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The Market for Voluntary Carbon Offsets

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The market for voluntary carbon offsets

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Abstract

We study pricing in the voluntary carbon market (VCM) using a novel proprietary dataset of sales of emission reduction certificates (credits) by a leading VCM dealer. We document extraordinary price dispersion, with carbon credits trading between a few cents and $100 per ton of CO_2. Prices are systematically related to the credit project, buyer, and trade characteristics, rather than to a common value of carbon emissions. Credits from the least reliable emission reduction technologies, but with positive non-carbon externalities, are twice as expensive as trusted industrial solutions. Buyers in low-emission industries, wealthier countries, and large firms pay a premium for carbon credits, while heavy polluters and firms with explicit sustainability commitments do not. VCM pricing also features volume and client relationship discounts typical for over-the-counter markets. Finally, we document a causal link between the introduction of the VCM futures market and price premia for credits eligible for expiring futures settlement.

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1 Introduction

While the prospect of a compulsory global carbon pricing mechanism remains elusive, the voluntary carbon market (VCM) has emerged as a private market-based alternative. Firms participate in the VCM to manage their carbon footprints and shape how investors and clients perceive their environmental performance. Within this market, companies purchase carbon credits issued by projects that claim to prevent the release of one metric ton of CO_2 or to remove an equivalent amount from the atmosphere. Despite growing criticism about the environmental integrity of many such projects, the supply of carbon credits is expanding rapidly. Yet, the economics of the VCM remain poorly understood, in part due to its opaqueness about the projects, their verification and specially its over-the-counter pricing structure. Indeed, the fundamental nature of the VCM itself remains unclear: does it function as a global, market-based carbon price signal, or do carbon credits primarily constitute tradable marketing instruments, with genuine emission reductions playing only a secondary role?

We address this issue by analyzing transaction prices for carbon credits and their determinants using a novel proprietary dataset containing detailed information on trades, projects, and buyers. Our data originates from one of the largest VCM dealers globally and covers more than 10% of the entire VCM trading volume from 2018 to 2024. Figure 1 presents prices of all sample transactions and demonstrates that the VCM does not provide one single global price signal for a ton of CO_2, as it may cost as little as several cents or as much as a hundred dollars. This is a remarkable level of price variability for a good that is destined to become a commodity, and for a good whose social value has been computed to be north of 100 dollars. In fact, the dispersion of prices in Figure 1, measured by the coefficient of variation, is considerably larger than in a residential property market of an economically developed country at the same point in time. Why is this the case? To answer this question, we set up a hedonic pricing model for the VCM market and we attribute price dispersion to specific project, buyer, and trade characteristics. By doing so, we can disentangle whether carbon offsets are priced as a commodity or as a luxury good. We demonstrate that carbon credits are indeed priced on their characteristics rather than the common value of carbon dioxide in the atmosphere. Furthermore, by interpreting the loadings on the characteristics, we can distinguish between the consequentialist and warm-glow motives of this pro-social behavior. Our results are more in line with the latter.

Figure 1: **Sales prices in the secondary market for voluntary carbon credits.** Each point represents a secondary market transaction between a large voluntary credits dealer (seller) and a non-dealer customer (buyer). The transaction date is on the x-axis. The transaction price, in $ per metric ton of the CO_2 equivalent, is on the y-axis (log-scale).

We start our empirical exploration by studying the correlation between CO_2 prices and the characteristics of the underlying projects. The major factor explaining the observed VCM price dispersion is the type of the underlying climate project technology, including, e.g., renewable energy power generation, avoided deforestation, or household-level interventions to improve cooking conditions in the least developed countries, or, increasingly, industrial or natural carbon capture projects. Some of these technologies have been found to be less reliable in delivering the promised emission reductions (Probst et al., 2024). Remarkably, we find that technologies with the lowest reliability, like household-level interventions and deforestation avoidance projects, trade at the highest prices. The price premia associated with such technologies is at 70-150% relative to industrial solutions, even after accounting for country-specific installation costs, project size, and a multitude of other characteristics. The result is consistent with VCM credit buyers paying for emotionally salient project features, possibly including positive externalities for local communities, rather than for emission reductions per se. Interestingly, there is no price premium for a particular credit buyer when they purchase emission reduction credits that originate close to their business location. Hence, the preference for technologies with externalities is not a home bias. Mechanisms that reduce the uncertainty about project quality are associated with positive price premia: Having a Gold Standard registry increases prices by up to 32%, and more recent vintages trade at 2% higher prices per vintage year.

Next, we ask if buyer characteristics play a role in explaining CO_2 prices. We find considerable variation in VCM prices across buyers, even within a given set of project characteristics. Buyers from the least polluting industries, the financial and consumer goods sectors, are paying 15-25% more for carbon credits than buyers from heavy polluting industries, the energy and transportation sectors. Other things being equal, buyers from wealthier countries pay a premium of up to 1.4% for a 10% difference in GDP per capita, and larger buyers pay up to 11% more than small and medium-sized firms. Interestingly, firms that publicly commit to long-term sustainability target, i.e., SBTi signatories, do not pay more for VCM credits and neither do firms domiciled in highly polluting countries. With high price dispersion, price premia for project features unrelated to emission reductions, and markups for wealthy buyers unrelated to their climate commitments, the VCM credits market appears to be closer to a marketplace for emotionally appealing marketing claims than a trading venue for carbon as a global commodity.

In addition, we document VCM pricing features that are common across other OTC markets with little pre-trade price transparency. For instance, we find volume discounts of 0.5-0.9% lower transaction prices per 10% larger trade volume, controlling for client identity, consistent with dealers giving price concessions for reducing holding costly inventory. The inventory cost here is arguably an adverse selection cost, since VCM dealers are specialized non-bank intermediaries subject to little regulation. There are also client relationship discounts in addition to the volume discounts; top-tier clients that generate substantial trading volume enjoy price discounts of up to 25%. Finally, projects denoted in non-standard currencies trade at a 28 to 38% premium, reflecting the foreign exchange risk borne by the dealer.

Despite being far from a commodity market in terms of pricing, the VCM has a sizable exchange market for standardized credit baskets, complemented by the futures exchange at the Chicago Mercantile Exchange (CME). The futures market was introduced during our sample period, but prices quickly raced to the bottom, stabilizing in the bottom decile of OTC transaction prices, consistent with the cheapest-to-deliver principle. However, the introduction of the futures market created two tiers of VCM credits: deliverable and non-deliverable against expiring VCM futures. We show, in a difference-in-difference analysis, that CME-deliverable credits trade at 6-20% price premia after the introduction of the futures market, consistent with futures market demand translating into price pressures in the underlying OTC market.

Our results contribute to the emerging literature on the economics of voluntary carbon markets. First, we add to studies examining the demand for carbon credits. Kim et al. (2024) show that, following an exogenous decline in ESG scores, firms offset a larger share of their emissions, suggesting that carbon credits are used to manage investors' perceptions of corporate sustainability. Rodemeier (2025) investigates consumers' willingness to pay for carbon offsetting in a large-scale field experiment and finds that this willingness is surprisingly insensitive to actual climate impact. We extend this literature by documenting substantial heterogeneity in firms' willingness to pay for carbon credits, with firms in low-emission industries, large firms, and firms from wealthier countries paying systematically and substantially higher prices.

Second, we contribute to research evaluating the climate effectiveness of carbon offset projects. Calel et al. (2025) show that most wind projects financed through carbon credits would likely have been implemented even without such support. In an interdisciplinary review, Probst et al. (2024) conclude that many common project types—such as renewable energy, avoided deforestation, and household-level interventions—fall short of their emission reduction claims. We build on these insights by demonstrating that carbon credit prices for several of these less reliable project types are nonetheless substantially higher than those for more credible alternatives.

Third, our analysis complements the literature on compliance carbon markets, which examines the effectiveness of mandatory emission trading systems in reducing global greenhouse gas emissions. Colmer et al. (2024) find that the EU Emissions Trading System has led to substantial emission reductions without dampening economic activity or inducing offshoring. Laurs et al. (2025) find that non-compliance with the EU ETS leads to substantial price shocks and corresponding hikes in the cost of capital. In contrast, Bartram et al. (2022) show that, under California's cap-and-trade system, financially constrained firms shift production to other states, whereas unconstrained firms do not adjust their emissions. Moreover, Akey et al. (2024) suggest that mandatory emission trading systems may crowd out voluntary emission reduction initiatives. We contribute to this literature by showing that, given current pricing structures, voluntary carbon markets are unlikely to serve as an effective substitute for compliance-based systems.

Our findings have important implications for policymakers. They indicate that, in its current form, the voluntary carbon market does not generate the much-needed global price signal for carbon emissions. Instead, firms appear to value project characteristics that are more closely related to the marketing claims that can be made based on the carbon credits, consistent with the warm-glow optimization approach. Given the substantial willingness to pay observed among certain buyers, policymakers may find it worthwhile to better align the marketing claims firms are permitted to make with actual climate outcomes—both from a climate policy and a fair competition perspective.

2 VCM and transaction price data

We begin by briefly discussing the institutional setting of voluntary carbon markets (VCM) and their intended role within the carbon trading ecosystem. We then proceed with a detailed discussion of our proprietary data on VCM transaction prices—to the best of our knowledge, the first of its kind to feature in academic finance studies.

2.1 Institutional setting

Carbon credits are tradable claims for a causal reduction or removal of greenhouse gas emissions commonly quantified in metric tons of CO_2 equivalents (CO_2e). These credits are primarily used by companies to offset their greenhouse gas emissions and, to a smaller extent, by individuals to offset their personal emissions.

Offset projects can include various approaches to avoid greenhouse gas emissions, such as renewable energy generation, methane capture, deforestation avoidance, or reduction of household-level emissions. Additionally, they can involve approaches to remove carbon from the atmosphere through industrial carbon capture and storage processes or nature-based measures, such as afforestation or soil carbon enhancement.

The generation of carbon credits is governed by voluntary standard-setting bodies such as Verra and Gold Standard, which usually operate registries that log all carbon credit transactions. Most standards require that offset projects apply approved methodologies, be independently verified by accredited third parties. Common quality requirements across methodologies include standardized measurement of climate outcomes, avoidance of leakage, additionality, and, in the case of a project removing carbon from the atmosphere, the permanence of such removals. Besides reducing or avoiding emissions, projects often advertise co-benefits or positive spillovers. For afforestation initiatives, for example, these can be contributions to local biodiversity, while renewable energy projects might advertise with the employment of local workers. Several standard-setters allow for the certification of such co-benefits.

Since its inception in the early 2000s, the VCM has increasingly taken on the characteristics of a traditional commodity market. Owners of offset projects, such as a wind energy park, issue carbon credits, with the issuance being administered by one of the standard-setting bodies. Each credit issued is assigned a "vintage" corresponding to the year in which the claimed emission reduction occurred. The issued carbon credits are typically sold to buyers through specialized brokers. While structured exchanges exist, most transactions occur over the counter. Once a buyer uses a carbon credit to substantiate an environmental claim, the credit is "retired, i.e., marked as permanently removed from circulation in the corresponding registry.

The size of the global VCM has surpassed a cumulative volume of 11 billion USD between 2005 and 2024 (Ecosystem Marketplace, 2025). This corresponds to around 2.5 billion tons of CO_2e transacted over the same period. Panel A in Figure 2 shows that total market activity remained relatively stable between 50-150 million tons of CO_2e traded annually from 2007 to 2019. Volumes rose sharply to 208 million tCO_2e in 2021 and 516 million tCO_2e in

2022, valued at approximately USD 2.1 billion and USD 1.9 billion, respectively. Following several controversies concerning the integrity of carbon offsets, trading volume declined to 112 million tCO_2e in 2023 and 84 million USD in 2024 (755 million USD and 535 million USD, respectively). Panels C and D show that new issuances have consistently exceeded retirements by an average of about 190 million tCO2e per year, leading to a substantial accumulation of active credits in the voluntary carbon market.

In response to recent criticism of the integrity of carbon offsets, the Integrity Council for the Voluntary Carbon Market has been formed as a private governance body for the VCM and introduced the Core Carbon Principles. These principles aim at providing a cross-standard framework to identify carbon offset projects that reliably cause the claimed climate outcomes. Moreover, independent rating agencies such as BeZero Carbon, Sylvera, and Calyx Global have emerged to assess the quality of carbon offset projects.

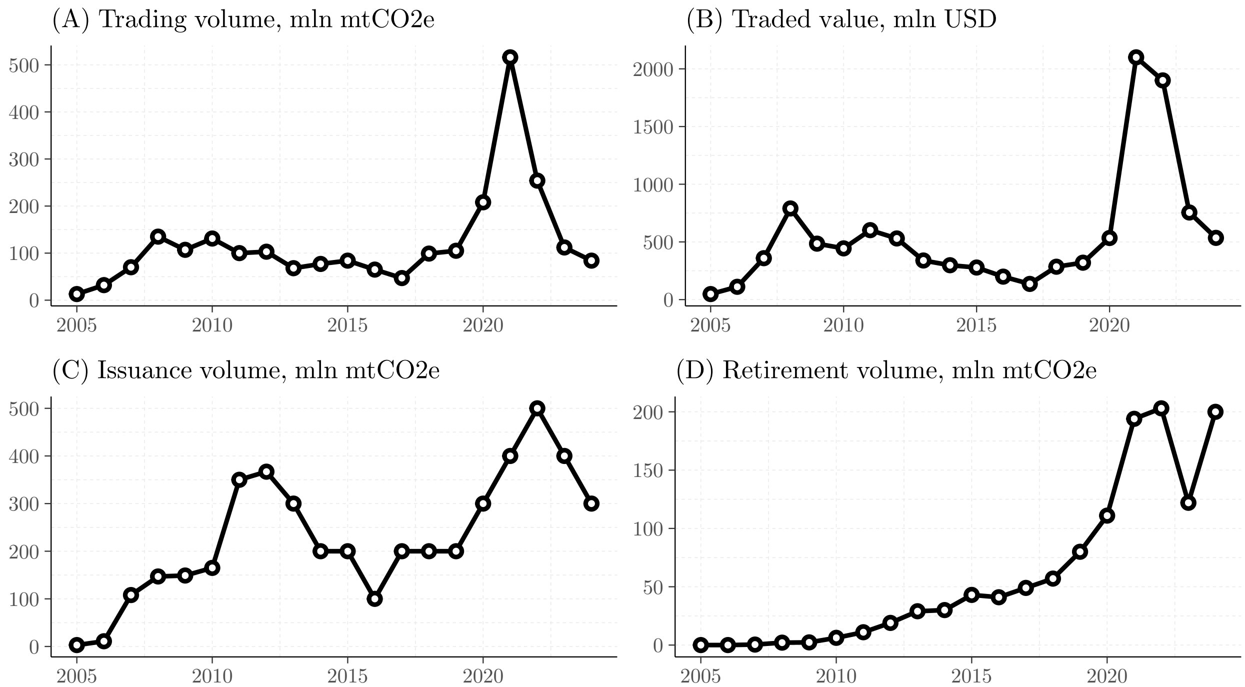

Figure 2: **VCM market size.**
The data for these plots is from the Ecosystem Marketplace and refers to the global trading in existing voluntary carbon credits (panels A and B), issuance of new credits (panel C), and retirement of existing credits (panel D). 'Mln mtCO_2e' stands for million metric tons of CO_2 equivalent.

2.2 VCM transactions data

Our proprietary dataset originates from one of the largest VCM broker-dealers globally and comprises over-the-counter (OTC) carbon credit sales by the dealer to its clients between 2018 and 2024. For each transaction, we observe trade characteristics, as well as credit project and client traits. Project and client identities are anonymized, but remain constant throughout the dataset, allowing us to track different trades by the same client as well as different transactions of the same project. The data, before applying several filters, contains transactions totaling almost 700 mn USD, which is approximately 11% of the total VCM secondary market transaction volume in the respective period, according to market statistics (Ecosystem Marketplace, 2025).

The transactions in the dataset differ in settlement characteristics. In particular, there are no standard delivery terms in the VCM, and delivery typically takes place several weeks after a contract signing date. We remove transactions with delivery nine months or later after the signing date, which comprise about a quarter of the original dataset. The transaction price is the dollar price of one metric ton of CO_2e ($mtCO_2e$) as of the signing date, and at the USD exchange rate of the signing date.[1] We remove transactions with prices below 10¢ and above $250 per $mtCO_2e$, which are close to the 0.5% and 99.5% percentiles of transaction prices, respectively. Since they are not comparable to voluntary carbon credits, we further remove transactions in credits eligible for local compliance markets (mainly in Australia, Colombia, and Switzerland), which make up 12% of transactions in the original sample. Finally, we remove about 100 transactions of credits from small local registries. After applying these filters, we end up with a dataset of about 7,200 transactions by around 1,200 unique clients in close to 400 unique projects. This final dataset covers about 7% of secondary VCM transactions by dollar value in the sample period.

[1] Effectively, transaction prices in our dataset are near-term futures prices. The exact tenor (the day count between the delivery and signing dates) within 9 months is not a price factor, as Section 3 will show.

	2018	2019	2020	2021	2022	2023	2024	Total
No. transactions	556	795	940	1,441	1,361	1,240	870	7,203
(A) By customer industry, % of total								
Manufacturing	41.2	24.9	25.3	23.2	17.9	20.2	23.9	23.6
Consumer	15.3	23.4	30.3	19.4	23.2	19.9	17.5	21.5
Energy	5.0	6.7	7.2	10.8	7.2	9.7	6.7	8.1
Finance	11.3	18.0	14.0	22.1	26.7	21.0	27.0	21.0
Other	23.2	21.1	15.9	16.4	17.2	13.5	19.5	17.4
Transport	4.0	5.9	7.2	7.9	7.9	15.6	5.4	8.3
(B) By project technology, % of total								
Industrial	2.5	1.1	2.2	3.9	2.5	1.6	1.4	2.3
Renewables	49.8	41.5	39.1	45.5	47.6	42.1	44.6	44.3
NB Removals	0.9	3.4	7.1	6.5	8.2	11.5	10.7	7.5
NB Avoidance	15.8	26.2	30.6	24.6	21.3	17.7	12.3	21.6
Household	20.5	16.0	14.0	9.4	9.3	16.3	18.4	13.8
Waste	10.4	11.8	6.8	10.1	11.1	10.8	12.6	10.5

Table 1: **Transactions by year, customer industry, and mitigation technology.** This table shows the sample composition over time, dividing transactions by the industry of the buyer (Panel A) and by the technology of the project (Panel B). Both customer industry and project technology classifications are in-house taxonomies of the data provider, yet the former closely follows the Standard and Poor's industry classification (GICS), while the latter is similar to the one by Ecosystem Marketplace. In particular, 'Industrial' projects are primarily aimed at recovering waste energy. 'Renewables' are mostly onshore wind turbines, solar, and hydro power plants. 'NB' stands for 'nature-based'. 'NB Removals' are afforestation, reforestation, and revegetation projects. 'NB Avoidance' is the protection of existing forests (REDD+). 'Household' primarily refers to projects aimed at improving cookstoves and household water filtering. 'Waste' refers to landfill gas, composting, industrial water filtering, and manure management improvements.

Table 1 presents the sample composition by transaction year, project technology, and customer industry affiliation. The transaction count increases between 2018 and 2021, before reverting to pre-2020 levels toward the end of the sample, similar to the dynamic of the aggregate market transaction volume in Figure 2. Panel (A) indicates that the split of credit buyers by industry affiliation in Table 1 is stable across years (except for the share of manufacturing customers in early sample years).[2] We treat energy, transportation, and

[2]The classification here is also provided by the dealer and is based on the taxonomy of Standard and Poor's (GICS). The term 'consumer' sector here refers to the manufacturing and provision of consumer goods

manufacturing as relatively heavy-polluting industries, while finance – as a lower-polluting one. Thus, about 40% of the buyers in our sample are from heavy-polluting industries.

In Panel (B) we observe that about 44% of the sample consists of transactions with credits from renewable energy projects, which is identical to the renewable share in credit issuance in Kim et al. (2024). Among the remaining categories, our secondary market transactions sample likely has a higher proportion of nature-based projects than the market at issuance, a similar proportion of waste projects, and a slightly lower proportion of household and industrial projects.[3] Given the size and the structure of the sample, we believe it is representative of the entire market. Also, technological shares in Table 1 are relatively stable across sample years, limiting the impact of changes in sample composition on our empirical results.

	By project technology, % total						Total no.
	IND	RNW	NBR	NBA	HLD	WST	trades
Manufacturing	2.0	49.8	6.1	18.6	14.9	8.6	1,702
Consumer	1.8	41.6	7.9	28.1	10.6	10.0	1,551
Energy	4.0	46.3	3.3	25.1	9.6	11.7	581
Finance	3.4	37.1	10.7	21.2	17.8	9.8	1,516
Other	1.8	44.4	8.8	19.5	13.0	12.4	1,254
Transport	1.2	51.3	3.5	15.2	15.2	13.7	599
Total	2.3	44.3	7.5	21.6	13.8	10.5	7203

Table 2: **Transactions by customer industry and project mitigation technology.** This table shows the sample composition by project technology, separately for buyers grouped by industry. The project labels stand for the following: 'IND' – industrial projects, 'RNW' – renewables, 'NBR' – nature-based removals, 'NBA' – nature-based avoidance, 'HLD' – household, and 'WST' – waste. The numbers in each line sum up to the total number of transactions with customers from a given industry.

and services, whereas 'manufacturing' consists of other industrial manufacturing activities to avoid confusion with 'industrial' emission reduction technologies.

[3]The definitions of project technologies are not standardized. We follow the granular classification provided by the dealer, which we then aggregate into a few broader categories following the definitions of the Ecosystem Marketplace. 'Nature-based solutions' in the dealer's classification is similar to 'Forestry and land use' in the Ecosystem Marketplace taxonomy. Our 'industrial' projects category also contains transportation, chemical, and carbon capture projects. We do not have any 'agricultural' projects in the final sample; the credits from all such projects in the original sample were eligible for local regulatory markets (primarily in Australia, Colombia, and Switzerland), which we removed from the sample for better comparability.

Interestingly, customers from different industries are purchasing, in aggregate, a similar mix of emission reduction technologies, as Table 2 demonstrates. Firms in the financial and consumer sectors purchase relatively more nature-based removals, (which will prove to be the technology with the highest market price of carbon credits), while manufacturing and transportation firms opt for a higher share of renewable-energy-based credits (which will be one of the cheaper technologies in the sample). Still, these differences in customer demand for project technology across industries are economically small. Note that the most frequent number of trades per unique buyer in the dataset (the statistical mode) is 1, the median is 3, and the average is 6. Hence, most customers in the sample only buy from one emission reduction technology, but the way they choose this technology does not seem to depend strongly on the customer's industrial affiliation.[4]

[4]Customers may choose to retire the purchased credits or resell them later. Retirement can be executed by the VCM dealer itself, along with the sale of credits, which occurs in approximately 75% of sample transactions. This fraction does not differ much across customer industries in the sample, including buyers from the financial sector (80% of their purchases are accompanied by credit retirement), suggesting that financial firms in the sample mostly purchase credits for redemption rather than for trading. Credits purchased for trading do not differ from those purchased for retirement, either unconditionally or conditional on other pricing factors.

	IND	RNW	NBR	NBA	HLD	WST	Total
No. projects	13	194	39	27	78	45	396
(A) By project region							
Africa	1	4	9	7	40	0	61
Americas	1	20	15	16	5	4	61
Asia	9	149	15	4	33	38	248
Europe	2	21	0	0	0	3	26
(B) By tercile of country per capita GDP							
T1 (poorest)	2	67	13	9	62	4	157
T2	7	94	21	17	14	35	188
T3 (richest)	4	33	5	1	2	6	51
(C) By tercile of country carbon emissions							
T1 (green)	0	5	3	5	21	0	34
T2	1	17	13	10	29	2	72
T3 (brown)	12	172	23	12	28	43	290
(D) By project registry							
CDM	4	44	1	0	9	10	68
Gold Standard	2	52	3	0	61	7	125
Verra	7	98	35	27	8	28	203

Table 3: **Sample projects across project and host country characteristics.** This table shows the sample compositions of the decarbonization projects in the sample. Specifically, it shows the counts of unique VCM credit projects, separately for several characteristics: region (Panel A), per-capita GDP (Panel B), country-level carbon emissions (Panel C), and project registry (Panel D). GDP per capita is expressed in constant 2021 USD. The carbon intensity of GDP is the total annual country CO_2 emissions per dollar of GDP. Both indicators are from the World Bank Global Development Indicators (WB GDI) dataset. GDP per capita and emission terciles are calculated in the cross-section of country averages (2018–2024) in the WB GDI datasets (i.e., these are population terciles). 'CDM' is the UN-mandated registry for 'certified emissions reductions'. Gold Standard and Verra are independent non-profit organizations. The project labels stand for the following: 'IND' – industrial projects, 'RNW' – renewables, 'NBR' – nature-based removals, 'NBA' – nature-based avoidance, 'HLD' – household, and 'WST' – waste.

The geographical distribution of projects in the sample is presented in Panel A of Table 3. About 60% of the sample projects are located in Asia, compared to 51% in the entire market by issuance (Kim et al., 2024). The Asian projects are predominantly renewable energy credits. African projects, as in the overall VCM, are mainly household projects focused on improving cooking technologies in the least developed countries. European projects make up only a small part of the sample and are predominantly renewable energy credits. As Panel B of Table 3 shows, sample projects are domiciled in countries with different levels of wealth, with 16% being in the world's richest countries (half of which are renewable energy projects). Panel C of Table 3 further shows that more than 70% of sample projects are located in heavily polluting countries (in absolute terms; half of these would be in the middle tier of countries by per capita emissions). This is aligned with the notion that the marginal carbon abatement costs, and with that the costs to generate carbon credits are substantially lower in countries with a lower level of existing climate policies

The projects in our sample come from several VCM credit registries. The majority is registered under Verra (50% of the sample) or Gold Standard (30%), closely matching similar market-wide statistics in Kim et al. (2024). We have several projects from CDM, a legacy UN-mandated registry established in 2005 under the Kyoto Protocol, which has seen many projects migrating to other registries lately.

Table 4 presents summary statistics for the transactions in our sample. The average carbon credit price is \$7.4 per mtCO_2e, which is about 80-85% cheaper than the simultaneous price at the ETS (European compliance emissions market) or the California cap and trade system.[5] Note, as in Figure 1, the extreme variability of transaction prices: The 5th price percentile is around \$1 per ton, while the 95th percentile is close to \$20. The average transaction is for about 12 thousand tons of emission reductions, bringing the average transaction close to \$90k. While we do not know the exact size of the companies that buy carbon credits, the data-providing dealer classifies about a third of the buyers as 'multinational companies'

[5]And it is only 3 percent of the estimated social cost of CO2.

(the largest in the sample) and another third as 'small and medium enterprises' (SMEs, the smallest). Given the transaction amounts in the sample, we assume that these SMEs are economically sizeable entities. About half of the sample companies are privately owned.

	Mean	S.D.	5th	25th	Med.	75th	95th	N.Obs.
Signing price, \$ per mtCO2e	7.4	7.6	1.1	3.0	5.6	9.7	19.3	7,203
Signing premium to ETS, %	-84.9	23.7	-97.5	-94.7	-90.1	-82.9	-56.7	6,912
Volume, thousand mtCO2e	12.2	39.5	0.0	0.4	1.8	8.0	52.7	7,203
Delivery – signing date, days	53.7	69.6	1.0	8.0	21.0	68.0	220.0	7,203
Delivery – vintage year, years	4.9	2.8	1.0	3.0	4.0	6.0	10.0	7,203
Vintage – project launch, years	3.4	3.0	0.0	1.0	3.0	5.0	10.0	7,203
Project size, thousand mtCO2e	323.5	810.0	0.0	0.0	59.5	264.0	1,259.7	7,203
Home bias (dummy)	0.02	0.15	0.00	0.00	0.00	0.00	0.00	7,203
Customer commited to SBTi	0.10	0.30	0.00	0.00	0.00	0.00	1.00	7,203
Non-standard currency	0.05	0.22	0.00	0.00	0.00	0.00	0.00	7,203

Table 4: **Summary statistics for the sample of VCM transactions.**
This table shows summary statistics for the main variables in the sample. Signing price is the transaction price agreed between the seller (VCM dealer) and a buyer (customer), expressed in USD per mtCO_2e at the exchange rate as of the signing date. Premium to ETS is the percentage difference between the transaction price and the price of the mtCO_2e in the European Emission Trading System as of the signing date (negative values represent a discount: VCM prices are below ETS prices). Volume is the number of credits traded, in thousand. The delivery is after the signing date (truncated at 270-day delay). Vintage refers to the year in which the traded carbon credit was issued. Project launch is the start of the crediting period (earliest available vintage). Project size is the total emission reduction expected per project at launch (self-reported). 'Home bias' equals 1 when the carbon credit buyer is domiciled in the country of the emissions reduction project, and 0 otherwise. SBTi commitment is 1 if the customer is explicitly committed to SBTi targets, and 0 otherwise. 'Non-standard currency' is 1 for transactions not settled in EUR, USD, GBP, AUD, or CHF.

Half of the sample transactions are settled within a month; the average delivery time is closer to two months, while the maximum is truncated at nine months. The average transaction is for a 5-year-old credit vintage, which comes from a project that had already been issuing credits for 3.5 years before that vintage year. The next section will show that the time difference between the transaction date and the credit vintage is an important price factor, while the difference between the credit vintage and the launch date of the project is not. The average carbon credit in the sample comes from a project with a total credit count of about 320 thousand tons of CO_2e, which is about 60% of the average project size in Kim et al. (2024). On the transaction side, about 5% of the trades are settled in currencies outside the major ones (defined here as EUR, USD, GBP, AUD, and CHF), which likely bear foreign exchange risk for the dealer who, in turn, might ask a premium on the selling price. Only about 2% of the transactions in the sample are in credits issued in the client's home country defined as the client's billing location. Finally, 10% of customers in the sample are explicitly committed to SBTi (Science Based Targets initiative), claiming allegiance to Paris Agreement goals and having clear plans to decarbonize.

3 Price dispersion in VCM transactions data

Transaction prices in the VCM vary significantly at every point in time, ranging from less than \$1 to over \$30 per $mtCO_2e$ as shown in Figure 1 in the Introduction. The degree of VCM price variability, as measured by the coefficient of variation, exceeds 100%. To put this number into context, the average within-month coefficient of variation of property sales prices in the UK—a market with huge variability in the underlying assets' worth—is lower, at around 85%.[6] Averaging VCM prices by project technology, we find a price range from \$2 to \$22 per $mtCO_2e$ toward the end of our sample. For reference, at the same point in time, the wholesale price of wheat in the U.S. varied from \$6 to \$8 per bushel across wheat grades; the price of a barrel of crude oil varied from \$59 to \$72.[7] This evidence suggests

[6]The underlying data is here. To calculate the coefficient of variation, we truncate prices at the 0.5% and 99.5% percentiles per month, like in the VCM sample, considering transactions between 2018 and 2024. Alternatively, taking the ratio of the 95^{th} to the 5^{th} price percentiles, we find a multiple of 20 for the VCM and 13 for the UK property market, again highlighting the larger dispersion in the VCM market.

[7]Data sources: wheat, oil.

that the VCM market is far from being commoditized. A ton of CO_2 is likely priced based on project, buyer, and transaction characteristics rather than the global value of carbon emissions reductions or removals. To shed more light on the VCM price dispersion, this section characterizes VCM pricing factors, separating them into project-, customer-, and transaction-specific characteristics.

3.1 Project-level factors

We begin by plotting the differences in average log-prices of carbon credits across project technologies, registries, and host country wealth and emissions. Panel A of Figure 3 reveals that, from the technological perspective, there is a clear split into 'discount' emission reduction technologies (industrial, renewables, and waste management projects) traded at low prices and 'premium' ones (nature-based solutions and household projects) traded at significantly higher prices. In absolute terms, the average price of discount-tech credits in the sample is around $4 per ton compared to $10 per ton for premium-tech credits and even $15 for nature-based removals, i.e., re-forestation projects.

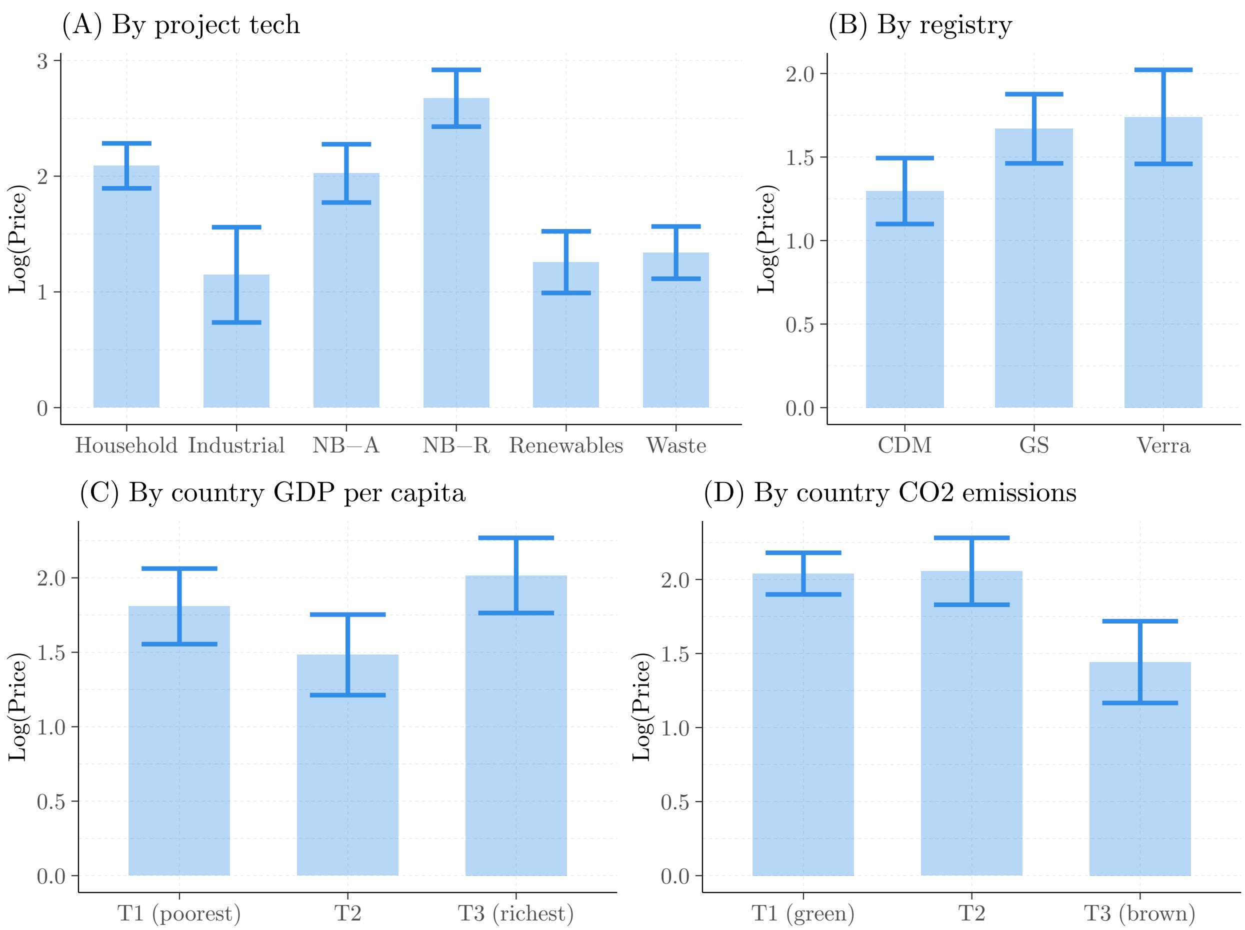

Figure 3: **Transaction log-price and project characteristics.**
This Figure plots the average transaction price separately by project technology (Panel A), registry (Panel B), issuing country GDP per capita (Panel C), and issuing country CO_2 emissions. Mitigation technologies correspond to those in Table 1 while GDP, GDP carbon intensity terciles, and registries correspond to those in Table 3. Bars are coefficient loadings from a multivariate regression of log-price on category dummies (separate regression for each panel). The figure also plots the 95% confidence bands based on standard errors clustered at the year level.

Such price differences are hard to reconcile with how 'trustworthy' different technologies are in delivering the promised emission reductions. Probst et al. (2024) compare promised and delivered reductions across project technologies and find that household projects score the lowest in delivery-to-promise ratio, with many nature-based technologies being the second lowest. Likewise, Guizar-Coutiño et al. (2022) find nature-based avoidance projects to be relatively inefficient in delivering real emission reductions. Therefore, the average price difference between premium and discount technologies is unlikely to be driven by technology-driven project quality. It is more likely that carbon credit buyers are willing to pay a premium for positive social and environmental spillovers typically associated with household and nature-based projects, or, more generally, for projects that with a high level of emotional tangibility.

Panel B of Figure 3 shows that credits from the legacy registry CDM are priced at a discount relative to Gold Standard and Verra. A considerable number of projects have recently migrated away from CDM due to concerns about the quality of project certification (Cames et al., 2017). Credits registered under Gold Standard and Verra are perceived by market practitioners as higher quality, and transaction price differences across registries support this perception.

One would expect credits from projects located in high-income countries to differ from those in low-income countries in terms of implementation costs. We proxy for these cost differences using the host country's GDP per capita. Panel C of Figure 3 shows that credits from high-income countries trade at a premium compared to credits from middle-income countries. Credits from the poorest countries also appear relatively expensive, however. This is likely due to a significant fraction of premium-tech household projects being located in low-income African countries (see Table 3). As we will demonstrate later in this section, controlling for project technology, the traded carbon credit price increases with the host country's per capita income. Again, this is not something one would expect to find in a commodity market. For instance, the cost of the extraction of crude oil from subterranean reservoirs varies strongly across countries and regions, but the market price for a barrel of crude oil is relatively insensitive to that cost in the short term (Toews and Naumov 2015).

Finally, Panel D of Figure 3 shows that credits issued in heavily polluting countries tend to be cheaper. The relation is similar for emissions per capita and per dollar of GDP (unreported). This may be due to a large supply of projects domiciled in more polluting countries (see Table 3), or, for example, the prevalence of discount-tech renewable projects in such countries.

To examine which project-level characteristics are associated with transaction prices in the presence of confounders, we turn to regression analysis. Specifically, we run Equation (1) below:

$$log(Price)_{i,j,t} = \alpha + \beta \ Project\ traits_{j,t} + \gamma \ Transaction\ traits_{i,j,t} + \delta_t + \Gamma_j + \epsilon_{i,j,t}. \quad (1)$$

The dependent variable, $log(Price)_{i,j,t}$, is the natural logarithm of the price at which customer i bought carbon credits from project j in year t. $Project\ traits_{j,t}$ is a set of (time-varying) project characteristics that, in the most strict specification, include the project technology, its registry, issuing country GDP per capital and emissions, and the project age and size. $Transaction\ traits_{i,j,t}$ covers transaction characteristics, namely the log volume of the trade, an indicator for top-tier clients, the credit vintage, whether the transaction is denominated in a non-standard currency, and the delivery delay. δ_t and Γ_j are, respectively, year and project-country fixed effects. $\epsilon_{i,j,t}$ is the error term, clustered at the transaction year level.

Table 5 presents the estimation results of Equation (1). Columns 1–6 are pooled sample models, while columns 7–10 add year and/or country fixed effects. Model 1 confirms that, relative to industrial projects, household and nature-based avoidance projects trade at a premium of approximately 90%. This number is even higher at 150% for nature-based removals. Importantly, the five project technology indicators in Model 1 alone already explain 29% of the variation in VCM transaction prices. Reassuringly, the magnitudes of the coefficients remain virtually unchanged after we include other project and transaction characteristics, as well as year and country fixed effects.

Model 2 adds project registry dummies to measure the price premium for projects registered in the Gold Standard and Verra registries — relative to projects registered under the legacy CDM registry. Such a premium appears insignificant in Model 2; however, its magnitude and statistical significance vary considerably across specifications. After including country fixed effects (columns 8, 9 and 10), the Gold Standard premium becomes significant and increases to 32%. This suggests that the project registry is important for explaining within-country price variation. Interestingly, the credits registered under Verra do not carry any significant premium compared to those under CDM.

	Dependent variable: log (Price)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	1.15***	1.11***	0.26	−0.01	−0.02	0.33				
	(0.21)	(0.20)	(0.54)	(0.57)	(0.55)	(0.57)				
Tech: Renewables	0.11	0.13	0.18	0.14	0.14	0.05	0.04	−0.02	0.03	0.03
	(0.17)	(0.17)	(0.18)	(0.18)	(0.18)	(0.17)	(0.16)	(0.20)	(0.19)	(0.19)
Tech: NB Removals	1.53***	1.56***	1.64***	1.46***	1.46***	1.34***	1.31***	1.49***	1.47***	1.47***
	(0.20)	(0.21)	(0.24)	(0.22)	(0.22)	(0.20)	(0.19)	(0.24)	(0.22)	(0.22)
Tech: NB Avoidance	0.88***	0.92***	1.07***	0.87***	0.88***	0.72***	0.76***	0.80***	0.82***	0.82***
	(0.17)	(0.21)	(0.26)	(0.23)	(0.24)	(0.18)	(0.18)	(0.19)	(0.16)	(0.17)
Tech: Household	0.94***	0.92***	1.11***	0.95***	0.95***	0.78***	0.71***	0.72***	0.72**	0.72**
	(0.12)	(0.12)	(0.19)	(0.17)	(0.18)	(0.18)	(0.18)	(0.20)	(0.20)	(0.20)
Tech: Waste	0.19	0.22	0.24	0.18	0.19	0.11	0.11	0.11	0.16	0.16
	(0.17)	(0.18)	(0.18)	(0.16)	(0.16)	(0.16)	(0.17)	(0.18)	(0.19)	(0.19)
Registry: GS		0.07	0.01	0.03	0.03	−0.03	0.09	0.21***	0.32***	0.32***
		(0.07)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.08)	(0.05)	(0.05)
Registry: Verra		−0.01	−0.06	−0.02	−0.03	−0.02	0.01	0.02	0.05	0.04
		(0.12)	(0.13)	(0.13)	(0.13)	(0.10)	(0.09)	(0.09)	(0.07)	(0.07)
log (GDP p.c.)			0.10**	0.18***	0.18***	0.17***	0.11**	1.30	−0.59	
			(0.05)	(0.06)	(0.05)	(0.05)	(0.04)	(1.60)	(0.56)	
log (Country emissions)				−0.06***	−0.06***	−0.06***	−0.05***	0.18	−0.01	
				(0.01)	(0.01)	(0.01)	(0.01)	(0.79)	(0.38)	
Project age					0.001	0.01	0.003*	0.004	0.003	0.004
					(0.01)	(0.01)	(0.001)	(0.01)	(0.01)	(0.01)
Project size					0.01	0.01	−0.01	−0.07*	−0.05*	−0.05*
					(0.05)	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)
log (Trade volume)						−0.10***	−0.11***	−0.09***	−0.09***	−0.09***
						(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Top-tier client						−0.24***	−0.25***	−0.25***	−0.26***	−0.26***
						(0.07)	(0.05)	(0.07)	(0.04)	(0.04)
Credit vintage						−0.01	−0.03***	−0.01	−0.02**	−0.02**
						(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Non-standard currency						0.26***	0.37***	0.28***	0.38***	0.37***
						(0.07)	(0.08)	(0.06)	(0.07)	(0.07)
Delivery delay (months)						−0.004	−0.003	0.004	−0.001	−0.001
						(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Year FEs	NO	NO	NO	NO	NO	NO	YES	NO	YES	YES
Country FEs	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES
Observations	7,203	7,203	7,203	7,203	7,203	7,203	7,203	7,203	7,203	7,203
Adjusted R^2	0.29	0.29	0.30	0.32	0.32	0.41	0.52	0.48	0.58	0.58

Table 5: **Panel models for VCM transaction prices and project characteristics.** This table shows OLS regression estimates that explore which project and transaction factors explain VCM transaction prices. The dependent variable is the natural logarithm of the transaction price. Technology and registry indicators correspond to the categories in Table 3). The reference (dropped) categories are, respectively, industrial projects (tech) and CDM (registry). Annual GDP per capita (expressed in constant 2021 USD) and country emissions are from the World Bank WDI dataset. Project age is the difference in years between the traded certificate's vintage year and the project launch (the earliest available vintage per project). Project size is the total emission reduction expected at project launch, standardized to zero mean and unit variance per project technology. 'Top-tier client' takes the value of 1 if the customer is in the top-20 trading accounts by transaction volume in the entire dataset. The carbon credit vintage is the year difference between the transaction date and the credit's vintage year. The non-standard currency indicator identifies transactions settled in a currency other than EUR, GBP, AUD, USD, or CHF. Delivery delay is the difference in months between the signing and delivery dates. The standard errors (in parentheses) are clustered at the transaction year level; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Models 3 and 4 add project country GDP per capita and CO_2 emissions (in logs). Higher host-country emissions are associated with lower carbon credit prices: 10% higher emissions relate to 6% lower prices. Controlling for emissions (model 4), credit prices increase with the host country's wealth: a 10% higher per capita GDP is associated with 1.8% higher prices. We interpret the latter as the installation cost effect, controlling for project technology. The magnitudes of both emissions and wealth effects decrease by about one-third when more confounders are added to the model, as in model 7. Importantly, host country emissions added in model 4 explain an additional 2% of the VCM price variation, and render the intercept small and insignificant. However, both wealth and emissions effects disappear once country fixed effects are added (models 8 and 9). This suggests that average differences across countries drive wealth and emissions effects, whereas within-country changes in emissions and wealth do not.

Model 5 adds project age (defined as the difference between the carbon credit issuance vintage and the project launch date) and project size (standardized to zero mean and unit variance per technology). The coefficient on age is statistically insignificant in all model specifications (except for marginal significance in Model 7). Project size is generally associated with lower carbon credit prices; however, the statistical significance and magnitude of the effect differ across models. Controlling for project country fixed effects (models 8–10), a one-standard-deviation increase in project size is associated with a marginally significant 5-7% decrease in credit price, which is likely a supply effect.

Model 6 extends the analysis to include transaction-level characteristics: trade volume, an indicator for top-tier clients (defined as being in the top 20 trading accounts based on volume), the vintage of the traded carbon credit (defined as the difference between the transaction date and the credit issuance year), and an indicator for non-standard settlement currencies. Trade volume is a strong pricing factor: a 10% increase in volume is associated with a 0.9-1.1% lower transaction price. The effect is beyond a discount for top-tier clients, which alone extends the discount to about 25%. Such volume discounts are typical in other OTC markets (e.g., Pinter et al., 2024) and are often linked to client relations and inventory management.

Older credit vintages are traded at a discount (a year older vintage bears a 1-3% discount). When VCM transactions are settled in currencies less prevalent in the foreign exchange market, the sales price is 26-38% higher, likely related to the FX risk that the dealer bears and the cost of hedging that risk. In the next section, we demonstrate that the foreign exchange premium is primarily driven by a few clients settling exclusively in non-standard currencies only. Delivery delay is not a price factor in our sample. Taken together, these transaction-level variables explain an additional 9% of the VCM transaction price variation, a sizeable portion, corresponding to roughly a third of the variation explained by the projects' technology.

Finally, models 7–10 add year and country fixed effects. Transaction year fixed effects (model 7) increase the Adjusted R^2 of the log-price model from 0.41 (model 6) to 0.52. A marginal R^2 contribution of project country fixed effects is lower at 0.07 (model 8 compared to model 6). Still, it suggests that project country characteristics beyond wealth and emissions likely matter for the pricing of the VCM credits. With both project country and time fixed effects (models 9 and 10), the models explain 58% of the variation in carbon credit prices.

3.2 Customer-level factors

This section explores the extent to which buyer characteristics matter for VCM prices. There is ample evidence from OTC markets that dealers exercise market power and price discriminate across customers (e.g., Graddy, 1995), which renders customer characteristics a factor in equilibrium pricing (Bretscher et al., 2024). We document which customer characteristics matter for VCM credit prices.

We start by documenting several stylized facts in Figure 4. Panel A shows substantial differences in average transaction prices across the industrial affiliation of carbon credit buyers. Clients from the finance, consumer goods, and services sectors pay a premium relative to buyers from other industries. Remarkably, the average price paid for a ton of CO_2e by energy, manufacturing, and transportation sector firms is about a third *lower* than that paid by financial firms ($4 against $6), even though the former are heavier CO_2 emitters. We do not find substantial differences in the average transaction price between firms of different sizes in Panel B of Figure 4. There is also no clear link between customer country emissions and VCM prices in Panel C of Figure 4.

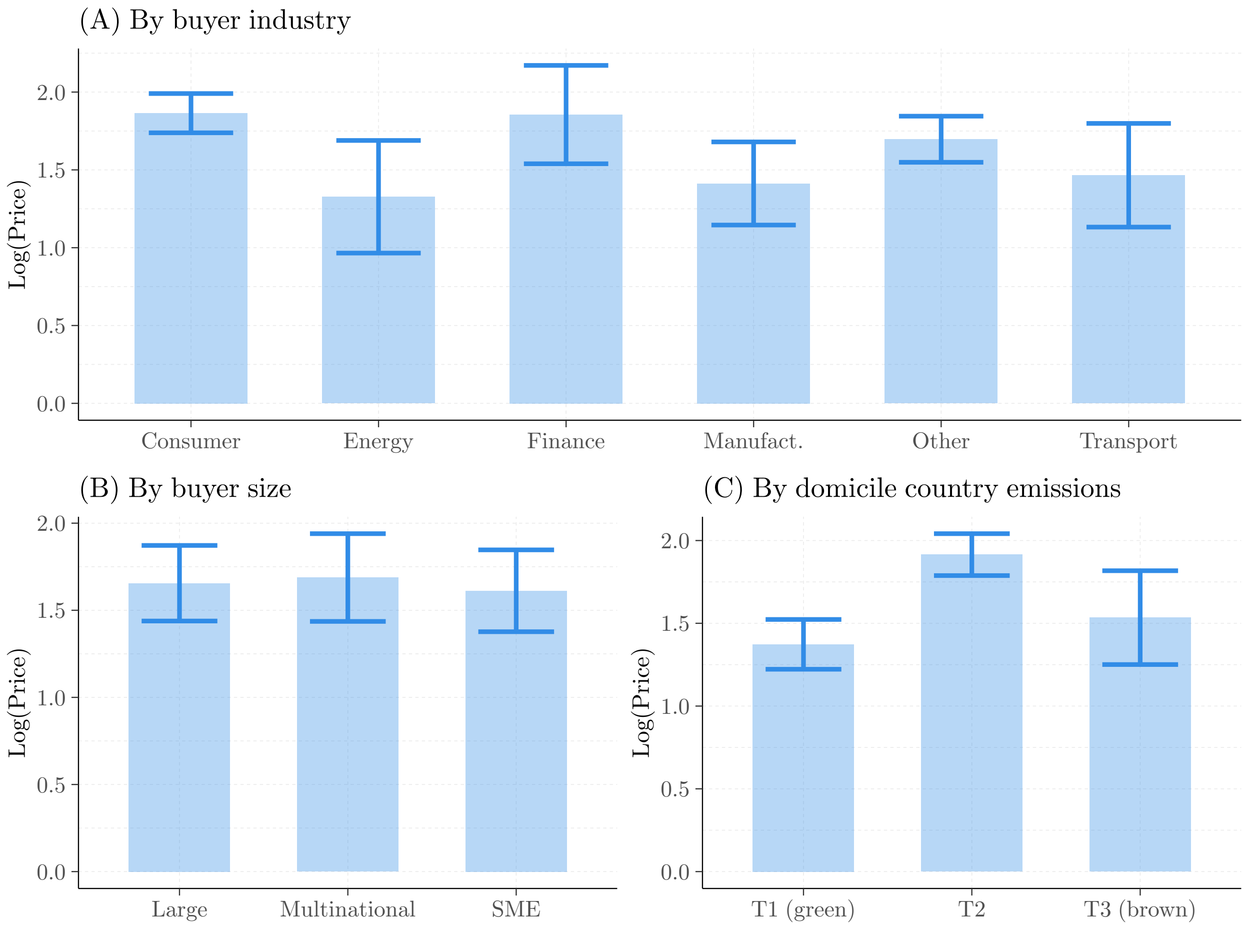

Figure 4: **Transaction log-price and buyer characteristics.**
This figure displays average transaction prices by buyer industry (Panel A), buyer size (Panel B), and by buyer domicile (Panel C). Buyer industry affiliation corresponds to those in Table 1. Transactions are split almost equally between buyer size categories (SMEs, Large, and Multinationals). Two-thirds of credit buyers are located in countries from the top tercile of global country emissions, 30% – in the middle tercile. Bars are coefficient loadings from a multivariate regression of log-price on category indicators (separate regression for each panel). The figure also plots the 95% confidence bands based on standard errors clustered at the year level.

To better evaluate price premia associated with different customer characteristics, net of project characteristics, we turn to regression analysis. Specifically, we estimate Equation (2) below:

$$log(Price)_{i,j,t} = \beta \ Client \ traits_{j,t} + \psi_{\mathbf{i,j,t}} + \delta_t + \epsilon_{i,j,t}. \tag{2}$$

The main explanatory variables of interest are captured in $\textit{Client traits}_{j,t}$, a set of buyer characteristics that include buyer industry, size, commitment to the SBTi, country GDP per capita and emissions, and an indicator for projects from the client's home country. $\psi_{\mathbf{i,j,t}}$ is the set of project and trade characteristics from Equation (1). δ_t is year fixed effects and $\epsilon_{i,j,t}$ is the error term, clustered at the year level.

Table 6 presents the results. Models 1–6 are estimated using the full sample, while models 7 and 8 are estimated in the subset of returning clients with at least 10 transactions in the dataset. Focusing first on client industrial affiliations, Table 6 confirms that financial and consumer sector firms—despite being only modest polluters—pay a sizeable premium of 15-25% per ton of CO_2 compared to industrial firms. It is important to stress that this premium is net of the effect stemming from project technology and other project and transaction characteristics. The effect is robust across model specifications and is not driven by clients with few transactions. Interestingly, we find that small and medium enterprises (SMEs) pay 7-11% less for credits compared to large firms once confounding price factors are accounted for.

Another notable result in Table 6 is the positive relation between the client home country wealth and the price paid for carbon credits. Clients from 10% richer countries, as measured by per capita GDP in constant 2021 USD, are paying 10-14% more for the same credits, according to models 4–7. The effect disappears in the subset of most frequent clients and when client fixed effects are included (model 8), suggesting that it operates only through the average differences in client country wealth. These results are consistent with dealers applying price discrimination only to coarse tiers of country wealth. We also find only limited evidence in favor of the home bias effect, where clients pay a premium for emission reductions realized in their home countries. The home bias is economically large at 36% but only marginally significant in the full sample. It remains large (44%) but becomes insignificant in the sample of frequent buyers, and disappears both economically and statistically once customer fixed effects are added (model 8), suggesting that the effect is largely driven by infrequent buyers of local carbon credits who appear in the dataset only a few times.

	Dependent variable: log (Price)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log (Trade volume)	-0.09^{***}	-0.09^{***}	-0.09^{***}	-0.09^{***}	-0.09^{***}	-0.09^{***}	-0.08^{***}	-0.05^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Top-tier client	-0.25^{***}	-0.23^{***}	-0.23^{***}	-0.23^{***}	-0.22^{**}	-0.21^{**}	-0.20^{***}	
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	
Credit vintage	-0.02^{**}	-0.02^{**}	-0.02^{**}	-0.02^{**}	-0.02^{**}	-0.02^{**}	-0.02^{**}	-0.02^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Non-standard currency	0.36^{***}	0.38^{***}	0.38^{***}	0.39^{***}	0.36^{***}	0.35^{***}	0.28^{**}	0.11
	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.10)	(0.09)
Project size	-0.05^{*}	-0.05^{*}	-0.05^{*}	-0.06^{*}	-0.06^{*}	-0.06^{*}	-0.08	-0.04
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)
Industry: Consumer	0.23^{**}	0.20^{**}	0.20^{**}	0.19^{**}	0.19^{**}	0.18^{**}	0.25^{**}	
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.10)	
Industry: Energy	-0.07	-0.10	-0.09	-0.08	-0.09	-0.10	0.02	
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.10)	
Industry: Finance	0.19^{***}	0.17^{***}	0.17^{***}	0.16^{***}	0.16^{***}	0.15^{***}	0.18^{**}	
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	
Industry: Other	0.19^{**}	0.16^{**}	0.16^{**}	0.15^{**}	0.15^{**}	0.14^{**}	0.16^{*}	
	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)	(0.07)	
Industry: Transport	0.06	0.04	0.04	0.05	0.02	0.02	0.08	
	(0.09)	(0.08)	(0.08)	(0.09)	(0.10)	(0.10)	(0.14)	
Size: Multinational		-0.01	-0.01	-0.01	-0.005	-0.003	-0.01	
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	
Size: SME		-0.08^{**}	-0.08^{**}	-0.08^{**}	-0.07^{**}	-0.08^{**}	-0.11^{**}	
		(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	
SBTi commitment			0.04	0.04	0.03	0.04	0.03	
			(0.06)	(0.06)	(0.06)	(0.06)	(0.08)	
log (Country GDP p.c.)				0.11^{**}	0.10^{**}	0.14^{**}	0.13^{*}	-1.08
				(0.03)	(0.03)	(0.04)	(0.06)	(0.58)
log (Country emissions)					-0.02	-0.02	-0.02	0.09
					(0.01)	(0.02)	(0.02)	(0.34)
Home bias						0.36^{*}	0.44	-0.12
						(0.18)	(0.30)	(0.23)
Project-related FEs	YES	YES	YES	YES	YES	YES	YES	YES
Clients >10 trades	NO	NO	NO	NO	NO	NO	YES	YES
Client FEs	NO	NO	NO	NO	NO	NO	NO	YES
Observations	7,203	7,203	7,203	7,203	7,203	7,203	3,974	3,974
Adjusted R^2	0.60	0.60	0.60	0.60	0.60	0.60	0.62	0.79

Table 6: **Panel models for VCM transaction prices and buyer characteristics.** This table shows OLS regression estimates that explore which client characteristics explain VCM transaction prices. Every model controls for project mitigation technology, domicile country, registry, and transaction year fixed effects. Volume, client tier, carbon credit vintage, currency, and project size variables are the same as those in the models in Table 5. The reference (dropped) category for the buyer industry is industrial manufacturing while for buyer size it is large firms. GDP per capita and emissions are for the *buyer* domicile country (as per billing address). Models 7 and 8 are estimated using the subsample of customers with at least 10 transactions. The standard errors (in parentheses) are clustered at the transaction year level; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Neither clients' SBTi commitments nor their countries' emissions are related to the price paid for carbon credits.[8] The absence of a link between SBTi commitments and firms' willingness to pay more for carbon credits is particularly surprising: one would expect firms setting voluntary climate targets to be willing to pay more to meet them. It is possible, though, that firms commit to SBTi only when they know that they will achieve targets by adjusting their production technologies at a lower cost than offsetting through the VCM.

The comparison of models 7 and 8 in Table 6 on the sample of repeated carbon credit buyers suggests that part of the VCM price variation is likely due to client characteristics unobserved in our dataset. With client fixed effects added to the model, the R^2 increases from 0.62 to 0.79. In comparison, observed client characteristics such as size, climate commitments, and home-country wealth and emissions explain less than one additional percentage point of price variation. Our interpretation of these results is that the dealer's price discrimination among customers is nuanced and does not rely solely on salient headline characteristics.

Finally, models 7 and 8 in Table 6 highlight the robustness of transaction- and project-level price factors. In particular, the volume discount is present even with client fixed effects, but it is reduced by roughly half. It suggests that both client relationship management and inventory management contribute almost equally to the observed volume discount. In contrast, the vintage discount remains unaffected by the inclusion of client fixed effects, suggesting that it is a common pricing feature rather than an effect specific to a particular group of carbon credit buyers. Among market practitioners, the vintage discount is typically

[8] In untabulated results, we confirm this non-result using multiple alternative measurements such as aggressive corporate SBTi commitments compared to peers, high carbon intensity per capita or per dollar of GDP at the country level. Across all these tests, we never find a significant relation to the VCM credit price.

associated with quality concerns (Probst et al., 2024), which are most pronounced for credit issuance under older, less stringent standards. In the next section, we provide additional evidence for this mechanism from the voluntary carbon futures market. Finally, model 8 in Table 6 shows that—once client fixed effects are absorbed—the non-standard currency premium becomes statistically insignificant.

4 Role of the Futures Market

Voluntary carbon markets, despite having a price dispersion more common to markets for goods that are heterogeneous in features and quality, are still equipped with a large derivatives market that is reminiscent of commodities.[9] In this section, we examine the relation between prices in the bilateral VCM spot market and activity in the VCM futures market.

The primary venue for trading VCM futures is the CME, with three core contracts: GEO (Global Emissions Offset), N-GEO (Nature-Based Global Emissions Offset), and C-GEO (Core Global Emissions Offset), which were introduced gradually between March 2021 and March 2022 to mirror similarly defined spot contracts at Xpansiv CBL, the largest VCM exchange launched earlier in 2018.[10] The main difference between the three is in the underlying: GEO is for aviation-sector-eligible credits (known as Carbon Offsetting and Reduction Scheme for International Aviation, CORSIA, developed by ICAO), N-GEO is for nature-based credits, and C-GEO is for non-nature-based credits satisfying stricter quality criteria

[9] In 2024 alone, more than 100 mln tCO_2e in carbon credit futures were traded (LSEG Commodities Research, 2025).

[10] There is also a futures contract for aviation-sector-grade voluntary credits at the ICE, which is less liquid than the CME ones. This section focuses on the CME market.

of Core Carbon Principles (CCP).[11] For most of 2024, all three of these futures prices were within \$1 per mtCO_2e of one another (LSEG Commodities Research, 2025).

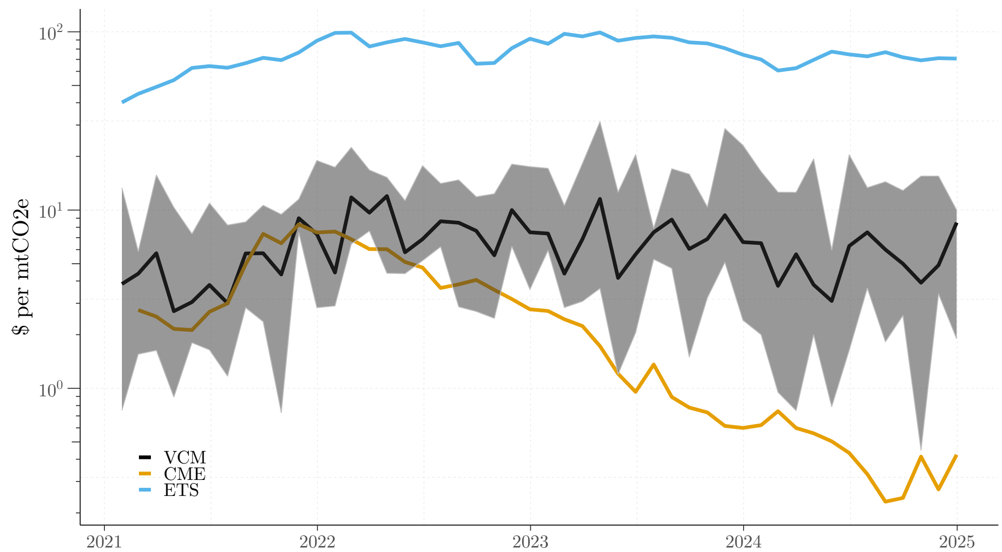

Figure 5: **Prices: VCM transactions, CME futures, and compliance market.** This figure shows the evolution of the median VCM price (black line) relative to the futures prices (orange line). The figure also includes the EU ETS prices (blue line) for reference. Prices are in \$ per metric ton of the CO_2 equivalent (log-scale). 'VCM' is the median monthly transaction price, conditional on delivery within 10 days of purchase (a proxy for a spot price). The shaded area is between the 10th and the 90th percentiles of spot VCM prices. 'CME' front-month futures price of the mtCO_2e for aviation-industry-grade carbon credits at the CME (GEO contract). 'ETS' is the emissions price in the European Union Emission Trading System.

Figure 5 plots the price of the front-month GEO futures (orange line) relative to the median VCM transaction price, the 10th and the 90th percentiles of spot prices (black line and shaded area), and the European compliance market (EU ETS) price (blue line) between 2021 and 2024. For most of the sample period, starting in the second quarter of 2022, the CME futures price was below the 10th percentile of VCM transaction prices and further decreasing. In absolute terms, in the last few sample years, while the futures VCM price is below \$1 per

[11]The CCPs were developed by the Integrity Council for the Voluntary Carbon Market, an independent industry governing body set up in 2021.

ton of CO_2, the median VCM transaction price remained at around \$6 per ton, and the ETS price is about \$70 per ton. The comparison between VCM futures and spot prices suggests that the futures market has 'raced to the bottom'. As CME futures are deliverable on expiry (the seller delivers a carbon credit), and a wide range of credits are eligible for delivery, the futures price is for the cheapest-to-deliver credit.[12] As Section 3 has discussed, carbon credit prices differ vastly, and such a cheapest-to-deliver credit is worth just a small fraction of the average. To put this into perspective, at a futures price of less than \$1 per ton, it costs less than \$2 in 2024 to formally offset the carbon emissions of a single return London-to-New York plane journey, amounting to approximately 1.7 tons of CO_2. Using the median VCM contract, this would be \$10, while with the ETS prices one would need to pay close to \$120.

[12]The same applies to the corresponding spot basket contracts at Xpansiv CBL: any single-name credit or a basket of credits that satisfy contract definition and delivery criteria is eligible for contract settlement.

	Dependent variable: log (Price)				
	(1)	(2)	(3)	(4)	(5)
CME eligible × Post-CME	0.15**	0.16***	0.16**	0.20**	0.06*
	(0.07)	(0.06)	(0.06)	(0.08)	(0.03)
CME eligible (dummy)	−0.03	−0.06**	−0.05*	−0.08**	−0.01
	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
Post-CME (dummy)	0.24*	0.22*	0.22*	0.18	0.22**
	(0.13)	(0.12)	(0.12)	(0.11)	(0.09)
log (Trade volume)	−0.08***	−0.08***	−0.07***	−0.06***	−0.03**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Top-tier client (dummy)	−0.25***	−0.22***	−0.22***	−0.23***	
	(0.10)	(0.06)	(0.08)	(0.06)	
Non-standard currency (dummy)	0.31***	0.35***	0.34***	0.33***	−0.04
	(0.07)	(0.06)	(0.06)	(0.09)	(0.12)
Project size (std. per tech)	−0.08**				
	(0.04)				
log (Customer GDP p.c.)	0.11***	0.14***	0.11***	0.11	2.35***
	(0.03)	(0.03)	(0.03)	(0.08)	(0.71)
Clients with 10+ trades	NO	NO	NO	YES	YES
Tech, Country, Registry FEs	YES	NO	NO	NO	NO
Project FE	NO	YES	YES	YES	YES
Client Industry FE	YES	NO	YES	YES	NO
Client FE	NO	NO	NO	NO	YES
Observations	7,203	7,203	7,203	3,974	3,974
Adjusted R^2	0.52	0.60	0.61	0.66	0.82

Table 7: **VCM transaction prices and CME delivery standards.**
This table shows OLS estimates exploring the pricing impact of contracts being eligible for delivery in the carbon offset futures markets. 'CME eligible' is an indicator that takes the value of 1 if the traded carbon credit can be delivered against an expiring CME futures, i.e, its vintage is not older than 5 years. 'Post-CME' is an indicator for transaction that start in April 2022 (full introduction of the CME futures contract offering). Other price factors are as in Table 6. The standard errors (in parentheses) are clustered at the transaction year level; ; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Despite an apparent decoupling of the central tendency in VCM transaction prices and the cheapest-to-deliver futures price, as in Figure 5, we find that the futures market delivery standards do affect VCM transaction prices. For N-GEO and C-GEO contracts, delivery is only allowed for carbon credits from the five most recent year vintages, with a reset on

July 1st of each year. Thus, in subsequent difference-in-difference analysis, we label as 'CME eligible' the credits from the most recent five vintages that are deliverable against an expiring CME futures. They constitute about 58% of our transaction sample. The second difference lies in the comparison of periods before and after the introduction of the CME futures market, the latter commencing in April 2022. Such 'Post-CME' period accounts for 43% of our sample by observation count and 56% of these trades are in CME-eligible credits.

Table 7 presents DiD estimates for the effect of CME eligibility on VCM transaction prices. Here, we regress the VCM log-price on significant price characteristics from Table 6, replacing the continuous variable for carbon credit vintage with the CME eligibility dummy and year fixed effects with the Post-CME dummy. We include either project technology, country, and registry fixed effects, or just project fixed effects, separately or together with client industry fixed effects (models 1–3). In addition, we consider the subset of repeated buyers (model 4), as in Section 3.2, and estimate the model with both client and project fixed effects (model 5). In the full sample estimates (models 1–3), we find that CME eligibility bears a statistically significant 15–16% price premium at the bilateral VCM market. In the sample of repeated buyers, the CME eligibility effect increases to 20% with client industry fixed effects. When we run a very restrictive specification including client fixed effects on top of the other controls, this premium reduces to 6% but remains marginally significant. We associate the CME eligibility effect with an additional demand for VCM credits in the bilateral market coming from futures sellers that need to deliver credits against expiring futures.

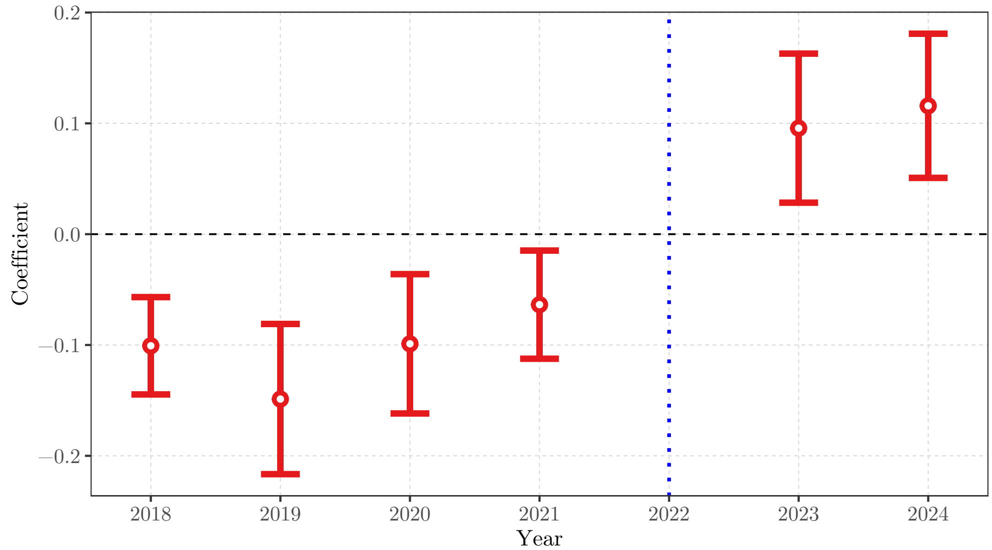

Figure 6: **Log-price premium and discount for CME-eligible carbon credits.** This figure shows the coefficient estimates of the premium that CME eligible contracts command. Points are the respective estimates from the regression similar to model 3 in Table 7, where a set of transaction year dummies replaces the post-CME dummy. Year 2022 is the reference year; the coefficients are thus the differences relative to the effect in 2022. The figure includes the 90% confidence intervals based on standard errors clustered at the year level.

Figure 6 illustrates the effect by plotting the estimates on the interactions of the CME eligibility dummy with calendar year dummies (year 2022 being a reference year) in a model otherwise identical to model 3 of Table 7. The plot shows that, before 2022, recent credit vintages were trading about 10% cheaper than in 2022, with only a muted pre-trend, which is likely explained by the gradual development and introduction of the CME futures market. Post-2022, CME-eligible credits are traded at a 10% and a 20% premium to the year 2022 and the pre-2022 period, respectively. This evidence confirms that the link between the futures market and the underlying carbon credit bilateral market is strong, both economically and statistically, despite the prices in the two markets appearing to be significantly different in absolute terms.

5 Discussion

Ultimately, firms participate in the VCM to satisfy consumers' and investors' demand for climate action. Accordingly, the structure of the VCM likely reflects the nature of this demand—specifically, how climate action enters the utility function of these agents. Building on theoretical work, we can distinguish between two conceptually distinct views of pro-social behavior. Consumers and investors may be seen either as (1) consequentialists, who seek to maximize their actual climate impact, or (2) as warm-glow optimizers, who maximize the emotional utility derived from engaging in ostensibly green consumption or investment. Although our results provide some empirical support for both mechanisms, the pricing patterns observed in the VCM are most consistent with the warm-glow interpretation.

From a consequentialist perspective, consumers and investors act as "pure" altruists who derive utility from the level of a public good—in this context, the atmospheric concentration of greenhouse gases. This assumption underlies much of the theoretical literature on green preferences among investors and consumers (e.g., Landier and Lovo, 2020; Broccardo et al., 2022; Oehmke and Opp, 2025; Green and Roth, 2025). For consequentialists, the pro-social utility gained from purchasing products or investing in firms that use carbon credits depends on the expected climate impact of those credits. If expectations about impact differ across projects—for instance, due to variation in perceived quality—such heterogeneity could account for the price dispersion we observe. However, this view cannot explain why prices are systematically higher for projects with lower reliability in achieving actual climate impact.

By contrast, under a warm-glow perspective, consumers and investors behave as "impure" altruists who obtain emotional satisfaction by selecting green investments or products regardless of their objective effectiveness. This view is taken up in theoretical work (Heinkel et al., 2001; Pedersen et al., 2021; De Angelis et al., 2023) and supported by empirical evidence (Heeb et al., 2023; Bonnefon et al., 2025). In this view, the emotional utility derived from a firm's use of carbon credits may depend on project attributes unrelated to their real climate effects. Psychological research on charitable giving suggests that emotional responses are stronger when beneficiaries are identifiable or when projects evoke empathy through emotionally salient subjects, such as animals or nature (e.g., Hsee and Rottenstreich, 2004; Small et al., 2007). Thus, a "warm glow" perspective can account for the markedly higher prices observed for household-focused, nature-based projects or projects with tangible co-benefits, relative to arguably more reliable, yet less emotionally engaging activities, such as methane reduction in waste treatment.

In sum, our evidence suggests that the VCM functions less as a market for carbon as a global commodity and more as a market for tradable emotional benefits conveyed through carbon credits.

6 Conclusion

We analyze a comprehensive dataset of secondary market transactions in voluntary carbon credits. The market exhibits extreme price dispersion, with prices tied to characteristics of emission reduction projects, buyers, and individual transactions rather than a common value of carbon emissions reductions. Heavy GHG emitters and firms with explicit climate targets do not pay higher prices for carbon credits. Overall, carbon credits appear to be priced as differentiated goods, with buyers paying premiums for the emotional benefits associated with specific projects rather than for a ton of carbon as a standardized commodity. This pattern raises important questions about the VCM's effectiveness in delivering cost-efficient carbon abatement. Nevertheless, given that some buyers display a substantial willingness to pay for carbon credits, policymakers may find it worthwhile to ensure that firms' marketing claims based on carbon credit usage are more closely aligned with actual climate impact.

Next steps: We are integrating additional data sources into our analysis, including market-wide trading insights from a commodity intelligence provider and transaction data from the leading carbon credit exchange. These data will enable us to assess the external validity of our results based on transactions from a major broker and to examine how carbon credits are priced across different trading platforms. In addition, we plan to conduct event studies to analyze how shocks to the perceived integrity of specific project types affect carbon credit pricing

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