Carbon VIX: Carbon Price Uncertainty and Decarbonization Investments

Abstract

We study the effects of carbon price uncertainty on firms' decisions to decarbonize their operations. We first use information on the pricing of options on emission allowances in the European Emissions Trading System to create the *Carbon VIX*, a market-based high-frequency measure of carbon price uncertainty. Carbon price uncertainty is high, varies substantially over time, and experiences persistent shocks around major climate policy events. To explore the effects of carbon price uncertainty on expected aggregate decarbonization investments, we analyze its effect on the stock returns of firms that help other businesses decarbonize. To identify these "carbon solution providers," we extract common types of decarbonization investments from a large survey of firms, and then identify companies that offer the associated goods and services. We find that the stock returns of these carbon solution providers vary positively with carbon prices, but negatively with carbon price uncertainty. The effect of increases in carbon price uncertainty on our proxy for expected decarbonization investments is economically large and of similar magnitude as the effect of declines in carbon prices. These findings support predictions from real options theory that firms may delay investments in decarbonization when faced with uncertainty about the future costs of emissions.

Keywords: Climate, Carbon Pricing, Emissions, Uncertainty, Investments

Reducing aggregate carbon emissions to mitigate climate change is a key global policy objective. A common policy tool to encourage firms to decarbonize their activities is to impose a price on carbon emissions, for example through cap-and-trade systems, which covered about 22% of global emissions in 2025 (World Bank, 2025). In such systems, regulators issue a limited number of permits to emit carbon. Companies then trade these permits among each other, creating a market price for carbon emissions and an incentive to decarbonize. While cap-and-trade systems allow regulators to achieve aggregate emission reduction goals without knowing firms' abatement costs, they also introduce uncertainty about future carbon prices, since changes in economic activity, abatement costs, and policy choices all affect the supply and demand for emission permits.

In this paper we study the effects of carbon price uncertainty in cap-and-trade systems. In particular, we test the predictions of real option theory that such price uncertainty leads firms to delay investments in decarbonizing their operations until the financial returns from these investments become more predictable. While carbon price uncertainty is frequently mentioned by market participants as an impediment to scaling up decarbonization investments,[1] a quantification of such effects has been hindered by the absence of measures of both carbon price uncertainty and decarbonization investments. We address both measurement challenges to show that carbon price uncertainty has a large negative effect on firms' decisions to decarbonize.

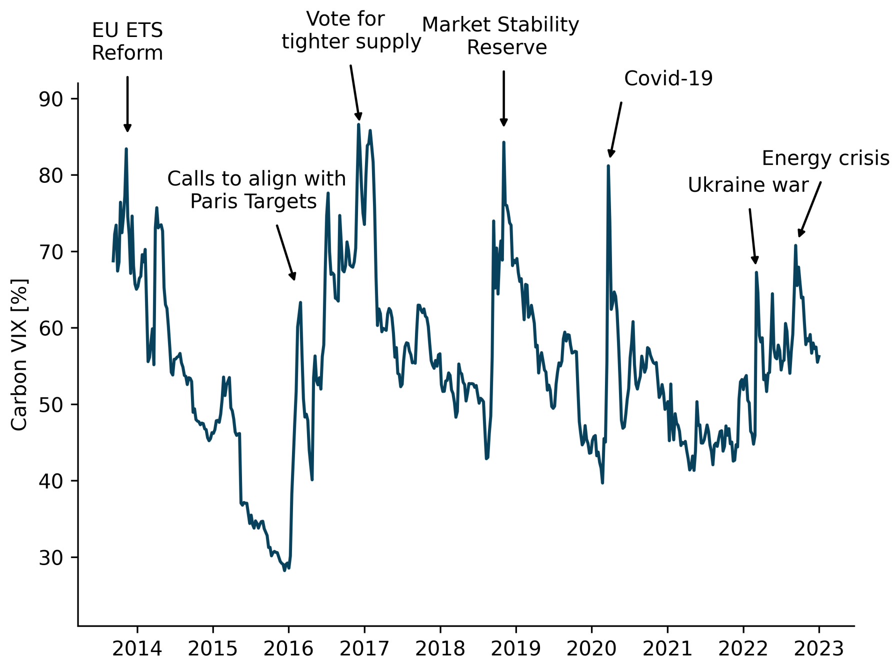
We study the effects of carbon price uncertainty in the European Union's Emissions Trading System (ETS), the world's largest cap-and-trade system. Our first contribution is to provide new measures of carbon price uncertainty based on the prices of options on EU emission allowances (EUAs), which allow traders to speculate on or hedge against EUA price changes. Intuitively, when the prices of both call and put options increase at the same time, this generally reflects a rise in the expected volatility of the underlying asset, allowing us to back out changes in carbon price uncertainty from changes in option prices.[2]

We operationalize this insight by constructing two high-frequency measures of carbon price uncertainty, the *Carbon VIX* and *Carbon Implied Volatility (CIV)*, which we make publicly available at `www.carbonvix.org`. The construction of the *Carbon VIX* follows the methodology for the well-known CBOE VIX index of S&P 500 stock price uncertainty. It is based on building a portfolio of options whose final payoff approximates the realized variance of EUA futures until option expiry, which, following the VIX methodology, is then transformed into an annualized volatility measure. Increases in the price of this options portfolio therefore reflect higher expected EUA price volatility. Our second measure, *Carbon Implied Volatility (CIV)*, measures expected EUA price volatility via the "implied volatility" of at-the-money options.

[1] For example, Clark, Bernstein, Beugin, Shaffer, and Wadland (2022) report that *"Over the course of dozens of conversations with industry, business associations, commercial investors, and other stakeholders, the authors heard again and again that the carbon-pricing certainty gap is inhibiting investment, and needs to be addressed urgently in order to accelerate industrial decarbonization."* In a joint statement of 16 European energy firms, a CEO argues that *"a carbon price floor would reduce volatility and uncertainty for any investor, which makes offshore wind projects without revenue stabilizing mechanisms more viable and thus increases the speed of the urgently needed transformation to low-carbon energy systems"* (EnBW, 2018).

[2] Option prices reflect both expected volatility and a volatility risk premium. Consistent with this, we find that implied volatility generally exceeds average realized volatility but closely comoves with it. Because the volatility risk premium is unlikely to vary substantially at high frequencies, we interpret short-run changes in option prices as primarily reflecting changes in expected volatility, following the approach of Bloom (2014), Cremers et al. (2021), Gao et al. (2022), and Bretscher et al. (2018).

Figure 1: The Carbon VIX



Note: This figure shows the level of the *Carbon VIX*, annotated with selected market events.

Each approach to measuring carbon price uncertainty has advantages and drawbacks. The *Carbon VIX* methodology does not require a pricing model, but uses observed option prices from a wide range of strike prices with varying liquidity. The *CIV* approach is only based on relatively liquid at-the-money options, but requires a pricing model to infer implied volatilities. Despite these differences, the two measures have near-identical levels and are highly correlated (weekly changes in *Carbon VIX* and *CIV* have a correlation of 0.95). We thus proceed by using the *Carbon VIX* as our main proxy for carbon price uncertainty, but show that our results are robust to analyzing *CIV*. For our baseline analysis, we consider uncertainty over the next 120 days. Changes in (annualized) carbon price uncertainty are highly correlated across the term structure, so varying the horizon of the uncertainty measure does not change our results.

We use these new measures to document several patterns regarding carbon price uncertainty (Figure 1 shows the development of the *Carbon VIX*, annotated with important market events). First, the level of carbon price uncertainty in the ETS is high: Between September 2013 and December 2022, carbon prices had an average annualized expected volatility of 55%. Second, carbon price uncertainty varies meaningfully over time, ranging between 28% and 87% over the same period. It also moves substantially around events that affect the supply of certificates (e.g., the introduction of the Market Stability Reserve) as well as events affecting the demand for certificates (e.g., the start of the Covid-19 epidemic). Increases in carbon price uncertainty are generally followed by periods of higher realized carbon price volatility. Third, carbon price uncertainty is relatively persistent. And fourth, the *Carbon VIX* is related to, but distinct from, the EU Equity VIX and the Oil VIX (correlations of 0.11 and 0.14, respectively), suggesting that it captures an important new dimension of economic uncertainty. We also note that the increased financialization of the European ETS over our sample period has not obviously changed the level of emission price uncertainty. Instead, the *Carbon VIX* fluctuates around a relatively stable mean.

In the second part of the paper, we explore the effects of carbon price uncertainty on the decisions of firms to invest in decarbonizing their operations. We begin by exploring a new survey dataset on realized decarbonization activities undertaken by firms. The data was collected by CDP, formerly known as the Carbon Disclosure Project, and constitutes the largest and most comprehensive information source on corporate climate action. In the annual survey, firms disclose information on implemented initiatives to decarbonize their direct (scope-1) emissions including the type of initiative, the investment amount, and a project description. Between 2015 and 2023, firms reported more than 12,500 unique decarbonization projects totaling about EUR 639 billion.

We then provide a first exploration of the effect of carbon price uncertainty on realized decarbonization investments. In a panel regression, we compare the CDP-reported decarbonization investments of firms whose operations are exposed to the EU ETS to investments of firms without such exposure at times of varying levels of carbon price uncertainty. We find that, during periods of higher carbon price uncertainty, firms with ETS exposure report lower decarbonization investment rates, defined as the ratio of a firm's decarbonization investments to its scope-1 emissions. Including various controls and fixed effects, a one standard deviation (or 4.5 percentage points) increase in the *Carbon VIX* is associated with an economically meaningful 1.6-2.2 EUR/tCO2e decrease in the investment rate, relative to an average rate of 18 EUR/tCO2e.

This analysis of real decarbonization activities encounters a key challenge: while the *Carbon VIX* allows us to measure changes in carbon price uncertainty at high frequencies, actual investment decisions are both implemented and measured at much lower frequencies. For example, we only observe completed investments at an annual frequency, and thus find it difficult to link carbon price uncertainty to the time at which the investment decision was made.

To better quantify the effects of carbon price uncertainty on decarbonization activities, we thus construct a higher-frequency measure of changes in the *expected investments in decarbonization* via the stock returns of firms that provide goods and services that help other firms decarbonize. These "carbon solution providers" should benefit when other firms increase their decarbonization investments. Thus, if investors expect spending on decarbonization activities to increase, this expectation would be reflected in higher stock returns of carbon solution providers.

To identify carbon solutions providers, we first use information on firms' reported decarbonization projects in the CDP data to identify common decarbonization activities, and then identify companies that provide the goods and services required to undertake such activities. We use GPT, an AI-based language processing tool from OpenAI (2024), to extract common activities of how firms reduce their carbon emissions from textual descriptions of decarbonization projects in the CDP data. We identify more than 1,200 types of decarbonization activities. Among the most common activities are investments in renewable energy such as wind and solar power, the prevention of waste energy, and the use of alternative fuels. The described activities also include many less-common industry-specific solutions such as boiler upgrades or the use of variable frequency drives.

To explore which firms offer these "carbon solutions", we collect textual descriptions of the products and services offered by more than 5,000 publicly listed European firms. We then use GPT to identify firms that provide carbon solutions similar to the most common solutions reported in the CDP data. After merging with stock return data, we obtain a sample of 201 "carbon solution providers" spanning 16 industries and 18 countries. On average, carbon solution firms are slightly smaller and younger than other firms. Moreover, they generally exhibit higher market-to-book ratios and higher capital expenditures per asset.

To quantify the impact of carbon price uncertainty on firms' expected decarbonization decisions, we estimate a panel regression of weekly stock returns on changes in carbon prices and carbon price uncertainty, interacting each measure with an indicator that identifies carbon solution providers. If higher carbon price uncertainty creates incentives for emitters to delay decarbonization investments, we would expect lower stock returns for carbon solution providers during periods of rising carbon price uncertainty. Similarly, we would expect these firms to have higher stock returns in weeks when increasing carbon prices create incentives for firms to invest in decarbonization. Our specifications ensure that our results are not driven by a possible differential exposure of carbon solution providers to uncertainty in the broader stock market or to oil price uncertainty.

We estimate this regression over two sample periods: the years 2013-2017, when the EU carbon price averaged about EUR 6 per EUA, and the years 2018-2022, when the carbon price averaged about EUR 40. This sample split is motivated by the intuition that carbon price returns and changes in carbon price uncertainty should have only small effects during periods of low prices, while they should be more important determinants of decarbonization decisions at higher prices.

We find that carbon price uncertainty substantially lowers expected decarbonization investments. Over the high-price sample, the stock returns of carbon solution providers respond more positively to carbon price returns and more negatively to changes in the *Carbon VIX* than the returns of other firms. Changes in carbon prices and carbon price uncertainty have similarly-sized effects: a one standard deviation increase in the carbon price return is associated with a 12.1 basis points relative increase in the stock returns of carbon solution providers, while a one standard deviation higher increase in the *Carbon VIX* is associated with a 13.5 basis points relative decrease. Put differently, a one percentage point increase in carbon price uncertainty has a similar (negative) impact on carbon solution providers' stock returns as a EUR 0.99 lower carbon price. Consistent with our intuition, we find no such effects during the low-price sample.

The finding that carbon solution providers are negatively exposed to carbon price uncertainty is robust to several alternative specifications. First, we consider two additional methods of identifying carbon solution firms. The first is based on firm-level measures of climate change exposure provided by Sautner et al. (2023). This data is based on firms' earnings calls and provides a measure of "climate opportunity" exposure at the firm-year level. Second, we use the holdings of the European Green Deal UCITS ETF (EUGD), an ETF that contains 50 European firms that *"could benefit from the European Green Deal, a landmark transaction enacted by the European Commission to make Europe the first carbon neutral continent"*. Our findings are qualitatively and quantitatively similar across these different measures of carbon solution providers. Additionally, we obtain almost identical regression estimates via either the *Carbon VIX* or *Carbon Implied Volatility* measure of carbon price uncertainty, and when we additionally include a measure of past realized carbon price volatility interacted with an indicator for climate solution providers. Finally, we provide direct evidence of the negative impact of carbon price uncertainty on carbon solution providers' sales.

Contribution. Our work contributes to a growing literature that studies the effects of carbon pricing regimes on firm behaviors. This literature has largely concluded that the presence of carbon pricing regimes has substantially reduced carbon emissions (e.g., Martinsson et al., 2024; Colmer et al., 2024). Green (2021) provides a recent review of this evidence. Our work expands on existing work by constructing a first direct measure of carbon price *uncertainty* and studying its effects on a high-frequency proxy for decarbonization investments. While this relationship between carbon price uncertainty and green investments had been well understood theoretically (see the contributions by Blyth et al., 2007; Yang et al., 2023; Fuss et al., 2009; Golub et al., 2020; Ginbo et al., 2021; Aldy and Armitage, 2020), measurement challenges in both decarbonization investments and carbon price uncertainty have precluded prior quantifications. Our findings show that the effects of changes in carbon price uncertainty on decarbonization activities are of the same magnitude as the effects of changes in the level of the carbon price. A key implications is that policy makers hoping to encourage firms to decarbonize should focus efforts on reducing market uncertainty with respect to carbon prices, for example by reducing climate policy uncertainty.

The idea that carbon price uncertainty can affect firms' decisions to decarbonize follows an extensive literature exploring the effects of uncertainty on firms' decision to make irreversible investments (Bernanke, 1983; Dixit and Pindyck, 1994; Abel and Eberly, 1996; Bloom, 2009). Most relevant to our study is Kaboski's (2005) model of the effects of factor price uncertainty on a firm's decision to switch between production technologies with different factor intensities (e.g., high-carbon or low-carbon technologies). When technology investments are partially irreversible, uncertainty about future carbon prices raises the real option value of potential decarbonization investments and thus makes it less likely that polluters execute such decarbonization investments.

Our work contributes towards recent efforts to measure climate policy uncertainty and to explore its effects (see, e.g., Gavriilidis, 2021; Berestycki et al., 2022; Fried et al., 2021; Bouri et al., 2022; Basaglia et al., 2021; Wang et al., 2023). While existing efforts to measure climate policy uncertainty are based on an analysis of newspaper coverage, our measure of carbon price uncertainty is based directly off market prices, varies at high frequencies, and has a direct quantitative interpretation. The *Carbon VIX* also captures all drivers of carbon price uncertainty, which include factors such as the broader economic environment and changes in abatement technology and cost in addition to changes in climate policy.

Our paper also provides insights into the costs and benefits of various carbon pricing regimes (see the discussions in Weitzman, 1974; Stavins, 2019). We show that the carbon price uncertainty that is inherent in cap-and-trade systems incentivizes firms to delay their decarbonization activities. This is possible because the EU ETS emission cap is not binding at the annual level, with many firms deciding to carry excess allowances into future years. Firms that choose to postpone their decarbonization investments due to carbon price uncertainty would then essentially purchase and surrender these excess allowances. Since the total cap is eventually binding, aggregate decarbonization investments would need to be higher in later years, which likely increases the total costs of achieving a given emissions reduction. Delayed decarbonization efforts are also environmentally costly: postponed emission reductions increase the risk of temperature overshoot and the likelihood of triggering irreversible tipping points or the loss of ecosystem services (IPCC, 2018; Giglio et al., 2025). Our work therefore supports proposals for various mechanisms to mitigate the permit price volatility in cap-and-trade systems, such as setting price ceilings and price floors (Burtraw et al., 2006, 2010, 2018; Schmalensee and Stavins, 2017; Flachsland et al., 2020). While such price floors have been included in some cap-and-trade systems, such as the Regional Greenhouse Gas Initiative (RGGI) and the California ETS in the United States, other large-scale ETS such as that in the European Union do not contain an explicit price floor.

I. Measuring Carbon Price Uncertainty

We next describe the construction of our two measures of carbon price uncertainty: the *Carbon VIX* and *Carbon Implied Volatility (CIV)*. First, we provide an overview of the EU Emissions Trading System and its associated spot and derivative markets for emissions allowances. We then detail our methodology for deriving these uncertainty measures from observed derivatives prices.

I.A. Cap-and-Trade Systems

In cap-and-trade systems, regulators impose a cap on total carbon emissions from certain sectors or corporate activities by issuing a corresponding quantity of emission allowances. Regulated entities must surrender an emission allowance for each unit of carbon emitted. The initial allocation of allowances can be for free or via auctions, and allowances are subsequently traded in a market-based system. The resulting equilibrium prices are determined by the supply of and demand for allowances, driven by factors such as climate policy, economic activity, and the cost of abatement.

I.B. The European Emissions Trading System

There are currently 37 cap-and-trade schemes in place covering 22% of global carbon emissions; in contrast, carbon taxes cover less than 6% of global emissions (World Bank, 2025). The EU Emissions Trading System (ETS) was launched in 2005 and is the oldest and largest cap-and-trade scheme. In 2022, it generated total revenues of $42bn, which constituted 44% of that year's global revenue from carbon pricing. The EU ETS covers carbon emissions of about 10,000 installations in the manufacturing and energy sectors as well as emissions of aviation firms operating flights within the EU. Emissions covered by the EU ETS account for about 40% of the European Union's total carbon emissions.

To comply with the EU ETS, firms have to report and verify their regulated emissions annually and surrender a corresponding number of EU allowances (EUAs), with heavy sanctions for non-compliant firms. Each EUA permits its holder to emit one ton of carbon dioxide equivalents. Firms can "bank" EUAs for use in subsequent years.

In 2013, an EU-wide cap of issued EUAs was set at 2.1 billion, based on the average number of total allowances issued in the five preceding years. To reduce aggregate carbon emissions, this cap is lowered annually by a predetermined number of EUAs. Initially, this linear reduction factor was set at 1.74% relative to the initial cap for years 2013–2020; this factor was subsequently increased to 2.2% (2021–2023), 4.3% (2024–2027), and 4.4% (2028–30). This should lead to a cap by 2030 that is 62% lower than 2005 emission levels (European Commission, 2023b).[3]

Despite the year-on-year decrease in the cap, the cumulative quantity of allowances issued led to an initial surplus in supply, resulting in a low market price for EUAs. To address the problem of excess supply of EUAs, the EU Commission proposed a market stability reserve. The market stability reserve works on a set of predetermined rules and withdraws (releases) a fraction of the total allowances in circulation if they are above (below) a certain threshold. Between its launch in January 2019 and December 2022, the reserve absorbed a total of 44% of newly issued EUAs (European Commission, 2023a).

Even after the introduction of the market stability reserve, the emission cap is not binding at an annual level. For example, during the 2022 compliance cycle, firms emitted a total of 1.36 billion tons of CO2e for which a corresponding number of permits had to be surrendered. At the end of this period, prior to any surrendering of permits, a total amount of about 2.1 billion permits remained outstanding (European Commission, 2022, 2023a). The constraint therefore only binds across multiple years. This intertemporal flexibility allows firms to postpone decarbonization investments, though these postponed decarbonization efforts increase the required rate of aggregate emission reductions in future periods.

Primary and Secondary Allowance Market. Allowances are either distributed via public auctions or allocated for free to emitting firms. The fraction of free allowances that regulated firms receive depends on the type of regulated activity and varies with sector-specific emissions-per-output benchmarks and firms' historic output. Between 2013 and 2023, aircraft operators received more than 80% of allowances for free, while firms in the power sector were generally not eligible for free allowances. The share of allowances industrial firms received for free gradually decreased from 80% in 2013 to 30% in 2020. In 2022, the total quantity of allowances issued amounted to 1.5 billion, of which 36% were free allocations.

Allowances that are not allocated for free are auctioned off via a central platform. Such auctions occur multiple times per week on pre-scheduled days. The quantity of EUAs for auction is known in advance and cleared in a single round at a uniform price. Auctions are also open to authorized bidders not covered by the ETS such as investment funds and credit institutions. In 2022, auctions were held on 220 days with an average of 20 participating bidders.

There exists a large and active secondary market for EUAs. While a total of 486 million allowances were auctioned in 2022, trading volume on spot markets was about 750 million EUAs, with secondary market prices closely mirroring auction settlement prices (DEHSt, 2023).

Allowance Futures Market. The most liquid venue to trade EUAs is in the futures market. In 2022, the trading volume of futures contracts was about 9 billion EUAs, accounting for 87% of total trading volume on auction, spot and futures markets (DEHSt, 2023). We obtain daily settlement prices of futures on EUAs traded on the London Intercontinental Exchange (ICE), which handles

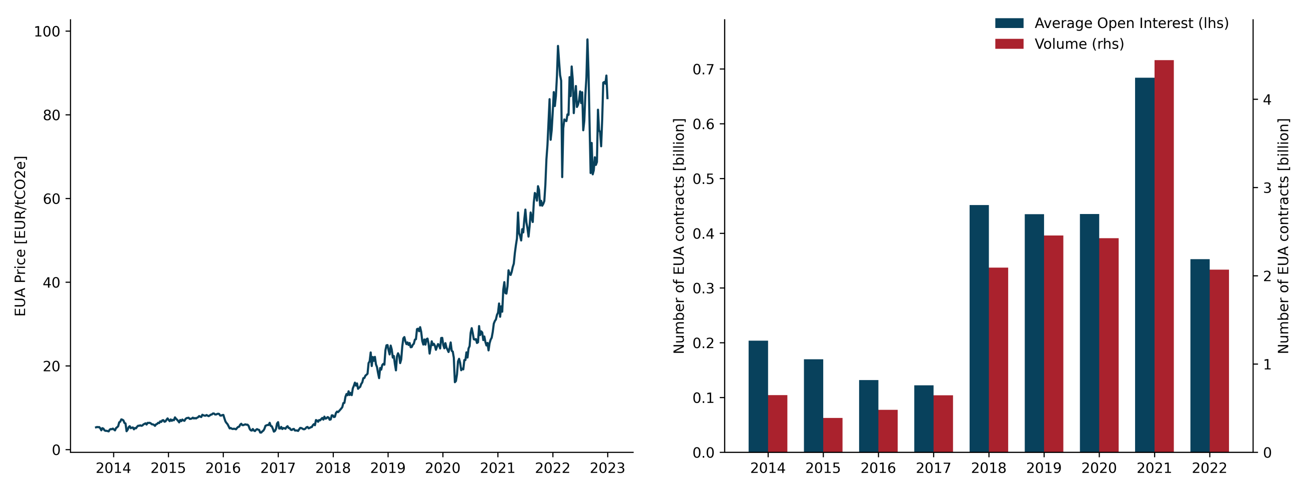
[3]For years 2013–2020, the linear reduction factor did not apply to emissions of the aviation sector. The cap reduction also includes planned one-off removals of 0.1 billion EUAs in 2024 and 2026.

85% of total open interest on EUA derivatives (ESMA, 2022). ICE EUA futures expire quarterly in March, June, September, and December; December futures are by far the most liquid, possibly due to their proximity to the EUA delivery date in April each year (ESMA, 2022). We therefore choose the closest December futures contract as our primary measure of carbon prices. Due to the bankability of EUAs, futures prices and spot prices are tightly linked, with a term structure relating largely to investor funding costs (Palao and Pardo, 2021). At expiry, the futures seller has to transfer EUAs to the futures buyers' EUA trading accounts (i.e., the futures involve "physical delivery" of EUAs). Each futures contract yields delivery of one lot (1,000) EUAs.

Carbon Prices Over Time. Carbon prices are volatile and have increased substantially over time (see Figure 2a). The early period of our sample is characterized by low prices as a result of the large surplus in emission allowances discussed above: between September 2013 and December 2017, the average carbon price was 6 EUR. After several policy changes limiting the supply of allowances, including the introduction of the market stability reserve, carbon prices reached levels of 30 EUR by December 2020 and further increased to above 80 EUR at the end of our sample in December 2022. The average price during the period 2018-2022 was 40 EUR.

Carbon prices are determined by the supply and demand for EUAs. The regulator can determine the supply via adjustments to the total cap or other policy choices affecting the quantity of available allowances, such as the cancellation of allowances via the market stability reserve. The demand for emission allowances is driven by economic activity and the cost of emission abatement. That is, demand increases with expected output by regulated firms and decreases as advances in abatement technologies lower the cost of emission reductions.

Figure 2: The EU Carbon Market



(a) Carbon Price

(b) Carbon Option Market Size

Note: Panel (a) shows the weekly price of December-expiry ICE EUA futures. Panel (b) shows the annual trading volume and annual average of open interest of EUA futures options traded on ICE (London). One option is written on one futures contract which in turn delivers 1000 EUAs. Volume and open interest are in billions of EUAs.

EUA Futures Options Market. EUA futures contracts function as the underlying for EUA futures options (hereafter, EUA options). EUA options expire on the same quarterly cycle as EUA futures. The underlying futures contract for all options that expire in a year is that year's December futures contract. EUA options are European, meaning they can only be exercised at expiration. At expiry, each EUA call option gives option holders the right, but not the obligation, to *buy* one EUA futures contract at the pre-specified strike price. Put options confer the corresponding right, but not obligation, to *sell* one futures contract at the strike price. Appendix Table A.2 provides further details on the contract specifications for EUA futures and options.

We obtain EUA options data from IVolatility.com (see Appendix A.1.A for details). The market for EUA options is large and liquid. Figure 2b shows the annual EUA options trading volume in billions of contracts.[4] Trading volume is lower at the start of our sample, with an annual volume of around 500m contracts, corresponding to 500m tons of CO2e emissions. Alongside the recent increase in EUA prices, the volume of EUA options has picked up, reaching more than 2bn contracts annually between 2018 and 2022. In terms of value, EUA option's annual trading volume reached EUR 10bn in 2021 and 2022. Options are used for hedging or speculation. The increasing use of EUA options after 2018 indicates the higher economic relevance of the EU ETS over the high-price sample, which corresponds to a period in which carbon prices—and carbon price uncertainty—played an increasingly important role for emitters' finances.

Table I shows EUA option volume across option contract type as a fraction of total option trading volume. The top panel shows call options, the bottom panel put options. Each panel splits options by their 'moneyness' and 'days to expiry.' An option's moneyness indicates the likelihood of a positive payoff at expiry. Call (put) options are further "in-the-money" when the current futures price is more above (further below) the options' strike price. Table I shows that 37.5% of call option volume in our sample is in deep-out-of-the-money options and 37.9% of the EUA call option volume is in options below 120 days to expiry. Similar patterns hold for put options. These volume patterns are typical for option markets, where volumes are often higher for out-of-the-money options with short maturities. Our construction of the *Carbon VIX* exploits these liquidity patterns by using the prices of out-of-the-money short-maturity options.[5]

I.C. Option Prices and Uncertainty.

Options-based uncertainty measures rely on the positive impact of the expected return volatility of the underlying asset on option prices. This positive relationship stems from the non-linearity in option payoffs: call options' final payoff rises if the futures price ends up further above the options' strike, while their final payoff is always zero no matter how far the prices end up below the strike. Thus, call options gain from a thicker right tail of the underlying return distribution, while they do not symmetrically lose from a thicker left tail. The reverse applies to put options. Therefore, the expected *payoff* of both put and call options is increasing in expected return volatility of the underlying. The same is generally true for option *prices*, which thus contain information about the expected return volatility of the underlying asset: when both EUA calls and EUA puts become

[4]Between July and October 2018, the vendor data display zero trading volumes on most days. This appears to be a data error, as the changes in option open interest over this period are similar to open interest changes over other periods. We replace the volume observations for those four months with the observations from June 2018. After consulting with the data vendor, other variables—in particular settlement prices—are reported correctly.

[5]Table A.4 shows option open interest, that is the number of outstanding options contracts, across contract types.

Table I: EUA Options Volume

		Days to Expiry				
		10-30	31-120	121-240	241-	All
				Calls		
$0.0 \leq F/K \leq 0.7$	Deep Out Of The Money	0.8	6.8	10.3	19.6	37.5
$0.7 < F/K \leq 0.9$	Out Of The Money	2.6	11.2	7.7	10.2	31.7
$0.9 < F/K \leq 1.1$	At The Money	4.6	9.8	5.0	6.9	26.4
$1.1 < F/K \leq 1.3$	In The Money	0.5	1.3	0.8	0.9	3.5
$1.3 < F/K$	Deep In The Money	0.0	0.3	0.3	0.3	0.9
All		8.5	29.4	24.2	37.9	100.0
				Puts		
$0.0 \leq K/F \leq 0.7$	Deep Out Of The Money	0.9	6.5	9.6	14.2	31.2
$0.7 < K/F \leq 0.9$	Out Of The Money	5.3	19.1	9.0	13.7	47.1
$0.9 < K/F \leq 1.1$	At The Money	3.5	8.8	3.2	5.2	20.7
$1.1 < K/F \leq 1.3$	In The Money	0.1	0.2	0.1	0.5	0.8
$1.3 < K/F$	Deep In The Money	0.0	0.1	0.0	0.1	0.2
All		9.7	34.6	21.9	33.7	100.0

Note: EUA futures options trading volume (number of contracts) in percent of the sample total (2013.9 - 2022.12), split by contract type. Different rows correspond to different values of "moneyness", where K is the option's strike price, and F is the current spot price of the underlying futures contract. Different columns correspond to different option expiration dates.

more expensive, the markets' expectation of EUA futures' return volatility has likely risen.

Options-based uncertainty measures then summarize the general option price level. There are two prominent approaches to constructing an options-based uncertainty measure: the price of an option portfolio, and options' implied volatilities. We next describe how we construct measures of carbon price uncertainty based on both approaches, before comparing and contrasting them.

I.D. The Carbon VIX.

For our main measure of carbon price uncertainty, the *Carbon VIX*, we follow the CBOE "VIX" methodology (CBOE, 2023), implemented using the code provided by Vilkov (2023). Conceptually, the *Carbon VIX* is obtained by constructing a portfolio of EUA options, with portfolio weights chosen such that the portfolio payoff at option expiry is approximately equal to EUA futures' realized variance until option expiry.[6] When expected EUA price variance rises—corresponding to periods with higher carbon price uncertainty—the price of this portfolio rises. The *Carbon VIX* is the square-root of the price of that portfolio, since the VIX method targets expected volatility, not variance. Following Bloom (2014), Bretscher et al. (2018), Cremers et al. (2021), Gao et al. (2022)

[6] The portfolio payoff is exactly equal to the realized variance of the underlying until option expiry if an infinite number of strike prices are available. This condition is obviously violated in empirical implementations. However, EUA options with sufficiently many liquid strike prices are available to obtain a meaningful approximation. The CBOE VIX methodology uses the prices of a range of out-of-the-money put and call options and Table I shows that this is exactly where EUA options are most liquid. See Appendix Section A.1.B for details.

and others, we thus interpret changes in the *Carbon VIX* as changes in carbon price uncertainty.[7]

To construct a constant-maturity *Carbon VIX* capturing the annualized expected volatility over the next 120 days, we linearly interpolate between $CarbonVIX_t^{120,-}$ and $CarbonVIX_t^{120,+}$, constructed from EUA options with maturities just below and above 120 days, respectively. We choose 120 days as our constant-maturity target to use the most liquid EUA options while minimizing the impact of price pressures around option expiry.[8] As a result, the *Carbon VIX* measures the expected annualized carbon price return volatility over the next approximately 120 days, capturing uncertainty about any information that could impact carbon prices within that time frame. When we explore the term structure of carbon price uncertainty in Section I.F below, we find only negligible differences across horizons. Thus, the horizon of our uncertainty measures does not appear significant for our economic conclusions.

As a first check on our construction of carbon price uncertainties, Appendix Figure A.1 shows that the *Carbon VIX* moves closely with realized EUA futures return volatility. Thus, the *Carbon VIX* captures fundamental information about the return volatility of the underlying asset.

I.E. Carbon Option Implied Volatility.

As an alternative measure of carbon price uncertainty, we construct an index of *Carbon Implied Volatility (CIV)* from the implied volatilities of EUA options. The implied volatility of option i, denoted as σ^i, represents the level of volatility in the underlying asset's returns that, when used as an input in an option pricing model, produces the current market price of that option. All else equal, a higher option price corresponds to a higher implied volatility. However, the specific change in implied volatility resulting from a given change in option prices depends on the particular option pricing model employed. Here, we use Black (1976)'s futures options pricing model to obtain EUA futures options' implied volatilities (see Appendix A.1.C for details).

Appendix Table A.3 shows EUA option's implied volatilities by contract type. For example, at-the-money EUA put options with between 31 and 120 days to expiry have an average implied volatility of 52.5% over our sample period. That is, these options' prices on average predict an annualized volatility for EUA futures of 52.5%. To obtain one index from the range of EUA option implied volatilities we follow Cremers et al. (2021) and calculate $CIV_t^{120,-}$ ($CIV_t^{120,+}$) as the average implied volatility of the two puts and two calls that, on day t, have just below (above) 120 days to expiry. Similar to the construction of the *Carbon VIX*, we linearly interpolate the two measures to a constant 120 day horizon.

[7]Changes in the *Carbon VIX* measure changes in carbon price uncertainty as long as any carbon price variance risk premium is constant. Below we show several properties of the Carbon VIX that are consistent with this assumption.

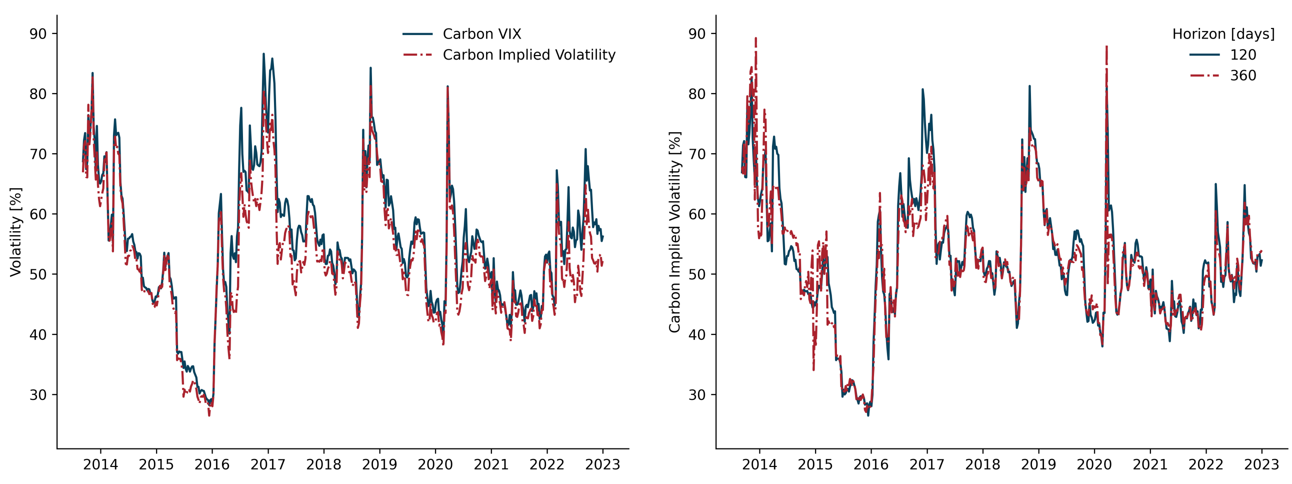
[8]Interpolation to horizon t' requires a range of options with time-to-expiry below t' and a range of options with time-to-expiry above t'. Option volume is highest for short-maturity options. Since EUA options have quarterly expiry, there is an expiry about every 90 days. Therefore, based purely on volumes, one would choose to interpolate to 90 days. However, we observe occasional large price pressures in options in the days before their expiry. To avoid holding options into expiry we interpolate to 120 days, such that options with approximately 29 days to expiry drop out of the measure and are replaced with the series of options that newly drop just below 120 days to expiry.

I.F. Exploring Carbon Price Uncertainty

The *Carbon VIX* and the *CIV* have distinct advantages and drawbacks. Most notably, the *Carbon VIX* methodology does not require a pricing model, but uses observed option prices from a wide range of strike prices with varying liquidity. In contrast, the CIV approach is only based on relatively liquid at-the-money options, but requires a model—in our case the one proposed in Black (1976)—to infer implied volatilities. Figure 3a shows that, despite these differences, *Carbon VIX* and *CIV* move closely together. They have near-identical levels and weekly changes have a correlation of 0.95. As a result, we proceed by using *Carbon VIX* as our main proxy for carbon price uncertainty, but show that our results are robust to analyzing *CIV*.

One application where CIV proves to be a useful auxiliary measure is in the study of the term structure of carbon price uncertainty. Figure 3b displays CIV as a 120 day measure and a 360 day measure, calculated by interpolating $CIV_t^{360,-}$ and $CIV_t^{360,+}$. The two measures move closely together in both levels and weekly changes. A flat term structure of option-implied uncertainty indicates that investors expect carbon price return volatility to be stable over the next 360 days, assuming a constant uncertainty risk premium (Johnson, 2017). In other words, the rate of information revelation is expected to be constant. We conclude that the horizon of our measure is not of central importance to the study of carbon price uncertainty. A 360 day *Carbon VIX* would suffer from illiquidity in $CVIX_t^{360,+}$, since we find little trading volume in out-of-the-money EUA options with more than 360 days to expiry. This reinforces our decision to focus on a 120 day *Carbon VIX* as our main measure of carbon price uncertainty.

Figure 3: Carbon Implied Volatility



(a) Carbon VIX and Carbon Implied Volatility (b) Carbon Implied Volatility Term Structure

Note: Panel (a) shows the Carbon VIX and Carbon Implied Volatility. Panel (b) shows Carbon Implied Volatility for horizons of 120 and 360 days.

We use these new measures to document several patterns regarding carbon price uncertainty.

Fact 1: Carbon price uncertainty is high over the entire sample period. The average value of the *Carbon VIX* over the sample is 55, implying that the market expects an annualized

EUA futures return volatility of about 55%. In comparison, the S&P 500 VIX index for US stock market volatility has an average value of about 20, and reaches values as high as 50 only during major market disruptions like the Global Financial Crisis of 2008 or the Covid Crash of 2020. This finding is consistent with Benmir et al. (2023) who show that carbon prices have the highest realized volatility across a range of commodities.

Realized EUA futures return volatility is about 45%. The difference between option implied return volatility and realized return volatility suggests a positive variance risk premium that raises option prices. This is consistent with the findings in Chevallier (2013), who find a positive variance risk premium in EUA options, and Heston and Todorov (2023), who find such premia in options across a range of asset classes. A positive variance risk premium in EUA options implies that *Carbon VIX* and *CIV* overestimate the level of expected carbon futures volatility. Yet, the average realized volatility is still substantial and our analysis of the real effects of carbon price uncertainty rely on uncertainty *changes*, not levels. Variance risk premia likely do not change much at the weekly frequency and so should not have large effects on weekly *Carbon VIX* changes.

Fact 2: Carbon price uncertainty varies substantially over time. The *Carbon VIX* has a sizable weekly standard deviation of around 11 percentage points (see Table II). Figure 1 annotates the *Carbon VIX* time-series with selected major market events, while Appendix Table A.5 includes further details.[9] Many of the large changes in *Carbon VIX* occur around events potentially affecting the supply of certificates (e.g., the introduction of the Market Stability Reserve). For example, Figure 1 shows high levels of carbon price uncertainty when the European Commission discussed postponing the auctioning of large quantities of emission allowances (so called back-loading) in late 2013, a move that was followed by structural reform proposals to address the excess supply of allowances in January 2014. In early 2016, the *Carbon VIX* increased by more than 30 percentage points when the EU Commission noted that further tightening in supply would be required to reach emission reduction targets consistent with the Paris Agreement adopted a few weeks earlier. After corporate lobby groups and politicians called for more ambitious targets in line with the Paris Agreement, the EU Parliament voted for large supply cuts of emission allowances in December 2016, a time when the *Carbon VIX* reaches levels of more than 80%.

In addition to these spikes in carbon price uncertainty related to regulatory actions that introduce uncertainty about the supply of EUAs, other spikes in carbon price uncertainty occur during events that raise uncertainty about the demand for EUAs. For example, the *Carbon VIX* spiked in March 2020 at the onset of the Covid-19 pandemic that led to large economic uncertainties.

Fact 3: Spikes in carbon price uncertainty are relatively persistent. For example, the *Carbon VIX* spike in mid 2018 took almost two years to resolve. Table II contains AR(1) coefficients for the carbon market: A one percentage point increase in the *Carbon VIX* predicts a 0.09 percentage point increase the following week. In contrast, the AR(1) coefficients for both Equity VIX and Oil VIX changes are negative (see Appendix Table A.6). Thus, we see reversal for Equity VIX and Oil VIX, but persistence for the *Carbon VIX*. Intuitively, persistent uncertainty shocks are more likely to have perceptible real effects.

[9] We collect information about important market events around *Carbon VIX* spikes from the websites of the European Commission and Carbon Pulse, a news service specialized on carbon pricing and climate change policies.

Table II: Carbon Market Summary Statistics

	Mean	Median	Std	AR(1)	Skew	Kurtosis
Carbon Price	24.38	13.94	25.16		1.41	3.78
Carbon VIX	54.92	54.19	11.26		0.17	3.15
Carbon Price Return	0.89	0.75	5.77	0.77	0.20	2.80
Carbon VIX Change	-0.14	-0.14	2.84	9.56	0.42	4.49

Note: Appendix Table A.1 defines the market variables. The data frequency is weekly. All market variables are winsorized at percentiles 2.5 and 97.5. The AR(1) coefficient is multiplied by 100. The sample period is 2013.9 - 2022.12.

Table III: Market Correlations

	Carbon Price Return	Carbon VIX Change	Equity Price Return	Equity VIX Change	Oil Price Return
Carbon Price Return					
Carbon VIX Change	-0.33				
Equity Price Return	0.19	-0.15			
Equity VIX Change	-0.17	0.11	-0.79		
Oil Price Return	0.14	-0.09	0.29	-0.24	
Oil VIX Change	-0.20	0.14	-0.41	0.45	-0.42

Note: Appendix Table A.1 defines the market variables. The data frequency is weekly. All market variables are winsorized at percentiles 2.5 and 97.5. The sample period is 2013.9 - 2022.12.

Fact 4: Carbon price uncertainty is distinct from other uncertainty measures. Table III shows weekly correlations between changes in the *Carbon VIX* and changes in the EU Equity VIX and the Oil VIX to be 0.11 and 0.14, respectively. These positive, but moderate, correlations highlight that while carbon prices reflect the supply and demand for emission allowances, which could also correlate with more general economic uncertainty or uncertainty in energy markets, carbon price movements are broadly independent of other prices in the economy.

II. Carbon VIX and Firm-Level Decarbonization Investments

In the second part of the paper, we explore the real effects of carbon price uncertainty by studying its effects on firms' decisions to decarbonize. We first explore firms' investment in decarbonization projects based on a large survey of firm-level emission abatement activities. We use this data to show a negative relation between firms' decarbonization investments and carbon price uncertainty at the annual level. In the subsequent section, we provide complementary high-frequency evidence from the stock returns of carbon solution providers.

II.A. Measuring Decarbonization Activities

Data. We work with survey data on firms' decarbonization efforts collected by CDP (formerly the Carbon Disclosure Project). CDP is a non-profit organization providing the largest survey-based information on corporate climate action, and its data serve as input for many commercial climate data, rating, and index providers such as Trucost, MSCI, and Bloomberg (CDP, 2022).

Each year, CDP asks a large set of firms to file a detailed questionnaire that spans a wide range of topics related to climate change. These topics include firm-level climate related risks and opportunities, emission targets, historical emissions, and emission-abatement initiatives. CDP covers firms globally across all major sectors. The criteria that determine the set of firms surveyed are based on both environmental impact (i.e., whether the firm belongs to a high-emitting sector such as materials, energy, or industrials), and market capitalization (i.e., whether a firm is constituent in one of the regional or global stock market indices). Firm responses are voluntary and disclosed information is not verified by CDP. By construction, survey respondents are relatively large and disclosed information may be subject to selection bias (Bolton and Kacperczyk, 2023). Over time, an increasing number of firms have started to report to CDP: between 2015 and 2023, the number of respondents grew from fewer than 2,000 to more than 10,000 firms.[10].

We focus our analysis on a part of the survey in which firms are asked to disclose detailed information on planned and implemented initiatives to reduce their carbon emissions.[11] For projects implemented during a reporting year, firms report an activity type (e.g., 'low-carbon energy generation' or 'energy efficiency in production processes'), provide a text-based description of the project, and indicate the investment amount in their respective currencies. This allows us to get rich project-level insights on firms' efforts to reduce their carbon emissions. We sort firms' type of decarbonization activities into seven broad categories.[12] We consider activity types in categories *low carbon energy*, *process efficiency*, *waste*, *building efficiency*, and *transportation* and disregard projects in categories *company policy or behavioral change*, and *product design*, as they are often not associated with specific third-party goods or services.

Since 2015, CDP has asked respondents to report whether an activity reduces direct emissions from firm-controlled sources (scope-1), indirect emissions from the consumption of purchased power (scope-2), or other indirect emissions (scope-3). As we are interested in firms' investments to reduce direct carbon emissions—the types of emissions for which EU-based firms require EUAs—we limit our sample to implemented carbon abatement projects of scope-1 emissions reported in CDP vintages 2015 to 2023. Out of 15,500 non-financial firms reporting to CDP during this period, about 2,800 firms provide details on more than 12,500 projects to reduce their scope-1 emissions (see further details in Appendix Section A.2).

Descriptions of Decarbonization Investments. Appendix Table A.7 provides summary statistics on the observed decarbonization projects. To our knowledge, these provide the most comprehensive account of firm-level decarbonization investments in the literature. The median project costs EUR 260k. Across all activities aimed at reducing scope-1 emissions, total investment

[10]The actual number of respondents is substantially higher but many firms do not allow for public disclosure of their responses. For example, in the 2023 vintage, 13,336 firms opted to not disclose their responses to the public including to research institutions. Detailed information on how CDP collects and treats climate-related data is available at `www.cdp.net`

[11]Previous studies working with CDP data have mainly focused on CDP disclosures of firms' overall climate risk assessment, historical carbon emissions, or emission targets (Matsumura et al., 2014; Jung et al., 2018; Bolton and Kacperczyk, 2023; Ilhan et al., 2023). Using additional CDP data on firms' reported carbon abatement initiatives, Ioannou et al. (2016) find emission target stringency is positively related to investment in such initiatives.

[12]Appendix Table A.8 provides stylized, GPT-generated examples of decarbonization project data and Appendix Table A.9 details the mapping of decarbonization activity types to categories.

sums to EUR 639 billion, or 62% of decarbonization investments reported to CDP.[13]

Panel A of Appendix Table A.7 reports emission abatement projects by country of firm origin. Firms located in the U.S. or in Europe account for the vast majority of total decarbonization investments by firms in our sample, both because the majority of reporting firms come from these regions, and because investment in emission reduction projects reported by firms located in other regions are substantially lower. For example, firms located in BRICS countries (Brazil, China, India, Russia, and South Africa) account for 20% of all firms reporting scope-1 decarbonization projects, but for less than 5% of total decarbonization investments.

Panel B of Appendix Table A.7 details carbon abatement projects across industries. Almost half of all firms disclosing scope-1 decarbonization projects belong to the manufacturing and materials sector. Their combined decarbonization investments, however, only account for about 10% of the total investment in emission abatement. In contrast, a relatively small number of firms in few industries are responsible for large parts of reported decarbonization investments. With about 70% of disclosed decarbonization investments, utility and power firms play a dominant role in corporate decarbonization activities. The remaining decarbonization investments stem largely from firms in the fossil fuel (6%), infrastructure (5%), transport (4%), and aviation (4%) industries.

Much of the observed variation in decarbonization investment across industries is likely driven by differences in baseline emission levels. Figure 4a therefore plots annual averages of industry-level decarbonization *investment rates* (the ratio of total decarbonization investment to total reported scope-1 emissions) against the industry share of scope-1 emissions. Across industries, there is substantial heterogeneity in investment rates for emission abatement activities. For example, the total decarbonization investment of firms in the manufacturing and materials industry is on average 7 EUR per ton of reported scope-1 emissions. The utility and power sectors account for a similar share in carbon emissions; however, with an average investment of 35 EUR per ton of emitted carbon, they report a decarbonization investment rate that is substantially higher. Relative to other industries, decarbonization investment rates are also high in the infrastructure (53 EUR/tCO2e) and aviation (38 EUR/tCO2e) industries.

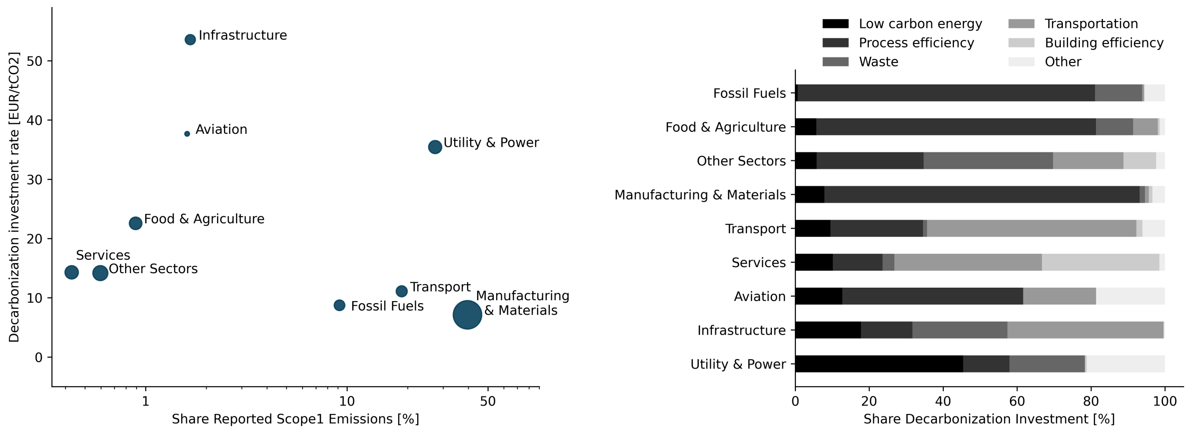
Figure 4b displays the share in decarbonization investment by type of decarbonization activity across industries. Utility and power firms report the largest share in low carbon energy investment. Firms in the fossil fuels, manufacturing, and materials sectors—which are often involved in energy intensive industrial processes—largely rely on improvements in process efficiencies to reduce their scope-1 emissions. Decarbonization activities in buildings efficiency projects are most prominent among firms in the services sector while firms in the transport sector largely invest in projects to abate transportation-related emissions.

II.B. Carbon Price Uncertainty and Decarbonization Investments

We use the survey information on realized decarbonization investments to conduct a first exploratory analysis of whether firms invest less to decarbonize when uncertainty about future carbon prices is high (as discussed before, in times of high carbon price uncertainty an increased

[13] Scope-2 and scope-3 emission abatement projects account for 14% and 5% of total decarbonization investment, respectively. The remainder comprises decarbonization projects of hybrid scopes.

Figure 4: Decarbonization Investments



(a) Investment rate

(b) Activity type

Note: Panel (a) plots annual averages of industry-level decarbonization investment rates on the average industry share of scope-1 emissions. Decarbonization investment rates are the ratio of total decarbonization investment to total reported scope-1 emissions. The bubble size corresponds to the number of firms reporting scope-1 decarbonization projects. Panel (b) presents the share of investments by activity type across sectors. Data are from CDP vintages 2015–2023. Appendix Table A.10 reports corresponding numbers. Appendix Section A.2 includes details on sample construction and Appendix Table A.9 outlines activity type classification.

option value incentivizes firms to delay their emission abatement initiatives).

To analyze such an effect, we construct a panel of firm-level investments in scope-1 decarbonization activities. For each survey vintage, firms provide information on the reporting period for which they disclose information to CDP, which are typically the twelve months coinciding with the firms' financial year. We use this information to infer the level of carbon price uncertainty firms experienced during their respective reporting periods. We additionally identify a set of firms that are exposed to ETS carbon price uncertainty by exploiting a part of the survey where firms report whether they are subject to certain carbon pricing schemes. This allows us to compare the decarbonization investments of firms exposed to the EU ETS to firms without such compliance obligations at times of varying levels of carbon price uncertainty.

Sample Description. We aggregate decarbonization investment at the firm-reporting period level and remove observations where firms do not report valid ISIN-identifiers or reporting periods (see Appendix Section A.2 for details). To focus on periods with higher coverage of CDP data and meaningful levels of carbon prices, we limit the sample to decarbonization investments reported during periods that start in 2018 at the earliest and end by 2022 at the latest. We end up with 67 distinct reporting periods. For each firm and reporting period, we calculate the average carbon price and average Carbon VIX. Based on reporting-period-ends and ISIN-identifiers provided by CDP, we additionally match firm financial data from Moody's Orbis database.

Regression Specification. To test whether the level of carbon price uncertainty influences decarbonization activities of firms exposed to carbon pricing, we estimate the following regression:

$$DIR_{i,\tau} = \beta_1 Exposure_i \times CarbonVIX_\tau + \beta_2 Exposure_i \times D_\tau + \beta_3 X_{i,\tau} + \psi_i + \delta_\tau + \epsilon_{i,\tau}. \tag{1}$$

Our main variable of interest is $DIR_{i,\tau}$, the ratio of firm i's total investment in decarbonization activities to its reported scope-1 emissions in period τ. We assign $Exposure_i$ a value of one if firm i disclosed that their operations are impacted by the EU ETS and reported corresponding positive regulated emissions at any time during the sample.[14] $CarbonVIX_t$ is the average level of the Carbon VIX during reporting period τ. Similarly, vector D_τ includes average carbon and oil prices over that period. Vector $X_{i,\tau}$ collects controls for firm characteristics including firm size, leverage, profitability, and capital expenditure. To deal with the substantial right-skew in reported investment amounts and other responses—some of which we believe to be the result of data entry errors—we winsorize all variables at the 95^{th} percentile. Measures of profitability and capital expenditure, which are not bound at zero, are winsorized at the 2.5^{th} and 97.5^{th} percentiles. Table A.11 presents summary statistics on the various variables in the regression. We also add firm and reporting period fixed effects denoted as ψ_i and δ_τ, respectively. In our most restrictive specification, we replace δ_τ with reporting period $\times$ country of firm origin fixed effects. We cluster standard errors at firm and reporting period levels.

Table IV: **Carbon VIX and Decarbonization Investment Ratios**

	Dependent variable: *Decarbonization investment rate* (DIR)					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure × Carbon VIX	-0.457**	-0.414**	-0.481**	-0.427**	-0.364*	-0.428*
	(-2.04)	(-2.08)	(-2.22)	(-2.25)	(-1.71)	(-1.73)
Exposure × Carbon Price			-0.042	-0.018	-0.071	-0.027
			(-1.15)	(-0.44)	(-1.02)	(-0.36)
Exposure × Oil Price					0.034	0.045
					(0.42)	(0.41)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	No	No
Firm Characteristics	No	Yes	No	Yes	Yes	Yes
Country × Period FE	No	No	No	No	Yes	Yes
Industry × Period FE	No	No	No	No	No	Yes
Observations	3,825	3,508	3,825	3,508	3,340	3,266
R2-Adjusted	0.47	0.45	0.47	0.45	0.43	0.44

Note: This table summarizes regression estimates of Equation (1). The dependent variable *Decarbonization investment rate* is the ratio of a firm's investment in decarbonization activities (EUR) to its scope-1 emissions (tCO2e) disclosed to CDP for a given reporting period. *Exposure* is an indicator of carbon price exposure that is equal to one if a firm disclosed that, throughout the CDP sample, any of the its operations is regulated by the EU ETS and zero otherwise. *Carbon VIX*, *Carbon Price*, and *Oil Price* are averages of weekly levels of Carbon VIX (%), carbon prices, and oil prices (EUR) over the firm's reporting period, respectively. Table A.1 details definitions of all variables. The sample covers decarbonization investment reported for periods between years 2018 and 2022. Summary statistics are reported in Table A.11. In parentheses, we report t-statistics based on standard errors clustered by firm and reporting period. *p<.1; **p<.05; ***p<.01

[14] Survey responses on carbon price exposure are sometimes inconsistent over time. As EU ETS compliance is based on business activity which typically does not change much over time, we suspect this is due to reporting inconsistencies.

Table IV presents estimates of the regression in Equation (1), which allows us to test the real-options prediction that increasing uncertainty should raise the value of delaying investment, leading to lower observed investment activity. Column (1) suggest that firms whose operations are exposed to ETS carbon prices report lower decarbonization investment rates than non-exposed firms during times of higher carbon price uncertainty. This effect is not explained by firm characteristics (column 2), carbon price levels (columns 3–4), oil price levels (column 5) or reporting period × country-specific characteristics (column 6), with the statistical significance bouncing around at the 5% level across specifications. A one standard deviation (or 4.5 percentage points) increase in the Carbon VIX is associated with a 1.6–2.2 EUR/tCO2e decrease in the decarbonization investment rates. Given that the average decarbonization investment rate is about 18 EUR/tCO2e, this economic magnitude is substantial.

While the basic findings in Table IV are consistent with our hypothesis that carbon price uncertainty reduces decarbonization investments, several factors complicate any confident interpretation of these results. First, CDP does not provide standards or guidelines on the reporting of decarbonization investment and does not verify their validity. As a result, it is difficult to interpret granular firm-level outcomes due to potential differences in definitions, valuations, or disclosure timings of emission reduction projects. For example, for projects spanning multiple reporting periods some firms disclose investment in the final period while others split the amount across all periods. Second, given that survey information is only available at annual frequencies and the high-carbon-price sample consists of only five years, a clean identification of the effects of carbon price uncertainty on decarbonization activity is challenging. Third, and perhaps most importantly, we only observe decarbonization investments *after* a project is realized. The timing of the investment *decision*, however, remains unclear, and it could be that some investments reported in period τ may actually have been started in prior periods. Since our mechanisms links carbon price uncertainty to the decision to invest, this complicates an interpretation of the results in Table IV. These factors may explain why, while we detect effects of carbon price uncertainty on decarbonization investments, we do not find evidence for the expected positive relationship between the level of carbon prices and decarbonization investments (this fact could be further explained by the substantial correlation between carbon prices and carbon price uncertainty at these lower frequencies). Consequently, for our main empirical results, we move away from trying to understand realized survey-reported decarbonization activities.

III. Carbon VIX and Stock Returns of Carbon Solution Providers

In this section, we present our preferred analysis of the effects of carbon price uncertainty on decarbonization activities. The key idea is to first identify firms that primarily provide goods and services that help *other* firms decarbonize—firms we call "carbon solution providers." We then study the stock returns of these firms as high-frequency proxies for the expected demand for decarbonization products and services, and thus expected aggregate decarbonization activities. When carbon prices rise, polluters have more incentives to decarbonize. If investors expect spending on decarbonization activities to increase, this should lead to higher stock returns for carbon solution providers. Similarly, if higher carbon price uncertainty reduces polluters' incentive to decarbonize today, we should observe lower stock returns for carbon solution providers.

This approach has several advantages over our analyses of survey-reported decarbonization investments in the prior section. First, analyzing stock returns allows us to exploit high-frequency variation in both carbon prices and carbon price uncertainty. Second, firms' decarbonization investments take time to plan and implement. Thus, realized decarbonization investments would reflect any impact of carbon prices only with a lag of uncertain length, making it hard to line up realized investments and carbon price uncertainty over the period when the investment decision was likely made. In contrast, market expectations of decarbonization investments should move contemporaneously with carbon price uncertainty, and stock prices should immediately reflect these shifts in expectations.

III.A. Identifying Carbon Solutions

To implement this approach, we first need to catalogue the goods and services demanded by firms hoping to decarbonize their activities, before identifying "carbon solution providers" as firms offering these goods and services. To understand firms' decarbonization activities and the goods and services demanded to achieve them, we exploit textual descriptions of individual emission abatement projects in the CDP data, where firms often describe their decarbonization projects in some detail. We collect more than 4,500 unique project descriptions, with an average length of 27 words and an interquartile range of 5 to 32 words.

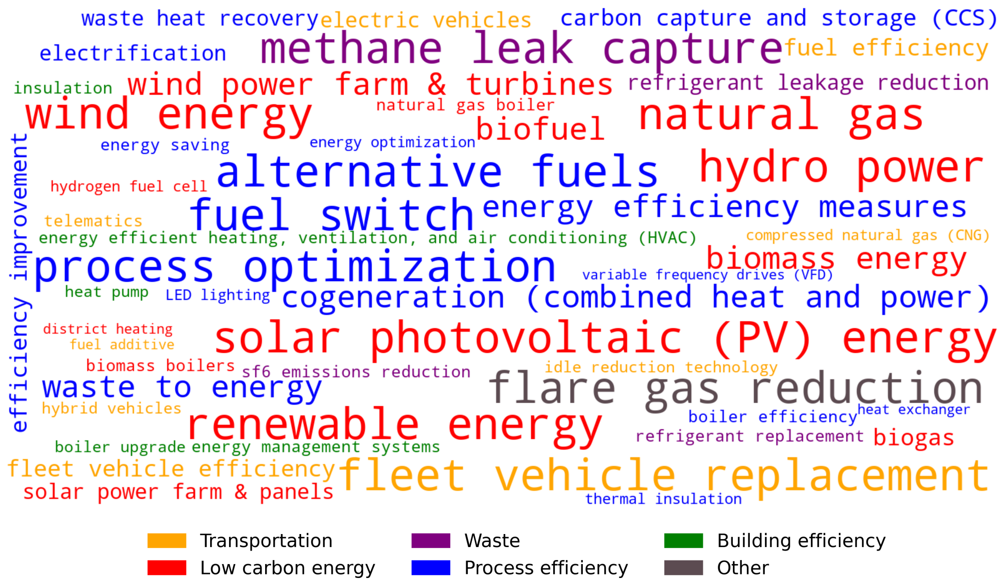
We rely on the large language model GPT 3.5 Turbo version 0125 (henceforth GPT) developed by OpenAI, to extract common carbon solutions from these descriptions of carbon abatement projects. For every project description, GPT returns a keyword or at most 3-word phrase that is most related to a product or service used to abate carbon emissions (see Appendix Table A.8 for stylized examples of project descriptions and corresponding carbon solutions identified by GPT).[15] We consolidate carbon solutions identified by GPT by merging similar keywords, providing the full term for acronyms and removing generic keywords.[16] This process identifies more than 1,250 unique carbon solutions.

Figure 5 presents the 50 most frequent carbon solutions extracted from the reported decarbonization projects. Together, they represent more than 75% of total investments in scope-1 emission abatement. The most popular decarbonization activities include investing in renewable energy sources such as wind and solar, waste energy prevention, and fuel and vehicle replacement in the transportation sector. Firms also report a wide range of other industry-specific solutions such as boiler upgrades, co-generation, or variable frequency drives. This granularity in carbon

[15] Specifically, we provide the following prompt to GPT: *"You will be provided with unstructured text in triple quotations, and your task is to find a single keyword or phrase of maximum 3 words that is most related to a measure or product to reduce carbon emissions. In case the text is not related to carbon emission reduction, provide N/A as keyword. Here is the text: [project description]"*. As the GPT system role carries a higher weight than the user role, we provide the prompt as part of the system content and insert the project description starting with "Here is the text:" as user content. To reduce the risk of hallucination, we set the temperature parameter to 0.3.

[16] For example, the carbon solution *carbon capture and storage (CCS)* unifies keywords returned by GPT such as CCS, carbon.*capture, co2.*capture, capture.*storage where .* indicates a placeholder of any length. We remove stand-alone generic keywords such as *substitution* or *reduction* that may not be helpful to detect specific carbon solution providers.

Figure 5: Carbon Solution Keywords by Category



Note: Carbon solutions are based on the 50 most frequent keywords extracted from descriptions of decarbonization projects. Larger font size corresponds to higher investment amounts. In some cases, a carbon solution occurs across multiple categories. In this case, we assign the category with most frequent occurrence. Appendix Table A.12 lists carbon solutions along with the corresponding investment amount.

solutions allows us to provide a rich characterization of firms' emission abatement strategies.

III.B. Identifying carbon solution providers

We next identify firms that sell carbon solution products or services, and that would thus benefit from increased investments into emission abatement efforts. To do this, we collect textual descriptions of firms' main products and services from Moody's Orbis database. We combine this information with trade descriptions—a standardized description of a firm's business model that Moody's collects from different sources—into a single text-based summary of a firm's main business activities. To focus on firms that would most benefit from decarbonization activities undertaken in Europe, and for which we can observe stock returns, we limit our main sample to publicly listed European firms. After removing short summaries with fewer than 10 words, we end up with 5,193 firm-level descriptions of associated business models and specific products offered. The average length of these descriptions is about 45 words. For example, the description of Waga Energy SA is: *Products and services: "Landfill gas upgrading into grid-compliant biomethane renewable natural gas (designs, builds, and operates landfill gas recovery, upgrades, and grid-injection projects)." Business Model: "The Company is developing biomethane projects for the energy transition."*

Based on these firm descriptions, we identify firms providing carbon solutions to other entities. Since detecting carbon solution providers requires semantic understanding and contextual awareness of text, we work with OpenAI's latest GPT Model 4 (GPT4). For every description of a firm's business model and products, we ask GPT4 to identify whether this firm is a carbon solution provider satisfying two criteria. First, the firm's *primary* business model must be to provide carbon solutions. Second, the carbon solutions must be investment goods or service purchased by other firms instead of retail products such as smart home appliances or electric scooters for which purchase decisions are not usually driven by carbon prices. As examples, we provide GPT4 with the 50 most common carbon solutions used by firms as identified in the CDP data.[17] Appendix Section A.3 provides further details on our approach, including the prompts given to GPT4.

GPT4 identifies 259 firms as providers of more than 600 carbon solutions, we release a list of carbon solution providers, along with corresponding carbon solutions at `www.carbonvix.org`. Figure A.2 presents a word cloud of the 50 most frequent carbon solutions provided. Many of the goods and services offered are similar to the carbon solutions extracted from project descriptions of decarbonization investments. GPT4, however, also detects carbon solutions different to those included in the list of example solutions. For example, GPT4 identifies *energy storage solutions* helpful to reduce energy demand and supply imbalances or *energy audits* conducted to identify energy conservation potential.

Alternative Approaches to Identifying Carbon Solution Providers. We consider two alternative approaches to identifying carbon solution providers. First, we make use of the firm-level climate change exposure data from Sautner et al. (2023). This data is based on firms' earnings calls and provides a measure of firms' "climate opportunities" at the firm-year level. Over the sample of 2013 to 2022 the measure is available annually for an average of around 700 European firms. We take the average of each firms' climate opportunity exposure across the sample and assign firms above the 95^{th} percentile as climate opportunity firms.

We create a second alternative measure of carbon solution providers as the set of firms held by ETFs that aim to profit from decarbonization. Specifically, we consider the January 2024 holdings of the "European Green Deal UCITS ETF (EUGD)". The ETF contains 50 European firms that *"could benefit from the European Green Deal, a landmark transaction enacted by the European Commission to make Europe the first carbon neutral continent"*. ETF holdings data make use of the knowledge of portfolio managers, which can include soft information that is not necessarily contained in official reports and accounting metrics.

Characteristics of Carbon Solution Providers. To explore the characteristics of climate solution providers, we obtain Compustat Global data via the code from Jensen et al. (2023). We subset the sample to firms that are listed in a country of the European Economic Area,[18] and to observations for which we observe all characteristics used in the regressions below. We obtain observations for around 7,000 firms (including 201 carbon solution providers) across 23 (two digit NAICS) industries in 29 countries.

Table V compares firm characteristics of carbon solution providers to the characteristics for the full sample of firms. Carbon solution providers are relatively small, with an average equity market capitalization of $1.5 billion, and relatively young (for European firms), with an average age of about 24 years since listing. At the same time, carbon solution provider's equity is relatively

[17] Additionally, we provide a total of seven stylized examples of firm descriptions along with expected output (see Appendix Table A.13). This few-shot prompting technique helps to produce reliable output and sort out certain edge cases such as firms providing environmental solutions unrelated to the reduction of greenhouse gases.

[18] As of 2024 the European Economic Area consists of 30 countries, but we lack stock return data for Liechtenstein. Appendix Table A.15 displays the list of countries in our sample.

Table V: Firm Characteristics

Firms:	Carbon Solution	Climate Opportunity	ETF	All
Nr. Firms	201	77	44	7,056
Nr. Industries	16	12	7	23
Nr. Countries	18	15	12	29
Market-Cap (Bil.)	1.5	14.0	17.1	2.1
Market-to-Book Ratio	1.3	1.2	1.7	0.6
Sales (Bil.)	1.5	15.3	13.9	1.7
Nr. Employees (1000s)	2.5	20.9	20.2	2.1
Age (Years since Listing)	23.9	33.8	33.8	27.6
Assets (Bil.)	2.7	38.2	25.7	8.1
CAPX per Assets (0.001s)	56.7	48.7	45.8	48.1

Note: This table shows firm characteristics of carbon solution providers, climate opportunity firms and ETF constituents in columns one, two and three, respectively. The three measures are described in subsection III.B. Column four contains the full sample of publicly traded European firms. Averages are over all weekly observations of the respective sample. The sample period is 2013.09 to 2022.12.

highly valued, judging by their market-to-book ratio; they also invest relatively more per book value of assets (see CAPX). To provide further insight into the types of businesses that help others to decarbonize, Table A.14 shows the full list of carbon solution providers. For example, "Aker Carbon Capture" helps hard-to-abate industries install devices that capture CO2 emitted in their production process; "Sweco AB" provides engineering and consulting services in the environmental space. The more represented industries are manufacturing, utilities, and services.

Merging climate opportunity firm identifiers—those identifying firms based on the Sautner et al. (2023) measure—with the stock return data yields a sample of 77 climate opportunity firms, where 10 firms overlap with the sample of climate solution firms. Merging the ETF constituents yields 44 firms with an overlap of seven. Columns two and three in Table V display the average firm characteristics for the respective samples. Compared to our sample of "carbon solution providers", the firms in the climate opportunity and ETF samples are relatively larger, with an average market capitalization around $15 billion; they are also relatively older, with an average age since listing of about 34 years and they invest less per book value of assets.

III.C. Carbon VIX and Carbon Solutions Providers' Stock Returns

Data. We use the approach of Jensen et al. (2023) to obtain daily stock returns data from Compustat Global. All returns are from the perspective of a European investor who does not hedge currency risk. To alleviate concerns of illiquidity and slow information diffusion (Menzly and Ozbas, 2010), we only consider firms with a lagged market capitalization above $100 million, reducing the sample of carbon solution providers to 157. Further, our regression estimates are based on weekly returns, which are less affected by illiquidity than daily returns.

Regression Specification. We explore the effects of carbon prices and carbon price uncertainty by estimating the following regression specification based on the idea that increases in carbon price uncertainty (and reductions in carbon prices) should reduce overall decarbonization investments and thus reduce carbon solution providers' firm value:

$$R_{i,t} = \beta_1 CarbSol_i \times R_t^{EUA} + \beta_2 CarbSol_i \times \Delta CarbonVIX_t + \mathrm{X}_{i,t} + \psi_i + \delta_{c(i)\times ind(i)\times t} + \epsilon_t^i, \quad (2)$$

where $R_{i,t}$ is the stock return of firm i in week t, $CarbSol_i$ is an indicator whether firm i is a carbon solution provider, R_t^{EUA} is the return of EUA futures and $\Delta CarbonVIX_t$ is the weekly change in the Carbon VIX. $\mathrm{X}_{i,t}$ contains controls for other market variables that we describe below. We add fixed effects by firm (ψ_i) and country $\times$ industry $\times$ week ($\delta_{c(i)\times ind(i)\times t}$). As a result, our analysis compares firms that do and do not provide carbon solutions within the same country, industry, and week (the industry classification is based on 2-digit NAICS codes). To reduce the impact of outliers, all explanatory variables are winsorized at the 2.5^{th} and 97.5^{th} percentiles. For ease of interpretation, carbon returns and Carbon VIX changes are normalized to have zero mean and unit variance. Standard errors are double clustered by firm and country $\times$ industry $\times$ week.

Carbon price returns correlate with general equity and energy market returns, in part because higher expected economic activity should increase both carbon prices and firm valuations. For similar reasons, carbon price uncertainty is naturally related to general economic uncertainty (the supply- and demand-side arguments for such market relations are described in Section I). One might thus be worried that carbon solution providers are just more exposed to general equity- or energy market uncertainty, and that β_1 and β_2 would at least in part pick up such relationships. To alleviate such concerns, we control for stocks' exposures to equity and energy markets via fixed effects of week $\times$ lagged-beta deciles, where betas capture the relationships with general equity price returns, equity VIX changes, oil price returns, and oil VIX changes. By estimating the betas over rolling windows, we allow for time-varying exposures. Thus, our regression estimates capture the different exposure of climate solution providers vs. other firms to carbon prices and uncertainty that is not explained by their covariances with general equity or energy markets.

Results. Table VI provides regression estimates of Equation (2). Columns (1) and (5) use our baseline method for identifying carbon solution providers, with the sample consisting of firms for which we could obtain firm descriptions from Orbis. Columns (2) and (6) use firms' climate opportunity exposures from Sautner et al. (2023), with the sample consisting of European firms in this dataset during at least one sample year. Columns (3) and (7) use holdings data, and the sample consists of all European listed securities in the Jensen et al. (2023) dataset. All measures are described above. Columns (4) and (8) identify a firm as a carbon solution provider if it is identified as such by at least one of our three methods. Similar to columns (3) and (7), we use the broadest available sample of firms. Columns (1) to (4) contain observations over the years from 2018 to 2022, the period when carbon prices in the EU ETS were relatively high (see Figure 2a). Columns (5) to (8) contain observations over the low-carbon-price years, 2013 to 2017.

Column (1) shows that, relative to other firms, stock returns of carbon solution providers move positively with carbon price increases and negatively with increases in carbon price uncertainty. This finding is consistent with the mechanism that when carbon price uncertainty rises, polluters have a lower incentive to invest into decarbonization. As a result, expected spending

Table VI: Regression: Carbon Solution Providers' Stock Returns

	2018 - 2022: High Carbon Price				2013 - 2017: Low Carbon Price			
	(1) Sol.	(2) Opp.	(3) ETF	(4) All	(5) Sol.	(6) Opp.	(7) ETF	(8) All
Carbon Solutions	12.1**	13.8**	7.0	9.3**	5.4	-5.0	4.7	3.6
× Carbon Price Return	(2.10)	(2.07)	(1.44)	(2.31)	(0.84)	(-0.70)	(0.72)	(0.81)
Carbon Solutions	-13.5**	-20.0***	-15.2**	-15.4***	6.1	-5.0	-0.7	1.8
× CVIX Change	(-2.09)	(-2.70)	(-2.50)	(-3.61)	(0.88)	(-0.79)	(-0.12)	(0.40)
Date × Beta Equity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date × Beta Equity VIX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date × Beta Oil	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date × Beta Oil VIX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ID	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date x Indu x Cntry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	393,994	211,369	535,305	535,305	252,100	94,548	403,745	403,745
R2-Adjusted	0.27	0.35	0.27	0.27	0.21	0.36	0.21	0.21

Note: This table presents regression estimates of equation (2). We regress weekly stock returns of European firms on the interactions between a carbon solution indicator and carbon price returns as well as the interaction of the carbon solution indicator and *Carbon VIX* changes. We apply four different measures for identifying carbon solution firms, as identified in subsection III.B. Columns (1) and (5) use our novel survey evidence. Columns (2) and (6) use data from Sautner et al. (2023). Columns (3) and (7) use ETF constituents. Columns (4) and (8) use the union of these three measures. Each sample consists of the firms for which the respective measure is available for the firm year. Columns (1) to (4) represent the high carbon price Sample 2018.01 to 2022.12. Columns (5) to (8) represent the low carbon price Sample 2013.09 to 2017.12. Explanatory variables are standardized to zero mean and unit variance. We add controls for exposure to both equity and energy markets, via fixed effects for week × lagged beta deciles. Further, we add fixed effects by stock ID (firm) and $week \times industry \times country$. Standard errors are double clustered by $firm$ and $week \times industry \times country$, and t-stats are presented in parentheses.

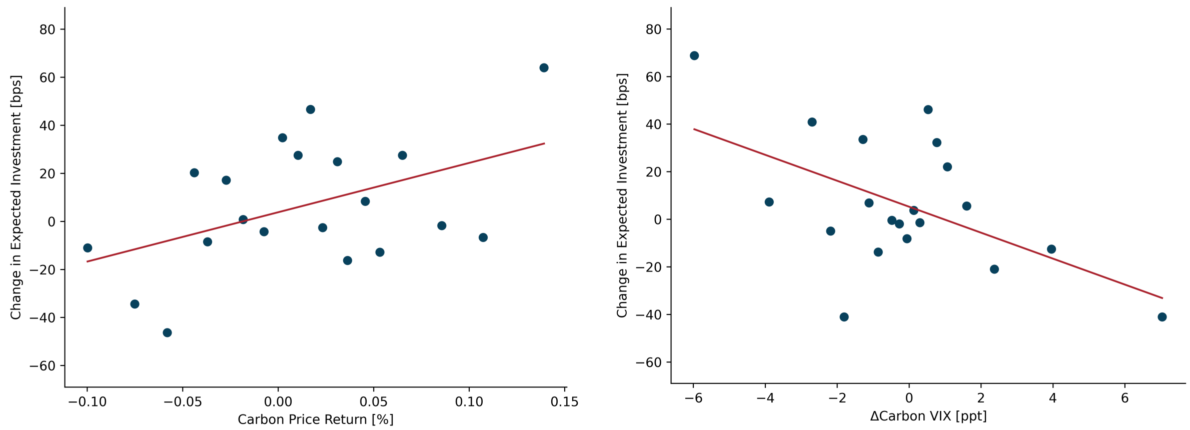
on decarbonization falls, leading to lower stock returns for carbon solution providers. Similarly, our findings suggest that expected decarbonization spending rises when carbon prices increase.[19] Columns (2) to (4) show that our estimates are robust to our alternative methods of identifying of carbon solution providers.

Importantly, the effect of increases in carbon price uncertainty on our proxy for expected decarbonization is of similar magnitude to the effect of declines in carbon prices. A one standard deviation increase in the carbon price return is associated with a 12.1 basis points relative increase in the stock returns of carbon solution providers, while a one standard deviation higher increase in the *Carbon VIX* is associated with a 13.5 basis points relative decrease in those stock returns. Put differently, a one percentage point increase in carbon price uncertainty has a similar impact on carbon solution providers' stock returns as a EUR 0.99 decline in the carbon price.[20]

[19] One alternative interpretation is that carbon prices and carbon price uncertainty represent discount rate news that are specific to carbon solution providers, though our analysis of firm sales in later sections suggest this is not the only channel. Another alternative is that our regressions suffer from reverse-causality whereby carbon solution providers stock returns drive carbon prices, though it is unclear what economic mechanism would drive such a relationship.

[20] We arrive at this approximation via $\frac{-13.5}{12.1} \times \frac{2.4}{2.7} = -0.99$, where 2.7 is the weekly standard deviation of *Carbon VIX* changes over 2018 - 2022 and 2.4 is the weekly standard deviation of carbon price returns in EUR, which we obtain as the

Figure 6: Expected Decarbonization Investment



(a) Carbon Price

(b) Carbon VIX

Note: Panel (a) plots the equal-weighted average residual returns of carbon solution providers by ventiles of the weekly EU ETS carbon emissions price return. Panel (b) plots the *Carbon VIX* change on the horizontal axis. Carbon solution providers are identified as described in Section III.A and residual returns are extracted as specified in regression (3) to provide a high-frequency measure of expected decarbonization investments. The sample period is 2018.01 to 2022.12.

Columns (5) to (8) show the same regressions, but estimated over the period 2013-2017, when average carbon prices were very low. In periods when carbon price levels are negligible, neither carbon price returns nor changes in carbon price uncertainty should have an impact on polluters' decarbonization decisions and thus on solution providers' stock returns. For example, when EU ETS carbon prices were around EUR 7 per ton of carbon emissions, BloombergNEF (2015) reported that *"to date, [the carbon price] has simply been too volatile and weak to bank investments on."* As a result, estimating the regressions over this period provides a 'placebo test' in which we would not expect to find strong relationships between carbon price returns and uncertainty and expected decolonization investment. Indeed, we find all estimates over this period to be small in magnitude and statistically insignificant.

Graphical Representation of Results. To obtain a graphical representation of our results from Table VI, we extract carbon solution providers' residual returns by estimating the following regression at the weekly level:

$$R_{i,t} = \mathrm{X}_{i,t} + \psi_i + \delta_{ind(i)\times c(i)\times t} + \epsilon_t^i. \tag{3}$$

Carbon solution providers' residual returns are the ϵ_t^i of firms that we identify as carbon solution providers in Subsection III.B. They capture each firms' weekly stock return that is not explained by security fixed effects (ψ_i), country $\times$ industry $\times$ week fixed effects ($\delta_{c(i)\times ind(i)\times t}$), or controls for equity- and energy-market betas ($\mathrm{X}_{i,t}$). As a result, carbon solution providers' residual returns capture additional news about these firms' expected cash flows, for example from changes in expected decarbonization investments. Figure 6 provides a binscatter plot of the average residual

product of the standard deviation of carbon price returns (0.06) and the average carbon price (EUR 40).

Table VII: Regression: Carbon Solution Stock Returns, Additions

	(1)	(2)	(3)	(4)	(5)	(6)
Carbon Solutions × Carbon Price Return	10.41***	8.96*	8.69**	6.38**	1.22	17.83***
	(2.65)	(1.83)	(1.96)	(2.06)	(0.85)	(2.88)
Carbon Solutions × Carbon VIX Change		-10.81**	-12.42**	-9.19***	-2.56**	-17.30***
		(-1.96)	(-2.37)	(-2.88)	(-2.16)	(-4.01)
Carbon Solutions × CIV Change	-15.10***					
	(-3.72)					
Carbon Solutions × Carbon Vol. Change						-11.28
						(-1.53)
Fixed Effects	Y	Y	Y	Y	Y	Y
Firm Size Restriction	\$100m	None	\$100m	\$100m	\$500m	\$100m
Frequency	week	week	week	week	day	week
Winsorized RHS	Y	Y	N	Y	Y	Y
Winsorized LHS	N	N	N	Y	N	N
Observations	535k	1,110k	535k	535k	976k	535k
R2-Adjusted	0.27	0.07	0.27	0.30	0.32	0.27

Note: This table presents regression estimates of Equation (2). We regress weekly stock returns of European firms on a carbon solution firm indicator interacted with various variables. The carbon solution firm indicator captures the union of our our three measures. Columns (1) to (3) contain our baseline regression, but (1) uses CIV changes instead of CVIX changes, (2) does not subset firms by market capitalization, (3) does not winsorize independent variables, (4) winsorizes stock returns at percentiles 2.5 and 97.5, (5) uses all variables at the daily level, and (6) adds an interaction with the change in lagged realized carbon return volatility. Explanatory variables are standardized to zero mean and unit variance. The firm size restriction states the lagged equity market capitalization in million dollars below which we drop return observations. We add controls for exposure to both equity and energy markets, via fixed effects for date × lagged beta deciles (see Table VI for details). Further, we add fixed effects by stock ID (firm) and $date \times industry \times country$. Standard errors are double clustered by $firm$ and $week \times industry \times country$, and t-stats are presented in parentheses.

returns against carbon price returns and *Carbon VIX* changes. The significantly negative relationship between *Carbon VIX* changes and carbon solution providers' residual returns is visible in the right panel of the figure. Beyond visualizing our regression results, an additional benefit of extracting the residual returns is that these returns might be useful in related research: carbon solution providers' residual returns should covary with *any* variable that impacts (decarbonization) investments into the goods and services provided by our carbon solution firms. We provide the residual return series at `www.carbonvix.org.`

Robustness Tests. The finding that carbon solution provider's (relative) stock returns decline with increases in carbon price uncertainty is robust to various adjustments to the regression specifications. Table VII displays the results of robustness checks, where carbon solution providers are identified as in column (4) of Table VI.

Column (1) uses changes in Carbon Implied Volatility instead of changes in the *Carbon VIX* to proxy for innovations in carbon price uncertainty. Column (2) does not exclude firms below \$100 million lagged market capitalization. Column (3) does not winsorize the right-hand-side variables.

Column (4) also winsorizes stock returns at the 2.5^{th} and 97.5^{th} percentiles. Our core results are highly robust to these variations. Column (5) estimates regression (2) at the daily instead of the weekly level. While stock returns are more noisy at higher frequencies, the basic relationships generally survive in this sample, though the statistical significance of the carbon return effect declines. The smaller absolute coefficients of the point estimates are largely due to the smaller standard deviations of daily vs. weekly returns.

Berger et al. (2020) show that many relationships that are often attributed to changes in expected volatility are in fact related to changes in realized volatility, which comoves with expected volatility. To see whether this might also be the case in our setting, column (6) also interacts the carbon solution firm indicator with the weekly change in *realized* past carbon price return volatility, measured as the daily volatility over the previous 120 days. The insignificant coefficient on realized volatility changes in column five shows that, in our setting, it is truly uncertainty about future carbon prices that affects the stock returns of carbon solution providers.

III.D. Carbon VIX and Carbon Solutions Providers' Sales

While the previous analysis of carbon solution providers' stock returns exploits the high-frequency nature of the *Carbon VIX* and addresses the problem of time-alignment between measured carbon price uncertainty and firm investment decisions, the evidence remains indirect, since stock returns capture changes in investors' expectations, instead of changes in realized variables. We next address this issue by regressing carbon solution providers' sales onto carbon price uncertainty. If carbon price uncertainty reduces aggregated decarbonization investments, then carbon solution providers' sales should correlate negatively with the level of the *Carbon VIX*.

Regression Specification. We explore the effect of carbon price uncertainty on firms' sales by estimating the following regression specification:

$$\frac{Sales_{i,t}}{Assets_{i,t}} = \beta_1 CarbSol_i \times EUA_{i,t} + \beta_2 CarbSol_i \times CarbonVIX_{i,t} + \mathrm{X}_{i,t} + \psi_i + \delta_t + \epsilon_t^i. \quad (4)$$

where $Sales_{i,t}$ are the sales of firm i in quarter t, $Assets_{i,t}$ are the assets of firm i in quarter t, $CarbSol_i$ is an indicator whether firm i is a carbon solution provider, $EUA_{i,t}$ is the mean level of the EUA price over the respective firms' reporting period and $CarbonVIX_{i,t}$ is the average level of the Carbon VIX over the same period. $\mathrm{X}_{i,t}$ contains controls for other market variables, which we describe below. We add fixed effects by firm (ψ_i), reporting quarter (δ_t), and firm $\times$ QuarterOfYear to capture firm-specific seasonality in sales. For ease of interpretation, all variables are normalized to have zero mean and unit variance. Standard errors are double clustered by firm and *quarter* $\times$ *country*. To reduce the impact of outliers, all explanatory variables are winsorized at the 2.5^{th} and 97.5^{th} percentile.

We obtain firm-level characteristics from Compustat Global, as described in subsection III.B. Since the high-price sample spans a relatively short four-year period, we focus on quarterly sales to ensure sufficient within-firm variation over time; we thus restrict the sample to firms that report on a quarterly basis. This restriction is consistent with prior work using similar data (e.g., Barrot

Table VIII: Regression: Carbon Solution Providers' Sales

	(1) All	(2) All	(3) All	(4) All	(5) Sol.
Carbon Solutions	-0.014	-0.005	-0.000	-0.017	-0.004
× Carbon Price	(-0.86)	(-0.23)	(-0.01)	(-0.81)	(-0.34)
Carbon Solutions	-0.022**	-0.019**	-0.018**	-0.025***	-0.016**
× Carbon Price Uncertainty	(-2.45)	(-2.57)	(-2.13)	(-2.73)	(-2.32)
Carbon Solutions		-0.011	-0.010		
× Oil Price		(-1.08)	(-0.59)		
Carbon Solutions		0.000	-0.001		
× Oil Price Uncertainty		(0.03)	(-0.13)		
Stock ID (Firm)	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes
ID × Quarter Of Year	No	No	Yes	No	No
Winsorized Sales	No	No	No	Yes	No
Observations	34,286	34,286	32,931	34,286	25,658
R2-Adjusted	0.318	0.318	0.182	0.908	0.296

Note: This Table presents regression estimates of Equation (4). We regress quarterly sales per assets of European firms on the interactions between a carbon solution indicator and carbon price as well as the interaction of the carbon solution indicator and *Carbon VIX*. Columns (1) to (4) identify carbon solution firms as the union of the three measures discussed in subsection III.B, while column (5) identifies carbon solution firms via our novel survey evidence. In column (4) sales per assets are winsorized at percentile 95. We restrict the sample to the high carbon price period of 2018.01 to 2022.12. Variables are standardized to zero mean and unit variance. We add controls for exposure to both equity and energy markets, via the interaction of the carbon solution indicator with the Oil Price and the Oil VIX. Further, we add fixed effects by stock ID (firm), *quarter* and $ID \times Quarter\ Of\ Year$. Standard errors are double clustered by $firm$ and *quarter* × *country*.

et al., 2024; Froot et al., 2017). Section A.4 provides further details on sales and asset variables.

Results. Table VIII reports estimates from Equation 4 for the high-price sample. Column (1) shows that a one-standard-deviation increase in the Carbon VIX is associated with a 0.022-standard-deviation decline in carbon solution providers' sales-to-assets ratio relative to other firms. Quantitatively, for a firm with EUR 1 billion in assets, a 6.6-point increase in the Carbon VIX corresponds to a relative reduction in sales of roughly EUR 22 million.[21]

Column (2) adds controls for the oil price level and oil-price uncertainty (OVX). The estimated effect of carbon price uncertainty remains largely unchanged, indicating that exposure to energy markets does not explain the covariance between carbon solution firms' sales and carbon price uncertainty. Column (3) introduces the most restrictive specification, including firm-quarter fixed effects constructed as the interaction of firm identifiers with $Quarter\ Of\ Year$. $Quarter\ Of\ Year$ denotes the calendar quarter and is defined independently of each firm's fiscal reporting cycle. Consequently, $ID \times Quarter\ Of\ Year$ does not absorb all firm-level quarterly variation but instead controls for seasonal patterns in sales. Including these fixed effects has little impact on

[21] The standard deviation of the Carbon VIX is 6.6, the regression coefficient on sales-to-assets is 0.022, and the standard deviation of sales-to-assets is 1. Thus, a 6.6-point increase in the Carbon VIX implies a 0.022 × 1 = 0.022 decline in sales-to-assets.

the estimated coefficients, suggesting that seasonal fluctuations in sales do not drive our results.

Section A.4 documents large positive skewness in firms' sales-to-assets ratios, raising the concern that our regression results might be influenced by outliers. Column (4) addresses this issue by winsorizing sales-to-assets at the 95th percentile across firms. The resulting estimates are slightly larger and more significant. Column (5) uses our novel survey-based measure to identify carbon solution providers and yields similarly robust results. Together, these findings indicate that our conclusions are not driven by outliers or by the specific definition of carbon solution providers.

In conclusion, the evidence from firms' sales aligns closely with the findings based on firms' survey-reported decarbonization investments and their stock returns: increases in carbon price uncertainty appear to reduce aggregate spending on decarbonization activities. Although the sales-based estimates are consistent with our proposed mechanism, they face the same time-alignment concern discussed in Section II. In particular, it is unclear how carbon-market variables should be lagged to ensure that investment responses are correctly mapped into subsequent sales outcomes. This time-alignment issue may also help explain why the regression does not yield a significantly positive effect of the carbon price level on carbon-solution providers' sales—a pattern that mirrors the challenge observed when examining completed decarbonization investment data.

Overall, evidence on the negative effects of carbon price uncertainty on decarbonization investment is consistent across three independent data sources: survey responses on firms' actual investments, stock returns, and sales data from carbon-solution providers.

IV. Conclusion

A common policy approach to reducing aggregate carbon emissions is to limit total emissions through cap-and-trade schemes. The resulting equilibrium carbon price, however, is inherently uncertain, reflecting fluctuations in the future supply of and demand for emission permits. This paper provides new evidence on the magnitude and economic effects of such carbon price uncertainty in the EU ETS, the world's largest cap-and-trade system. We construct novel, high-frequency measures of carbon price uncertainty and use them to show that heightened uncertainty delays firms' decarbonization investments.

These findings have important policy implications. Most importantly, policymakers may wish to account for the adverse effects of uncertainty when designing carbon-pricing mechanisms aimed at promoting decarbonization. Such uncertainties could be mitigated institutionally—for example, by providing clearer guidance about future policy adjustments—or through market-based instruments such as explicit carbon price floors or ceilings. We leave to future research the question of how to optimally design such interventions to improve the performance of carbon-pricing schemes. To facilitate further work, we make our high-frequency measures of carbon price uncertainty and expected decarbonization investments publicly available at `www.carbonvix.org`

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Carbon VIX: Carbon Price Uncertainty and Decarbonization Investments

Appendix

Section A.1 contains further details on the data and the onstruction of variables. Section A.2 describes the construction of the CDP-survey sample. Section A.3 includes additional information on firm descriptions and GPT-prompting for the identification of carbon solution providers. Section A.5 provides supplementary tables and Section A.6 provides additional figures.

A.1. Markets

A.1.A. EU ETS Derivatives — Additional Information

We obtain daily settlement prices of futures on EU carbon emission allowances (EUA) traded on the London Intercontinental Exchange (ICE) from Bloomberg. For carbon prices we consider the closest-to-maturity December-futures contract, since December EUA futures are typically the most liquid and close-to-expiry contracts are less sensitive to time-varying risk premia (Känzig, 2023; Baumeister and Kilian, 2016).

We obtain daily data on EUA futures options from IVolatility. The sample is 2013.09 to 2022.12. The data include contract details, like expiry-date and strike price, as well as the daily settlement price, volume and open interest at the contract level. We use the daily settlement price as the options price. The full sample includes 4,281,336 observations. We exclude options with a negative time value, which we observe for 3.2% of the data.

Between 2019 and 2020, the EUA options' daily settlement style changed. Before 2019.03, EUA futures options on ICE were settled in the standard way: At the time of purchase, the options' buyer pays the purchase price to the options' seller. The options seller has to maintain a margin account with the clearing house to reduce counterparty credit risk. After 2020.12, EUA futures option on ICE are settled similar to futures contracts: At the time of purchase, no money is transferred between buyer and seller. Instead, the purchase price and any option payoff are aggregated and paid at option expiry. In the meantime, both option buyer and seller maintain a margin account with the clearing house. Between 2019.03 and 2020.12 both types of options traded in parallel. We adjust option prices for futures-style settlement by discounting them at the risk-free rate. Alternatively, we discount option prices at the futures yield. The difference between the two approaches is not perceptible in CVIX or CIV.

A.1.B. The Carbon VIX — Additional Information

Following CBOE (2023) we construct the Carbon VIX as

$$CarbonVIX_t^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q\left(K_i\right) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2, \tag{A.1}$$

where $CarbonVIX_t^2$ is the squared level of the Carbon VIX at time t, T is the time to expiry (in years) for the respective options, F is the option-implied forward price, K_0 is the first strike price equal to—or otherwise immediately below—F, ΔK_i is the difference between two strike prices

(EUR 0.5 for EUA futures options), R is the risk-free interest rate to expiration, and $Q(K_i)$ is the options' price. See CBOE (2023) for a step-by-step guide through the VIX methodology. CBOE obtains option prices as the mid-point between each option's bid- and ask quote. We use the option's daily settlement price instead.

The Carbon VIX portfolio payoff is equal to EUA futures' variance if an infinite number of options strikes is available. EUA Options strike price interval is EUR 0.5 and we find options liquidity that extends beyond 30% moneyness. Thus, at least in the recent sample, there are more than 80 liquid strike prices available to form the Carbon VIX portfolio.

We apply equation (A.1) on the range of EUA options with just below (above) 120 days to expiry to obtain $CarbonVIX_t^{120,-}$ ($CarbonVIX_t^{120,+}$). Subsequently, we linearly interpolate between the two measures via

$$CarbonVIX_t = CarbonVIX_t^{120,-} + \frac{CarbonVIX_t^{120,+} - CarbonVIX_t^{120,-}}{\tau_t^{120,+} - \tau_t^{120,-}} \times (120 - \tau_t^{120,-}), \tag{A.2}$$

where $\tau_t^{120,-}$ ($\tau_t^{120,+}$) is the time to expiry, in number of calendar days, for the options with just below (above) 120 days to expiry. Thus, we obtain $CarbonVIX_t$ as a daily uncertainty measure with a constant 120 calendar day horizon throughout our sample.

A.1.C. Carbon Option Implied Volatility — Additional Information

We construct an alternative measure of carbon price uncertainty from the implied volatilities of at-the-money options. We call this measure "Carbon Implied Volatility" (hereafter, CIV). In constructing the measure we follow Cremers et al. (2021): For every day t, among the options with just below 120 days to expiry, we pick the put-call option pair whose strike price is just below the current spot price of the December EUA futures contract and the put-call option pair whose strike price is just above the current spot price of the December EUA futures contract. We denote the equal-weighted average over those four options' implied volatilities as $CIV_t^{120,-}$. The same procedure for the options with just above 120 days to expiry yields $CIV_t^{120,+}$. To obtain CIV_t we linearly interpolate between $CIV_t^{120,-}$ and $CIV_t^{120,+}$ following equation A.2.[22]

We calculate EUA options' implied volatilities via the options pricing model from Black (1976), which is a common choice for the pricing of options on futures contracts. Standard option pricing models, like the model applied here, cannot be solved for σ_t analytically. That is, there is no formula to link the current market price of the option P_t to the expected return volatility of the underlying σ_t that justifies this price. Instead, we find σ_t numerically.

Relative to CVIX, CIV has the advantage of being based on implied volatilities, the expected underlying volatility (under the model assumptions). This is what we want. The disadvantage is that implied volatilities require an option pricing model. Thus, CIV is not model-free. Another distinction is that CIV is based only on at-the-money options, while VIX-based measures can be sensitive to option price activity in the tails (Griffin and Shams, 2018). Our central results are robust to the measurement of carbon price uncertainty via either CVIX or CIV, and the two measures display a correlation above 98% in levels and 95% in weekly changes.

[22] If an options chain has exactly 120 days to maturity we choose only that chain and thus calculate CIV as the average of the four implied volatilities.

A.1.D. Other Data — Additional Information

We obtain data on European risk-free rates from OptionMetrics. We obtain data on stock prices and firm characteristics from Compustat Global via the code from Jensen et al. (2023). To obtain large exposure to European economic activity we subset to securities that are listed in a country of the European Economic Area as of January 2024. This subsetting yields a sample of 29 countries (there are no data for Liechtenstein). Table A.15 lists the countries in our sample. We follow the "suggested screens" by Jensen et al. (2023), which involves subsetting to common stocks, primary securities and prominent exchanges. Further, we subset to firms with a lagged equity market capitalization above $100 million. We consider only observations where all necessary characteristics are available for the respective period. We drop weekly returns above 500% or below -80%.

We obtain data on equity indices and energy markets from Bloomberg. Table A.1 provides the tickers. We measure European equity index returns via the Euro Stoxx 50 return index. One major advantage of the Euro Stoxx 50 is that it functions as the underlying for extremely liquid options contracts, which in turn yield a widely used uncertainty index: the VStoxx. The VStoxx employs the VIX method to measure expected return volatility in the Euro Stoxx 50. We measure oil prices via Bloombergs' generic Brent futures contract and oil price uncertainty via the OVX index. The OVX index employs the VIX method and is based on options on a U.S. oil ETF.

Where necessary, market returns are translated from USD to EUR via equation A.3:

$$r_{t+1}^{EUR} = \frac{P_{t+1}^{USD} \times E_{t+1}}{P_t^{USD} \times E_t} - 1, \tag{A.3}$$

where r_{t+1}^{EUR} is the Euro net return from t to $t+1$, P_t^{USD} is the asset price in USD at the end of period t and E_t is the spot exchange rate in EUR per USD. Thus, all returns are from the perspective of a European investor investing in Euro terms.

A.2. Survey data

We construct a sample of firms' self-disclosed decarbonization initiatives from survey data collected by CDP. We combine survey vintages 2015—when CDP first asked to report decarbonization activities by emission scope type—through 2023. CDP provides unique firm-identifiers for each response that allows us to track firm-level information across survey vintages. We collect information on firms' country of origin, industry, sector, and ISIN (CDP items country, primary industry, primary sector, and primary ISIN). CDP's industry classification changed after its 2017 survey. We use the more granular industry information provided from 2018.[23] Throughout our analysis, we remove firms in the financial services sector. In case firms' country or industry classifications change across survey vintages, we assign the most frequent provided information.

For information on investment in decarbonization projects, we collect firms' disclosures on initiatives to reduce their carbon emissions. In each annual survey vintage, respondents are asked to *"provide details on the [emissions reduction] initiatives implemented in the reporting year in the table below"*. Corresponding details are provided in CDP sub-question CC3.3b for vintages 2015–2017 and C4.3b for vintages 2018–2023. Among others, firms can choose to provide an activity

[23] In few cases where firms stopped reporting to CDP after 2017, we assign industries based on the most common mapping of old to new industries derived from firms reporting in vintages of both before and after 2017.

type, the emission scope for which reductions occur, the required investment, a textual description of the initiative, and a comment section to detail additional information.

We first sort firms' initiatives in categories of decarbonization activities. The category of firms' decarbonization activities is based on their provided information in CDP column "activity type". In 2020, CDP renamed the field to "initiative category & initiative type_g". Most survey respondents select the type of initiative based on pre-defined categories but also have the option to specify individual initiative types. In addition, the categories defined by CDP change slightly across survey vintages. For example, the definitions of "Energy efficiency: Building services" and "Energy efficiency: Building fabric" merged to "Energy efficiency in buildings" in 2020. Based on these definitions, we sort initiative types into seven broad categories: *low carbon energy*, *process efficiency*, *waste*, *building efficiency*, *transportation*, *company policy or behavioral change*, and *product design*. Table A.9 presents a mapping of CDP activity types to corresponding categories. Where possible, we also add initiative types provided via free-text based on a simple search of related keywords. We cannot assign a category for $< 1\%$ of initiative categories; they become *other*.

Firms often provide the required investment amount in their respective currency. We convert investment values into EUR using annual exchange rates of 41 major currencies from the OECD (2023) exchange rates database. We match values on currencies specified by firms (CDP sub-question C.04) based on the year prior to the survey publishing year which marks the end of the reporting period for the vast majority of respondents. We disregard investments in currencies that we are unable to match to exchange rates. The most frequent carbon abatement investments not matched to exchange rates are denominated in TWD, THB, PHP and MYR. As CDP does not validate any information reported, the investment amount provided may be prone to errors. We therefore remove extreme outliers where the investment amount of individual projects exceeds 50% of total industry-level investment. This removal affects a total of four projects or less than 0.1% of all scope-1 projects with positive investment value.

A.2.A. A panel of decarbonization investment

We construct a firm-level panel of decarbonization investment by aggregating individual project investment at the firm and survey year levels. Within every survey vintage and for each firm, we retrieve the period for which the firm is reporting data (CDP sub-question C02.2 for survey vintages 2018–2023).[24] In case a firm provides data for multiple reporting periods, we use the most recent one. We remove observations with invalid reporting periods where (1) reporting period start is after the reporting period end (2) the length of the reporting period is outside of the 250–450 day range (3) the year of the reporting date-end is greater than the year in which the survey was conducted (4) the reporting period ends more than three years before the year in which survey was conducted (5) the reporting period in a given survey vintage overlaps by more than 95 days with the reporting period of the previous year's survey. In total we remove 123 observations, fewer than 1% of all firm-year observations.

Next, we construct $Exposure_i$, an indicator of firms' exposure to carbon pricing that is based on a CDP question asking to *"select the carbon pricing regulation(s) which impacts your operations"* (sub-question C11.1a). The indicator is equal to one if the answer includes *European Union ETS*

[24] In our panel of decarbonization investments, we only consider data reported for years 2018–2023, see Section II in the main text.

or *EU ETS* and the firm disclosed corresponding positive verified Scope-1 emissions (sub-question C11.1b) in any of the CDP vintages.[25]

Finally, we merge firm-level financial data from Moody's Orbis database via the end date of the reporting period in CDP and the financial year closing date in Orbis as well as ISIN-identifiers provided in both datasets.[26] Orbis includes financial information at different consolidation levels from either annual reports or local registry filings. At the firm level, we choose data sources ranked by (1) highest data availability, (2) consolidated statements—as CDP disclosures are mainly based on consolidated information—and (3) annual report filings. After obtaining the Orbis items total assets, tangible fixed assets, long term debt, EBIT, and depreciation and amortization our final panel consists of 4,098 non-missing firm-year observations.

A.2.B. Project descriptions

To identify common climate solutions through carbon abatement, we collect textual project descriptions of implemented carbon abatement initiatives reported in CDP vintages 2015–2023.[27] We only consider scope-1 emission reduction initiatives with positive investment amounts. The project descriptions are primarily based on firms' responses to "description of initiative," where firms typically provide a high-level summary on the nature of the emission reduction activity. From 2018, CDP allows to select from some pre-defined descriptions such as *solar hot water* or *landfill methane capture* in addition to a free-text response option. From the 2020 vintage, CDP renamed "description of initiative" to "initiative category & initiative type" while preserving similar pre-defined descriptions and free-text response options. Firms make extensive use of the possibility to individually describe their decarbonization activities. About 40% of all project descriptions are provided via free text. In some cases firms provide no description of initiatives or invalid inputs such as empty strings. If firms provide a free-text response in the comment section, we instead rely on the comment for the corresponding project description. Table A.8 provides stylized, GPT-generated examples of project descriptions along with the corresponding category and type of decarbonization activities.

A.3. Identifying carbon solution providers — Additional Information

A.3.A. Firm descriptions

We obtain firm descriptions from Moody's firmographics database. Moody's collects and combines firm-level descriptions of business activities from various public and non-public sources such as annual reports or local registry filings, standardizes them in a common format, and translates its information to English language. The data are a single cross section of firms as of January 2024. We remove descriptions of firms in the banking, insurance & financial services sectors and limit the sample to firms incorporated in countries of the European Economic Area.[28] We include both

[25] In 2017, the EU and Switzerland agreed to link their emission trading systems. We therefore also include firms reporting compliance obligations to the Swiss ETS.

[26] 35% of firms representing 95% of total decarbonization investment provide ISIN-identifiers. In case an ISIN is not provided in a given survey vintage, we backfill this information from more recent data. For about 1% of firms where we cannot match ISINs to valid Orbis identifiers, we hand match firms based on firm name and location.

[27] Like other details on decarbonization activities, project descriptions are based on CDP sub-questions CC3.3b for vintages 2015–2017 and C4.3b for vintages 2018–2023.

[28] As of January 2024 these are 27 EU countries plus Iceland, Liechtenstein, and Norway.

active and inactive firms and use the 'Quoted' indicator to limit the sample to listed firms only. We then match gvkeys to isin codes provided by Moody's and only keep descriptions of firms with valid isin-gvkey matches.

We combine Moody's data on products and services that contain textual information about specific products and services offered by the firm with corresponding trade descriptions that include a curated narrative about the firm's business model. For descriptions of products offered, we prefer information from column "main products and services" and in rare cases fill empty values from "products and services". Trade descriptions are based on the version that is translated into English from its original language. We concatenate product and trade descriptions in the format: "Product and Services: [*product and services description*]. Business Model: [*trade description*]". We clean firm descriptions by removing source indicators such as "[source: Bureau van Dijk]", line breaks, or redundant whitespace. Finally, we remove observations where firm descriptions are less than 10 words.

A.3.B. GPT4

To identify carbon solution providers based on textual firm descriptions, we use OpenAI's API that allows for detailed control of GPT4's behavior such as access to various model parameters or the option to apply certain prompt engineering techniques outlined below.[29] Our analysis is based on the chat completion module of OpenAI's API that enables access to GPT4 via a system role that controls overall model behaviour as well as user and assistant roles resembling user prompts and GPT4 responses, respectively. We first provide general instructions on how to identify carbon solution providers via GPT4's system role:

Enclosed in triple quotes ("""), you will be provided with an unstructured description of a firm's business model and its products and services offered. Based on this firm description, your task is to determine whether the firm is a 'climate solution' firm. Return "true" only if all three criteria below are satisfied:
1: The business model is based on climate solutions.
2: The majority of products and services are related to climate solutions.
3: The climate solutions offered help other firms to reduce their climate impact and are not lifestyle products offered to retail customers such as smart home appliances, electric scooters or bikes.
Below you find a list of examples of climate solutions separated by ";". In case the firm provides climate solutions, return the climate solutions found in the firm description in the format: [Format Specification].
Examples of climate solutions: [List of Climate Solutions]

The system instruction includes (1) a description of the type of input to expect, (2) the key objective to identify carbon solution firms, (3) a set of criteria based on carbon solutions that define a carbon solution firm, (4) examples of carbon solutions, and (5) a description of the desired output format.[30] For examples of carbon solutions, we provide a list of the 50 most frequent solutions identified from carbon abatement projects in Section III and displayed in Figure 5.

Next, we provide a limited amount of stylized firm descriptions along with desired output as

[29] Since model version gpt-4-1106-preview, OpenAI allows for reproducable output via a seed parameter. We set seed to 1. However, reproducable output is not guaranteed if, for example, OpenAI decides to change backend model configurations.

[30] We require an output in structured form by providing the following format specification: "*climate_solution1; climate_solution2. In case the firm does not provide climate solutions, return an empty string: "". Return your answer in the following JSON format:*{*"is_opportunity":true, "climate_solution":"climate_solution1; climate_solution2"*}."

part of a so called "few-shot" prompting technique. Providing examples via few-shot prompting allows for context-based learning and helps to condition GPT4 to produce reliable output and thus avoids the need for resource intensive fine-tuning (Brown et al., 2020). We consider seven examples of firm descriptions: four examples of carbon solution providers and three negative examples that are designed to contextualize expected input-output outcomes. Table A.13 presents the examples and—for firm descriptions of carbon solution providers—the corresponding carbon solutions. We provide examples of firm descriptions via the user role and corresponding desired output via the assistant role mimicking a GPT4 response. Finally, for each firm analyzed, we add its description of business activities enclosed in triple quotations along with a reminder to follow the system instructions.

A.4. Firm Sales

This section provides additional evidence on the sales and asset distributions of the European firms in our sample. Table A.16 reports summary statistics for the variables used in the sales regressions of Section III.D, focusing on the high-price sample from 2018 to 2022. Average firm sales amount to EUR 2.03 billion, with a median of EUR 90 million, indicating substantial positive skewness. A similar pattern holds for total assets, which have a mean of EUR 11.63 billion, a median of EUR 170 million, and a skewness of 17.94. The primary dependent variable, sales-to-assets, exhibits a lower standard deviation but even more pronounced skewness than sales or assets individually. This skewness raises the concern that the estimates reported in Section III.D might be influenced by outliers. Table VIII column (4) addresses this concern by estimating Equation 4 after winsorizing the sales-to-assets ratio at the 95th percentile. This adjustment mitigates the influence of extreme positive outliers in firm performance. Results remain virtually unchanged. Hence, the estimated effects are not driven by outliers, reinforcing the robustness of our main findings.

A.5. Tables

Table A.1: Variable definitions

Variable	Definition	Unit	Source
Panel A: Markets			
Carbon VIX	Carbon Price Uncertainty Index	%	Subsection I.D
CIV	Alternative Carbon Price Uncertainty Index	%	Subsection I.E
Carbon Price	Settlement price of EUA Futures December front contract	EUR	IVolatility
Equity Price	Total return index of Euro Stoxx 50	EUR	Bloomberg Ticker: SX5GT
Equity VIX	VSTOXX index based on Euro Stoxx 50	%	Bloomberg Ticker: V2TX
Oil Price	Settlement price of Brent crude oil futures front contract	EUR	Bloomberg Ticker: CO1
Oil VIX	OVX index based on crude Oil ETF	%	Bloomberg Ticker: OVX
Panel B: Firm Financials			
DIR	Ratio of total decarbonization investment to scope-1 emissions	EUR/ tCO2e	CDP
Scope-1	Reported scope-1 emissions	tCO2e	CDP
Total Assets	Total assets	EUR	Moody's Orbis
ROA	EBIT divided by total assets	%	Moody's Orbis
Leverage	Long term debt divided by total assets	%	Moody's Orbis
Capex	Change in tangible fixed assets plus and depreciation and amortization divided by total assets	%	Moody's Orbis

Table A.2: Contract Specifications of EU Emission Allowance Derivatives

Contract	**EUA Futures**	**EUA Futures Options**
Underlying	EUA	December Future of the relevant year
Contract Series	Up to 7 December, 9 quarterly,	Up to 7 December, 9 quarterly,
	3 August, 2 monthly contracts	3 August, 2 monthly contracts
	No contracts beyond Dec. 2030	No contracts beyond Dec. 2030
Expiry	Last Monday of contract Month	3 business days before futures expiry
Strikes		Min. 5 strikes above and below the at-the-money strike, in €0.50 intervals
Option Style		European
Settlement	Daily marked-to-market	2006.11 to 2020.12: Standard 2019.03 onwards: Futures Style
Min Trade Size	1 lot (= 1000 EUA = 1000 tons CO2)	1 lot
Tick Value	€10.00	€5.00
Trading Hours	0700 to 1700 (London time)	0700 to 1700 (London time)

Note: This table summarizes the contract specifications for EU carbon allowance futures and EU carbon allowance futures options. Standard margin: Buyer pays the option premium at purchase, while the seller provides a daily margin. Futures-style margin: Both buyer and seller provide a daily margin, as is typical for futures contracts.

Table A.3: EUA Options Implied Volatility

		Days to Expiry				
		10-30	31-120	121-240	241-	All
				Calls		
$0.0 \leq F/K \leq 0.7$	Deep Out Of The Money	112.5	70.1	55.3	50.1	60.8
$0.7 < F/K \leq 0.9$	Out Of The Money	56.4	52.1	50.7	48.2	49.3
$0.9 < F/K \leq 1.1$	At The Money	54.7	52.5	51.4	48.5	49.5
$1.1 < F/K \leq 1.3$	In The Money	66.8	58.5	54.5	49.7	51.7
$1.3 < F/K$	Deep In The Money	127.0	95.1	80.1	62.0	70.8
All		111.6	77.4	62.4	53.4	62.4
				Puts		
$0.0 \leq K/F \leq 0.7$	Deep Out Of The Money	204.2	114.4	79.7	58.9	73.1
$0.7 < K/F \leq 0.9$	Out Of The Money	67.8	58.3	54.3	49.5	51.5
$0.9 < K/F \leq 1.1$	At The Money	54.7	52.5	51.4	48.5	49.5
$1.1 < K/F \leq 1.3$	In The Money	56.1	52.2	50.8	48.3	49.4
$1.3 < K/F$	Deep In The Money	71.9	64.2	54.9	49.9	54.3
All		120.7	77.7	61.0	52.0	58.5

Note: EUA futures options implied volatilities, split by option contract type. Different rows correspond to different values of "moneyness", where F is the strike price, and K is the current spot price. Different columns correspond to different option expiration dates. Implied Volatilities are from Black's futures options pricing model for futures options. We describe the procedure in section A.1.C. The sample period is 2013.9 - 2022.12.

Table A.4: EUA Options Open Interest

		Days to Expiry				
		10-30	31-120	121-240	241-	All
				Calls		
$0.0 \leq F/K \leq 0.7$	Deep Out Of The Money	2.3	10.3	12.3	13.8	38.8
$0.7 < F/K \leq 0.9$	Out Of The Money	1.5	6.9	6.0	5.5	19.9
$0.9 < F/K \leq 1.1$	At The Money	1.8	6.9	6.0	6.0	20.7
$1.1 < F/K \leq 1.3$	In The Money	1.2	4.1	3.9	3.2	12.4
$1.3 < F/K$	Deep In The Money	0.8	3.2	3.0	1.3	8.3
All		7.7	31.3	31.2	29.8	100.0
				Puts		
$0.0 \leq K/F \leq 0.7$	Deep Out Of The Money	5.2	18.6	17.6	14.9	56.3
$0.7 < K/F \leq 0.9$	Out Of The Money	3.3	10.9	8.0	6.6	28.8
$0.9 < K/F \leq 1.1$	At The Money	1.4	4.4	2.9	2.6	11.3
$1.1 < K/F \leq 1.3$	In The Money	0.2	0.9	0.6	0.5	2.3
$1.3 < K/F$	Deep In The Money	0.2	0.7	0.3	0.3	1.4
All		10.4	35.5	29.4	24.8	100.0

Note: EUA futures options open interest (by number of contracts) in percent of the sample total, split by option contract type. Different rows correspond to different values of "moneyness", where F is the strike price, and K is the current spot price. Different columns correspond to different option expiration dates. The sample period is 2013.9 - 2022.12.

Table A.5: Carbon VIX and Events: Descriptions and Sources

Date	Event	Description	Source
Nov-2013	Back-loading	A majority of Member States endorsed a mandate to start negotiations with the European Parliament on the back-loading proposal	EU Commission
Jan-2014	EU ETS Reform	Commission launches second step to reform the EU ETS	EU Commission
Feb-2016	Calls to align with Paris targets	Corporate lobby groups and member of EU parliaments call for tighter EU ETS cap to align with Paris targets	Carbon Pulse IDs 15778, 15650, 16207
Dec-2016	Vote for tighter supply	EU Parliament's ENVI votes for more ambitious ETS reform package	Carbon Pulse ID 28148
Dec-2018	Market Stability Reserve	Much of the volatility has been linked to speculative options buying, which in turn stems from investors betting on big gains ahead of the January launch of the MSR.	Carbon Pulse ID 64645
Mar-2020	Covid-19	Measures to combat Covid-19 lead to market turmoil	Carbon Pulse ID 94852
Mar-2022	Ukraine war	High energy prices due to uncertainty about Russian gas supply	Carbon Pulse ID 152973
Sep-2022	Energy crisis	Proposal to release EUR 20 billion out of stability reserve as part of REPowerEU to decrease EUA price in light of high energy prices resulting from energy crisis	EU Commission

Note: Market events around spikes of *Carbon VIX* are collected from the websites of the European Commission `https://ec.europa.eu/commission/presscorner`, `https://climate.ec.europa.eu/news-your-voice/news/`, and Carbon Pulse `https://carbon-pulse.com/`. Carbon Pulse article IDs in the source column correspond to articles accessible via *carbon-pulse.com/[ID]/*.

Table A.6: Market Summary Statistics

	Mean	Median	Std	AR1	Skew	Kurt
Equity Price	1,345.11	1,327.07	233.75		0.50	2.38
Equity VIX	20.69	19.27	7.49		2.27	13.03
Oil Price	58.95	55.68	18.48		0.73	3.22
Oil VIX	38.64	35.63	18.87		3.62	24.72
Equity Price Return	0.20	0.32	2.31	-2.02	-0.24	3.03
Equity VIX Change	-0.10	-0.16	3.03	-10.41	0.06	3.46
Oil Price Return	0.04	0.36	4.43	7.94	-0.26	3.14
Oil VIX Change	-0.17	-0.16	4.36	-8.33	-0.03	4.28

Note: Appendix Table A.1 defines the market variables. The data frequency is weekly. All market variables are winsorized at percentiles 2.5 and 97.5. The AR(1) coefficient is multiplied by 100. The sample period is 2013.9 - 2022.12.

Table A.7: Summary Statistics: Decarbonization Investment

	Projects	Reporting Firms		Investment [EUR million]				
	#	#	% any project	Mean	P25	P50	P75	Total
Panel A: by Country								
USA	1,983	432	49	132.67	0.06	0.37	3.69	263,094
Italy	396	77	49	233.87	0.15	1.47	10.08	92,610
Spain	483	74	69	117.70	0.05	0.25	2.48	56,847
Sweden	232	62	63	217.43	0.05	0.26	1.39	50,443
Japan	1,467	349	45	13.41	0.06	0.31	1.50	19,665
France	530	97	57	35.43	0.07	0.38	2.98	18,777
United Kingdom	1,139	233	55	13.05	0.02	0.14	1.18	14,859
Republic of Korea	488	106	47	29.14	0.04	0.29	1.49	14,221
Portugal	118	15	65	117.17	0.26	1.03	16.73	13,825
China & Hong Kong	519	296	30	25.13	0.00	0.03	0.19	13,044
Canada	507	89	67	22.25	0.10	0.56	4.48	11,278
Brazil	330	120	58	25.69	0.08	0.72	4.36	8,477
India	541	81	50	13.25	0.01	0.08	0.78	7,166
Germany	483	91	49	12.84	0.08	0.41	2.00	6,200
Colombia	53	13	54	107.22	0.02	0.84	7.31	5,682
Singapore	94	12	57	59.50	0.09	1.80	3.48	5,592
Denmark	144	25	51	33.17	0.03	0.31	1.32	4,776
Chile	32	8	72	111.50	0.05	13.08	144.09	3,567
Turkey	200	42	51	16.09	0.02	0.06	0.42	3,217
Ireland	178	32	64	14.53	0.03	0.14	1.24	2,586
Other Countries	2,669	498	52	8.53	0.04	0.23	1.69	22,755
Panel B: by Industry								
Utility & Power	1,263	148	82	348.04	0.45	7.57	125.44	439,570
Manufacturing & Materials	5,106	1,298	44	12.56	0.03	0.17	1.09	64,150
Fossil Fuels	1,218	116	88	28.70	0.04	0.52	3.55	34,951
Infrastructure	605	132	55	53.53	0.03	0.21	1.74	32,387
Transport	910	162	67	30.63	0.14	0.71	5.40	27,869
Aviation	117	27	100	207.49	0.13	1.15	40.65	24,276
Food & Agriculture	1,158	210	67	8.39	0.05	0.23	1.21	9,716
Retail	456	137	42	5.15	0.04	0.22	1.38	2,350
Services	929	290	35	2.51	0.02	0.11	0.72	2,330
Health care	513	118	57	0.99	0.03	0.13	0.54	506
Other Sectors	311	116	43	1.88	0.02	0.10	0.54	583
Total	12,586	2,754	48	50.75	0.04	0.26	2.00	638,693

Note: scope-1 decarbonization projects by country (*Panel A*) and industry (*Panel B*) of the reporting firm. Column 1 presents the number of projects. Columns 2 and 3 show the number of firms reporting scope-1 decarbonization projects and the share of firms disclosing any project, respectively. Columns 4–8 report summary statistics of required project investments. We describe details on sample construction in Appendix Section A.2.

Table A.8: CDP Decarbonization Projects – Stylized Examples

Category	Activity type	Project Description	Carbon Solution
Process efficiency	Process emissions reductions	Adoption of an innovative carbon capture system at the manufacturing plant to significantly reduce CO2 emissions from production processes. The project includes the installation of new equipment and training for staff.	carbon capture system
Process efficiency	Energy efficiency: Processes	Optimization of steam usage by installing advanced steam traps and conducting regular maintenance checks to prevent leaks and inefficiencies in our textile plant in India.	steam traps
Transportation	Transportation	Expansion of electric vehicle (EV) charging infrastructure at our sites across North America to support the transition of our corporate fleet to 100% electric vehicles by 2025.	EV charging infrastructure
Low carbon energy	Low-carbon energy installation	Installation of a geothermal heating and cooling system at the corporate headquarters, replacing the old, inefficient HVAC system and significantly cutting the building's carbon footprint.	geothermal system
Waste	Fugitive emissions reductions	Adoption of advanced monitoring technologies to detect and repair leaks in natural gas pipelines, significantly reducing methane emissions across our operations in the Middle East.	leak monitoring technologies

Note: This table shows stylized, GPT-generated examples of scope-1 decarbonization projects reported to CDP. *Activity type*, and *project description* are provided in the CDP-survey and *category* is based on our own classification (for a mapping, see Appendix Table A.9). CDP additionally investment required for each project. Based on 27 randomly selected responses on firms' scope-1 emission reduction activities (three for each survey year), we ask GPT4 to generate "five similar decarbonization projects that include the same activity types but different project descriptions of similar length and content." Carbon solutions are keywords extracted by GPT3.5 based on the procedure outlined in Section III.A.

Table A.9: Decarbonization investment classification

Activity Type Category	CDP Activity Type
Building efficiency	Energy efficiency: Building services Energy efficiency in buildings Energy efficiency: Building fabric
Company policy or behavioral change	Company policy or behavioral change Behavioral change
Low carbon energy	Low-carbon energy generation Low-carbon energy consumption Low-carbon energy installation Low-carbon energy purchase
Other	Other Green project finance
Process efficiency	Energy efficiency: Processes Energy efficiency in production processes Process emissions reductions Non-energy industrial process emissions reductions
Product design	Product design
Transportation	Transportation Transportation: fleet Transportation: use
Waste	Fugitive emissions reductions Waste reduction and material circularity Waste recovery

Note: Mapping of types of decarbonization activities as provided by CDP to corresponding activity type categories used in our analysis.

Table A.10: Decarbonization Investment by Activity Type

Investment Type Sector	Building efficiency	Low carbon energy	Other	Process efficiency	Transportation	Waste
Utility & Power	0.50	45.41	21.14	12.51	0.06	20.38
Infrastructure	0.11	17.76	0.30	13.92	42.19	25.73
Aviation	0.00	12.69	18.64	48.95	19.71	0.00
Services	31.75	10.14	1.52	13.45	39.92	3.23
Transport	1.63	9.52	6.10	25.04	56.64	1.07
Manufacturing & Materials	0.96	7.87	3.40	85.27	1.05	1.44
Other Sectors	8.82	5.75	2.40	28.94	19.10	35.00
Food & Agriculture	0.50	5.70	1.44	75.61	6.70	10.05
Fossil Fuels	0.02	0.62	5.61	80.46	0.57	12.73

Note: This table reports the share of decarbonization investment by activity type. Data are from CDP vintages 2015–2023. Appendix Section A.2 includes details on sample construction and Table A.9 outlines activity type classification.

Table A.11: Summary Statistics: Decarbonization Investment Panel

	Mean	P10	P50	P90	Std	Obs.
DIR [EUR/tCO2e]	18.23	0.00	1.01	58.44	40.81	4,630
Total Assets [EUR billion]	16.95	1.18	7.96	51.61	20.52	4,098
ROA [%]	11.43	4.34	10.59	19.75	6.41	4,098
Leverage [%]	23.02	3.57	22.20	43.44	14.12	4,098
Capex [%]	6.33	0.26	5.26	13.93	5.72	4,098
Carbon VIX	53.71	45.79	55.72	57.51	4.49	4,630
Carbon Price [EUR]	41.73	16.08	25.06	81.64	24.21	4,630
Oil Price [EUR]	62.18	37.97	59.77	94.14	18.23	4,630

Note: This table present summary statistics of the decarbonization investment panel outlined in Section II. *DIR* is the ratio of a firm's investment in decarbonization activities (EUR) to its scope-1 emissions (tCO2e) disclosed to CDP for a given reporting period. *Total assets*, *ROA*, *leverage*, and *capex* are based on firm-level information from Moody's Orbis. *CVIX*, *Carbon Price*, and *Oil Price* are averages of weekly CVIX levels, carbon, and crude oil prices (EUR) over the firm's reporting period, respectively. Table A.1 details definitions of all variables. The sample covers reporting periods in years 2018–2023.

Table A.12: Common Carbon Solutions

Carbon Solution	Type	Investment [MEUR]
renewable energy	Low carbon energy	143,706
methane leak capture	Waste	89,797
solar photovoltaic (PV) energy	Low carbon energy	45,518
wind energy	Low carbon energy	43,284
fuel switch	Process efficiency	42,779
process optimization	Process efficiency	20,551
alternative fuels	Process efficiency	12,585
fleet vehicle replacement	Transportation	12,093
natural gas	Low carbon energy	8,007
hydro power	Low carbon energy	7,592
flare gas reduction	Other	6,861
cogeneration (combined heat and power)	Process efficiency	6,311
energy efficiency measures	Process efficiency	6,281
waste to energy	Process efficiency	6,212
wind power farm & turbines	Low carbon energy	4,982
biomass energy	Low carbon energy	4,443
biofuel	Low carbon energy	4,014
carbon capture and storage (CCS)	Process efficiency	3,727
fuel efficiency	Transportation	3,642
biogas	Low carbon energy	2,541
fleet vehicle efficiency	Transportation	1,789
efficiency improvement	Process efficiency	1,322
refrigerant leakage reduction	Waste	941
waste heat recovery	Process efficiency	771
solar power farm & panels	Low carbon energy	629
electric vehicles	Transportation	611
electrification	Process efficiency	595
energy efficient HVAC	Building efficiency	300
sf6 emissions reduction	Waste	273
telematics	Transportation	265
refrigerant replacement	Waste	238
boiler efficiency	Process efficiency	174
energy saving	Process efficiency	159
insulation	Building efficiency	142
energy management systems	Building efficiency	127
biomass boilers	Low carbon energy	102
natural gas boiler	Low carbon energy	85
idle reduction technology	Transportation	71
heat pump	Building efficiency	51
hybrid vehicles	Transportation	51
boiler upgrade	Building efficiency	24
compressed natural gas (CNG)	Transportation	23

Table A.12 (continued from previous page)

Carbon Solution	Type	Investment [MEUR]
hydrogen fuel cell	Low carbon energy	19
thermal insulation	Process efficiency	18
LED lighting	Process efficiency	16
energy optimization	Process efficiency	15
variable frequency drives (VFD)	Process efficiency	7
heat exchanger	Process efficiency	7
district heating	Low carbon energy	5
fuel additive	Transportation	3

Note: Common carbon solutions are based on the 50 most frequent keywords extracted from descriptions of decarbonization projects. Section III.A describes the approach to identify carbon solutions.

Table A.13: GPT4 few-shot prompt examples

#	Stylized firm description	Carbon solution
1.	Products and Services: "High-tech equipment for photovoltaic, solar, and hydrogen industries to provide renewable energy." Business Model: "GREEN LC specializes in solar systems, photovoltaic (PV) panels, and hydrogen infrastructure. The company also offers marketing services in B2B channels."	renewable energy; solar systems; photovoltaic (PV) panels; hydrogen infrastructure
2.	Products and Services: "Energy efficient heating and insulation solutions." Business Model: "The Company provides technical climate solutions for energy efficient heating systems, consultancy services, and energy efficient insulation products for industrial buildings."	energy efficient heating systems; energy efficient insulation; climate solutions
3.	Products and Services: "Flaring prevention and waste heat recoverage." Business Model: "The company develops and markets cleantech solutions for reutilizing energy and cleaning of flue and flaring gases."	flaring prevention; waste heat recoverage; energy reutilization
4.	Products and Services: "Optimization of energy and energy management." Business Model: "XYZ produces software that is used to safe and conserve electricity."	Optimization of energy; energy management; electricity conservation
5.	Products and Services: "Oil and gas energy products." Business Model: "The company is involved in the sourcing and distribution of petroleum products."	
6.	Products and Services: "Hazardous waste treatment." Business Model: "The Company recycles and disposes hazardous material and radioactive waste. The main activity is the decommissioning of nuclear facilities and designing radioactive waste management processes."	
7.	Products and Services: "Water purification and waste water treatment." Business Model: "WaterPure Inc develops innovative solutions to treat residual industrial effluents and waste water conservation. The Company also manages maritime aquaculture facilities including recirculation aquaculture systems."	

Note: This tables summarizes stylized examples of firm descriptions and desired output of carbon solutions provided to GPT4. Appendix Section A.3.A details the prompting procedure.

Table A.14: Carbon Solution Provider's Firm Names

7C SOLARPARKEN AG, A.I.S. AG, A2A S.P.A., ABO WIND AG, ABSOLICON SOLAR CO, ACCIONA SA, ACEA SPA, ACINQUE S.P.A., AEGA ASA, AFYREN SA, AGRIPOWER FRANCE SA, AKER CARBON CAPTURE AS, AKER HORIZONS ASA, AKILES CORPORATION SE, ALEIA HOLDING AG, ALERION CLEAN POWER S.P.A., ALFEN N.V., ALGOWATT SPA, ALTEO ENERGY SERVICES PUBLIC LIMITED COMPANY, ALTERNUS ENERGY GROUP PLC, ARISE AB, ASCOPIAVE S.P.A., ASETEK AS, ATOMENERGOREMONT AD, ATON GREEN STORAGE S.P.A., AUMANN AG, AUREA, AXOLOT SOLUTIONS HOLDING AB, AZELIO AB, BETOLAR OYJ, BIOMASS ENERGY PROJECT SA, BLUE SHARK POWER SYSTEM, BONHEUR ASA, BRAS SA, BRAVIDA HOLDING AB, BW IDEOL AS, CADELER A/S, CAMBI ASA, CAVERION CORPORATION, CENTROTHERM INTERNATIONAL AG, CIE AUTOMOTIVE S.A., CIRCA GROUP AS, CIRCHEM AB, CLEAN LOGISTICS SE, CLEARVISE AG, CLIMEON AB, CLOUDBERRY CLEAN ENERGY AS, CORPORACION ACCIONA ENERGIAS RENOVABLES S.A., CR ENERGY AG, CROPENERGIES AG, DB ENERGY SA, DEKTRA SA, DESERT CONTROL AS, DLABORATORY SWEDEN AB, EAM SOLAR ASA, EBUSCO HOLDING N.V., ECOENER S.A., ECOMB AB, ECOSUNTEK SPA, EDDA WIND ASA, EDP - ENERGIAS DE PORTUGAL S.A., EDP RENOVAVEIS SA, EEMS ITALIA S.P.A., ENAPTER AG, ENCE ENERGIA Y CELULOSA S.A., ENEFI ASSET MANAGEMENT PLC., ENEFIT GREEN AS, ENERGA S.A., ENERGIA INNOVACION Y DESARROLLO FOTOVOLTAICO S.A., ENERGIEKONTOR AG, ENERSIZE OYJ, ENERTIME, ENERTRONICA SANTERNO SPA, ENNOGIE SOLAR GROUP A/S, ENOGIA SA, ENVITEC BIOGAS AG, EO2, EOLUS VIND AB, ESI SPA, EVERFUEL A/S, FARMY FOTOWOLTAIKI POLSKA SA, FASADGRUPPEN GROUP AB, FERNHEIZWERK NEUKOELLN AG, FORSEE POWER SAS, FRENDY ENERGY S.P.A., G-ENERGY SA, GREEN HYDROGEN SYSTEMS A/S, GREENCOAT RENEWABLES PLC, GREENTHESIS S.P.A, GREENVOLT - ENERGIAS RENOVAVEIS, S.A., GRENERGY RENOVABLES SA, GRINO ECOLOGIC S.A., GRODNO S.A., HAV GROUP ASA, HEXICON AB, HOFFMANN GREEN CEMENT TECHNOLOGIES, HOLALUZ-CLIDOM, S.A., HORISONT ENERGI AS, HYBRICON AB (PUBL), HYDRO EXPLOITATIONS, HYDROGEN REFUELING SOLUTIONS SA, HYDROGENE DE FRANCE SA, HYDROGENPRO ASA, HYNION AS, IBERDROLA SA, INIZIATIVE BRESCIANE - INBRE - S.P.A., INNOVATEC S.P.A., INSTALCO AB, INTEGRATED WIND SOLUTIONS ASA, INTRACOM HOLDINGS S.A., IREN S.P.A., KINGSPAN GROUP PLC, KLAPPIR GRAENAR LAUSNIR HF., KORADO BULGARIA AD, KYOTO GROUP AS, LANDI RENZO S.P.A., LIGHTNING GROUP AB, LOKOTECH GROUP AS, LUCIBEL SA, MAIRE TECNIMONT S.P.A., MANTEX AB, MANZ AG, MARTIFER SGPS S.A., MASTERPLAST NYILVANOSAN MUKODO RESZVENYTARSASAG, MCPHY ENERGY, MELTRON AB, MERIAURA GROUP OYJ, MERUS POWER OYJ, METACON AB, MIDSUMMER AB, MINESTO AB, ML SYSTEM S.A., MOULINVEST, NEL ASA, NEOEN, NFO DRIVES AB, NHOA SA, NIBE INDUSTRIER AB, NILAR INTERNATIONAL AB, NORDEX SE, NORDIC FLANGES GROUP AB, OCEAN SUN AS, ONDE SA, ORRON ENERGY AB, OX2 AB, PHOTON ENERGY N.V., PLC S.P.A., PNE AG, POLENERGIA S.A., POWERCELL SWEDEN AB, PRIVANET GROUP OYJ, PRYME N.V., PRZEDSIEBIORSTWO MODERNIZACJI URZADZEN ENERGETYCZNYCH REMAK S.A., PSI SOFTWARE SE, PVA TEPLA AG, QLEANAIR AB, QUANTAFUEL AS, R ENERGY 1 SA, RAFAKO S.A., REC SILICON ASA, RENERGETICA S.P.A., ROCKWOOL A/S, SALTX TECHNOLOGY HOLDING AB, SAXLUND GROUP AB, SCATEC ASA, SEATWIRL AB, SENVION SA, SERI INDUSTRIAL S.P.A, SMA SOLAR TECHNOLOGY AG, SMART GRIDS AG, SOLAR-FABRIK AKTIENGESELLSCHAFT FUER PRODUKTION UND VERTRIEB VON SOLARTECHNISCHEN PRODUKTEN, SOLARIA ENERGIA Y MEDIO AMBIENTE S.A., SOLARWORLD AG, SOLTEC POWER HOLDINGS S.A., SOLTECH ENERGY SWEDEN AB, STEICO SE, SUMMA DEFENCE OYJ, SUNEX SA, SUSTAINABLE ENERGY SOLUTIONS SWEDEN HOLDING AB, SVENSKA AEROGEL HOLDING AB, SWECO AB, SWEDISH STIRLING AB, TECHNIP ENERGIES N.V, TERMO2POWER S.A., TERMOEXPERT S.A., TERNA ENERGY S.A., TION RENEWABLES AG, UNIPER SE, VALOE OYJ, VA-Q-TEC AG, VELCAN HOLDINGS, VERBIO VEREINIGTE BIOENERGIE AG, VERGNET S A VSA, VESTAS WIND SYSTEMS A/S, VIATRON SA, VITEC SOFTWARE GROUP AB, VOLTALIA, VOOLT SA, VOW GREEN METALS AS, WAGA ENERGY SA, WEBUILD S.P.A., ZENERGY AB

Note: Names of firms that we identify as Carbon Solution Providers in section III.B.

Table A.15: Countries in the European Economic Area

Countries with Carbon Solution Firms

Germany (deu), Spain (esp), France (fra), Italy (ita), Austria (aut), Denmark (dnk), Finland (fin), Ireland (irl), Netherlands (nld), Norway (nor), Sweden (swe), Poland (pol), Iceland (isl), Portugal (prt), Hungary (hun), Greece (grc), Estonia (est), Bulgaria (bgr), Cyprus (cyp), Romania (rou)

Countries without Carbon Solution Firms

Belgium (bel), Luxemburg (lux), Lithuania (ltu), Czech Republic (cze), Slovenia (svn), Slovakia (svk), Croatia (hrv), Latvia (lva), Malta (mlt)

Note: Countries in the European Economic Area as of 2024.01, excluding Liechtenstein. These countries form the sample for our stock return analysis. Countries are split between countries with- and without idetified carbon solution firms.

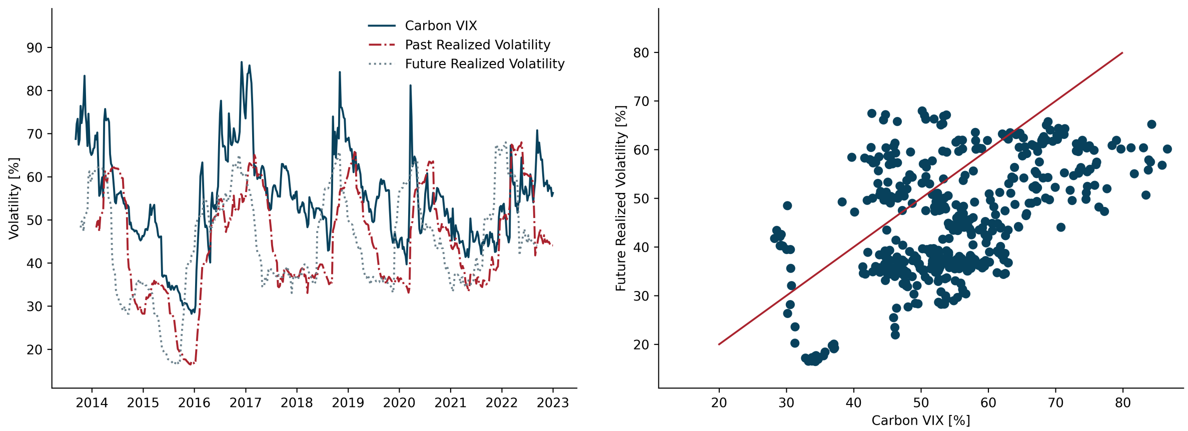
Table A.16: Carbon Market Summary Statistics

	Mean	Median	Std	Skew	Kurtosis
Sales per Assets	0.77	0.60	1.66	55.88	4,661.91
Sales (Eur bn.)	2.03	0.09	8.37	8.78	104.73
Assets (Eur bn.)	11.63	0.17	97.26	17.94	395.77
Carbon Price (Eur)	39.32	26.93	24.71	0.77	2.01
Carbon VIX (%)	54.08	53.45	6.60	0.95	4.13
Oil Price (Eur)	61.80	59.42	18.65	0.67	3.07
Oil VIX (%)	43.11	39.23	17.24	2.25	8.65

Note: This table displays summary statistics for the variables used in the sales regressions of section III.D. The data frequency is quarterly. Carbon market and oil market variables are winsorized at percentiles 2.5 and 97.5. The sample period is 2018.01 - 2022.12.

A.6. Figures

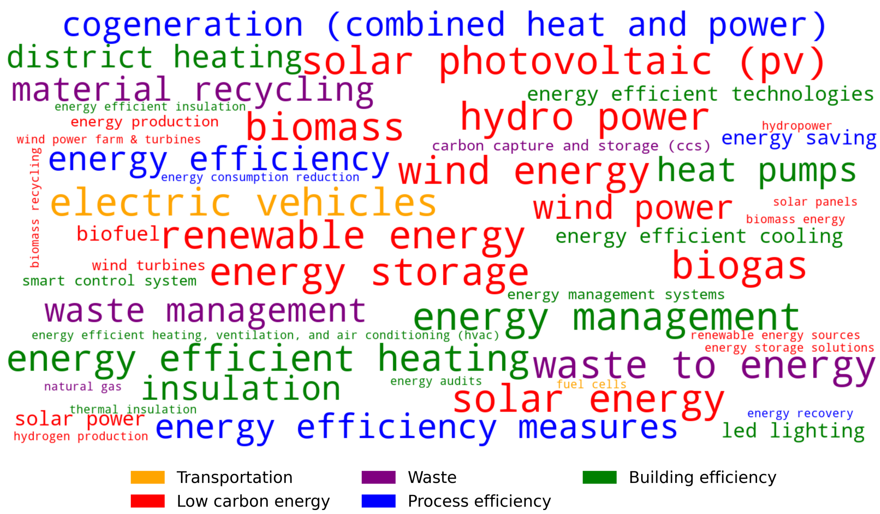
Figure A.1: Carbon VIX and realized carbon volatility.



(a) (b)

Note: Panel (a) shows weekly Carbon VIX (solid blue), 120-day realized past (future) volatility in red dash-dotted (dotted grey), where future realized volatility is 16 weeks ahead of past realized volatility. Panel (b) plots weekly levels of future realized volatility on the level of Carbon VIX along with a 45 degree line.

Figure A.2: Provided Carbon Solutions



Note: Carbon solutions are based on 50 most frequent decarbonization products offered by carbon solution providers identified in Section III. Categories of provided carbon solutions are based on the closest cosine similarity to carbon solutions identified from CDP survey-responses.