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Carbon productivity and volatility

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ABSTRACT

This study investigates the relationship between firm-level carbon productivity and volatility. With increasing interest in sustainable investing and inclusion of carbon productivity in financial assessments, we examine whether the market considers firms with high carbon productivity as less risky. Using U.S. firm-level carbon emission data, we find that carbon productivity is negatively associated with total and idiosyncratic volatilities. Our main findings hold under propensity score matching and coarsened exact matching. We also show that this relationship is significant when the binding intergovernmental regulations such as the Paris Agreement is active.

1. Introduction

Climate change is an important factor that affects corporate performance; thus, environmental resource preservation should be considered in a firm's business activities. Climate change may affect a firm's supply chain, damage facilities and infrastructure, energy costs, and consumer and investor behavior.[1] Climate change also affects firm's dividend policy and the issuance of municipal bonds (Balachandran and Nguyen, 2018; Painter, 2020). Overall, the impacts of climate change can result in decreased productivity and profitability for companies and increased risk and uncertainty in their operations.

Among the various channels, carbon emissions are the main driver of climate change (Jackson et al., 1996; Stocker, 2014; Wang et al., 2016; Li and Wang, 2019). Thus, firms and governments consider carbon productivity—the concept of carbon efficiency focusing on the revenue generated by a unit carbon emission (Kaya and Yokobori, 1997; Tahara et al., 2005)—as an important indicator, as carbon productivity is a metric used to assess a firm's efficiency.

Financial markets recognize the importance of a company's carbon productivity, and some investors are starting to factor this metric into their investment decisions (Hu and Liu, 2016; Giannarakis et al., 2017). Interest in sustainable investing is increasing, and

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[1] For instance, extreme weather events, such as hurricanes, droughts, and floods, can disrupt the production and delivery of raw materials and finished products. Climate-related natural disasters, such as sea-level rise, wildfires, and storms, may also damage or destroy facilities and infrastructure, leading to lost productivity (Bernstein et al., 2019). Furthermore, it affects the decisions of consumers and investors. As consumers and investors become more environmentally conscious, there may be a shift in the demand for environmentally friendly products, which can affect the competitiveness of companies that are not adaptable.

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some investors use carbon productivity as a criterion for selecting investments (De Souza Cunha et al. (2021); Gabriel et al. (2022). Additionally, some financial indices and rating agencies incorporate carbon productivity into their assessments of companies, which can affect their stock prices and investment opportunities.[2]

Studies have examined how carbon productivity affects a firm's financial performance (Rajesh and Rajendran, 2020). However, how the financial market evaluates firm-level carbon productivity, especially concerning risk level, has yet to be explored. Furthermore, prior literature reviews that financial, political and external risk factors are potential determinants of volatility. Therefore, if the climate change is considered a climate risk factor, then the carbon productivity may be one of the determinants of the volatility.

In this paper, we thus try to examine whether the market considers carbon productive firms less risky. We conjecture that the market would consider carbon-productive firms less risky through three main channels: sustainability, cost savings, and increased competitiveness. Companies that are more carbon efficient are likely to be more environmentally sustainable and resilient in the face of increasingly stringent regulations and public pressure to reduce carbon emissions. Reducing carbon emissions can lead to cost savings by reducing energy costs and waste, and thus improving resource efficiency. Finally, firms with high carbon productivity may have a competitive advantage in attracting environmentally conscious consumers and investors.

Using manually collected U.S. firm-level carbon emission data, we find that carbon productivity is negatively associated with total and firm-specific volatility. Furthermore, among various channels we have tested, we found out that the government driven climate policies or governmental decisions on climate policies is a statistically significant channel through which firm-level carbon productivity reduces stock price volatilities. To show that, we have tested an exogenous event of the US' entry into the Paris Agreement and withdrawal from the Paris Agreement. Showing that the statistical significance between the carbon productivity and volatility is valid only when the Paris Agreement was active, we conclude that the firms with good carbon productivity may better cope with the government's climate policy constraints, which is ultimately reflected in the reduction of the total and idiosyncratic volatilities.

Even if OLS regression shows that the carbon productivity has positive effects on firm-level volatilities, results may be biased due to endogeneity issues. Therefore, we employ propensity score matching and coarsened exact matching to first show that the results are relatively free from issues of observable covariates. Furthermore, results may contain an interfering explanation that firms with good ESG performance may have higher carbon productivity and smaller volatility. To control for such an unobservable bias, we further control for ESG performance and show that results are still robust.

A strong correlation between increased carbon productivity and reduced risk for firms has key implications for both businesses and investors. First, our findings may facilitate better investment decisions. Investors would have more information to make informed investment decisions and could potentially favor companies with higher carbon productivity, which would have a lower risk profile. Firms have financial incentives to improve their carbon productivity, which could lead to more sustainable and environmentally responsible business practices. Second, we demonstrate the necessity of increased support for climate action. An association between carbon productivity and reduced risk could increase support for climate action, as it would demonstrate that acting on climate change can lead to positive financial outcomes.

Finally, we contribute to the climate finance and volatility literature. As climate issues are rising concerns for firms, studies on examining climate change in financial context are increasing (Azam et al., 2022; Hunjra et al., 2022; Coderoni and Vanino, 2022; Chen et al., 2023; Sertyesilisik, 2023; Wang and Tang, 2022). We add to the literature by showing how carbon productivity is evaluated by the financial market. Furthermore, studies investigating risk factors are increasing (Hsu and Huang, 2016; Roger and Schatt, 2016; Baek et al., 2020; Li et al., 2020; He et al., 2022; Qadan and Shuval, 2022). We contribute to the growing literature by showing that climate risk may be another factor influencing firm risk. Overall, demonstrating a relationship between increased carbon productivity and reduced risk could have far-reaching and positive impacts on businesses, investors, and society.

The rest of the paper is organized as follows. Section 2 discusses the data and methodology where we show how we retrieved carbon productivity variables and volatility measures. We then show main results in Section 3. Section 4 visualizes robustness results. Section 5 concludes with discussions and limitations of the paper.

2. Data and methodology

2.1. Carbon productivity variables

Since 2010, the EPA has required all facilities in the U.S. that emit over 25 metric kilotons of carbon emissions to report their emission status. Thus, firms report all facilities that emit emissions over the reporting threshold to the local EPA. The EPA then verifies the validity of the emission report and releases the annual facility-level carbon emission reports to the public. The main issue with using EPA data is that it reports facility-level emissions. Therefore, we identify and aggregate emissions from facilities by their parent company. The EPA also identifies a list of owners and shares of facilities. Thus, we match the facilities to a parent company if the parent company owns more than 50% of the facility (Cooper et al., 2018). Another challenge is to match the parent company to the company identifiers (such as ticker symbols, CUSIP, or PERMNO) from the Compustat or CRSP database. Furthermore, the EPA's parent company name did not match the company names in Compustat. Thus, we manually searched online to match the parent company to the Compustat company names. While matching the parent company, we exclude private and government-owned companies to reduce

[2] MSCI and Sustainalytics state that their services are designed to help investors identify and understand financially material ESG risks and opportunities, in order to integrate these factors into their portfolio construction and management process (https://www.oecd.org/finance/ESG-Investing-Practices-Progress-Challenges.pdf)

Table 1
Summary statistics.

Variables	Obs.	Mean	Std.	Min.	Max.	Skew.
Risk measures						
$TVOL_t$	2526	.343	.199	.12	1.044	2.674
$IVOL_t$	2526	.294	.192	.104	.995	3.136
$MTVOL_t$	2526	.323	.210	.086	1.106	2.576
$MIVOL_t$	2526	.309	.348	.081	1.194	22.628
Main variables						
CPS_{t-1}	2526	.126	2.22	0	1.125	45.495
CPA_{t-1}	2526	.238	3.736	0	2.401	38.359
Control variables						
$SIZE_{t-1}$	2526	8.829	1.65	5.085	12.708	-0.044
MB_{t-1}	2526	1.508	.81	.614	4.6	4.844
LEV_{t-1}	2526	.314	.197	0	.856	.631
$CASH_{t-1}$	2526	.08	.1	0	.491	2.471
DIV_{t-1}	2526	.762	.426	0	1	-1.234
ROA_{t-1}	2526	.112	.108	-0.246	.327	-5.196
$R\&D_{t-1}$	2526	.013	.029	0	.143	3.534
AGE_{t-1}	2526	3.412	.809	1.386	4.248	-0.813
CAP_{t-1}	2526	.082	.083	.006	.428	2.62

Note. This table reports the descriptive statistics for risk measures (measured by daily total and idiosyncratic volatilities), main variables of interest (carbon productivity scaled by total assets and sales), and other control variables. The sample covers 2526 US public firm-year observations from CRSP and Compustat database. We use EPA database to calculate annual firm level carbon emission. Due to carbon emission data limitation, observations span from 2011 to 2020.

any biases arising from those samples.

Following prior studies, we calculate firm-level carbon productivity using calculated carbon emission data (Ekins et al., 2012; Shao et al., 2014; Hu and Liu 2016; Jung et al., 2021; Deng et al., 2023). Studies commonly define carbon productivity as the amount of revenue (firm level) or GDP (national level) produced per unit of carbon emissions. The underlying idea is that carbon emissions produced from energy consumption are considered a type of environmental input and that the amount of profit generated from this input is carbon productivity (Haliu and Veeman, 2001). We use two firm-level carbon productivity measures: sales per carbon emission ($CPS_{i,t}$) and total assets per carbon emission ($CPA_{i,t}$).

2.2. Volatility variables

The main dependent variables used in this study are total volatility and idiosyncratic volatility. We follow prior studies in computing these measures (Bouslah et al., 2013; Bernile et al., 2018). Total volatility is measured as the annualized standard deviation of daily stock returns over the past year. Idiosyncratic volatility (unsystematic volatility) is measured as the standard deviation of the residuals over the four-factor Carhart (1997) model based on the daily excess stock returns from the previous year:

$$R_{i,t} - R_f = \alpha_i + \beta_{i,M}\left(R_{Mt} - R_f\right) + \beta_{i,s}SMB_t + \beta_{i,h}HML_t + \beta_{i,u}UMD_t + \in_{i,t}$$

where R_{it} is the return of firm i on day t. R_f is the one-month T-bill risk-free rate. ($R_{Mt} - R_f$) is the excess return on the CRSP value-weighted index for day t. SMB_t is the difference between the returns on portfolios of small and large capitalization stocks for day t. HML_t is the return difference between the returns on portfolios of high and low book-to-market stocks for day t. UMD_t is the difference between the returns on portfolios of high and low prior return stocks. $\in_{it}$ is the stochastic error term. We used factor values from Kenneth French's website. We then use daily excess returns over the previous year to estimate idiosyncratic volatility using time-series regression analysis for each firm-year sample. We repeat this process to retrieve time-varying idiosyncratic volatility measures.

We also include various control variables (Bernile et al., 2018). We then merge the carbon productivity data with the volatility variables and other control variables. The matching process leaves us with the final set of firm-year observations comprising 2526 samples spanning from 2011 to 2020.

3. Main results

3.1. Descriptive analysis

Table 1 reports the descriptive statistics of carbon productivity, volatility, and control variables. The average carbon productivity scaled by sales is 0.126—indicating that an average firm emits 1 ton of carbon dioxide to generate $0.126 million in revenue. Both $CPA_{i,t}$and $CPS_{i,t}$measures are positively skewed—indicating that many firms' carbon productivity is low, with few exceptions. The statistics of volatility variables and control variables are similar to those from prior literature on volatilities (Bernile et al., 2018).

Table 2
Baseline regression.

Variables	(1) $TVOL_t$	(2) $TVOL_t$	(3) $IVOL_t$	(4) $IVOL_t$
CPS_{t-1}	-0.0006*		-0.0007**	
	(0.053)		(0.017)	
CPA_{t-1}		-0.0004**		-0.0004**
		(0.040)		(0.026)
$SIZE_{t-1}$	-0.0382***	-0.0382***	-0.0407***	-0.0407***
	(0.000)	(0.000)	(0.000)	(0.000)
MB_{t-1}	0.0021	0.0021	0.0012	0.0011
	(0.777)	(0.777)	(0.884)	(0.884)
LEV_{t-1}	0.3370***	0.3369***	0.3438***	0.3437***
	(0.000)	(0.000)	(0.000)	(0.000)
$CASH_{t-1}$	0.0070	0.0071	0.0170	0.0171
	(0.908)	(0.907)	(0.785)	(0.783)
DIV_{t-1}	-0.0534***	-0.0534***	-0.0543***	-0.0543***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.2554***	-0.2555***	-0.2709***	-0.2710***
	(0.000)	(0.000)	(0.000)	(0.000)
$R\&D_{t-1}$	0.4249*	0.4250*	0.5787**	0.5788**
	(0.074)	(0.074)	(0.018)	(0.018)
AGE_{t-1}	-0.0250***	-0.0250***	-0.0249***	-0.0249***
	(0.000)	(0.000)	(0.000)	(0.000)
CAP_{t-1}	-0.1705*	-0.1704*	-0.2110**	-0.2110**
	(0.054)	(0.054)	(0.017)	(0.017)
Constant	0.6567***	0.6566***	0.5922***	0.5921***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2520	2520	2520	2520
Adjusted R-squared	0.660	0.660	0.638	0.638
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm-year cluster	Yes	Yes	Yes	Yes

Note. This table reports OLS regression results where dependent variables are risk measures. The sample covers 2526 U.S. public firm-year observations in CRSP and Compustat database from 2011 to 2020 with non-missing values for the risk measures, carbon productivity measures, and all other control variables. All models include year, industry, and firm fixed effects. Reported in parentheses are p-values based on standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

3.2. Baseline regression analysis

Table 2 presents the baseline regression analysis results. Columns (1) and (2) report the regression analysis results for total volatility regressed on the two carbon productivity measures, and Columns (3) and (4) report the results for idiosyncratic volatilities. We find a significant negative association between carbon productivity and total and firm-specific volatilities, regardless of the volatility and carbon productivity measures. Regarding economic magnitude, we find that a one standard deviation increment in carbon productivity scaled by firm sales reduces total volatility (idiosyncratic volatility) by 0.13% (0.15%), which amounts to roughly 38% (51%) of the mean total volatility (idiosyncratic volatility) Considering that the average volatility level is 0.34% (0.29%) for total (idiosyncratic) volatility in Table 1, the carbon productivity impact is economically significant. Overall results imply that carbon productivity has a significant effect on the firm-level volatilities.

The findings imply that the market positively values carbon-productive firms and that investors consider carbon-productive firms less risky. These findings also support prior studies that show that improved environmental performance is negatively associated with a firm's risk (Feldman et al., 1997; Sharfman and Fernando, 2008; El Ghoul et al., 2011; Bouslah et al., 2013). Environmentally friendly firms are perceived as less risky because of the reduced cost of complying with environmental regulations. Berman et al. (1999) argued that environmental performance may also improve a firm's image and ultimately enhance the loyalty of key stakeholders, such as customers and investors.

3.3. Paris agreement withdrawal effects

Our underlying assumption is that the market considers carbon-productive firms to be less risky. For instance, environmental performance may affect financial institutions' lending decisions (Goss and Roberts, 2011; Wellalage and Kumar, 2021). Because of easier access to the financial market, more carbon-productive firms may have a lower level of total and idiosyncratic risk (Godfrey et al., 2009; Jo and Na, 2012; Farza et al., 2021; Wellalage et al., 2022).

The cost of capital and related decisions by financial institutions are largely affected by national policies (Drobetz et al., 2018; Xu, 2020). On June 1, 2017, U.S. President Donald Trump announced that the U.S. would cease participation in the 2015 Paris Agreement on climate change mitigation, contending that the agreement would undermine the U.S. economy and put the U.S. at a permanent

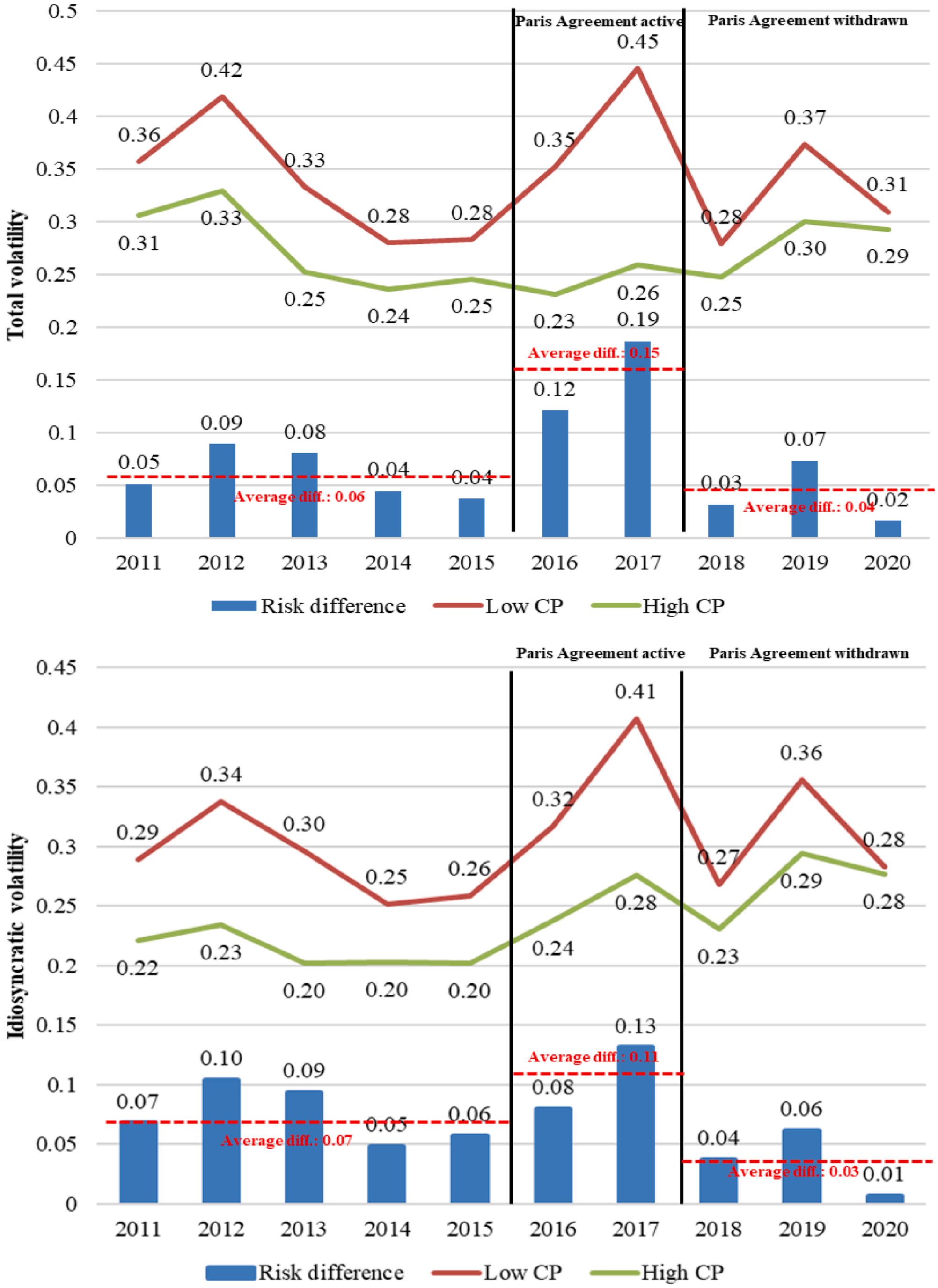

Fig. 1. Year trend of total volatility and idiosyncratic volatility grouped by carbon productivity level.
Note. This figure illustrates the annual trend of volatility measures grouped by carbon productivity level. The red line displays the risk trend for low-carbon productive firms, and the green line shows the risk trend for firms with high carbon productivity. The histogram shows the average risk difference between low- and high-carbon productive firms. CP = carbon productivity.

disadvantage. The Paris Agreement withdrawal decision has largely affected the economic structure and decision-making of financial institutions (Zhang et al., 2017; Nong and Siriwardana, 2018; Liu et al., 2020; Jung and Song 2023a, 2023b). Withdrawal has altered climate change governance (Zhang et al., 2017), and economic structures (Nong and Siriwandana, 2018; Liu et al., 2020) in a less environmentally friendly manner.

Therefore, we conjecture that the market response to carbon-productive firms would differ before and after the withdrawal of the Paris Agreement. Specifically, we hypothesize that the relationship between carbon productivity and volatilities manifests only during

Table 3
Paris Agreement effects.

Variables	(1) $TVOL_t$	(2) $TVOL_t$	(3) $IVOL_t$	(4) $IVOL_t$	(5) $TVOL_t$	(6) $TVOL_t$	(7) $IVOL_t$	(8) $IVOL_t$
CPS_{t-1}	-0.0081***		-0.0069**		0.0351		0.0398	
	(0.003)		(0.015)		(0.256)		(0.213)	
CPA_{t-1}		-0.0050**		-0.0043*		0.0026		0.0036
		(0.037)		(0.077)		(0.588)		(0.488)
$SIZE_{t-1}$	-0.0425***	-0.0424***	-0.0440***	-0.0439***	-0.0398***	-0.0392***	-0.0431***	-0.0424***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MB_{t-1}	0.0034	0.0033	0.0007	0.0006	0.0011	0.0011	0.0014	0.0014
	(0.782)	(0.787)	(0.957)	(0.961)	(0.907)	(0.907)	(0.889)	(0.889)
LEV_{t-1}	0.4200***	0.4198***	0.4149***	0.4148***	0.3387***	0.3393***	0.3411***	0.3416***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$CASH_{t-1}$	-0.0386	-0.0379	-0.0350	-0.0344	0.1232	0.1278	0.1535	0.1585
	(0.573)	(0.580)	(0.620)	(0.625)	(0.315)	(0.292)	(0.216)	(0.196)
DIV_{t-1}	-0.0460**	-0.0461**	-0.0458**	-0.0459**	-0.0602***	-0.0612***	-0.0597***	-0.0609***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.2358***	-0.2360***	-0.2345***	-0.2346***	-0.3219***	-0.3239***	-0.3401***	-0.3423***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$R\&D_{t-1}$	0.6278**	0.6292**	0.7209**	0.7221**	1.1600**	1.2061**	1.2942**	1.3448**
	(0.040)	(0.039)	(0.023)	(0.023)	(0.030)	(0.022)	(0.017)	(0.012)
AGE_{t-1}	-0.0216***	-0.0217***	-0.0226***	-0.0227***	-0.0250***	-0.0250***	-0.0245***	-0.0245***
	(0.006)	(0.006)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
CAP_{t-1}	-0.3118**	-0.3127**	-0.3074***	-0.3081***	-0.1970	-0.1938	-0.2156*	-0.2121*
	(0.011)	(0.011)	(0.009)	(0.009)	(0.121)	(0.127)	(0.080)	(0.086)
Constant	0.5434***	0.5429***	0.5317***	0.5313***	0.6112***	0.6087***	0.6187***	0.6162***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1039	1039	1039	1039	757	757	757	757
Adjusted R^2	0.683	0.683	0.674	0.674	0.634	0.633	0.622	0.621
Paris Agreement?	Joined	Joined	Joined	Joined	Withdrawn	Withdrawn	Withdrawn	Withdrawn
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-year cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. This table reports OLS regression results grouped by Paris Agreement status. Columns (1) to (4) present results for the period when the US government joined Paris Agreement (2015 to 2017). Columns (5) to (8) show results for the period when the US government withdrew the Paris Agreement (2018 to 2020). All models include year, industry, and firm fixed effects. Reported in parentheses are p-values based on standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

the Paris Agreement. To test this hypothesis, we subsample the observations by the U.S. government's Paris Agreement status and run the regression analysis specified in subSection 3.2.

Fig. 1 illustrates the year trend of total volatility and idiosyncratic volatility grouped by the carbon productivity level. The difference in risk levels between high- and low-carbon productive firms was quite in parallel prior to, but increased during the Paris Agreement. However, after withdrawal, the difference became non-significant, implying that carbon productivity is not necessarily a factor that explains the risk level. Thus, we further employed multivariate analysis to test the effects.

The subsample analysis results are presented in Table 3. Columns (1) to (4) show the regression analysis results for the samples after joining the Paris Agreement but before the withdrawal. Columns (5) to (8) present the results for the samples after ceasing participation in the Paris Agreement. Consistently, the relationship between carbon productivity and volatility is significant only during the Paris Agreement. That is, investors consider carbon-productive firms less risky when the government supports pro-environmental policies, where the country-level policy directions ultimately affect the financial institutions' cost of capital policies.

4. Robustness tests

4.1. PSM and CEM

To alleviate possible endogeneity concerns of observable bias, we employed the PSM and CEM procedure to match firms with higher carbon productivity (top quartile) to control firms with lower carbon productivity ratios (below the top quartile). Both PSM and CEM methods allow us to distinguish the effects of carbon productivity from those of other firm characteristics (Armstrong et al., 2010; Blackwell et al., 2009).

Table 4 reports the estimation results using the matched sample. The control variables are identical to variables used for analysis in Table 2, except that we retain only those firms with a high proportion of carbon productivity and match the firms identified using the PSM approach. Panel A reports regression results for PSM samples and Panel B reports results for CEM samples. The negative association between carbon productivity measures and volatilities still holds even after applying the PSM and CEM method. Results confirm that selection bias endogeneity is not an issue.

Table 4
PSM and CEM regression.

Panel A. PSM samples				
	(1)	(2)	(3)	(4)
Variables	$TVOL_t$	$TVOL_t$	$IVOL_t$	$IVOL_t$
CPS_{t-1}	-0.0007***		-0.0008***	
	(0.005)		(0.001)	
CPA_{t-1}		-0.0004***		-0.0004***
		(0.003)		(0.006)
Constant	0.6925***	0.6924***	0.6148***	0.6146***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1262	1262	1262	1262
Adjusted R-squared	0.683	0.683	0.666	0.666
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm-year cluster	Yes	Yes	Yes	Yes
Panel B. CEM samples				
	(1)	(2)	(3)	(4)
Variables	$TVOL_t$	$TVOL_t$	$IVOL_t$	$IVOL_t$
CPS_{t-1}	-0.0053		-0.0086*	
	(0.126)		(0.071)	
CPA_{t-1}		-0.0012*		-0.0015*
		(0.079)		(0.088)
Constant	0.3543***	0.3536***	0.2747***	0.2758***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1262	1262	1262	1262
Adjusted R-squared	0.691	0.691	0.665	0.665
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm-year cluster	Yes	Yes	Yes	Yes

Note. This table reports PSM regression results (Panel A) and CEM regression results (Panel B) where dependent variables are risk measures. To conduct PSM test, we match firms with high carbon productivity (top 20%) to firms with low carbon productivity (bottom 20%). We use all control variables as covariates. Similar methods are used for CEM. For both matching approaches, the difference between covariates is insignificant, indicating that the variables are well-matched. All models include year, industry, and firm fixed effects. Reported in parentheses are p-values based on standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.2. *Alternative volatility measures*

Another potential concern was measurement bias. Daily volatility measures may contain noise, which may incorrectly measure the effects of carbon productivity. Thus, we recalculate both the total and idiosyncratic volatilities on a monthly basis. We then tested its effects on carbon productivity (Table 5). Again, we find a consistent and significant result that carbon productivity is negatively associated with total and idiosyncratic volatilities.

4.3. *Excluding ESG effects*

Another concern is that some companies with good ESG performance are likely to have higher carbon productivity and smaller volatility. Therefore, the current empirical findings of the article need to exclude the influence of confounding factors such as ESG performance. Using the KLD data source to retrieve the ESG performance data, we match the ESG performance data to our dataset.[3] We then tested the regression analysis using the updated data, where we control the ESG performance.

The results are reported in Table 6. Similar to the baseline regression results, we find that the relationship between the carbon productivity and firm-level volatilities are generally significant even after controlling for ESG performance. That is, the results are not necessarily driven by omitted variable factors such as a firm's good characteristics or ESG performance.

Based on the results from the propensity score matching and regression analysis controlling for ESG performance, we conclude that

[3] To assess ESG, we use a widely used measurement tool called KLD score. KLD score assesses 13 dimensions such as community, diversity, corporate governance, employee relations, environment, human rights, product, alcohol, gambling, firearms, military, tobacco, and nuclear power. The first seven dimensions are assigned both strengths and concerns while the final six dimensions are only used for exclusionary screening, and concerns can only be registered in those categories. For example, a company can receive credit for having a strong environmental policy while also having a concern registered for its environmental record. We follow the prior studies to calculate ESG score, which is calculated by subtracting the total concerns from the total strengths (Goss and Roberts, 2011; Jiraporn and Chintrakarn, 2013; Withisuphakorn and Jiraporn, 2016).

Table 5
Alternative risk measures.

Variables	(1) $MTVOL_t$	(2) $MTVOL_t$	(3) $MIVOL_t$	(4) $MIVOL_t$
CPS_{t-1}	-0.0008*		-0.0008*	
	(0.098)		(0.055)	
CPA_{t-1}		-0.0006*		-0.0006**
		(0.067)		(0.029)
$SIZE_{t-1}$	-0.0338***	-0.0338***	-0.0292***	-0.0292***
	(0.000)	(0.000)	(0.001)	(0.001)
MB_{t-1}	0.0050	0.0050	-0.0039	-0.0039
	(0.535)	(0.536)	(0.677)	(0.676)
LEV_{t-1}	0.3441***	0.3441***	0.3178***	0.3177***
	(0.000)	(0.000)	(0.000)	(0.000)
$CASH_{t-1}$	-0.0301	-0.0300	-0.0041	-0.0040
	(0.585)	(0.586)	(0.949)	(0.950)
DIV_{t-1}	-0.0496***	-0.0496***	-0.0934***	-0.0933***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.1468***	-0.1468***	-0.0851*	-0.0851*
	(0.002)	(0.002)	(0.098)	(0.098)
$R\&D_{t-1}$	0.1401	0.1402	0.3185*	0.3186*
	(0.424)	(0.424)	(0.094)	(0.094)
AGE_{t-1}	-0.0267***	-0.0267***	-0.0508**	-0.0508**
	(0.000)	(0.000)	(0.026)	(0.026)
CAP_{t-1}	-0.2350**	-0.2348**	-0.0376	-0.0375
	(0.034)	(0.034)	(0.886)	(0.886)
Constant	0.6053***	0.6053***	0.6463***	0.6463***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2526	2526	2526	2526
Adjusted R-squared	0.538	0.538	0.212	0.212
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm-year cluster	Yes	Yes	Yes	Yes

Note. This table reports OLS regression results where dependent variables are monthly total volatility and monthly idiosyncratic volatility. All models include year, industry, and firm fixed effects. Reported in parentheses are p-values based on standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

the results are relatively free from various endogeneity issues.

5. Conclusion

This study examines whether carbon productivity affects a firm's total and idiosyncratic risk using a U.S. panel dataset of 2526 firm-year observations from 2011 to 2020. Using two different carbon productivity measures (scaled by total assets and sales) and two volatility measures (total and idiosyncratic volatilities), we find that carbon productivity is negatively associated with firm risk. For the whole sample period, we find statistically significant results for the sample period. However, the carbon productivity effects manifest only when the Paris Agreement is active in the U.S. We also show that the results are not necessarily driven by endogeneity.

Our finding that investors consider carbon-productive firms to be less risky is consistent with prior models investigating the relationship between firm-level environmental performance and firm risk (Feldman et al., 1997; Sharfman and Fernando, 2008; El Ghoul et al., 2011; Bouslah et al., 2013). Results have important implications for investors and corporate managers. For investors, our results facilitate portfolio construction by accounting for the impact of carbon productivity on risk. For corporate managers, our results should lead to improved risk management based on the relative impact of carbon productivity. Lacy et al. (2010) argue that corporate managers should incorporate sustainable growth strategies as sustainability becomes more important. Our findings may enlarge a firm's investor base by attracting more environmentally responsible investors such as environmental, social, and governance-related and pension funds. Furthermore, it may be useful to test the effects of the Paris Agreement re-joining in 2020. With sufficient data, we expect the positive effects of carbon productivity on firm risk to be significant. Such tests would also allow us to consider the different attitudes of the Democratic Party and the Republican Party towards climate policy.

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Table 6
Controlling ESG effects.

Variables	(1) $TVOL_t$	(2) $TVOL_t$	(3) $IVOL_t$	(4) $IVOL_t$
CPS_{t-1}	-0.0006*		-0.0007**	
	(0.055)		(0.016)	
CPA_{t-1}		-0.0004**		-0.0004**
		(0.041)		(0.028)
ESG_{t-1}	-0.0379	-0.0379*	-0.0410*	-0.0410
	(0.105)	(0.095)	(0.083)	(0.101)
$SIZE_{t-1}$	-0.0000	-0.0000	0.0000	0.0000
	(0.650)	(0.647)	(0.597)	(0.600)
MB_{t-1}	0.0022	0.0022	0.0011	0.0011
	(0.773)	(0.774)	(0.889)	(0.889)
LEV_{t-1}	0.3373***	0.3373***	0.3434***	0.3433***
	(0.000)	(0.000)	(0.000)	(0.000)
$CASH_{t-1}$	0.1844***	0.1845***	0.1848***	0.1848***
	(0.000)	(0.000)	(0.000)	(0.000)
DIV_{t-1}	0.0074	0.0075	0.0165	0.0166
	(0.902)	(0.901)	(0.791)	(0.789)
ROA_{t-1}	-0.0537***	-0.0537***	-0.0540***	-0.0540***
	(0.000)	(0.000)	(0.000)	(0.000)
$R\&D_{t-1}$	-0.2559***	-0.2559***	-0.2705***	-0.2705***
	(0.000)	(0.000)	(0.000)	(0.000)
AGE_{t-1}	0.4221*	0.4221*	0.5820**	0.5821**
	(0.078)	(0.078)	(0.018)	(0.018)
CAP_{t-1}	-0.0250***	-0.0250***	-0.0249***	-0.0249***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.1719**	-0.1718**	-0.2095**	-0.2094**
	(0.050)	(0.050)	(0.017)	(0.017)
Observations	2520	2520	2520	2520
Adjusted R-squared	0.660	0.660	0.638	0.638
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm-year cluster	Yes	Yes	Yes	Yes

Note. This table reports OLS regression results where dependent variables are risk measures. The sample covers 2526 U.S. public firm-year observations in CRSP and Compustat database from 2011 to 2020 with non-missing values for the risk measures, carbon productivity measures, and all other control variables. All models include year, industry, and firm fixed effects. Reported in parentheses are p-values based on standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

CRediT authorship contribution statement

Hail Jung: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft. **Junyoup Lee:** Conceptualization, Investigation, Data curation, Writing – review & editing, Visualization. **Chang-Keun Song:** Conceptualization, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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