(0.01)
AAA – AA-	– 0.032**	– 0.034**
	(0.02)	(0.02)
A+ – A-	– 0.012*	– 0.015**
	(0.05)	(0.02)
BBB+ – BBB-	0.004	0.003
	(0.32)	(0.57)
BB+ – D	0.009**	0.008*
	(0.03)	(0.09)
AGE	0.035***	0.033***
	(0.00)	(0.00)
Q	– 0.003***	– 0.003***
	(0.01)	(0.00)
CAPEX	– 0.446***	– 0.445***
	(0.00)	(0.00)
Constant	0.589***	0.594***
	(0.00)	(0.00)
N	65,339	83,666
Adj. R^2	0.8852	0.8844
Firm FE	Yes	Yes

Table 6
Effects of Natural Disasters

This table presents the moderating effects of natural disasters on the relationship between CPU and lease intensity. We construct the dummy variables "*SALIENT LOSS*", which is equal to 1 f the firm-year observation contains total financial loss more than 1 billion USD, and "*SALIENT INSURED LOSS*", which is equal to 1 if the firm-year observation contains total insured loss more than 1 billion USD. We then include these dummy variables as interaction effects to investigate the effect on operating lease intensity (*LEASE*) in conjunction with climate policy uncertainty (*CPU*). In models (1) and (3), we include *SALIENT LOSS* for all natural disasters and climate-related disasters, respectively. In models (2) and (4), we include *SALIENT INSURED LOSS* for all natural disasters and climate-related disasters, respectively. All variables are defined in the Appendix. We include p values in parentheses based on robust standard errors clustered at the firm level. We use *, ** and *** to denote findings that are significant at the 1%, 5% and 10% levels, respectively.

	All disasters		Climate– related disasters	
	Dependent Variable: *LEASE*			
	Total Loss	Insured Loss	Total Loss	Insured Loss
	(1)	(2)	(3)	(4)
CPU	0.014***	0.025***	0.014***	0.012***
	(0.00)	(0.00)	(0.00)	(0.00)
SALIENT LOSS	– 0.021**		– 0.036*	
	(0.03)		(0.08)	
SALIENT INSURED LOSS		0.066***		– 0.046**
		(0.00)		(0.02)
CPU × SALIENT LOSS	0.004*		0.006	
	(0.06)		(0.19)	
CPU × SALIENT INSURED LOSS		– 0.014***		0.008*
		(0.00)		(0.05)
NODIV	– 0.002	– 0.002	– 0.005	– 0.005
	(0.59)	(0.60)	(0.27)	(0.29)
OIBDP/SALE	0.000	0.000	0.000	0.000
	(0.56)	(0.56)	(0.72)	(0.71)
STLCF	0.011***	0.010***	0.005	0.004
	(0.00)	(0.00)	(0.31)	(0.35)
LTLCF	0.020***	0.018***	0.017***	0.016***
	(0.00)	(0.00)	(0.00)	(0.01)
SIZE	– 0.051***	– 0.051***	– 0.051***	– 0.051***
	(0.00)	(0.00)	(0.00)	(0.00)
LOSS	0.004**	0.004**	0.003	0.003
	(0.02)	(0.02)	(0.35)	(0.34)
TAX RATE	– 0.003***	– 0.003**	– 0.008***	– 0.008
	(0.01)	(0.02)	(0.00)	(0.00)
AAA – AA-	– 0.025	– 0.023	– 0.014	– 0.013
	(0.17)	(0.19)	(0.38)	(0.40)
A+ – A-	– 0.018**	– 0.018**	0.005	0.005
	(0.04)	(0.05)	(0.70)	(0.69)
BBB+ – BBB-	– 0.001	– 0.001	0.002	0.002
	(0.84)	(0.86)	(0.84)	(0.83)
BB+ – D	0.004	0.004	– 0.002	– 0.002
	(0.43)	(0.42)	(0.78)	(0.79)
AGE	0.031***	0.030***	0.016***	0.014***
	(0.00)	(0.00)	(0.00)	(0.00)
Q	– 0.002**	– 0.002**	– 0.004***	– 0.005***
	(0.03)	(0.03)	(0.01)	(0.01)
CAPEX	– 0.542***	– 0.537***	– 0.464***	– 0.466***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.600***	0.555***	0.623***	0.637***
	(0.00)	(0.00)	(0.00)	(0.00)

N	73,807	73,807	19,533	19,533
Adj. R^2	0.8925	0.8926	0.9220	0.9220
Firm FE	Yes	Yes	Yes	Yes

Table 7
Effects of Emissions

The tables present the effects of greenhouse gas emissions on lease intensity using two panels of GHG emissions. We construct the dummy variable "*HIGH*" if the firm-year observation is greater than the sample median for the variable of interest. We then include these dummy variables as interaction effects to investigate the effect on operating lease intensity (*LEASE*) in conjunction with climate policy uncertainty (*CPU*). Both Panels A and B include three different columns explaining *HIGH GHG*, *HIGH GHG DIRECT* and *HIGH GHG INDIRECT*. All variables are defined in the Appendix. We include p values in parentheses based on robust standard errors clustered at the firm level. We use *, ** and *** to denote findings that are significant at the 1%, 5% and 10% levels, respectively.

Panel A: Raw Greenhouse Gas Emissions			
	Dependent Variable: *LEASE*		
	Total	Direct	Indirect
	(1)	(2)	(3)
CPU	0.008**	0.009**	0.009**
	(0.02)	(0.02)	(0.02)
HIGH GHG	– 0.033*		
	(0.09)		
HIGH GHG DIRECT		– 0.033	
		(0.10)	
HIGH GHG INDIRECT			– 0.037*
			(0.06)
CPU × HIGH GHG	0.008**		
	(0.05)		
CPU × HIGH GHG DIRECT		0.008*	
		(0.07)	
CPU × HIGH GHG INDIRECT			0.007*
			(0.08)
NODIV	– 0.001	– 0.001	– 0.001
	(0.80)	(0.82)	(0.84)
OIBDP/SALE	– 0.001**	– 0.001**	– 0.001**
	(0.02)	(0.02)	(0.02)
STLCF	0.006	0.006	0.006
	(0.14)	(0.14)	(0.15)
LTLCF	0.017***	0.017***	0.017***
	(0.01)	(0.01)	(0.01)
SIZE	– 0.041***	– 0.040***	– 0.040***
	(0.00)	(0.00)	(0.00)
LOSS	0.003	0.003	0.003
	(0.27)	(0.27)	(0.27)
TAX RATE	– 0.003*	– 0.003*	– 0.003*
	(0.07)	(0.08)	(0.07)
AAA – AA-	– 0.009	– 0.009	– 0.009
	(0.51)	(0.52)	(0.50)
A+ – A-	– 0.006	– 0.006	– 0.006
	(0.29)	(0.28)	(0.28)
BBB+ – BBB-	0.004	0.004	0.004
	(0.46)	(0.46)	(0.46)
BB+ – D	0.003	0.003	0.003
	(0.58)	(0.60)	(0.59)
AGE	0.016***	0.016***	0.016***
	(0.00)	(0.00)	(0.00)
Q	– 0.005**	– 0.005**	– 0.005**
	(0.03)	(0.03)	(0.03)
CAPEX	– 0.232***	– 0.232***	– 0.232***
	(0.00)	(0.00)	(0.00)
Constant	0.597***	0.596***	0.598***
	(0.00)	(0.00)	(0.00)

N	16,768	16,768	16,768
Adj. R^2	0.9282	0.9282	0.9282
Firm FE	Yes	Yes	Yes

Panel B: Greenhouse Gas Emission Intensity			
	Dependent Variable: *LEASE*		
	Total	Direct	Indirect
	(1)	(2)	(3)
CPU	0.008**	0.013***	0.008**
	(0.02)	(0.00)	(0.03)
HIGH INTENSITY	– 0.032*		
	(0.09)		
HIGH INTENSITY DIRECT		– 0.008	
		(0.65)	
HIGH INTENSITY INDIRECT			– 0.047**
			(0.01)
CPU × *HIGH INTENSITY*	0.009**		
	(0.03)		
CPU × *HIGH INTENSITY DIRECT*		0.002	
		(0.69)	
CPU × *HIGH INTENSITY INDIRECT*			0.010**
			(0.01)
NODIV	– 0.001	– 0.001	– 0.001
	(0.80)	(0.80)	(0.83)
OIBDP/SALE	– 0.001**	– 0.001**	– 0.001**
	(0.02)	(0.02)	(0.02)
STLCF	0.006	0.006	0.006
	(0.14)	(0.14)	(0.14)
LTLCF	0.017***	0.017***	0.017***
	(0.01)	(0.01)	(0.01)
SIZE	– 0.040***	– 0.040***	– 0.040***
	(0.00)	(0.00)	(0.00)
LOSS	0.003	0.003	0.003
	(0.28)	(0.27)	(0.27)
TAX RATE	– 0.003*	– 0.003	– 0.003*
	(0.07)	(0.07)	(0.07)
AAA – AA-	– 0.009	– 0.010	– 0.009
	(0.49)	(0.48)	(0.50)
A+ – A-	– 0.006	– 0.006	– 0.006
	(0.27)	(0.26)	(0.27)
BBB+ – BBB-	0.004	0.004	0.004
	(0.48)	(0.48)	(0.48)
BB+ – D	0.003	0.003	0.003
	(0.60)	(0.60)	(0.61)
AGE	0.016***	0.016***	0.016***
	(0.00)	(0.00)	(0.00)
Q	– 0.005**	– 0.005**	– 0.005**
	(0.02)	(0.03)	(0.03)
CAPEX	– 0.232***	– 0.232***	– 0.232***
	(0.00)	(0.00)	(0.00)
Constant	0.594***	0.579***	0.600***
	(0.00)	(0.00)	(0.00)
N	16,768	16,768	16,768
Adj. R^2	0.9283	0.9282	0.9283
Firm FE	Yes	Yes	Yes

Table 8
Alternative Measures

Panel A presents the results of our robustness tests for alternative measures of operating lease intensity through the OLS regression with firm-fixed effects model. The dependent variable shifts from operating lease intensity (*LEASE*) to *LEASE 2* and *LEASE* 3 in models (1) and (2), respectively. We then restrict our sample to manufacturing firms in model (3) using the *LEASE*. Panel B utilizes the mean of the natural logarithm of the WSJ Climate Change News Index produced by Engle et al. (2020) as an alternate scale of CPU. All variables are defined in the Appendix. We include p values in parentheses based on robust standard errors clustered at the firm level. We use *, ** and *** to denote findings that are significant at the 1%, 5% and 10% levels, respectively.

Panel A: Alternative Measures of Operating Lease Intensity			
	All firms		Manufacturing
	(1)	(2)	(3)
	LEASE 2	*LEASE 3*	*LEASE*
CPU	0.010***	0.012***	0.014***
	(0.00)	(0.00)	(0.00)
NODIV	– 0.000	– 0.022***	– 0.001
	(0.90)	(0.00)	(0.89)
SALE	0.000	– 0.000	– 0.001
	(0.43)	(0.35)	(0.36)
STLCF	0.007***	– 0.007	0.017***
	(0.00)	(0.16)	(0.01)
LTLCF	0.015***	– 0.007	0.022***
	(0.00)	(0.22)	(0.01)
SIZE	– 0.042***	– 0.080***	– 0.038***
	(0.00)	(0.00)	(0.00)
LOSS	– 0.001	– 0.016***	0.009**
	(0.64)	(0.00)	(0.05)
TAX RATE	– 0.001	– 0.000	– 0.006*
	(0.54)	(0.94)	(0.06)
AAA – AA-	– 0.011	– 0.041*	– 0.058**
	(0.15)	(0.10)	(0.01)
A+ – A-	– 0.002	– 0.072***	– 0.030**
	(0.58)	(0.00)	(0.04)
BBB+ – BBB-	0.008**	– 0.075***	– 0.008
	(0.03)	(0.00)	(0.49)
BB+ – D	0.008*	– 0.124***	0.019*
	(0.08)	(0.00)	(0.07)
AGE	0.011***	– 0.008**	0.027***
	(0.00)	(0.02)	(0.00)
Q	0.002**	0.008***	0.005
	(0.04)	(0.00)	(0.24)
CAPEX	– 0.465***	– 0.110***	– 0.499***
	(0.00)	(0.00)	(0.00)
Constant	0.570***	1.008***	0.401***
	(0.00)	(0.00)	(0.00)
N	69,352	69,044	7,729
Adj. R^2	0.8803	0.7285	0.8290
Firm FE	Yes	Yes	Yes

Panel B: Alternative Measures of Climate Policy Uncertainty

	(1)	(2)	(3)	(4)
	LEASE	*LEASE2*	*LEASE3*	*LEASE_manufacturing*
CPU_{WSJ}	0.060***	0.031***	0.066***	0.052***
	(0.00)	(0.00)	(0.00)	(0.00)
NODIV	-0.000	-0.000	-0.022***	-0.001
	(0.88)	(0.94)	(0.00)	(0.92)
SALE	0.000	0.000	-0.000	-0.001
	(0.88)	(0.42)	(0.36)	(0.33)
STLCF	0.010***	0.008***	-0.007	0.016**
	(0.00)	(0.00)	(0.14)	(0.01)
LTLCF	0.018***	0.015***	-0.008	0.021***
	(0.00)	(0.00)	(0.16)	(0.01)
SIZE	-0.052***	-0.042***	-0.081***	-0.039***
	(0.00)	(0.00)	(0.00)	(0.00)
LOSS	0.004**	-0.000	-0.015***	0.009**
	(0.02)	(0.96)	(0.00)	(0.05)
TAX RATE	-0.003***	-0.001	-0.000	-0.005*
	(0.00)	(0.46)	(0.90)	(0.08)
AAA – AA-	-0.025**	-0.011	-0.039	-0.056**
	(0.04)	(0.16)	(0.12)	(0.02)
A+ – A-	-0.013**	-0.003	-0.071***	-0.030**
	(0.02)	(0.52)	(0.00)	(0.04)
BBB+ – BBB-	0.003	0.008**	-0.074***	-0.008
	(0.46)	(0.03)	(0.00)	(0.46)
BB+ – D	0.007*	0.006	-0.124***	0.017
	(0.10)	(0.10)	(0.00)	(0.11)
AGE	0.037***	0.012***	-0.010***	0.027***
	(0.00)	(0.00)	(0.00)	(0.00)
Q	-0.003***	0.002*	0.008***	0.004
	(0.00)	(0.06)	(0.00)	(0.36)
CAPEX	-0.463***	-0.460***	-0.098***	-0.494***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.969***	0.764***	1.406***	0.729***
	(0.00)	(0.00)	(0.00)	(0.00)
N	83,666	69,352	69,044	7,729
Adj. R^2	0.88	0.88	0.73	0.83
Firm FE	Yes	Yes	Yes	Yes

Table 9
Additional Controls

The three panels under additional controls present the results of our robustness tests for alternative explanations beyond climate policy uncertainty (*CPU*). In Panel A, we control for EPU, firm-level uncertainty in Panel B and macroeconomic uncertainty in Panel C. All variables are defined in the Appendix. We include p values in parentheses based on robust standard errors clustered at the firm level. We use *, ** and *** to denote findings that are significant at the 1%, 5% and 10% levels, respectively.

Panel A: Policy Uncertainty Index (Baker et al., 2016)				
	Dependent Variable: *LEASE*			
	(1)	(3)	(4)	(5)
	BBD index	Economic policy news	Change in tax code	Forecaster disagreement
CPU	0.016***	0.020***	0.016***	0.017***
	(0.00)	(0.00)	(0.00)	(0.00)
BBD	0.011***			
	(0.00)			
EPU NEWS		– 0.013***		
		(0.00)		
Δ*TAX*			– 0.001***	
			(0.72)	
DISAGREE				0.014***
				(0.00)
NODIV	– 0.001	0.000	0.000	– 0.001
	(0.62)	(0.95)	(0.83)	(0.66)
SALE	0.000	0.000	0.008	0.000
	(0.88)	(0.88)	(0.00)	(0.90)
STLCF	0.009***	0.010***	0.016***	0.010***
	(0.00)	(0.00)	(0.00)	(0.00)
LTLCF	0.017***	0.018***	– 0.053***	0.018***
	(0.00)	(0.00)	(0.00)	(0.00)
SIZE	– 0.053***	– 0.053***	0.004***	– 0.052***
	(0.00)	(0.00)	(0.03)	(0.00)
LOSS	0.003	0.003**	– 0.003**	0.002
	(0.11)	(0.05)	(0.02)	(0.15)
TAX RATE	– 0.003***	– 0.003***	– 0.019**	– 0.003***
	(0.01)	(0.01)	(0.10)	(0.01)
AAA – AA-	– 0.024**	– 0.026**	– 0.009	– 0.026**
	(0.05)	(0.03)	(0.10)	(0.03)
A+ – A-	– 0.011**	– 0.012**	0.005	– 0.012**
	(0.04)	(0.03)	(0.28)	(0.03)
BBB+ – BBB-	0.004	0.004	0.008	0.004
	(0.38)	(0.40)	(0.05)	(0.41)
BB+ – D	0.008**	0.008*	0.032*	0.008*
	(0.05)	(0.06)	(0.00)	(0.05)
AGE	0.034***	0.036***	– 0.002***	0.036***
	(0.00)	(0.00)	(0.02)	(0.00)
Q	– 0.002**	– 0.003***	– 0.454**	– 0.002**
	(0.02)	(0.00)	(0.00)	(0.02)
CAPEX	– 0.464***	– 0.473***	0.008***	– 0.468***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.551***	0.645***	0.570***	0.549***
	(0.00)	(0.00)	(0.00)	(0.00)
N	83,666	83,666	83,666	83,666
Adj. R^2	0.8772	0.8770	0.8779	0.8770
Firm FE	Yes	Yes	Yes	Yes

Panel B: Controlling for firm level uncertainty				
	Dependent Variable: *LEASE*			
	(1)	(2)	(3)	(4)
	Return volatility	Sales volatility	Cash flow volatility	Profit volatility
CPU	0.012***	0.017***	0.017***	0.017***
	(0.00)	(0.00)	(0.00)	(0.00)
σ(RETURN)	0.004***			
	(0.00)			
σ(SALES)		0.018**		
		(0.01)		
σ(CASH)			0.071***	
			(0.00)	
σ(PROFIT)				0.034***
				(0.00)
NODIV	– 0.002	– 0.001	– 0.000	– 0.001
	(0.47)	(0.84)	(0.89)	(0.83)
SALE	– 0.000	0.000	0.000	0.000
	(0.53)	(0.93)	(0.76)	(0.73)
STLCF	0.008***	0.010***	0.010***	0.010***
	(0.00)	(0.00)	(0.00)	(0.00)
LTLCF	0.017***	0.018***	0.018***	0.018***
	(0.00)	(0.00)	(0.00)	(0.00)
SIZE	– 0.047***	– 0.052***	– 0.051***	– 0.051***
	(0.00)	(0.00)	(0.00)	(0.00)
LOSS	0.005***	0.003	0.002	0.002
	(0.00)	(0.11)	(0.16)	(0.34)
TAX RATE	– 0.003***	– 0.003***	– 0.003***	– 0.003**
	(0.01)	(0.01)	(0.01)	(0.01)
AAA – AA-	– 0.027**	– 0.026**	– 0.026**	– 0.026**
	(0.03)	(0.03)	(0.03)	(0.03)
A+ – A-	– 0.012**	– 0.012**	– 0.012**	– 0.012**
	(0.04)	(0.03)	(0.03)	(0.03)
BBB+ – BBB-	0.002	0.004	0.004	0.004
	(0.58)	(0.33)	(0.37)	(0.38)
BB+ – D	0.006	0.009**	0.009**	0.008*
	(0.16)	(0.04)	(0.04)	(0.05)
AGE	0.030***	0.036***	0.036***	0.036***
	(0.00)	(0.00)	(0.00)	(0.00)
Q	– 0.001	– 0.003***	– 0.003***	– 0.003***
	(0.24)	(0.01)	(0.00)	(0.01)
CAPEX	– 0.435***	– 0.469***	– 0.470***	– 0.469***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.585***	0.586***	0.579***	0.583***
	(0.00)	(0.00)	(0.00)	(0.00)
N	74,041	83,427	83,417	83,426
Adj. R^2	0.8948	0.8779	0.8780	0.8780
Firm FE	Yes	Yes	Yes	Yes

Panel C: Controlling for macroeconomic indicators					
	Dependent Variable: *LEASE*				
	(1)	(2)	(3)	(4)	(5)
	Real GDP growth	Inflation	Unemployment	Consumer confidence	Change in FFR
CPU	0.019***	0.017***	0.018***	0.011***	0.021***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Δ*GDP*	0.063*				
	(0.08)				
INFLATION		0.413***			
		(0.00)			
UNEMPLOY			– 0.226***		
			(0.00)		
CC				– 0.059***	
				(0.00)	
Δ*FFR*					0.304***
					(0.00)
NODIV	– 0.001	– 0.002	– 0.001	– 0.002	– 0.000
	(0.82)	(0.51)	(0.76)	(0.60)	(0.95)
SALE	0.000	0.000	0.000	0.000	0.000
	(0.89)	(0.90)	(0.89)	(0.89)	(0.87)
STLCF	0.010***	0.009***	0.010***	0.010***	0.009***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LTLCF	0.018***	0.018***	0.018***	0.019***	0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SIZE	– 0.053***	– 0.052***	– 0.053***	– 0.051***	– 0.054***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LOSS	0.003*	0.002	0.002	0.002	0.004**
	(0.09)	(0.13)	(0.17)	(0.15)	(0.03)
TAX RATE	– 0.003***	– 0.003***	– 0.003***	– 0.003***	– 0.003***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
AAA – AA-	– 0.026**	– 0.024**	– 0.025**	– 0.025**	– 0.024**
	(0.03)	(0.05)	(0.03)	(0.03)	(0.05)
A+ – A-	– 0.012**	– 0.011**	– 0.012**	– 0.012**	– 0.011**
	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
BBB+ – BBB-	0.003	0.004	0.003	0.004	0.004
	(0.42)	(0.38)	(0.43)	(0.41)	(0.35)
BB+ – D	0.008*	0.008*	0.008*	0.008*	0.008*
	(0.06)	(0.05)	(0.06)	(0.06)	(0.05)
AGE	0.035***	0.034***	0.035***	0.036***	0.034***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Q	– 0.003***	– 0.002**	– 0.002***	– 0.002*	– 0.003***
	(0.01)	(0.03)	(0.01)	(0.08)	(0.00)
CAPEX	– 0.471***	– 0.458***	– 0.465***	– 0.468***	– 0.469***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.587***	0.573***	0.601***	0.872***	0.590***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	83,666	83,666	83,666	83,666	83,666
Adj. R^2	0.8769	0.8773	0.8769	0.8773	0.8770
Firm FE	Yes	Yes	Yes	Yes	Yes

Appendix

Appendix A: Lease data

Table A: Sample distribution by year and industry classification.

Panel A displays the number of observations and their relative and cumulative proportion year-on-year for the 2000–2017 sample period. In Panel B, we present the distribution of firms across Fama-French 48 industries. The 'other' industry classification represents firms that do not belong to the other 47 industries[11].

Panel A: Sample distribution by fiscal year			
Variables	Obs.	%	Cumulative %
2000	4,448	5.3%	5.3%
2001	5,291	6.3%	11.6%
2002	5,034	6.0%	17.6%
2003	4,748	5.7%	23.3%
2004	5,321	6.4%	29.7%
2005	5,274	6.3%	36.0%
2006	5,174	6.2%	42.2%
2007	5,014	6.0%	48.2%
2008	4,769	5.7%	53.9%
2009	4,548	5.4%	59.3%
2010	4,437	5.3%	64.6%
2011	4,333	5.2%	69.8%
2012	4,249	5.1%	74.9%
2013	4,265	5.1%	80.0%
2014	4,361	5.2%	85.2%
2015	4,299	5.1%	90.3%
2016	4,191	5.0%	95.3%
2017	3,910	4.7%	100.0%
Total	83,666	100.0%	

[11] This study uses Fama-French 48 industry classification Standard Industry Classifications (SIC) codes available at: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html.
Firms belonging to the 'other' industry belong to sanitary services (SIC codes 4950–4959), steam and air conditioning supplies (SIC codes 4960-4961), irrigation systems (SIC codes 4970–4971) and cogeneration of small to medium power producers (SIC codes 4990–4991).

Panel B: Sample distribution by Fama-French 48 industry classification					
Industry	Obs.	%	Industry	Obs.	%
Agriculture	222	0.3%	Machinery	2,345	2.8%
Aircraft	358	0.4%	Measuring and Control Equipment	1,557	1.9%
Apparel	930	1.1%	Medical Equipment	2,766	3.3%
Automobiles and Trucks	1,140	1.4%	Non-Metallic and Industrial Metal Mining	475	0.6%
Banking	8,134	9.7%	Other	1,416	1.7%
Beer and Liquor	258	0.3%	Personal Services	928	1.1%
Business Services	10,643	12.7%	Petroleum and Natural Gas	3,793	4.5%
Business Supplies	768	0.9%	Pharmaceutical Products	6,000	7.2%
Candy and Soda	243	0.3%	Precious Metals	696	0.8%
Chemicals	1,551	1.9%	Printing and Publishing	392	0.5%
Coal	236	0.3%	Real Estate	729	0.9%
Communication	2,814	3.4%	Recreation	510	0.6%
Computers	2,712	3.2%	Restaurants, Hotels, Motels	1,374	1.6%
Construction	855	1.0%	Retail	3,466	4.1%
Construction Materials	1,308	1.6%	Rubber and Plastic Products	480	0.6%
Consumer Goods	956	1.1%	Shipbuilding, Railroad Equipment	167	0.2%
Defence	160	0.2%	Shipping Containers	205	0.2%
Electrical Equipment	1,173	1.4%	Steel Works	952	1.1%
Electronic Equipment	5,156	6.2%	Textiles	195	0.2%
Entertainment	971	1.2%	Tobacco Products	96	0.1%
Fabricated Products	178	0.2%	Trading	2,500	3.0%
Food Products	1,126	1.4%	Transportation	2,560	3.1%
Healthcare	1,376	1.6%	Utilities	2,297	2.7%
Insurance	2,059	2.5%	Wholesale	2,440	2.9%
			Total	83,666	100.0

Appendix B: Variable Definitions

Variables	Definition (COMPUSTAT codes in parentheses)
A. Operating Lease Intensity Variables	
LEASE	The numerator is the sum of the current rental expense (*XRENT*) and the discounted future rental commitments for up to five years (*MRC1* – *MRC5*) and discounted rental commitments beyond five years up to ten years (MRCTA). We assume rental commitments beyond year five are evenly split up to year ten. We adopt a 10% discount rate. The denominator is property, plant, and equipment (*PPE*) plus the numerator. Source: Compustat.
LEASE2 *(alternative)*	The numerator is capitalized lease expenditure which is equal to the lagged value of first-year rental commitment (*MRC1*) multiplied by 10 and then divided by the sum of net property, plant and equipment (*PPENT*) and capitalized lease expenditure. Source: Compustat.
LEASE3 *(alternative)*	The numerator is the sum of the current rental expense (*XRENT*) and the present value of operating lease commitments for up to five years (*MRC1* – *MRC5*). We adopt a 10% discount rate. The denominator is long-term debt (*DLTT*) including capitalized leases (*DLCO*) plus the numerator. Source: Compustat.
LEASE SUB	The numerator is the sum of the current rental expense (*XRENT*), discounted future rental commitments for up to five years (*MRC1* – *MRC5*) and capitalized lease (*DLCO*). The denominator is total debt (sum of *DLC* and *DLTT*) plus the numerator. Source: Compustat.
B. Policy Uncertainty Variables	
CPU	Mean of the natural logarithm of Climate Policy Uncertainty (CPU) index constructed by Gavriilidis (2021).
CPU_{WSJ}	Natural logarithm of the climate change uncertainty using the Climate Change News Index developed by Engle, Giglio, Kelly, Lee, and Stroebel (2020).
BBD	Natural logarithm of the Baker-Bloom-Davis index constructed by Baker et al. (2016).

EPU NEWS	Natural logarithm of News-based EPU index constructed by Baker et al. (2016).
ΔTAX	Natural logarithm of changes in Federal tax provisions index.
DISAGREE	Natural logarithm of the index measuring disagreements in forecaster expectations on inflation and government spending index.

C. Baseline Controls

NODIV	Dummy variable equal to 1 if a firm does not pay a dividend in year *t* of the 2000–2017 sample period and 0 otherwise. This is based on ordinary dividends (*DVC*).
OIBDP/Sale	Operating income before depreciation (*OIBDP*) divided by total sales (*SALE*).
STLCF	Dummy variable equal to 1 if the tax loss carried forward (*TLCF*) is positive and less than the operating income before depreciation (*OIBDP*) in a given year and equal to 0 otherwise.
LTLCF	Dummy variable equal to 1 if the tax loss carried forward (*TLCF*) is positive and greater than the operating income before depreciation (*OIBDP*) in a given year and equal to 0 otherwise.
SIZE	Natural logarithm of total assets (*AT*).
LOSS	Dummy variable equal to 1 if a firm made a loss (*IBC* is less than 0) in a given year and equal to 0 otherwise.
TAX RATE	Corporate tax rate in a given year measured as total income tax (*TXT*) by pretax income (*PI*).
AAA – AA-	Equal to 1 if the Standard and Poor Domestic Long Term Issuer Credit Rating correspond to AAA – AA- rated firms and 0 otherwise. These firms have an "extremely strong capacity" to make repayments after issuing investment-grade long-term bonds.
A+ – A-	Equal to 1 if the Standard and Poor Domestic Long Term Issuer Credit Rating correspond to A+ – A- rated firms and 0 otherwise. These firms have a "strong capacity" to make repayments after issuing investment-grade long-term bonds.
BBB+ – BBB-	Equal to 1 if the Standard and Poor Domestic Long Term Issuer Credit Rating correspond to BBB+ – BBB- rated firms and 0 otherwise. These firms have an "adequate capacity" to make repayments after issuing investment-grade long-term bonds.

BB+ – D	Equal to 1 if the Standard and Poor Domestic Long Term Issuer Credit Rating correspond to *BB+ – D* rated firms and 0 otherwise. These firms are "currently or highly vulnerable" when making repayments after issuing speculative long-term bonds, have "filed a bankruptcy petition" or are "in default."
AGE	Natural logarithm of the difference between the current year and the first year the firm was listed on COMPUSTAT.
Q	Tobin's Q is calculated as the sum of total assets (*AT*) plus the product of annual closing share price (*PRCC_F*) and common shares outstanding (*CSHO*) *less* deferred taxes (*TXDB*) divided by total assets.
CAPEX	Capital investment is proxied by capital expenditure (*CAPX*) divided by net PPE for the beginning period (*PPENT*).

D. Other Controls

σ*(RETURN)*	Volatility of firm returns. We compute *RETURN* as the percentage change in the annual closing share price. We construct σ*(RETURN)* as the mean of the 3-year standard deviation.
σ*(SALES)*	Volatility of firm sales. We compute *SALES* as sales (*SALE*) divided by total assets (*AT*). We construct σ*(SALES)* as the mean of the 3-year standard deviation.
σ*(CASH)*	Volatility of firm cash flow. We measure *CASH* as net cash flow from operating activities (*OANCF*) divided by total assets (*AT*). We construct σ*(CASH)* as the mean of the 3-year standard deviation.
σ*(PROFIT)*	Volatility of firm profits. Profit is proxied by return on assets (ROA) which is measured as net income (*NI*) divided by total assets (*AT*). We construct σ*(PROFIT)* as the mean of the 3-year standard deviation.
GVKEY	Global Company Key is the unique firm identifier used in COMPUSTAT.
INFLATION	Annual change in the Consumer Price Index (CPI) for the U.S.
ΔGDP	Absolute difference in real Gross Domestic Product (GDP) by year for the U.S.
UNEMPLOY	Annualized "number of individuals without work, seeking to work and are currently unavailable to work, including those who lost their jobs or have voluntarily left work" as a portion of all people who can work in the U.S.

CC	Natural logarithm of the annual Consumer Confidence index. This index uses interview results of a representative sample of U.S. households with an equal probability of selection.
ΔFFR	Absolute difference in the Federal Funds Rate year-on-year. This interest rate is the overnight interbank lending rate and is manipulated by the Federal Reserve through, for example, open market operations to change the supply and demand of money in the economy.
SALIENT LOSS	Dummy variable equal to 1 if the year's total financial loss exceeds 1 billion USD and 0 otherwise. Total financial loss encompasses "all damages and economic losses directly or indirectly related to the disaster."
SALIENT INSURED LOSS	Dummy variable equal to 1 if the year's total insured loss exceeds 1 billion USD and 0 otherwise. Insured loss is the "economic damages covered by insurance companies."
GHG	Total scope 1, scope 2 and scope 3 CO_2 emissions in tonnes.
GHG DIRECT	Scope 1 CO_2 emissions in tonnes.
GHG INDIRECT	Scope 2 and scope 3 CO_2 emissions in tonnes.
INTENSITY	Total amount of scope 1, scope 2 and scope 3 CO_2 emissions in tonnes emitted to generate 1 million USD in revenue.
INTENSITY DIRECT	Scope 1 CO_2 emissions in tonnes emitted to generate 1 million USD in revenue.
INTENSITY INDIRECT	Scope 2 and scope 3 CO_2 emissions in tonnes emitted to generate 1 million USD in revenue.

Appendix C
Propensity score matching and entropy balancing results before and after sample matching

This table presents the results of PSM and entropy balancing sample matching estimation techniques. Panels A and B record the results before and after PSM, respectively. We choose a calliper of 0.01 with no replacement. We include p values in parentheses in column (5) based on robust standard errors clustered at the firm level. Panels C and D record the results before and after matching for entropy balancing, respectively. We measure the convergence based on three dimensions: mean, variance and skewness.

Panel A: PSM sample analysis of the differences between group covariates before matching

	(1)	(2)	(3)	(4)	(5)
Variables	*Treatment group (high CPU)*	*Control group (low CPU)*	*Difference (high – low)*	*t-stat for (3)*	*p value*
NODIV	0.573	0.653	– 0.080	– 23.70	(0.00)
SALE	– 1.074	– 0.919	– 0.155	– 2.67	(0.01)
STLCF	0.221	0.158	0.062	23.18	(0.00)
LTLCF	0.298	0.252	0.046	15.07	(0.00)
SIZE	6.698	6.055	0.643	42.12	(0.00)
LOSS	0.334	0.342	– 0.008	– 2.45	(0.01)
TAX RATE	0.176	0.185	– 0.009	– 3.23	(0.00)
AAA – AA-	0.011	0.013	– 0.001	– 1.71	(0.09)
A+ – A-	0.049	0.054	– 0.005	– 3.10	(0.00)
BBB+ – BBB-	0.095	0.091	0.004	2.20	(0.03)
BB+ – D	0.147	0.134	0.012	5.19	(0.00)
AGE	2.415	2.259	0.156	23.04	(0.00)
Q	1.858	2.002	– 0.144	– 13.19	(0.00)
CAPEX	0.043	0.048	– 0.005	– 13.45	(0.00)
N	39,862	43,804			

Panel B: PSM sample analysis of the differences between group covariates after matching

	(1)	(2)	(3)	(4)	(5)
Variables	*Treatment group (high CPU)*	*Control group (low CPU)*	*Difference (high – low)*	*t-stat for (3)*	*p value*
NODIV	0.611	0.605	0.006	1.61	(0.11)
SALE	– 0.955	– 0.971	0.016	0.25	(0.80)
STLCF	0.187	0.193	– 0.006	– 2.12	(0.03)
LTLCF	0.285	0.288	– 0.003	– 0.82	(0.41)
SIZE	6.401	6.435	– 0.033	– 2.00	(0.05)
LOSS	0.336	0.336	0.001	0.20	(0.84)
TAX RATE	0.181	0.181	0.001	0.18	(0.86)
AAA – AA-	0.012	0.012	0.000	– 0.11	(0.92)
A+ – A-	0.050	0.052	– 0.001	– 0.87	(0.39)
BBB+ – BBB-	0.093	0.094	0.000	– 0.17	(0.86)
BB+ – D	0.143	0.142	0.001	0.27	(0.79)
AGE	2.340	2.347	– 0.007	– 0.91	(0.36)
Q	1.903	1.899	0.004	0.32	(0.75)
CAPEX	0.045	0.045	0.220	0.82	(0.00)
N	39,862	43,804			

Panel C: Entropy balancing proof of convergence before weighting						
	(1)	(2)	(3)	(4)	(5)	(6)
	Treatment group (High CPU)			Control group (Low CPU)		
Variables	*Mean*	*Variance*	*Skewness*	*Mean*	*Variance*	*Skewness*
NODIV	0.574	0.245	– 0.297	0.653	0.227	– 0.643
SALE	– 1.074	78.990	– 9.318	– 0.919	62.640	– 10.380
STLCF	0.221	0.172	1.346	0.158	0.133	1.872
LTLCF	0.298	0.209	0.883	0.252	0.188	1.144
SIZE	6.698	4.781	0.130	6.055	4.939	0.240
LOSS	0.334	0.223	0.703	0.342	0.225	0.665
TAX RATE	0.176	0.176	– 1.610	0.185	0.147	– 1.920
AAA – AA-	0.011	0.011	9.241	0.013	0.012	8.739
A+ – A-	0.049	0.047	4.168	0.054	0.051	3.948
BBB+ – BBB-	0.095	0.086	2.757	0.091	0.083	2.847
BB+ – D	0.147	0.125	1.995	0.134	0.116	2.143
AGE	2.415	0.984	– 0.598	2.259	0.920	– 0.463
Q	1.858	2.186	3.201	2.002	2.769	3.014
CAPEX	0.043	0.003	2.584	0.048	0.003	2.449

Panel D: Entropy balancing proof of convergence after weighting						
	(1)	(2)	(3)	(4)	(5)	(6)
	Treatment group (High CPU)			Control group (Low CPU)		
Variables	*Mean*	*Variance*	*Skewness*	*Mean*	*Variance*	*Skewness*
NODIV	0.574	0.245	– 0.297	0.574	0.245	– 0.297
SALE	– 1.074	78.990	– 9.318	– 1.074	78.990	– 9.318
STLCF	0.221	0.172	1.346	0.221	0.172	1.346
LTLCF	0.298	0.209	0.883	0.298	0.209	0.883
SIZE	6.698	4.781	0.130	6.698	4.781	0.129
LOSS	0.334	0.223	0.703	0.334	0.223	0.702
TAX RATE	0.176	0.176	– 1.610	0.176	0.176	– 1.610
AAA – AA-	0.011	0.011	9.241	0.011	0.011	9.241
A+ – A-	0.049	0.047	4.168	0.049	0.047	4.168
BBB+ – BBB-	0.095	0.086	2.757	0.095	0.086	2.757
BB+ – D	0.147	0.125	1.995	0.147	0.125	1.995
AGE	2.415	0.984	– 0.598	2.415	0.984	– 0.598
Q	1.858	2.186	3.201	1.858	2.187	3.201
CAPEX	0.043	0.003	2.584	0.043	0.003	2.584

Appendix D
Implementation of State Climate Adaptation Plans

state	State Name	Year Implemented
AK	Alaska	2010
CA	California	2009
CO	Colorado	2011
CT	Connecticut	2013
DE	Delaware	2015
DC	D.C.	2016
FL	Florida	2008
ME	Maine	2010
MD	Maryland	2008
MA	Massachusetts	2011
NH	New Hampshire	2009
NY	New York	2010
OR	Oregon	2010
PA	Pennsylvania	2011
VA	Virginia	2008
WA	Washington	2012