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Offset Credits in the EU ETS: A Quantile Estimation of Firm-Level Transaction Costs

Helene Naegele

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Abstract

International carbon offset certificates are cheaper than European Union Allowances (EUAs), although they are substitutes within the EU Emissions Trading System (EU ETS). Thus, firms had a strong incentive to use offset certificates. However, a considerable number of firms did not exhaust their offset quota and, by doing so, seemingly forwent profits. While most literature on emissions trading evaluates the efficiency of regulation in a frictionless world, in practice firms incur costs when complying with regulation. In order to assess the relevance of trade-related fixed transaction costs, this study examines the use of international offset credits in the EU ETS. It establishes a model of firm decision under fixed (quantity-invariant) entry costs and estimates the size of trading costs rationalizing firm behavior using semi-parametric binary quantile regressions. Comparing binary quantile results with probit estimates shows that high average transaction costs result from a strongly skewed underlying distribution. For most firms, the bulk of transaction costs stems from certificate trading in general, rather than additional participation in offset trading.

JEL : C25, D23, H23, Q58.

Keywords : Binary quantile estimation, CDM, climate change, carbon emissions trading, entry costs, EU ETS, offset certificates, semi-parametric estimation, transaction costs.

1 Introduction

The EU Emissions Trading System (EU ETS) aims at achieving the EU’s carbon emission goals at minimum cost. Instead of imposing a tax, the policy determines an emission cap and lets the market determine the equilibrium emissions price. Ideally, all firms incur the same price for emissions and abatement is realized where it is cheapest, so that the aggregate abatement cost is minimized. However, abatement and certificate costs are not the only costs arising from an emissions trading scheme: just like any other regulation, this policy has to be implemented by firms, causing a wide range of administrative, managerial, and information-related transaction costs. Typically, such frictions are unobserved by the econometrician. Presumably, many firms themselves do not track the value of their employees’ time and resources spent in the course of EU ETS compliance and optimization. This study considers such unobserved trading cost, i.e. transaction costs that are conditional on trading.

This study focuses on the possibility for firms to use not only European certificates but also international offset credits. The EU ETS is linked to the international certificate market of the Kyoto Protocol. On aggregate, these additional foreign certificates increase the cap for European polluters and decrease their compliance cost. Offset credits were cheaper than European credits (European Union Allowances, EAUs) throughout Phase II of the EU ETS (2008-2012). However, the EU limited the quantity of offset credits by a firm-specific offset quota (*entitlement*). For the firms, offset usage was an unambiguous way to reduce compliance cost. Nevertheless, over twenty percent of regulated firms did not use any offsets.

This study uses firm-level data on offset usage to estimate the distribution of fixed trading costs, both for general entry into certificate trade and for offset use in particular. It brings together elements, first, from theoretical literature on transaction costs in emissions trading; second, from empirical literature on transaction costs in European emissions trading; and, third, from the small literature on the use of offset certificates in the EU ETS. Methodologically, this research uses binary quantile methodology.

While the abatement incentives of cap-and-trade schemes are amply discussed, most of the literature does not consider transaction costs. However, emissions trading – just like any other market transaction – is unlikely to be completely free of frictions. In his seminal article, Coase (1960) underlines that the irrelevancy of initial property allocation for final resource allocation holds only if “costs to use the price mechanism” are negligible. The theoretical model of Stavins

(1995) focuses on variable (quantity-dependent) trading costs, i.e. transaction costs arising from each certificate traded. Singh and Weninger (2016) build on this seminal work and show what distinguishes the impacts of variable and fixed (quantity-independent) trading costs. Fixed trading costs, as analyzed in this study, suppress some of the potential trades and lead to capacity- and permit-underutilization; they also make initial allocation non-neutral, as firms only trade if their optimal emissions and initial allocation are far away from each other.

Empirical evidence on transaction costs in environmental policy is scarce, as McCann et al. (2005) note in their literature review. Literature suggests that transaction costs and other market imperfections have hampered the impact of US environmental trading programs (Tietenberg 2006, Hahn and Hester 1989). For example, Atkinson and Tietenberg (1991) argue that trading is too scarce to reach a cost-effective outcome; they claim that this inefficiency stems from the bilateral, sequential nature of trades leading to frictions and thus transaction costs in a broad sense.

Concerning the EU ETS, the literature generally finds that small firms trade more “passively” and that many firms lack the inherent institutional capacity for optimal trading, e.g. Sandoff and Schaad (2009) on a sample of Swedish firms. Many German SMEs trade only at the end of the year and *only if* the grandfathered allocation does not suffice (Löschel et al. 2011). Schleich and Betz (2004) state that for small firms, transaction costs likely exceed certificate cost. Zaklan (2013) shows that most transactions take place between plants belonging to the same firm, which could be seen as a way to reduce trading cost. Surveys show that large emitters face smaller per-tonne transaction costs (Heindl 2015, Jaraitė et al. 2010, Löschel et al. 2010, 2011). For example, Jaraitė et al. (2010) estimate that in Ireland *per tonne* transaction costs of the largest firms were €0.05 per tonne of emissions, while they were up to €2 per tonne for small firms. This suggests that transaction costs are mostly composed of fixed (quantity-independent) costs, potentially combined with smaller variable (per unit) costs. However, different authors use different definitions of transaction costs, making literature comparison difficult. Some studies include monitoring, reporting and validation (MRV) costs that occur for *all* regulated firms, while others concentrate on transaction costs that occur conditionally on trading. Virtually all empirical work on trading costs in the EU ETS relies on survey-data, except Jaraitė-Kažukauskė and Kažukauskas (2015) who use transaction data from Phase I (2005-2007). They find that trading costs were a substantial factor inhibiting firms from actively trading European certificates, but they do not directly estimate their magnitude.

While the previously cited literature examines trading schemes with only one type of certificate, few articles deal with linked schemes with two certificate types. Trotignon (2012) shows that firms initially used few offsets until 2011, when there was a sharp increase. He estimates the cumulated savings of firms at €1.5 billion. Ellerman et al. (2016) provide an aggregate description through the end of Phase II in 2012.

Binary choice methods are an established way to identify latent variables which shape behavior around some cut-off. In particular, one can identify unobserved costs from observed participation behavior to some cost-saving or profit-yielding activity. Anderson et al. (2011) use this approach on the marginal costs of regulating fuel-standards by observing to what extent car producers use a regulatory loophole of known costs to avoid the fuel-efficiency standards. Attanasio and Paiella (2011) similarly identify fixed household costs of financial market activity from household's participation choice in the market. Conceptually, this resembles the present study, which identifies fixed costs by measuring the returns that firms forwent by avoiding trade. Quantile models are developed by Koenker and Bassett Jr. (1978), and applied to binary choice by Kordas (2006). Belluzzo Jr (2004) uses them to estimate the distribution of willingness-to-pay for a public good, analogous to the present study: I measure transaction costs here from the observed “unwillingness-to-benefit” of firms. Going beyond usual estimation of the mean, this quantile methodology allows me to estimate the median as well as (a discrete approximation to) the whole distribution of transaction costs across 19 quantiles.

This study provides both an analytical and empirical contribution to the literature. First, it describes the observed offset usage behavior. Among the firms that did not use offsets, there are mostly small firms and, more particularly, firms with generous free allocations of European certificates. Across all firms, forgone revenue adds up to around €1.37 billion.

In a second step, I argue that firms' reluctance to trade can be interpreted as transaction costs. Without such unobserved transaction costs, the offset entitlement would be an unequivocal “free lunch” opportunity. The share of firms incurring this opportunity cost can only be explained by the interference of some unobserved frictions: trading costs, as defined in this study, can include employees' time/salaries, training and consultancy costs. These are assumed fixed (quantity-independent) and payable whenever a firm first decides to engage in emissions trading in general or offset trading in particular; therefore, they might also be called entry costs.

The theoretical section lays out how trading costs change the firms' optimization problem. Building on the standard model, I introduce a second type of certificate and fixed transaction

costs. The model establishes that such costs make the firms' free allocation of permits non-neutral, as firms with allocations larger than their emission do not *need* to engage in emissions trading: they can avoid transaction costs of active trading, such that they are less likely to use their offset entitlement. The model establishes a link between, on one hand, the decision to trade on the offset market and, on the other hand, both the initial net allocation status and offset entitlement. This relies on the fundamental assumption that a firm enters offset trading if and only if (observed) trading benefits exceed (unobserved) trading costs.

The empirical section uses this insight to estimate the latent transaction costs rationalizing a firm's decision to not to enter the offset market. To the best of my knowledge, this is the first study to estimate costs using binary quantile regression. I identify the distribution of two trading cost components: general transaction cost of trading and offset-specific cost. The empirical results show that trading cost to the offset market is low for most firms, with a median of €905. The general trading cost is much higher with a median cost of €7,770. However, the estimated distribution of these costs is highly skewed, such that the means are much higher than the medians (€21,519 for mean general entry and €83,675 for offset market entry), resulting from some large outliers. Thus, a probit regression of the conditional mean is misleading about the costs faced by the majority of firms. Although these transaction costs are often small compared to other production factors, they make the use of offsets unprofitable for 21% of the firms. For bigger firms, investment in offset certificates mostly remains profitable.

The remainder of this paper is organized as follows. After introducing the institutional and legal framework of international offset certificates (Section 2.1), I briefly explain the aggregate impact of offset trading in the EU ETS (Section 2.2) and the definition of transaction costs in this context (Section 2.3). I then set up a model of firm-behavior in the reference case, i.e. without any transaction/entry costs (Section 3.1), which I extend by adding entry costs (Section 3.2). Finally, I present the data and some stylized facts, explain the econometric methodology (Section 4) and present the estimated distribution of transaction costs (Section 5).

2 Background

The EU ETS and the international offset credits are based on a complex regulatory framework. This section briefly explains the key elements of this regulation. It further sketches out the aggregate mechanics of introducing a second type of certificate into an emissions trading system.

Finally, this section explains in detail exactly which transaction costs this study examines.

2.1 Institutional framework

Each year, the European Union issues EU emission allowances (EUAs) that, in total, equal the overall EU ETS emission cap. In Phase II – the period under study here – virtually all these certificates were distributed free of charge to the regulated firms, according to their historical emission levels (*grandfathered allocation*). At the end of each year, firms have to report their emissions and *surrender* certificates equaling their emissions: one for each tonne of CO₂. Other greenhouse gases are included as well, e.g. methane (CH₄) and nitrous oxide (N₂O). Emissions of these other gases are converted with specific factors to CO₂ equivalent masses; hence the use of *tonnes of CO₂ equivalent* (tCO₂e) as a unit measuring quantities of certificates. Used certificates disappear, while unused certificates are *banked*, as they remain valid in subsequent years.

In order to coordinate international emission reduction efforts and to lower abatement cost for EU-based companies, the EU linked its ETS to the international framework established by the United Nations Framework Convention on Climate Change (UNFCCC, 1992) and the Kyoto Protocol. According to these international conventions, suitable projects that save emissions in unregulated parts of the world¹ can be validated and certified by UNEP. This procedure then generates Certified Emission Reductions (CERs, from Clean Development Mechanism) or Emission Reduction Units (ERUs, from Joint Implementation) that can be used to cover emissions in regulated parts of the world. CERs and ERUs are commonly called *international offset certificates*.² The EU does not distribute offset certificates, meaning that firms can only use them after actively acquiring them, either by conducting projects generating offsets or by buying them on the market.

Within their obligations under the EU ETS, firms could substitute a limited amount of European certificates with offset certificates. Such a substitution is attractive because offset certificates are cheaper than European certificates. However, to ensure that the bulk of emission reduction was achieved domestically, the EU restricted the quantity of offsets usable by each firm. The exact definition of this quota depends on the national government, but most

¹Kyoto “non-Annex I” countries, in practice mostly China, Ukraine and India.

² CERs and ERUs can be used interchangeably under this legislation. I will only use the term “offsets” from now on, as everything applies equally to CERs and ERUs.

countries computed it as a percentage share of the grandfathered allocation, cf. Table 4 on page 34 in Appendix A. This yields a firm-specific *offset entitlement*, as a product of firm-specific allocation and country-/sector-specific percentage share. While European certificate allocations were distributed each year, the total offset entitlement was determined only in 2008; once fixed entitlements could then be used at any point in time over Phase II.

Offset entitlements were set in advance for the entire Phase II. In the middle of Phase II (April 2009), EU Directive 2009/29/EC announced that the usage limits of certain offsets should be transferable (*bankable*) into Phase III (2013-2020); however it was unclear what amounts and which types of certificates were involved. It was clear that "industrial gas" certificates, which constituted the bulk of offsets traded (Ellerman et al. 2016), would not be valid anymore. Due to institutional obstacles, the final regulation ensuring the bankability and its conditions only appeared in November 2013,³ i.e. *after* the original claims for Phase II expired. From the perspective of a firm acting during Phase II, the end of Phase II had therefore to be considered as the temporal limit when planning the use of its offset entitlement.⁴

An alternative explanation for limited offset use would be that offset use was limited by supply side constraints. However, the central registry of the UNEP shows that the number of offsets generated at the end of 2012 was much higher than aggregate offset usage rights within the EU.⁵ Offset prices collapsed to virtually zero after the end of Phase II, which shows that the EU ETS demand was the driving force behind offset valuation.

2.2 Why are offset certificates cheaper?

Before looking at the impact of transaction costs, it is useful to consider the impact of offset certificates in general (without transaction costs) and in particular show why they have been cheaper than European certificates. Transaction costs are added in Section 3.2. International offset credits cover emissions from geographic regions that are not previously included in the scope of EU ETS. As such, they are a *spatial flexibility mechanism* (Stevens and Rose 2002)

³Commission Regulation (EU) No 1123/2013

⁴See Appendix B on page 35 for more detail.

⁵Theoretically, in addition to EU firm-level demand (analyzed in this study) there was scope for additional demand coming from the state-level; however, at the state-level of the Kyoto framework, offsets were perfect substitutes for Assigned Amount Units (AAUs). Given the large AAU overallocation to ex-Soviet Union states (so-called "hot air"), the evidence suggests that AAUs are usually sold far below the price of EUAs, CERs, and ERUs (Aldrich and Koerner 2012).

marginal abatement cost/prices

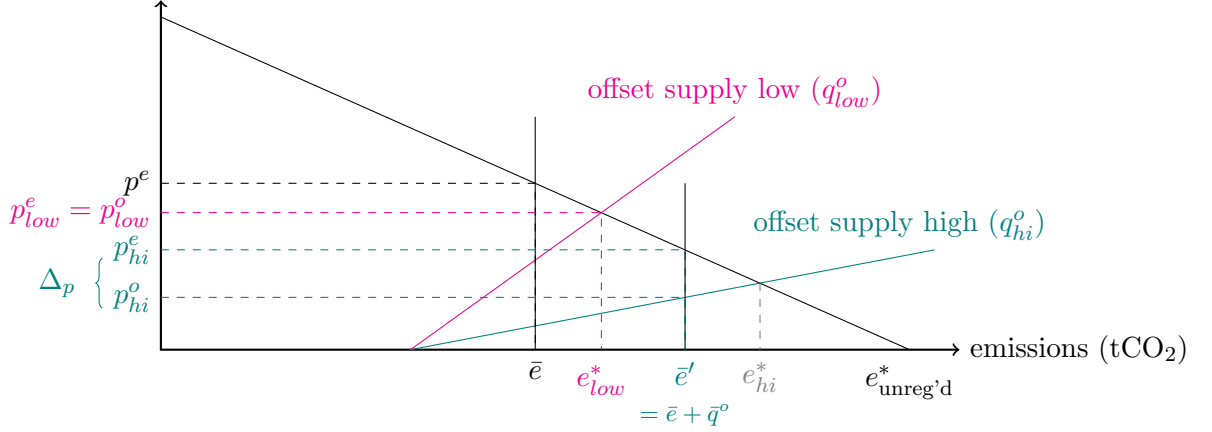


Figure 1: Aggregate market equilibrium, with two alternative offset supply levels

allowing firms to abate where it is cheapest and have the abatement credited via the creation of offset credits. The introduction of offsets increases the overall cap imposed by the EU ETS. Potentially, the cap could increase by an amount equal to the sum of all firms' offset quotas (*entitlements*).⁶

Figure 1 illustrates the resulting market equilibrium: in an unregulated situation, emissions have no cost and firms emit e_{unreg}^* . In an ETS without offset credits, the standard result for emissions trading holds: the market clears at the regulated maximum emission level \bar{e} at price p^e , equal to the marginal abatement cost at \bar{e} (Trotignon 2012). When offsets are introduced, they are perfect substitutes for European certificates up to the quota. When offsets are costly to produce (supply q_{low}^o), their availability increases the overall cap, lowers the price and moves the equilibrium to e_{low}^* , where prices are set at the level for which offset supply clears. This equalizes European certificate and offset prices $p_{low}^e = p_{low}^o$. When offset creation is cheap (supply q_{hi}^o), firms would like to buy more offset certificates than allowed and emit up to e_{hi}^* . The aggregate offset quota \bar{q}^o binds in that case. The resulting constrained equilibrium at $\bar{e}' = \bar{e} + \bar{q}^o$, no longer ensures equal prices: European certificates trade at marginal abatement cost p_{hi}^e at \bar{e}' . The over-supply of offset certificates drives their price down to p_{hi}^o . The price differential $\Delta_p = p^e - p^o$ is always positive or zero; its magnitude depends on the difficulty to generate offsets and on the stringency of the offset quota.

⁶See Mansanet-Bataller et al. (2011), Nazifi (2013) for more details from a finance perspective.

2.3 Definition and interpretation of transaction costs

The EU ETS causes direct costs through abatement and certificate prices. Besides this direct (and intended) cost, the EU ETS causes a number of (unintended) information-, administration- and management-related frictions, which in this paper are broadly understood under the term transaction costs.

I separate these costs into two parts according to their contingency: the first are “administrative costs” due to mandatory actions, such as costs for monitoring, reporting and validating emissions (MRV) as well as the EU registry service charges. These administrative costs are unavoidable and thus cannot explain firms’ (non-)entry to the offset market. The second, generally known as trading or entry costs, are the consequence of voluntary trading choices, such as information gathering, forecasting of allowance prices, finding trading partners, bargaining, contracting, managing price risk, or finally simply the costs of out-sourcing the whole trading process. This study concentrates on the latter, i.e. trading costs, which are defined as all frictions that are important for a firm’s decision to actively enter the permit market. While some firms have to trade, others have allocations large enough to avoid any active involvement in the certificate market.

This definition is narrower than in other works which consider the overall cost of establishing, managing, monitoring and enforcing a policy (Krutilla and Krause 2010, Joas and Flachsland 2016).⁷ However it is also broader than the definition used in some of the literature, as it includes *all frictions* preventing firms from entering the certificate market, in particular it includes outsourcing costs and purely psychological factors that discourage managers from devoting resources to certificate trading.

Heindl and Lutz (2012) finds that information-procurement alone – the biggest upfront cost – costs firms about 17 employee-workdays. He also finds that information and trading costs do not depend on firm size. While this indicates fixed costs, most surveys present their results on a per-tonne basis, i.e. interpreting them as variable rather than fixed costs, cf. Table 1. None of them asks about offset-related costs. The brokerage fees of an individual transaction are low,⁸

⁷In particular, this study concentrates on costs borne by firms and does not take into account what Joas and Flachsland (2016) call “public-sector costs” borne by the regulatory authority.

⁸Convery and Redmond (2007) establish a list of direct transaction fees: brokers have large minimum trade sizes and take between 1 and 5 cent fee per certificate (tCO₂e). Exchanges take smaller trades and charge between 0.5 and 3 cent per certificate.

	Average transaction costs	Cost structure	Scope	Time
Heindl and Lutz (2012)	€4,193 information	fixed +	Germany	2009
	€4,659 trading	variable		and 2010 (yearly)
	€12,223 MRV			
Jaraitė et al. (2010)	€71,860 early implementation	variable	Ireland	Phase I
	€74,180 MRV			
Löschel et al. (2010)	€1.79/tCO ₂ e if emissions < 25,000t	variable	Germany	2009
	€0.36/tCO ₂ e if emissions ≥ 25,000t			
Löschel et al. (2011)	€11,136 MRV and information	fixed +	Germany	2010
	€2,654 trading	variable		
Jaraitė-Kažukauskė and Kažukauskas (2015)	show significance, no magnitude		EU	Phase I

Source: Cited studies and own computation from estimated parameters stated in the original studies.

Table 1: Overview of transaction cost estimates per firm in the EU ETS in the literature while there are upfront entry costs. Just as an example, setting up a trading account at the ICE (the biggest exchange, clearing about 90% of emission certificate trade in Europe) costs €2,500 in direct fees,⁹ while an individual transaction thereafter costs only cents.¹⁰

A multitude of news and data providers (Point Carbon), consulting firms (ICIS/Tschach), and financial transaction services (brokerage like TFS Green, exchange platforms like ICE) have emerged. The fact that firms use such costly services indicates a lack of cost-free information. Moreover, descriptive management literature highlights the discrepancy between actual and intended market practice: firms use simple heuristics instead of fully optimizing their behavior (e.g. Veal and Mouzas 2012). These anecdotal elements support the idea of transaction costs, even though firms may rarely account for them as such explicitly.

⁹As indicated on <https://www.theice.com/fees> (March 1, 2015)

¹⁰Internationally operating firms could decide to create offset certificates in their own plants abroad, rather than purchasing the certificates on a market place. This study assumes that the large majority of firms bought their certificates, which matches anecdotal evidence about offsets. However, this claim cannot be proven due to data restrictions. If this claim is not true, the estimations in this study remain valid, but their interpretation changes from trading costs to transaction costs in the generation of offsets.

3 Model

First, a static model describes firm's optimization problem in presence of two types of emission certificates without transaction costs. In a second step, I examine how optimal behavior changes in the presence of fixed transaction costs. Simply put, firms always want to use offset credits, unless transaction costs are higher than potential returns from using the cheaper offset credits. Given the institutional background, the model is static with just one period corresponding to Phase II of the EU ETS.

3.1 Emissions trading with offset credits: reference scenario without trading costs

For the purpose of this study, it is useful to look at firms' optimization problem aggregated over Phase II. As a reference case, this subsection extends the standard emissions trading model with a second type of certificate and *without* adding trading costs. It appears that firms can separate the decision of optimal emission levels and produced quantities from the partitioning between European and offset certificates.

In the absence of offsets, it is shown (e.g. by Montgomery 1972) that there is a market equilibrium ensuring that marginal abatement cost is constant across firms and equal to the European certificate price p^e . Each firm i jointly produces some quantity y and emissions e , maximizing profits:

$$\max_{y_i, e_i, q_i^e, q_i^o} \pi = y_i - C(y_i, e_i) - p^e(q_i^e - q_i^{e0}) - p^o q_i^o, \quad (1)$$

$$\text{subject to } e_i = q_i^o + q_i^e, \quad (2)$$

$$q_i^o \leq \bar{q}_i^o, \quad (3)$$

where π is profit and $C(y_i, e_i)$ production cost, which depends on emissions e_i and output y_i sold at a price normalized to 1. I assume that reducing emissions at a given production level increases cost, $C_e < 0$.¹¹ q_i^o is the amount of offsets and q_i^e the amount of European certificates used. At the beginning of Phase II, firms are given a free allocation of European certificates q_i^{e0}

¹¹ C_y and C_e denote the partial derivatives with respect to y and e , respectively. The production cost function includes abatement cost, as the marginal cost of reducing emissions by a tonne at same output equals $-C_e$ (see Singh and Weninger 2016, for further details).

and a firm-specific offset entitlement \bar{q}_i^o . They can buy and sell European certificates at market price p^e and offsets at price p^o .

The firm must simultaneously solve three problems: decide on the optimal produced quantity y_i^* , determine the optimal emission level e_i^* , and split compliance (i.e. an amount of certificates equal to e_i) between the international offset and European certificates. The first-order conditions require the quantity to be chosen optimally given production cost $C(y_i, e_i)$ and prices. Let us assume that the production cost function C is such that there exists function $y_i^*(e_i)$ giving the optimal (profit-maximizing) quantity produced for any given emission level at given prices.¹² To satisfy the first-order condition, emissions e_i^* have to be such that marginal abatement cost is equal to the marginal certificate price:

$$-\frac{\partial C(y_i^*(e_i^*), e_i^*)}{\partial e_i} = p^o \frac{\partial q_i^o}{\partial e_i} + p^e \frac{\partial q_i^e}{\partial e_i} \quad (4)$$

The compliance cost is composed of the cost of buying the certificate quantities q_i^e and q_i^o necessary to cover the emission level e_i^* , abatement cost and the forgone revenue of optimally adjusting production relative to an optimal production level at zero emission cost. The marginal cost is either p^e or p^o depending on which type of certificate is used to cover the last (marginal) emission. Offsets are perfect substitutes for European certificates up to the quota; their price difference is thus zero or positive: $p^e - p^o =: \Delta_p \geq 0$.¹³ The result is straightforward: as a perfect substitute at a lower price, offset credits are unambiguously preferable to European certificates, up to the regulated entitlement \bar{q}_i^o . Only if emissions are above \bar{q}_i^o , will the firm cover the remaining emissions by using the more expensive European certificates. Compared to a system with only European certificates, the firm saves an amount equal to $\bar{q}_i^o \Delta_p$. The

¹²A competitive market hypothesis simplifies this part, but it is not essential to the subsequent argument, as long as there is a single equilibrium quantity $y^*(e^*)$.

¹³For the purpose of this study, I only consider situations in which offset certificates are strictly cheaper than European certificates, as the alternative where both prices are equal is qualitatively not different from a system without offsets. Moreover, the data reveals that in practice there has always been a clear price discount for offset certificates.

optimization problem can be simplified as follows:¹⁴

$$\max_{e_i} \pi(y^*(e_i), e_i) = \begin{cases} y^*(e_i) - C(y^*(e_i), e_i) - p^o e_i, & \text{if } 0 < e_i \leq \bar{q}_i^o \\ y^*(e_i) - C(y^*(e_i), e_i) - p^e e_i + \bar{q}_i^o \Delta_p, & \text{if } \bar{q}_i^o < e_i \end{cases} \quad (5)$$

In the EU ETS, the offset entitlement \bar{q}_i^o is, in practice, small compared to emissions. Virtually all firms need to use European certificates in addition to offsets, meaning that the constraint in equation (3) is binding. The usual result that marginal abatement cost should be equalized across firms at the price level p^e remains valid.

3.2 Trading costs for both certificate markets

I now assume that firms face some general entry trading cost in order to enter any certificate market, i.e. the cost of setting up a trading department no matter the type of certificates. Only once they have such a trading department will they learn about the existence of offsets and incur an additional cost contingent on entering the offset market. They can avoid both costs if they only use their freely allocated European certificates. Firms with emissions greater than their allocation have to buy certificates and cannot avoid the general component of trading cost. Profit equation (1) has now two additional fixed cost terms:

$$\pi = y^*(e_i) - C(y^*(e_i), e_i) - p^e q_i^e - \mathbb{1}^e \kappa^e - p^o q_i^o - \mathbb{1}^o \kappa^o, \quad (6)$$

$$= y^*(e_i) - C(y^*(e_i), e_i) - p^e e_i - \mathbb{1}^e (\kappa^e + \mathbb{1}^o (\kappa^o - \Delta_p q_i^o)), \quad (7)$$

$$\text{where } \mathbb{1}^o = 1 \text{ iff } q_i^o > 0 \quad (8)$$

$$\mathbb{1}^e = 1 \text{ iff } q_i^o > 0 \vee q_i^e - q_i^{e0} > 0 \quad (9)$$

where a firm incurs general entry trading costs κ^e if it buys any certificates, but also needs to pay additional information costs, κ^o , to enter the less well-known offset market. Firms that are “long” in equilibrium, i.e. which received more free allocations than needed for their optimal emissions ($q_i^{e0} > e_i^*$), are not obliged to actively trade certificates. “Short” firms cannot behave “autarkic” (Jong and Zeitlberger 2014): they must enter the market to buy some certificates and, thus, should consider the general trading cost κ^e sunk when deciding about offset usage. The impact of transaction costs on offset usage and incurred total cost depends on the relative

¹⁴The allocation term in equation (1) $p^e q_i^{e0}$ is a choice-independent lump-sum transfer and can be dropped from the maximization problem.

magnitudes of κ^o , $\kappa^o + \kappa^e$ and $\bar{q}_i^o \Delta_p$.

As usual with fixed entry costs, firms will enter trading if and only if profits are higher with entry relative to non-entry. Given the specific cost structure assumed here, short firms enter the offset market if $\kappa^o < \bar{q}_i^o \Delta_p$, while long firms enter if $\kappa^o + \kappa^e < \bar{q}_i^o \Delta_p$. Thus, entry to the offset market is a binary choice, yielding “all-or-nothing” behavior.¹⁵ In this situation, grandfathered allocations create a discontinuity that impacts optimal firm behavior.

This assumes firms take their allocation status as given when deciding about their entry to the offset market. The fixed cost at emission level $e_i = q_i^{e0}$, i.e. the switching point between short and long, could cause firms to restrict their emissions to q_i^{e0} . The Appendix C on page 36 formalizes this condition and tests whether there is any empirical evidence for such behavior, i.e. bunching of firms at the threshold. While theoretically possible, there is no empirical evidence for such an adjustment. Trading costs do not impact the marginal cost-benefit trade-off: both above and below q_i^{e0} , firms face a certificate price of p^e , such that the main mechanism of the ETS is independent of fixed transaction costs.¹⁶

Let firm “net allocation status” $\mathbb{1}_i^{long}$ be a dummy variable indicating that allocation q_i^{e0} is larger than emissions e_i^* ,¹⁷ and $\mathbb{1}_i^o$ is again the dummy indicating the use of offset certificates.

$$\mathbb{1}_i^o = \begin{cases} 1 & \text{if } \bar{q}_i^o \Delta_p > \kappa^o + \mathbb{1}_i^{long} \kappa^e, \\ 0 & \text{otherwise.} \end{cases}$$

¹⁵This part assumes that firms have emissions greater than their offset entitlement, which is the case for over 98% of the firms.

¹⁶An underlying assumption is that firms take prices as given: every individual firm is too small to consider its own impact on the price level, i.e. it has no market power on the certificate market. On the aggregate, p^e depends on the number of firms using offset certificates. To the extent that transaction costs reduce access to the offset market, they are neither neutral for p^e nor, consequently, for y^* and e^* : second-order effects decrease the offset price p^o and increases the European certificate price p^e . While these price effects are essential for a general equilibrium and welfare assessment, they are not informative on transaction costs and are beyond the scope of this study.

¹⁷The dummy variable is defined at the firm level, thus allowing for cost-free within-firm trade. Moreover, it includes dynamic considerations: given firms could bank allowances, $\mathbb{1}_i^{long} = 1$ if the *cumulative* sum of emissions does not exceed the *cumulative* sum of allocation in any year of Phase II.

4 Data and empirical research design

I use administrative data from the EU ETS. Descriptive data analysis reveals four stylized facts that my empirical analysis relies on: (a) offset certificates are cheaper than European certificates; (b) virtually all firms have emissions greater than their offset entitlement; (c) a non-negligible number of firms (22%) does not use their offset entitlements; and (d) the distributions of firms' emissions and entitlements are highly uneven.

4.1 Emissions, allocation and offset entitlement

This study mainly relies on compliance data of the European ETS Registry (European Union Transaction Log, EUTL), which combines all member states' national registries of Phase II (2008-2012). This comprehensive administrative data comprises the allocated European certificates, verified emissions, and surrendered certificates (EUAs, CERs and ERUs) for *all* 13,590 plants subject to the ETS.

I aggregate the data over Phase II, because offset quotas were defined over the whole period and could be used at any point during the phase, without any yearly constraint, so that the decision whether to use offsets or not was ultimately only revealed once, on the last day of Phase II. The data does not contain transactions *per se*, but it is clear that all firms using offsets must have acquired them previously. Firms had no interest to stockpile offsets beyond the end of Phase II if they could also use them for compliance: in this study, offset usage is thus equated with offset acquisition. Moreover, all firms which were “short” in allocation, i.e. had emissions larger than their free allocation, had to buy certificates, either European or offset.¹⁸

A matching with Bureau van Dijk's Orbis company database reveals ownership structures that link many of these individual plants.¹⁹ This matching matters as the relevant decision likely happens at the firm level, even though regulation, allocation, and offset entitlements are defined at plant level. After some data cleaning,²⁰ around 9,000 plants belonging to 4,578 firms

¹⁸There are certainly *some* firms that entered the market without being legally obliged by being short. If many firms fall into this case, the ratio between offset cost and general cost is biased towards general cost, while the overall distribution still holds. In presence of transaction costs however, only short firms have an interest to buy additional European certificates.

¹⁹For more information on this extensive matching to the “global ultimate owner” level, see Jaraitė et al. (2013); or their website <http://fsr.eui.eu/CPRU/EUTLTransactionData.aspx>

²⁰Plants from countries that do not participate in the standard way, as described in Section 2.1 (Estonia, Iceland, Lithuania, Liechtenstein, Malta and Norway; 220 plants), and firms that have offset-use beyond the

	Mean	Median	SD	Min	Max
Number of countries active	1.13	1	.728	1	17
Number of plants	1.88	1	5.03	1	158
Number of sectors active (NACE definition)	1.12	1	.566	1	11
Free allocated EUAs (ktCO ₂ e)	1,975	112	13,831	.015	380,586
Emissions (ktCO ₂)	1,919	78.5	16,148	.003	563,608
International credit entitlement (ktCO ₂ e)	272	12	2,335	.001	91,537
Used offset credits (ktCO ₂ e)	208	8.34	1,494	0	55,536
Savings from offset use (k €)	799	31.2	5,836	0	217,412
Unexploited profits from offsets (k €)	627	22	7,370	.00465	200,316
Firms using all offset entitlement (in %)	50.5				
Firms using no offsets (in %)	22				
Observations					4578

Table 2: Descriptive firm statistics

remain. Over half of the plants belong to firms that own just one plant.

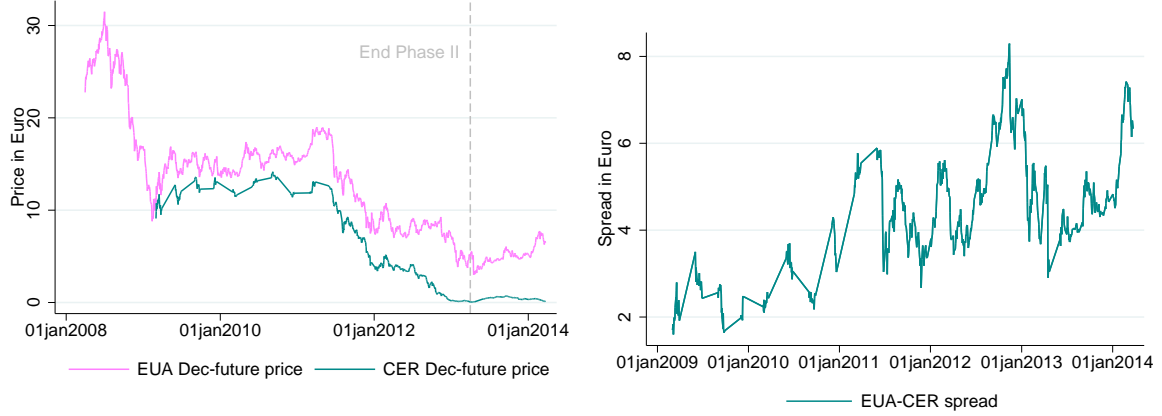
The plant-specific offset quota (*entitlement*) \bar{q}_i^o is the product of a country-specific offset percentage multiplied by the plant's free allocations q_i^{e0} over Phase II. For the purpose of this study, the entitlement has been computed using this rule and verified using the International Credit Entitlement tables published by the EUTL in 2014.

Allocations have been generous, such that 80% of the firms could cover all of their emissions using only grandfathered allocations; these firms are called the “long” firms in the remainder of this study. Offset entitlement \bar{q}_i^o is so small that only 2.8% of firms are able to comply by using offsets only. Table 2 shows that free allocation has, on average, been just above emissions. Firms have a wide variety of sizes, with some firms owning up to 158 plants and being active in 11 sectors or 17 countries.

4.2 Price spread and realized savings

Daily price data for offsets (CERs) and European certificates (EUAs) is available from Intercontinental Exchange. Offsets are expected to trade at a lower price compared to European certificates. Indeed, offsets have always traded at a positive discount from European certificates. Figure 2 shows that the price differential was rather small in the beginning. After few months, the spread increased and offsets have been up to €7 cheaper than European certificates, with a mean price difference of €3.60.

legal limit (most likely because of merger and acquisition transactions that are unobserved in this data set; 94 plants) are excluded. Also excluded are about 4,000 plants that never registered any emissions, or cease existing in 2011/12, or have their first emissions after 2009.



(a) Prices of EUAs and CERs on the secondary market

(b) EUA-CER price spread

Figure 2: Prices of EU certificates and offsets (Source: www.theice.com)

This price spread allowed firms to achieve considerable savings,²¹ reaching €217.4 million for the largest firm. Cumulatively, the 78% of firms which used offsets have together saved €3.6 billion.²² The 22% of firms which did not use offsets could have used another 288 million tCO₂e certificates and generated €1.37 billion at 2012 prices. Among firms that used offsets, firms have saved on average €799,000, while the median is only €31,200.

4.3 Descriptive evidence for transaction costs

Many firms did not use their offset entitlements. Given the large supply of offset certificates and their low price, this is surprising. Factors that prevented firm entry are interpreted as transaction costs by this study, such as the costs of information procurement and other frictions.

The stylized facts supporting the idea of fixed (rather than quantity-dependent) costs are (a) a largely binary behavior between using either the maximum allowed or no offsets at all; (b) the non-neutrality of European certificate net allocation status for entering the offset market; and (c) an increasing likelihood of entry to the offset market as offset entitlement increases.

²¹Savings are approximated by multiplying the annual average price spread with the amount of offset certificates used in that year, because the actual transaction prices are not observed.

²²These numbers take prices as given, so they cannot be interpreted as the general-equilibrium savings from offset usage: as seen in Section 2.2, the counterfactual EUA price in absence of offset credits would have been higher than the observed prices. The estimates used in Table 2 are thus a lower bound for the *de facto* achieved savings from offset usage. Stephan et al. (2014) estimate demand elasticity as being high, such that actual firms' savings may be as high as €20 billion, as offset availability decreased the overall stringency of the cap. Moreover, it does not account for the incurred transaction costs.

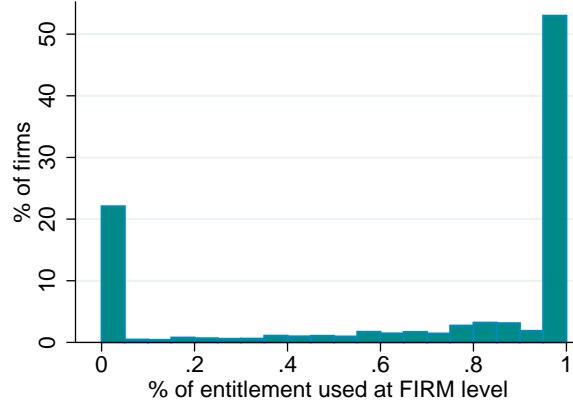


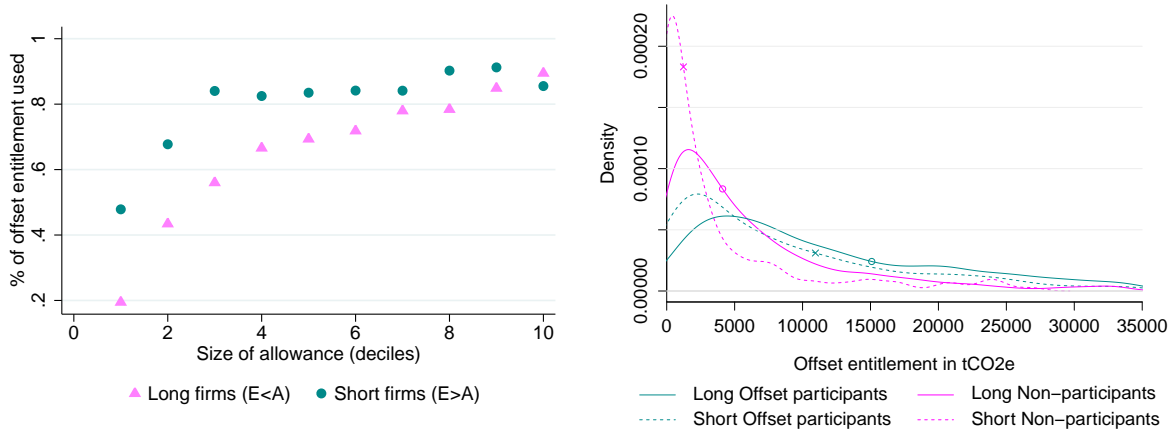
Figure 3: Ratio of used offset credits over overall offset entitlement (Source: EUTL and own computations)

The offset usage of firms mostly followed a binary “all-or-nothing” pattern, suggesting the presence of fixed trading cost. Figure 3 shows used offsets as a percentage of the total offset entitlement: Over half of the firms used *all* their offset entitlements and almost a quarter of the firms used *none*. While per-unit costs would lead to a trade-off and, thus, intermediate usage rates, fixed entry costs for market entry can explain such binary behavior. Most multi-plant firms with intermediate usage are composed of plants that exhibit an all-or-nothing behavior: it seems likely that this results from coordination problems within firms.

Transaction costs depend on initial allocation. Short firms are legally bound to trade, meaning that they should consider general trading costs as sunk, whereas offset-specific cost applies to both long and short firms. Moreover, with fixed costs, firms with large offset entitlements are more likely to trade, as the potential gain becomes larger compared to entry costs. Figure 4a shows the interaction between size and allocation status: at lower size deciles, firms use offsets rarely, with a large difference between long and short firms. As size increases, firms become more likely to use offsets, while at the same time the difference between long and short firms becomes less marked. At the tenth size decile, virtually all firms trade and there is no significant difference between long and short firms’ behavior.

Assuming that firms make rational decisions, plants that do not trade must estimate their trading costs to be higher than their potential profit, such that the mean offset entitlement multiplied by the mean price spread should give us a lower bound of the magnitude of these

²³Density estimation using Gaussian kernel from `density()` in R, with smoothing bandwidths calculated by Silverman’s rule of thumb; for readability, the graph is cut at 50 ktCO₂e, although both densities continue beyond. Crosses and circles indicate median values.



(a) Offset usage by allocation and according to size deciles of offset entitlement, or potential profit (b) Distribution of offset entitlement in the different groups of firms

Figure 4: Relationship between offset use, offset entitlement and net allocation status (Source: EUTL and own computations)²³

transaction costs (similar to the reasoning in Attanasio and Paiella 2011). At the same time, the opposite is true for firms that do enter the offset market. These two distributions largely overlap, but Figure 4b shows that the means and medians are strongly different. In general firms that do not use offsets tend to be smaller, with half of firms below 3,600 tCO₂e of offset entitlements (while the median is 16,600 tCO₂e for firms that use offsets). Nevertheless, both distributions stretch out above 50,000 tCO₂e, showing that the separation is not clear cut. The largest firm without offset use has a 262,000 tCO₂e entitlement; 9% of the firms have larger entitlements and they *all* enter the offset market. Among firms with offset use, the size distribution of long and short firms is similar. On the opposite, small short firms are overrepresented in the group that does not use offsets.

The size distribution of firms' offset entitlements in Figure 4b is highly dispersed; similar levels of inequality are found for emissions, number of plants and grandfathered allocations. The empirical methods used need to be chosen such that they are robust to rare but extremely large outlier firms.

4.4 Econometric methodology

The model links binary firm behavior, i.e. using any offset credits or not, and the magnitudes of unknown entry costs κ^o and κ^e , to the known quantities q_i^{e0} , e_i and $\bar{q}_i^o \Delta_p$. We want to measure the latent fixed transaction cost κ_i^* , while observing only the binary outcome $\mathbb{1}_i^o$ equal to 1 if κ_i

is smaller than opportunity cost $\bar{q}_i^o \Delta_p$:

$$\begin{aligned} \mathbb{1}_i^o &= \mathbb{1}\{\bar{q}_i^o \Delta_p > \kappa_i^*\} \\ &= \mathbb{1}\left\{ \underbrace{\bar{q}_i^o \Delta_p}_{\text{potential profit}} > \underbrace{\kappa^o + \kappa^e \mathbb{1}_i^{long} + \epsilon_i}_{\text{trading cost}} \right\} \end{aligned} \quad (10)$$

In this binary choice setup, $\bar{q}_i^o \Delta_p$ is the firm-specific cut-off value relevant for the decision to trade. Other than in most binary choice settings with a common cut-off at zero, e.g. standard probit, a firm-specific cut-off allows us to identify an intercept as it fixes a scale for the two estimated parameters κ^o and κ^e in terms of units of $\bar{q}_i^o \Delta_p$ (i.e. euros).²⁴

This method relates to binary methods to measure “willingness-to-pay” (WTP). Here, rather than estimating WTP, I identify transaction costs by interpreting any forgone profits $\bar{q}_i^o \Delta_p$ as “unwillingness-to-benefit” or, in other words, opportunity costs. If the error term was assumed to be *iid* following a normal distribution, equation (10) would describe a standard probit model in which coefficients are normalized such that the coefficient of the potential profit equals 1. The other coefficients then measure transaction costs in euros, as when willingness-to-pay is estimated by normalizing the utility of income to 1.²⁵ However, the stylized facts presented in Section 4 strongly suggest that this homoskedastic normality assumption does not hold; consequently, probit is not an appropriate model. If the distribution of transaction costs is skewed, an estimation of the mean cost is not the most representative summary statistic as it might be driven by large outliers.

Following empirical work by Kordas (2006) and Belluzzo Jr (2004), I estimate a range of binary quantile regressions to analyze the conditional *distribution* of transaction costs rather than just the conditional mean. This semi-parametric method is more robust to non-symmetric error distributions and outliers. For all quantiles $\tau \in [0, 1]$, I define the conditional quantile $Q_{\kappa^*}(\tau)$ as the τ^{th} quantile of the transaction cost distribution F_{κ^*} :

$$Q_{\kappa^*}(\tau | \mathbb{1}_i^{long}) := F_{\kappa^*}^{-1}(\tau) = \kappa_\tau^o + \kappa_\tau^e \mathbb{1}_i^{long} \quad (11)$$

These quantiles are identified using the observed offset-market entry $\mathbb{1}_i^o$ and the monotone

²⁴ \bar{q}_i^o is measured in tCO₂e of offset entitlement and Δ_p is the mean price spread measured in €/tCO₂e.

²⁵The standard normalization of a probit sets the standard deviation σ to 1; in contrast, the standard deviation is a free parameter here (see Train 2009).

transformation of equation (10). Then $Q_{\mathbb{1}_i^o}(\tau)$ may be written as:²⁶

$$Q_{\mathbb{1}_i^o}(\tau | \mathbb{1}_i^{long}, \bar{q}_i^o \Delta_p) = \mathbb{1}\{\bar{q}_i^o \Delta_p \geq \kappa_\tau^o + \kappa_\tau^e \mathbb{1}_i^{long}\} \quad (12)$$

The probit regression draws its identification from the conditional mean assumption $E(\epsilon_i | x) = 0$ and the normality assumption, while the following methodology estimates the median and draws its identification from the assumption that the conditional *median* error is zero. The earliest estimator using this semi-parametric assumption is the maximum score estimator by Manski (1975). At the median with $\tau = .5$, this estimator maximizes the number of “correct predictions” using an indicator function:

$$\max_{\kappa_\tau^o, \kappa_\tau^e} S_{n\tau}(\kappa_\tau^o, \kappa_\tau^e; \bar{q}_i^o \Delta_p) = n^{-1} \sum_{i=1}^n [\mathbb{1}_i^o - (1 - \tau)] \mathbb{1}\{\bar{q}_i^o \Delta_p - \kappa_\tau^o - \kappa_\tau^e \mathbb{1}_i^{long} \geq 0\} \quad (13)$$

Similar to the median, we can estimate other conditional quantiles. While intuitive, this estimator is not continuous, which makes it difficult to optimize and determine standard errors. To resolve this issue, Horowitz (1992) formulates a smoothed maximum score estimator using a kernel function to obtain a continuous function of the estimated parameters, which Kordas (2006) extends to quantiles other than the median. The smoothed binary quantile estimator at quantile $\tau \in (0, 1)$ solves the following problem:

$$\max_{\kappa_\tau^o, \kappa_\tau^e} S_{n\tau}^*(\kappa_\tau^o, \kappa_\tau^e; h_n, \bar{q}_i^o \Delta_p) = n^{-1} \sum_{i=1}^n [\mathbb{1}_i^o - (1 - \tau)] \Phi \left((\bar{q}_i^o \Delta_p - \kappa_\tau^o - \kappa_\tau^e \mathbb{1}_i^{long}) / h_n \right) \quad (14)$$

where $\Phi(\cdot)$ is a continuous, differentiable kernel function and h_n an appropriate bandwidth that tends to zero as sample size increases.

The estimation of this model involves optimization over a complex function, in particular when using the discrete version of equation (13). I use R to implement Kordas’ S-Plus/Fortran code to perform simulated annealing following the algorithm of Goffe et al. (1994). Simulated annealing has the advantage of being more robust to starting values, local optima and discrete parts of the objective function; although computationally more demanding, the full code including bootstrapping runs in less than six hours. With a large sample, such as the one used in this study, the results of Manski’s discrete quantile maximum estimator and of Horowitz’

²⁶We observe a transformation of the latent variable by an indicator function that is a monotone transformation. See Koenker and Hallock (2001) on the equivariance of quantile estimates to monotone transformations.

smoothed estimator turn out to be virtually identical. Standard errors are calculated by bootstrap methods.

5 Estimation results

According to my results, transaction costs are around €100,000 on average. Their distribution is skewed: many firms face small transaction costs, while a few firms have high costs. In particular, the offset-specific cost is much smaller than general entry cost for most firms. This section illustrates how quantile regressions can add valuable information if the underlying distribution is asymmetric.

The binary quantile regression estimates the distribution of transaction costs from which each firm draws its transaction cost. As this distribution is not assumed to follow a known functional form, it is described here by estimating 19 quantiles, from the 5th to the 95th percentile in steps of 5 percentage points. For better readability, Table 3 shows only selected quantiles, while Figure 5 shows the full estimation for all quantiles (19 separate estimations).

The transaction cost components are measured in units of potential profit, i.e. in euros. The median offset-specific cost κ^o is estimated around €905, which means that a short firm with enough offset entitlement to generate €905 of offset revenue has a 50% chance of participating. While transaction costs are low, at around €500 for the lower quarter of the transaction cost distribution, their values are high at the upper end with €201,919 for the highest quantile ($\tau = .95$). The distribution for κ^e indicates that long firms (with generous initial allocations) are much more reluctant to trade. At the median, their behavior is consistent with an *additional* cost equivalent to €7,770. This goes up to the higher quantile estimates around €41,900 for $\tau = 0.95$. A long firm thus needs potential profits of €7,770+ €905= €8,675 to have a 50% probability to use offsets.

The quantile analysis reveals that the transaction cost distribution spans a large range and is strongly skewed: while the difference between the median quantile and lower quantiles is small, there are large outliers driving the estimates of the highest quantiles. Consequently, the means (bottom of Table 3)²⁷ can be misleading about the transaction cost distribution. Of a similar

²⁷Means from the quantile regression are computed with the following steps: (a) estimate quantile parameters in 5% steps from the 5th percentile to the 95th; (b) predict market entry probability depending on firm characteristics (see Appendix E); (c) impute transaction cost from τ equal to predicted probability; and (d) take average across all observed firms.

τ	All firms		Manufacturing		Electricity	
	\hat{T}^o offset-sp.	\hat{T}^e general	\hat{T}^o offset-sp.	\hat{T}^e general	\hat{T}^o offset-sp.	\hat{T}^e general
0.05	35.0*** [25; 152]	1.0 [-94; 587]	950.6*** [345; 1,308]	12.5 [-89; 2,335]	35.6*** [21; 143]	-13.2 [-87; 1,140]
0.1	35.0*** [30; 344]	1.0 [-96; 1,824]	1,013.8*** [354; 1,359]	936.0 [-64; 2,919]	32.7*** [25; 284]	-.7 [-93; 1,373]
0.25	472.9*** [35; 587]	2,817.5*** [1,444; 4,675]	965.0*** [330; 1,378]	2,732.8*** [797; 4,429]	338.5*** [32; 906]	4,198.3*** [718; 7,867]
0.5	904.7*** [378; 2,753]	7,769.5*** [3,976; 10,616]	1,045.3*** [340; 1,538]	5,417.8*** [4,015; 10,696]	917.0*** [393; 5,169]	7,695.8*** [2,880; 15,417]
0.75	9,352.6*** [2,746; 12,741]	17,876.2*** [9,995; 30,478]	1,295.6*** [393; 11,331]	21,376.0*** [11,276; 36,002]	12,587.2*** [3,970; 26,390]	15,291.6** [1,466; 29,466]
0.9	28,392.9*** [17,596; 99,858]	57,135.0** [1,712; 165,116]	21,426.0*** [11,018; 52,336]	63,250.2*** [32,879;132,068]	88,307.2*** [29,228;170,252]	108,950.3* [1,223; 141,695]
0.95	201,919.4*** [79,334;304,069]	7,184.6*** [264; 476,038]	301,294.8*** [23,545;309,215]	13,588.2* [102; 486,145]	165,532.4*** [65,021;236,666]	31,900.4* [5,274; 388,442]
Mean	83,675	21,519	123,133	64,269	65,322	62,542
Probit	109,557***	44,302***	173,656***	98,911***	48,632**	4,059
N	4,578		2,938		1,640	

Note: Function optimized by simulated annealing, significance and point-wise 95% confidence intervals are determined by bootstrap (500 replications). Columns 1 and 2 show the result of the binary quantile regression, dependent variable is the offset use dummy equal to 1 if the firm used any offsets, regressors are forgone profits, i.e. offset entitlement multiplied by price spread (coefficient normalized to one), “long” allocation dummy equal to 1 if the firm could cover all emissions with its allocation and a constant. Columns 3 to 6 show the result of the same regression with additional dummies for sector affiliation (and their interaction with the allocation dummy). Manufacturing includes cement, pulp and paper, glass, ceramics, metals, oil refining and “other”.

Table 3: Estimates from binary quantile estimation and probit regression

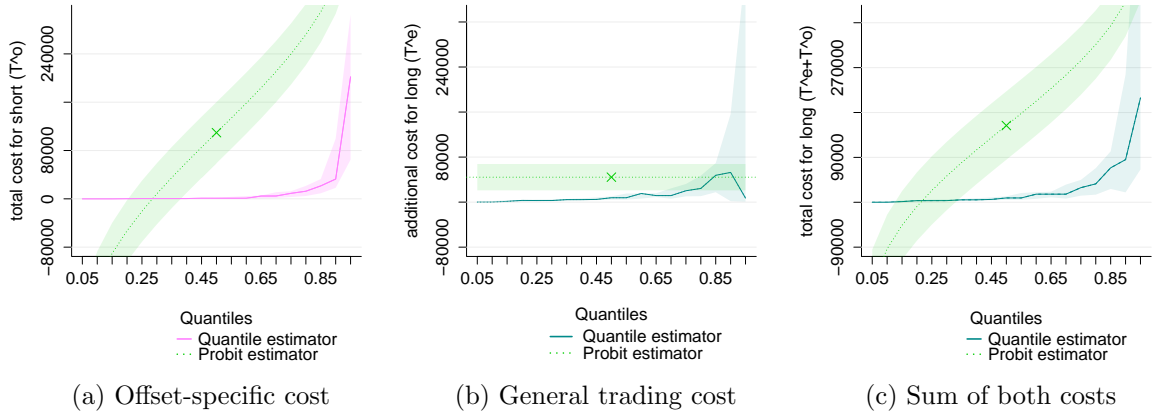


Figure 5: Estimated transaction cost (in €) - quantile plot³⁰

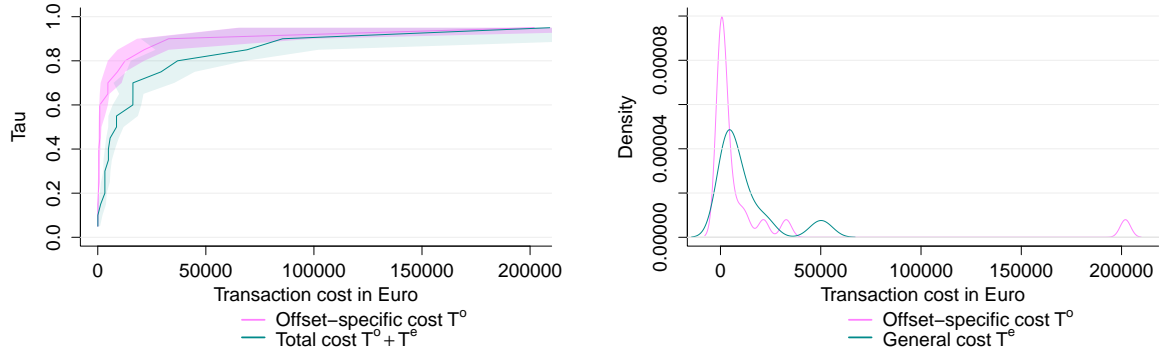
order of magnitude, the probit estimates of the conditional mean are also much higher than the median.²⁸ Figure 5 plots probit estimates with a cross and adds the distribution of the normal error to represent the distribution implied by probit assumptions.²⁹ Despite the similar means, quantile and probit estimates are significantly different for most quantiles and yield different perspectives on the transaction cost distribution. For virtually all quantiles, the impact of net allocation status exceeds the offset-specific cost: the bulk of transaction costs stems from the general cost component κ^e . Firms thus refrained from using their offset entitlement not because of offset-specific trading costs, but rather to avoid certificate trading altogether. However, the means, both from probit and from quantile regression (bottom of Table 3), obscure this finding and suggest that transaction cost for offset are *on average* larger than the ones for general trading. There are some large outliers in the distribution of κ^o .

These results are more intuitive if we switch the axis of the standard quantile plot Figure 5, such that we get the estimated cumulated density function of firm's transaction costs as shown in Figure 6a. From there, one can infer a probability density function from this CDF by using standard kernel density methods (Figure 6b). Again, these figures show how some large outliers drive the high mean of κ^o : the tail of the probability density function of the offset-specific transaction cost shows a bump that is driven by the only four non-participating firms with potential profits above €200,000. The mean and thus the results of a probit regression may be

²⁸More detail on these parametric estimations can be found in Appendix D on page 39.

²⁹Due to the renormalization, the error term does not follow a standard normal distribution, instead having a larger standard deviation.

³⁰Quantile estimates for all 5th percentiles from 5% to 95%. The dotted green line shows the mean estimate from probit, the shaded bands represent the point-wise 95% confidence intervals.



(a) Cumulative density function

(b) Probability density function

Figure 6: Estimated transaction costs³¹

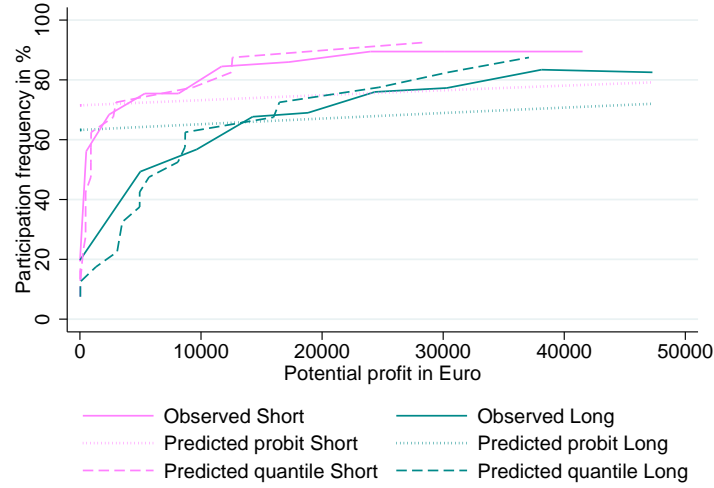


Figure 7: Observed frequencies and predicted probabilities of quantile method and probit (cut at 40,000 tCO₂e for better readability)

considered a misleading statistic in such a case. Figure 7 compares the estimated probability of entering the offset market from the probit and quantile model to the observed frequencies at different entitlement magnitudes. Particularly for smaller emitters, the quantile method predicts entry probability much better than the probit. Analogously, the fit of the quantile estimation is strong if evaluated with the method outlined by Kordas (2006), i.e. checking whether predicted and observed probabilities coincide (cf. Appendix E on page 42).³²

³¹Probability density function in Figure 6b estimated from cumulative density function in Figure 6a using kernel density in R.

³²The better fit does not come as a surprise: the quantile model fits 38 free parameters, while the probit only fits three free parameters.

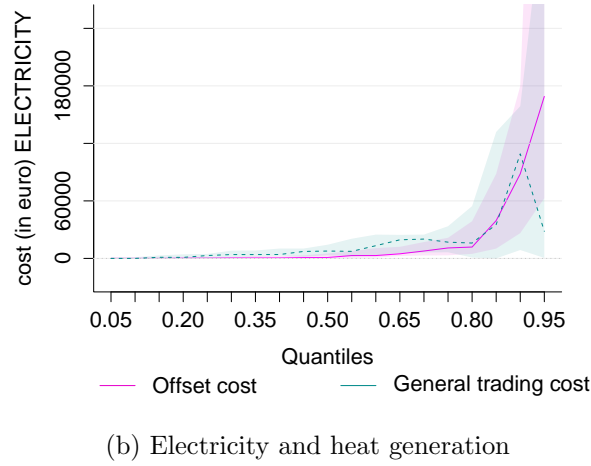
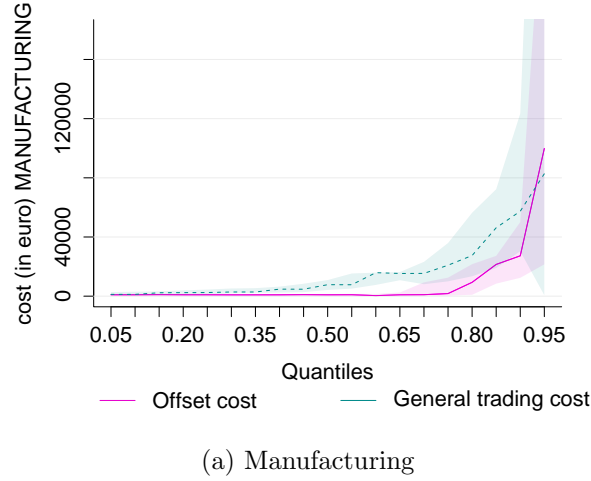


Figure 8: Sector-specific quantile estimation results (in €)

5.1 Sector-specific results

While the data set is too small for a full sector-specific analysis, the right-hand side of Table 3 shows the result separately for manufacturing and electricity-generating firms. Electricity and heat generation account for one-third of all firms, but half of total emissions. Electricity firms are known to have active and sophisticated compliance and trading behavior, likely because of the experience from electricity trading (Heindl 2015, Jong and Zeitlberger 2014).

Results (Table 3 and Figure 8) show that the sectors explain some of the observed transaction cost heterogeneity: while costs are similar around the median for manufacturing and electricity firms, I do not find any large outliers in the electricity sector, meaning that this sector's means are considerably lower than that of manufacturing. Thus, a handful of manufacturing firms is driving the high result at the 95th percentile of the pooled estimation.

For electricity and heat generation firms, the estimates for several quantiles of the general cost κ^e are not significant. Moreover, the probit estimate is not significant. As virtually all large electricity firms trade emission certificates and most are short on certificates, this general component is difficult to identify: as noted in Jong and Zeitlberger (2014) (on Phase I), the "energy sector was 'forced' to trade allowances as it was the only 'under-allocated' sector", although this refers to Phase I. The offset-specific cost remains significant and similar to the main estimation.

For manufacturing, both estimates are similar to the ones for the general case: means are much higher than medians, offset-specific costs are less relevant than general costs for most of the distribution and, nevertheless, the means are higher for κ^o . Carbon cost is a less important cost factor for manufacturing firms and they own, on average, fewer plants with smaller emissions than electricity and heat generation firms.

6 Conclusion

Within their obligations from the EU ETS, firms had the opportunity to reduce expenses by using their right to substitute European certificates with international offset certificates: *a priori*, it is profitable to use cheaper offset certificates. However, many firms did not use their offset entitlement. After briefly explaining the aggregate mechanics of offsets in the EU ETS, this study shows the impact of fixed transaction costs on offset usage and estimates a (discrete approximation to the) distribution of fixed transaction costs rationalizing firms' entry into the offset market.

Prior work mostly uses survey data to show that compliance with the EU ETS generates transaction costs. To the best of my knowledge, this is the first study to establish a framework to assess the magnitude of transaction costs empirically through the use of compliance data. Moreover, this is the first study to use binary quantile methodology, which allows for comparing quantiles (in particular the median) of the cost distribution, thus revealing its skewness. Entry costs are estimated to be at the median €7,770 (mean €21,519) for general entry to the certificate market (any type of certificate) plus €905 (mean €83,675) for entry to the offset market: for most firms, transaction costs are largely due to trading in general, rather than the offset-specific entry costs. The quantile estimation shows, thus suggesting that these means are largely driven by few large outliers. Consequently, this study illustrates the advantage of using

binary quantile methods in addition to the typical parametric approaches.

Environmental policy aims at reducing ecological harm at minimum cost to society. Nevertheless, most academic and policy-related work only accounts for the compliance and abatement costs of the EU ETS. However – just like any regulation – the EU ETS causes administrative and management-related transaction costs. My estimates suggest that trading costs are relevant in practice: firms significantly deviate from the least-cost scenario. Designing policy remains “an empirical matter” (Montero 1998). Usually, optimal regulation aims at giving the optimal incentive structure, while this study argues that regulatory complexity also creates costs. As the objective of a regulation becomes more complicated, there appears to be a trade-off between incentive perfection and a need to keep complexity for the regulated firms at bay – incentives only work as intended if they are understood and implemented at low cost. Note that with fixed trading costs, only large firms benefit from the cost reduction of offset certificates, meaning that small firms are disadvantaged. On this point, some action has been taken with the possibility for small emitters to opt-out of the EU ETS.³³ Alternatively, Heindl (2015) and Joas and Flachsland (2016) suggest moving to more upstream regulation.

This study addresses only part of the actually arising transaction costs: all administrative costs that are not contingent on trading – cannot be influenced by firm behavior – cannot be captured using my methodology, e.g. monitoring and reporting costs and registry fees.³⁴ My estimates are thus only one part of the costs that should be included in the policy discussion. Importantly also, these transaction costs are not synonymous with overall efficiency loss: while effort spent in information gathering certainly does not improve welfare, a real welfare effect analysis needs to look at the bigger picture of the general equilibrium. It would be interesting to estimate the impact of offset certificates on European certificate prices, as well as to examine more closely the price distortions (both on European certificates and offsets) caused by trading costs.

The estimated residual transaction cost is essentially a black box measuring *all* the frictions preventing firms from investing in offsets. It remains to be analyzed in detail what these costs include and how they could be reduced in order to implement a less distortionary policy. In

³³The possibility for such an opt-out for firms with emissions below 25,000 tonnes was created with Directive 2009/29/EC in June 2009 (Art. 27). However, not all member states have implemented this rule and in Germany, for example, only a handful of installations have used this option.

³⁴Registry fees in Phase II ranged from €100 for the period to €15,000 per year, depending on the country and (for some countries) emission size, cf. EUTL website.

fact, this study encompasses both "hard" financial costs and more "soft" behavioral factors, such as inattention, salience, or risk aversion, etc.

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Appendix

A National offset entitlement rules

	Annual Cap Ph.II (MMt CO ₂ e)	Offset limit (%)	Annual offset limit (MMt CO ₂ e)	Banking/ Borrow- ing	Industry	Energy	Other sector differen- tiation	Included in this study
Austria	30.7	10	3.1	Yes/yes				
Belgium	58.5	8.4	4.9	-	Flanders 24% Walloon 4%	Flanders 7% Walloon 8%		
Bulgaria	42.3	12.6	5.3	Yes/yes				
Cyprus	5.48	10	0.5	Yes/yes				
Czech Rep.	86.8	10	8.7	Yes/yes				
Denmark	24.5	17	4.2	Yes/yes	6.50%	28.70%		
Estonia	12.72	10	1.3	No/no	(started only in 2011)			No
Finland	37.6	10	3.8	Yes/Yes	8 / 8.5%	8.5 / 9.5 /23.9%		
France	132.8	13.5	17.9	Yes/Yes				
Germany	453.1	22	99.7	Yes/Yes				
Greece	69.1	9	6.2	Yes/Yes				
Hungary	26.9	10	2.7	-				
Ireland	22.3	10	2.2	Yes/Yes	5%	11%	Cement 11%	
Italy	195.8	15	29.4	Yes/no	7.2%	Electricity 19.3%	"Other" com- bustion 7.2%	
					Ferrous metal 16.7%	Refineries 13.2%		
Latvia	3.43	10	0.3	Yes/Yes				
Lithuania	8.8	20	1.8	No/no				No
Luxembourg	2.5	10	0.3	Yes/Yes				
Malta	2.1	10	0.2	Yes/Yes				No
Netherlands	85.8	10	8.6	Yes/Yes				
Norway		13		Yes/No	13% of actual emissions (rather than allocation)			No
Poland	208.5	10	20.9	Yes/No				
Portugal	34.8	10	3.5	Yes/Yes				
Romania	75.9	10	7.6	Yes/Yes				
Slovakia	30.9	7	2.2	Yes/Yes				
Slovenia	8.3	15.8	1.3	Yes/Yes				
Spain	152.3	20.6	31.4	Yes/No	7.90%	42%		
Sweden	22.8	10	2.3	Yes/Yes				
UK	246.2	8	19.7	Yes/No	8%	9.30%		

Table 4: Offset limits collected from National Allocation Plans by Elsworth et al. (2012)

B Offset use as a fixed horizon problem

Offset use was introduced for Phase II of the EU ETS; however, later it was extended to Phase III. This study assumes that firms operated under a fixed horizon conjecture, i.e. believed that their offset entitlement ended with the end of Phase II. While my assumption is an approximation, I rely on regulatory evolution and empirical elements to justify this assumption.

The ETS is based on the Kyoto Protocol (to the United Nations Framework Convention on Climate Change) that was signed in 1997, ratified by the EU in May 2002, and became effective in February 2005. It established the possibility to “transfer emission reduction” across geographical regions using flexibility mechanisms, mainly the named offset credits (CER and ERU). The Kyoto Protocol is thus the legal basis for the creation and validity of offsets.

The EU ETS was established with the “Emissions Trading Directive” (Directive 2003/87/EC in October 2003). In 2004, the EU ratified the “Linking Directive” (Directive 2004/101/EC in October 2004) as a basis for Phase II (2008-2012). It allowed the use of offset certificates, but left it to Member States to regulate the details. Concrete provisions are introduced “until 31 December 2012”, while nothing points out how regulation will change after the end of Phase II.

After the introduction of offset certificates to the EU ETS by all Member States, Directive 2009/29/EC (June 2009) set out to harmonize offset use across Member States. However, the Kyoto Protocol’s first commitment period ended in 2012 without a follow-up treaty being effective until the time of writing of this study. The 2009 Directive’s preamble clearly states the uncertainty of international climate negotiations:

Once there is an international agreement on climate change, additional use of CERs and ERUs should be provided for.... In the absence of such an agreement, providing for further use of CERs and ERUs would undermine this incentive.

Moreover, problems with the environmental value-added of certain project-types have become clear and “measures may be applied to restrict the use of specific credits from project types” (Art. 11a(9) of amended Emissions Trading Directive). The 2009 Directive remains elusive however on exactly which offsets will not be usable anymore in Phase III. Commission Regulation (EU) No 550/2011 (June 2011) prohibited so-called industrial gas projects. As it was not clear to certificate holder which certificates fell under this definition, incentives have been particularly strong to submit any purchased offsets before the end of Phase II. As the end of Phase II approached, stakeholders began to worry about the legal foundation of offset use after May

2013. The EU Commission’s publication “Questions and answers on use of international credits in the third trading phase of the EU ETS”³⁵ attempts to reduce uncertainty, but many answers start with “details in this regard will be determined in a forthcoming amendment.” Legal advisory pages published cautious warnings about the lack of legal base for offsets beyond the end of the Kyoto Protocol first commitment period (which equaled the end of Phase II).³⁶

Finally, it was not until Commission Regulation (EU) No 1123/2013 in November 2013 that the bankability of offset entitlements was finally confirmed and specified in detail. This regulation was established *after* the end of Phase II; no regulation regarding offset prolongation was effective at the moment when firms surrendered the last certificates for Phase II. Except for new entrants, no new entitlements were created, but operators can use up remaining entitlements using certificates from specific project-types in LDCs. Until then, the bulk of offset certificates had been based on industrial-gas projects from India, China and Ukraine (Ellerman et al. 2016) and, thus, were suddenly useless.

Anecdotally, in the compliance data, all of the largest 9% of firms (in terms of emissions) used up their offset entitlement at the end of Phase II. These are the firms have the largest stakes and that were particularly well informed and/or influential, so it would be unlikely that the small firms driving to a large extent the identification of this study were better informed about the actual bankability of offset entitlements.

C Exogeneity of allocation status

In Section 3.2, I claim that firms do not strategically constrain their emissions to be just below allocation level, even though firms face a cost jump when emissions increase beyond this level. This assumption is important, as I use the fact that *short* firms, with emissions above allocations, are constrained to trade while *long* firms can choose whether to incur trading costs. This methodology is flawed if *transaction costs lead firms to manipulate their net allocation status*. This section argues that this case is unlikely to be relevant in actual practice. Theoretically, firms choose their production and emissions given production cost and certificate prices; the

³⁵Published on 14/11/2011 under http://ec.europa.eu/clima/policies/ets/markets/docs/q_a_20111114_en.pdf, consulted on August 5, 2016.

³⁶For example <http://www.emissions-euets.com/cers-erus-market-as-from-2013> or <http://ieta.org/the-consequences-of-the-durban-cop-for-the-carbon-market-and-climate-finance> both consulted on August 5, 2016.

additional transaction cost is likely to be smaller than the cost of adjusting emissions *and production*. Empirically, there is no significant discontinuity around the net allocation status threshold.

First, note that the firm faces the same marginal cost p^e for emissions both below and above the allocation level, such that marginal abatement cost does not play a role. Thus, the firm compares two situations: one situation where it reduces emissions to allocation level q_i^{e0} , producing $y^*(q_i^{e0})$ *without* incurring entry costs, and another situation where its optimal emission level e_i^* equalizes CO₂ price, the firm buys additional certificates and incurs trading cost. The firm reduces its emissions to q_i^{e0} if the change in profit Δ_π resulting from this reduction is positive:

$$\begin{aligned} \Delta_\pi &= \pi(y^*(q_i^{e0}), q_i^{e0}) - \pi(y^*(e_i^*), e_i^*) & (15) \\ &= \underbrace{y^*(q_i^{e0}) - y^*(e_i^*)}_{\Delta_{y^*} < 0} - \underbrace{C(y^*(q_i^{e0}), q_i^{e0}) + C(y^*(e_i^*), e_i^*)}_{\Delta_C \geq 0} - \underbrace{p^e (q_i^{e0} - e_i^*)}_{\Delta_{qe} < 0} + \underbrace{\kappa^e + \min\{\kappa^o - \bar{q}_i^o \Delta_p, 0\}}_{>0: \text{ transaction costs}} \end{aligned}$$

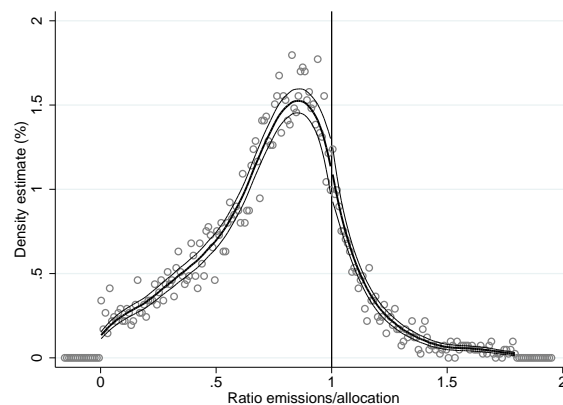
<0 : deviation from (least-cost) optimum

(16)

By assumption, we are looking at cases where optimal emissions $e_i^* > q_i^{e0}$ and, thus, $y^*(e_i^*) > y^*(q_i^{e0})$. By definition of the optimal emission level e_i^* , the first part of Δ_π is negative while the transaction cost terms of equation (16) are positive.

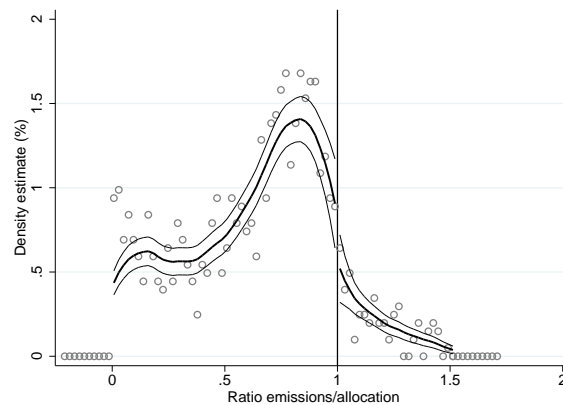
A priori this assumption cannot be verified in practice; information on prices, quantities y and production costs are not available, thus neither the cost function $C(y, e)$ nor the profit change Δ_π can be estimated. Instead, one way of gathering (descriptive) evidence on this point is to check whether we observe any crowding or “bunching” of emissions just below $e_i = q_i^{e0}$. If firms were manipulating their net allocation status, the distribution of this ratio would be somewhat discontinuous around $e_i/q_i^{e0} = 1$. Figure 9 implements McCrary’s test for continuity (McCrary 2008). The estimated densities on the left and on the right of the cut-off where $q_i^{e0} = e_i$ seem smooth on Figure 9a: at a discontinuity magnitude of .0116 (in logs) and a standard error of .1133, we cannot reject the hypothesis that there is no bunching around the threshold, or put differently, that the ratio’s density function is continuous around this point. Moreover, restraining emissions to become *long* should be particularly relevant for firms that do not use offset certificates. Therefore Figure 9b shows the McCrary test only for the firms that do not trade in the offset market: there is still no significant bunching at $e_i = q_i^{e0}$ (discontinuity

estimate at $-.3910$ with standard error of $.2766$).



(a) All firms

– discontinuity estimate (in log) $.0117$, se $.1133$



(b) Only firms which do not submit offsets

– discontinuity estimate (in log) $-.3910$, se $.2766$

Figure 9: McCrary’s test for continuity of the running variable (ratio emissions/allocations) ³⁷

Anecdotal and survey evidence (Löschel et al. 2010, 2011) suggests that firms do not have precise and continuous control over their emissions, or rather that there are considerable transaction costs to obtain such control. Only large companies regularly track their emissions throughout the year. The trading scheme’s incentives to reduce emissions do not work on a short-term “accurate to the tonne” level, but rather on a long-term technology-inducing level.

Most technologies are such that in the short term the actual technological margin to reduce emissions without a complete corresponding reduction of output is limited; reducing emissions by a certain share is thus equivalent to reducing production by the same share. After all, emissions are just one production cost factor among many others and the short-run flexibility

³⁷Estimated using Stata DCdensity command by Kovak and McCrary, available under <http://eml.berkeley.edu/~jmccrary/DCdensity/>

of the cost function is usually low. Emission reductions are mostly accomplished in the long term through technical change, whereas this study examines short term behavior. Even for a small difference between e_i^* and q_i^{e0} it is likely that Δ_π is negative.

A notable exception might be emission savings by electricity generating plants, as some firms have scope for fuel-switching across different plants and emission costs are a more important cost factor in this industry (Jong and Zeitlberger 2014). However, the McCrary test also does not show a significant bunching if we are only looking at electricity firms.

While theoretically not fully sound, the assumption of exogenous allocation status thus seems empirically valid and in line with anecdotal evidence.

D Parametric estimation results

In the standard way to estimate the parameters of equation (10), one assumes that error term ϵ_i follows a standard normal distribution. The model then becomes a standard probit model: opportunity cost $\bar{q}_i^o \Delta_p$ is included as a regressor and coefficients are normalized so that the coefficient on \bar{q}_i^o equals -1. The estimation equation reads:

$$\mathbb{1}_i^o = \mathbb{1} \left\{ \beta_0 + \beta_1 \mathbb{1}_i^{long} + \beta_2 \bar{q}_i^o \Delta_p + \epsilon_i > 0 \right\} \quad (17)$$

Standard statistical packages normalize the standard deviation σ to 1. A re-normalization then yields the parameters of interest:³⁸

$$\hat{\kappa}^o = -\frac{\hat{\beta}_0}{\hat{\beta}_2}; \quad \hat{\kappa}^e = -\frac{\hat{\beta}_1}{\hat{\beta}_2}; \quad \hat{\sigma} = \frac{1}{\hat{\beta}_2} \quad (18)$$

The stylized facts presented in Section 4 strongly suggest that this homoskedastic normality assumption does not hold. As shown before, the distribution of offset entitlements is highly skewed with some firms more than 500 times bigger than the median. Some firms with high \bar{q}_i^o still do not exploit their offset entitlement, such that the distribution of ϵ_i from the transaction cost equation (10) is likely to have some large outliers. The (conditional) mean is a statistic much more sensitive to outliers than the (conditional) median; differently put, the normal distribution assumption has light tails that, consequently, give large weight to outliers.

³⁸Standard errors for the re-arranged parameters are computed using Stata's nlcom command, based on the delta method.

A slightly more flexible functional form relaxing the homoskedasticity assumption, would be the mixed probit: error terms are still assumed to have a normal distribution, but the variance scales with the size (here \bar{q}_i^o) of the firm. In such a location-scale model, the variance of each ϵ_i depends on some scaling variable and a parameter γ (to be estimated):

$$\epsilon_i \sim \mathcal{N}(0, \sigma_i^2), \text{ where } \sigma_i = \exp(\bar{q}_i^o \gamma) \quad (19)$$

This section shows the results for both assumptions, while claiming that they are not an appropriate description of the data. The results the probit estimation in both the homoskedastic and (linearly) heteroskedastic versions are shown in Table 5.³⁹ The costs indicated are measured in euros, as they are normalized by the cut-off value's $\bar{q}_i^o \Delta_p$ coefficient. The estimate for κ^o , the transaction cost for offset usage, exceeds the estimate for κ^e , while both are significant. When I include the sectors, the estimates for transaction costs in the manufacturing sector are much higher than in the electricity and heat generation sector. In particular, the general trading cost, κ^e , seems not relevant for electricity and heat generating firms.

³⁹Estimated using Stata `oglm` command by Williams (2010).

	Probit	Heterosk. probit	Probit with sectors	Heterosk. probit with sectors
\hat{T}^o (intercept)	109557*** (4.24)	102660*** (4.36)		
\hat{T}^e (1^{long})	44302*** (3.70)	42798*** (3.79)		
\hat{T}^o Manufacturing			171436*** (4.48)	161416*** (4.63)
\hat{T}^e Manufacturing			96475*** (4.42)	92138*** (4.53)
\hat{T}^o Electricity			48383** (2.58)	278077*** (4.54)
\hat{T}^e Electricity			4169 (0.25)	5065 (0.32)
σ	192950*** (5.77)	182835*** (6.04)	192434*** (5.82)	182472*** (6.09)
γ		6.96e-08*** (18.15)		6.95e-08*** (18.24)
R2	.1274	.128	.1372	.1378
Completely determined	371	.	369	.
N	4578	4578	4578	4578

Note: t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Parametric mean estimates for transaction costs

E Quantile regression fit

Kordas (2006) suggests verifying the fit of the quantile regressions by predicting probability intervals for each observation and verifying that each interval group has an entry rate close to the predicted probability. In order to predict probabilities from the binary quantile regression, one needs to find the smallest quantile $\hat{\tau}_i$ such that the profit-net-of-transaction costs is positive:

$$\hat{\tau}_i = \operatorname{argmin}\{\tau : \bar{q}_i^o \Delta_p - \kappa_\tau^o - \mathbb{1}_i^{\log} \kappa_\tau^e \geq 0\} \quad (20)$$

Then this gives us an interval for the conditional entry probability:

$$\hat{P}_i \in [1 - \hat{\tau}_i, 1 - \hat{\tau}_{i-1}] \quad (21)$$

where $\hat{\tau}_{i-1}$ is the quantile immediately preceding $\hat{\tau}_i$.

For the data used in this study, this provides the predicted and observed probabilities displayed in Table 6. Except for the lowest quantile, the models seem to fit the data reasonably well. On the opposite, the probit model predicts for *all* firms an entry probability above 50%: one could say that *all* non-participating firms are unpredicted outliers (false-negatives) with the probit model.

Predicted probability	<15%	[15- 25%]	[25- 35%]	[35- 45%]	[45- 55%]	[55- 65%]	[65- 75%]	[75- 85%]	>85%
Number of observations	85	130	65	49	153	414	613	971	2098
Observed frequency	11%	17%	32%	43%	46%	58%	72%	81%	94%

Table 6: Specification test of binary regression quantile models (predicted and observed probabilities)