Counterpart Choice in Emission Markets: Beyond Pollution Abatement Motives

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ABSTRACT

This paper examines the determinants of electricity generator's trading strategies in the U.S. Acid Rain Market. Model estimates show that the SO_2 allowances market is *de facto* regionalized due to the regionalization of the electricity market. The national dimension only appears when there are local imbalances in the electricity market that give strong incentives to search for a better deal outside of the generator's regional market. We also identify the importance of counterpart differentiation and the influence on the counterpart choice of the regulatory framework, market evolution and transaction size. These findings are shown to be robust to Enron's abnormal behavior during 2000–2001 and its subsequent bankruptcy. The results suggest that, contrary to received knowledge, abatement costs are not the only consideration when trading pollution allowances: market microstructure can play a crucial role.

Keywords: tradable emission permits, counterpart choice, acid rain market.

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1. INTRODUCTION

Emission permits (or allowances) markets are proliferating as a way to reduce greenhouse-gas (GHG) emissions at the least cost for society but the debate on the best way to regulate such markets is still open. The market microstructure literature underlines the difficulty of studying and regulating decentralized markets since each transaction is unknown to other market participants (O'Hara, 1995 and Acharya and Bisin, 2014). In an effort to understand the determinants of agents' counterpart choice in the U.S. Acid Rain Market,[1] we examine aspects of crucial importance for regulatory policy, namely: *(i)* how the structure of the underlying electricity market influences agents' trading behavior in the permit market; *(ii)* how the rules imposed by environmental regulation impact the number (and type) of agents entering the market at each point in time[2] and, consequently, market evolution; and *(iii)* what the role of professional traders is as the market evolves and whether their presence has an impact on efficiency. Many papers have underlined the link between permit markets and the structure of the output market in polluting industries (e.g., Montero, 2009, Eshel, 2005, De Feo et al., 2013, Sanin and Zanaj, 2011), but none has assessed this link empirically.[3] The U.S. Acid Rain Market provides a unique opportunity to study this link since only the electricity sector is subject to the Acid Rain regulation.

1. See Schmalensee and Stavins (2013) for a detailed analysis of the economic history of this market.
2. Measuring the number of agents active in a certain market is a way of building a measure of liquidity and therefore a measure of market efficiency (Cohen-Cole et al., 2014).
3. Other papers have profit from this specificity to prove theoretical concepts (e.g. Di Maria et al., 2014).

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To study the determinants of counterpart choice, we obtained a database that collects all transactions registered for the U.S. Acid Rain Market in the Environmental Protection Agency's (EPA) Allowance Tracking System[4] (ATS) between January 1995 and December 2005. We cross-referenced this information with data on local electric market conditions to account for the link with the electricity market.

To the best of our knowledge, this is the first attempt to study market microstructure in an emission permits market. Methodologically, this paper relates to empirical papers examining the choice of competing trading platforms (see Hendel et al., 2007 and Bernheim and Meer, 2008 for applications to the housing market). Each time an electricity generator enters the Acid Rain Market he must choose between three alternative trading counterparts: market maker[5], broker or another electricity generator also entering the market in order to comply with environmental regulations. Both Hendel et al. (2009) and Bernheim and Meer (2008) show that agents using a broker find a counterpart more quickly than those selling bilaterally. Additionally, Hendel et al. (2009) find that bilateral trade is associated with agents that are either better bargainers or have a lower need for immediacy. In this sense, Hendel et al. (2009) show how individual characteristics and platform characteristics influence the choice between bilateral trade and brokered trade.[6] This "differentiation" is in line with our results: since alternative counterparts are different, one will be chosen over the other depending on the transaction and counterpart characteristics. In fact, Hendel et al. (2009) claim that it might be socially efficient to have multiple platforms (in our case alternatives), offering different service levels, catering to different types of houses and sellers (in our case, transactions and agents). There is other related literature on the informational motives for self-selection into trading venues that offer different services and trading conditions. Barclay et al. (2003) study competition between Electronic Communication Networks and NASDAQ, whereas Bessminder and Kaufman (1997) study competition between the National Association of Security Dealers and the NYSE. Both find, as we do, that agents seeking to trade large quantities usually prefer the centralized market since, otherwise, multiple transactions would be needed to fulfill a single order of large size.

In addition to the results just mentioned, our estimations show evidence to support the hypothesis that the SO_2 market inherits the regional dimension from the electricity market and that this determines how agents choose their trading counterparts. This finding has a direct regulatory implication: the reason for creating a tradable permit market is to give the possibility of abating emissions at the lowest marginal cost nationwide (Montgomery, 1972). If most private trading of permits is done within regions, then the main objective in creating this market, as formulated above, is not achieved. By contrast, the national dimension appears when there are local imbalances in the supply or demand for permits, which also influences an agent's preferences with respect to each type of trading counterpart. In particular, our results show that, on average, generators prefer to trade within their own region with other generators or brokers, but when there is a shock in the local electricity market that could make SO_2 allowances locally scarce, generators are more likely to buy allowances from market makers, which operate nationwide. This suggests that market makers, by posting a single (bid-ask) price, serve as a link between local allowance markets, thereby increasing the efficiency of the environmental regulation.

Regarding the market conditions imposed by environmental regulation, we investigate what influences counterpart choice with respect, first, to the need for immediacy and the increase in

4. This database was first given to us by Denny Ellerman and then updated with data obtained in the ATS of the EPA.

5. A definition of *market maker* and the distinction with *broker* is provided at the beginning of Section 2.

6. Another related literature in terms of methodology studies frictions influencing consumer choices in electricity retail markets. See for example Hortaçsu et al. (2017).

the number of private participants when the allowance surrender date is approaching and, second, to the change in market configuration when moving from Phase I to Phase II. We find that, during Phase II, agents are more likely to prefer professional traders. This could be due to the increase in counterpart identification costs and the increasing need to disaggregate orders into multiple transactions due to the small size of the new market participants.[7]

Finally, we account for changes in preferences across alternatives as the market develops. We find that trade with private counterparts increases over time (as more firms are covered by the regulation) but that trade with market makers increases to an even greater extent during the last two years considered (since more liquid markets entail higher counterpart risks).

Enron's activity as a market maker was very important in the SO_2 market during 2000 and until its bankruptcy in 2001. One concern is that the increase in Enron's activity[8] during those years could be due to fraudulent behavior that would bias our results. Another concern is that Enron's disappearance in 2001 may have caused a dramatic change in agent preferences with respect to counterpart choice. We assess the impact that both of the previous issues may have showing that our estimates are robust to Enron's behavior and the impact that its disappearance has had in terms of counterpart choice.

The paper is organized as follows. In Section 2, we introduce the empirical model and we discuss identification assumptions. In Section 3, we describe the data and provide some descriptive statistics. In Section 4, we present the results. In Section 5, we conclude leaving the assessment of the goodness of fit of the model to the Appendix.

2. EMPIRICAL MODEL

SO_2 emission allowances are property rights that were introduced as part of the environmental regulation supported by the EPA to reduce the emissions produced by fossil-fueled electricity generators and is commonly known as the "Acid Rain Program". Its name refers to the acid rain created in certain areas of the U.S. due to SO_2 emissions. A number of allowances coinciding with the cap are allocated for free on an annual basis among electricity generating units. To comply with the environmental regulation, electricity generators must surrender to the EPA an amount of allowances equal to verified emissions every year (by 1st of March). The allowances that are not surrendered to the EPA can be banked (i.e., saved) for use or trade in subsequent years. The idea behind the creation of the SO_2 market is that generators with different pollution abatement costs are able to exchange their surplus or deficit of allowances throughout the year, equalizing marginal abatement costs to the unique allowance price. To this end, generators hold an inventory of SO_2 allowances, and they enter the market to optimize such allowance holdings, being able to trade among themselves or with other agents not subject to the environmental regulation such as professional traders (brokers and market makers).

A *broker* is experienced at negotiating standard and non-standard volumes, as well as at negotiating trading terms with a large number of market participants. Brokers also provide information regarding region-specific market conditions and rules and benefit from economies of scale that reduce search costs and allow them to split single orders into multiple transactions. Brokers do not trade on their own behalf but negotiate the price and trading conditions with one or several third parties in the name of a client. A fixed brokerage fee must be paid.

7. See O'Hara, 2015 for a discussion on this in a different context.
8. This increase can be observed in terms of both volume and the number of transactions.

A *market maker*, by contrast, trades on his own behalf. Holding allowances requires market makers to have detailed knowledge of the underlying fundamentals of the market. This knowledge is reflected in the (bid and ask) prices at which they stand ready to buy and sell. Market makers provide continuity to the market, particularly in newly created markets in which transactions are discontinuous due to the small number of participants and the latter's lack of trading experience. Market makers also play a very important role once the market has developed and the number of participants has increased. This is the case because as the number of participants increases, the counterpart risk associated with each transaction increases.

In addition to trading with professional traders, it is also possible to trade with a *private counterpart*, i.e., an electricity generator that operates in one or more of the U.S. regional electricity markets and that are subject to the Acid Rain Program.

Our intuition is that, when choosing a counterpart from which to buy a certain number of permits, the agent searches for the transaction with the lowest associated costs (and risks).[9] Then, agents select their preferred counterpart. They do so based on the conditions of the permit market and the electricity market at each point in time (i.e., the local scarcity of allowances, the time left before the next allowance surrender date, whether the transaction is in Phase I or in Phase II), the characteristics of the transaction the agent wishes to undertake (e.g., the size of the transaction) and the distinctive characteristics of each type of counterpart (i.e., the information available about them, the service provided, how difficult is to find them).

2.1 Trading counterpart choice

Regarding the estimation method, our model is similar to those used by labor selection theory (see, for example, Boskin, 1974). Similar to an agent who must choose a job according to his skills and the benefits offered by the prospective employer, a generator chooses a counterpart based on its own characteristics, transaction characteristics, market characteristics and counterpart characteristics. We assume that generators maximize their utilities independent of what they have chosen in previous transactions as follows:

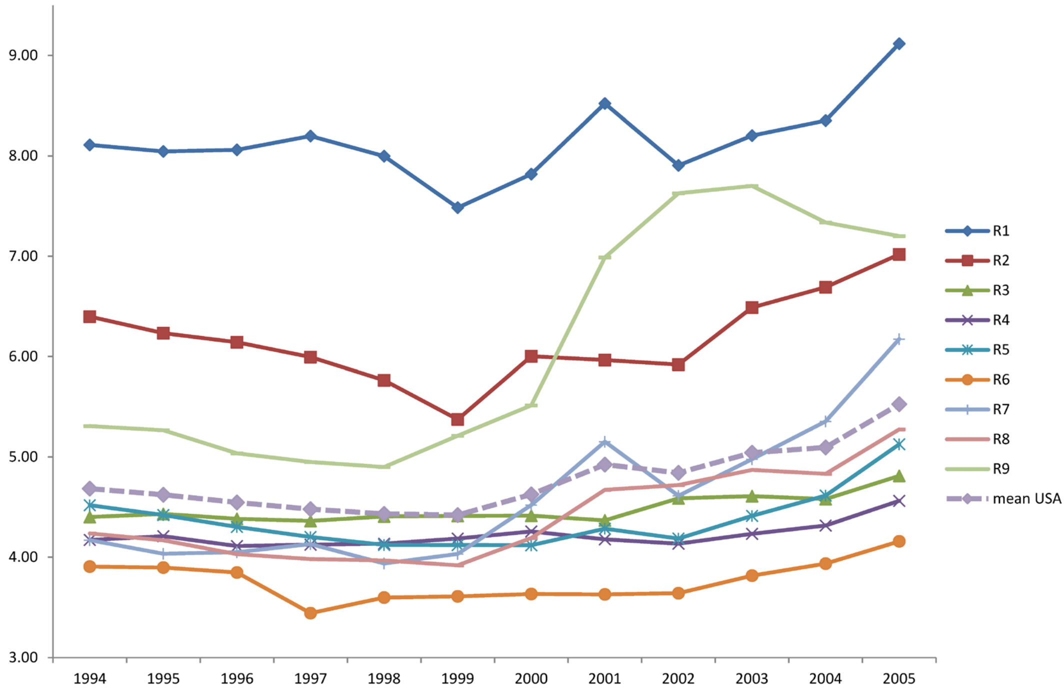
$$U_j^i = V_j^i + \varepsilon_j^i, \tag{1}$$

where i indexes each transaction and j indexes possible counterparts from the set $J = \{b,m,p\}$, where b stands for broker, m for market maker and p for private.

In equation (1), V_j^i denotes the deterministic component, which is a function of observable characteristics, and ε_j^i denotes the stochastic component, which represents the unobserved characteristics. To estimate the model we must specify a functional form for the deterministic component of the utility function and a distributional assumption regarding the idiosyncratic component. In this regard, we assume that V_j^i is a linear function of *(i)* a component that represents the participation in the market by each alternative -measured by the number of participants per year- (denoted $particip_j^i$) as a proxy for the supply of each type of counterpart; *(ii)* a component ($samer^i$) that reflects the utility (due to informational advantage) derived from trading with a counterpart that is located in the same region as opposed to a different region; *(iii)* two components that capture shocks to the supply/demand in the local electricity market ($difdifpos^i$ and $difdifneg^i$); *(iv)* a dummy variable that denotes the two months prior to the allowance verification period as opposed to the rest of the year (jf^i); *(v)* a dummy variable capturing the utility derived from trading during Phase II as opposed to Phase I

9. An agent also searches for the lowest buying price, but we do not account for this motive due to the lack of price information in bilateral markets.

Figure 1: Mean yearly electricity price per region in American dollars



(ph^i); *(vi)* a set of dummies accounting for regional heterogeneity ($rb\#^i$) that take value one for the region to which the buying agent belongs; *(vii)* a component specific to the size of the transaction measured by the amount of allowances traded ($qasc^i$); and *(viii)* three components that capture the change in the buyers' preferences over time regarding each counterpart ($ytrend_j$, $ytrendsq_j$ with intercept asc_j). When considered appropriate, we will also account for interactions between some of these components.

A few remarks on the construction of *difdifpos* and *difdifneg* are in order. Figure 1 shows that there are some regions in which the monthly retail electricity price is systematically below or systematically above the national average. These differences are due to the electricity market fundamentals. Moreover, Figure 1 shows that this difference between the regional price and the national average may increase or decrease up to three times during the period of our study, suggesting the presence of local supply/demand shocks. Since we are interested in accounting for the latter local shocks that may make allowances locally scarce (or abundant) relative to the rest of the country at a certain point in time, we must control for the shocks that affect all regions, which are captured by changes in the national average price. Consequently, we first consider the difference between the monthly price in the region ($p_{r\#}$) and the monthly national average (p_n). Then, we compare it with (subtract if from) the mean annual difference between those prices ($mean_a(p_{r\#} - p_n)$). That is, we define $difdif = p_{r\#} - p_n - mean_a(p_{r\#} - p_n)$. The difference in fundamentals among local markets is then considered when constructing $mean_a(p_{r\#} - p_n)$ accounting for demand or supply shocks only. Finally, we define *difdifpos* to be equal to *difdif* when the latter is positive, zero otherwise, whereas *difdifneg* is equal to the absolute value of *difdif* when the latter is negative, zero otherwise.

In our model, the probability of choosing a certain counterpart among the three possible alternatives is based on the difference in utility from choosing that counterpart over the utility from choosing the others. Consequently, utilities are normalized using a reference alternative, in our case the private alternative (p). This normalization is common practice in conditional logit models (see McFadden, 1973, for details, McFadden, 1974, for an example and Manski, 2001, for a summary of the estimation method).

Under the previous assumptions, the deterministic component of the utility function for each choice can be expressed as

$$V_p^i = \beta_{p0} particip_p^i; \tag{2}$$

$$V_b^i = (\beta_{b0} particip_b^i + \beta_{b1} samer^i + \beta_{b2} difdifpos^i + ...); \tag{3}$$

$$V_m^i = (\beta_{m0} particip_m^i + \beta_{m1} samer^i + \beta_{m2} difdifpos^i + ...) \tag{4}$$

where β_{jn} are the parameters for each alternative $j \in J = \{p,b,m\}$ and where all parameters for the reference alternative p are zero due to normalization, except for β_{p0}.

In the case of the SO_2 market, the three alternatives are very different. Brokers are able to assist in complex transactions and in the negotiation of transaction and credit conditions, whereas private counterparts are agents that enter the market to comply with the environmental regulation and may be partners (or competitors) if they belong to the same local electricity market. Furthermore, professional traders seem to be very different from other actors in the SO_2 market: by holding stocks and standing ready to buy or sell, market makers reduce the counterpart risk, whereas brokers only reduce search costs and customize transactions. Then, the three mutually exclusive alternatives seem to be independent allowing us to use a conditional logit model. To validate this intuition, in the next section we apply the Hausman test of the independence of irrelevant alternatives (IIA) (see Hausman, 1978).

The probability that alternative $k \in J$ is chosen for transaction i is then

$$P_k^i = P[U_k^i > U_m^i \forall m \neq k], \tag{5}$$

where we consider a distribution of U_j^i such that the probability of ties is zero. In particular, if we assume that the error terms in (1) are independent and identically distributed (*iid*) as an extreme value distribution with constant variance (McFadden, 1973), the probability that alternative $k \in J$ is chosen can be expressed as follows:

$$P_k^{iCL} = \frac{e^{V_k^i}}{\sum_1^J e^{V_j^i}}, k \in J. \tag{6}$$

We estimate these probabilities using the maximum likelihood (ML) method.

2.2 Identification assumptions

We assume that the variables on the right-hand side of (2)–(4) are uncorrelated with the error term in (1). A priori, one could be concerned that this assumption may not hold for the variable that accounts for the participation by each alternative trading counterpart ($particip_j^i$) in the market. This variable accounts for the number of brokers, market makers and private buyers that participate in the market each year and enters the equation with a one-year lag. In fact, even if the number of market makers and brokers present in the market does not change significantly over time, the num-

Table 1: Yearly volume of trade per counterpart in 10^4 tons

		market maker			
year	broker	Enron	other	private	Total
1995	4.762	5.495	27.382	1555.670	1.593.308
1996	0.026	63.085	65.109	477.114	605.333
1997	1.005	119.906	107.800	807.372	1.036.083
1998	0.049	214.964	136.326	616.141	967.380
1999	12.478	109.115	115.014	881.407	1.118.014
2000	40.536	151.933	174841	1827.311	2.194.620
2001	52.994	57.674	22.221	1844.720	1.977.608
2002	4.938	3.149	142.133	1885.788	2.036.007
2003	0.002	0.135	142.709	1324.790	1.467.636
2004	1.779	0	191.786	1194.305	1.387.870
2005	43.897	0	159.4239	1479.714	1.683.035
Total	162.464	752.355	1285.744	13894.332	16.066.894

Table 2: Yearly number of transactions per trading counterpart

		market maker			
year	broker	Enron	other	private	Total
1995	4	32	52	387	475
1996	2	66	78	647	793
1997	3	91	135	773	1002
1998	4	84	107	1039	1234
1999	35	134	71	1978	2221
2000	70	400	143	2910	3523
2001	102	147	47	4173	4469
2002	30	1	112	5511	5654
2003	7	1	233	3620	3862
2004	41	0	229	4245	4515
2005	105	0	279	4524	4909
Total	403	959	1486	29807	32655

ber of transactions and the volume of transactions exhibit important changes (compare the values in Table 1 and 2 with those in Table 3), suggesting the non-endogeneity of the variable $particip_j^i$.

We compute robust standard errors in estimating all model specifications to ensure homoskedasticity.

3. STYLIZED FACTS AND DATA DESCRIPTION

We considered all transfers registered in the ATS between January 1995 and December 2005 after excluding auction data, as well as compensation and surrender allowance transfers.[10] From the database, we selected all transactions in which a private agent appears as a buyer.[11] We extracted those transactions because we are only interested in the choices of private counterparts[12]

10. The great mayority of trade has been bilateral in this market where auctions have represented less than 2% of allowance trading per year.

11. We verified that, had we considered transactions that have a private agent as a seller instead of a buyer, those results would mirror the results stated hereafter.

12. Our analysis does not follow individual units due to the impossibility of identifying the technology and production for each unit as well as the ownership behind each unit's transaction. This is the case mainly due to the fact that different firms

Table 3: Summary statistics for variable *particip*

	j	*particip*	%	cumul.
1995	b	2	0.84	0.84
	m	4	17.68	18.53
	p	138	81.47	100.00
1996	b	1	0.25	0.25
	m	4	18.16	18.41
	p	237	81.59	100.00
1997	b	1	0.30	0.30
	m	5	22.55	22.85
	p	232	77.15	100.00
1998	b	1	0.32	0.32
	m	4	15.48	15.80
	p	245	84.20	100.00
1999	b	4	1.58	1.58
	m	5	9.37	10.94
	p	279	89.06	100.00
2000	b	1	1.99	1.99
	m	7	15.41	17.40
	p	407	82.60	100.00
2001	b	6	2.28	2.28
	m	9	4.34	6.62
	p	739	93.38	100.00
2002	b	3	0.53	0.53
	m	10	2.00	2.53
	p	790	97.47	100.00
2003	b	2	0.18	0.18
	m	10	6.06	6.24
	p	859	93.76	100.00
2004	b	5	0.91	0.91
	m	9	5.07	5.98
	p	829	94.02	100.00
2005	b	6	2.14	2.14
	m	10	5.68	7.82
	p	844	92.18	100.00

Entries considered in the year of occurance, exits considered in the following year

participating in local electricity markets (see yearly volume of trade per counterpart in Table 1 and yearly number of transactions in Table 2).

The ATS is an automated system for tracking allowance transfers (and holdings). As described in Solomon (1998), all allowance trades and transfers are triggered by the submission of an allowance transfer form signed by the two parties. Allowances can be held in “unit accounts” belonging to power plants that are required to comply with the Acid Rain Program or in “general accounts” for trading allowances. Only unit accounts are subject to allowance deductions to cover annual SO_2 emissions at the surrender date, March 1. Electricity generators generally hold both types of accounts. By contrast, professional traders only hold “general accounts”. We consider as brokers all professional traders that do not hold stocks in their accounts at the end of each compliance period,[13] which ensures that they only trade on someone else’s behalf. We consider as market

may share the use of some generation units and due to the fact that a single person designed as representative may perform transactions for more than one unit account (see EPA, 1994).

13. If some profesional trader holds fewer than 1000 allowances at the end of each period while in the subsequent months its stock of allowances tends to zero, this trader is also considered a broker.

Table 4: Transactions that take place inside the same region

samer	frequency	%	cumul.
0	17410	53.02	53.02
1	15426	46.98	100

makers all professional traders that hold stocks of allowances at that time. The ATS is the primary source of allowance trading data. However it does not include all transactions at any given time since the submission of allowance trade information to the EPA is voluntary and the only deadline is March 1. This means that our model may underestimate the importance of brokers: as they do not hold allowances for themselves, brokers do not necessarily need to open a general account with the ATS. In this sense, transactions originally negotiated through a broker may appear in our database as one or many transactions between private counterparts.[14] However, Joskow et al. (1998) report that, to the best of their understanding, prompt recording of transactions was the rule rather than the exception and that transactions registered in the ATS are the best available lower-bound estimate of transactions among private buyers, market makers and brokers.

There is no national U.S. market for electricity. According to Joskow (1997), in 1997, retail consumers still had to buy their electricity from the regulated monopoly supplier that had the legal right to distribute electricity in their locations and at prices approved by the state regulatory commission. Most of these utilities had historically been vertically integrated and operated the four primary electricity supply functions: generation, transmission, distribution and retailing. In late 1999, the Federal Energy Regulatory Commission (FERC) began moving toward the introduction of institutional change in the wholesale electricity market with the intention of connecting local grids and increasing competition. This ceased after California's 2000–2001 electricity crisis (see Joskow, 2005 for details). The previous evidence highlights that, during the period of this study, the electricity market is divided into local markets that are poorly interconnected. Additionally, agents participating in each local market have well-established business relations; in fact, they are likely to be either competitors or partners (some even vertically integrated in the near past) in the wholesale electricity market and able to use well-established communication channels. This likely represents an informational advantage when trading SO_2 allowances with one another. Indeed, in our sample, 53% of transactions happen in the same region (See Table 4). We expect to observe a larger amount of intra-regional private trade. Tables 5 and 6 show the importance of intra-regional trade in the sample. We observe that most trading by brokers and market makers is national, whereas most private transactions are local.

To place the transactions in each local electricity market we divided the U.S. into nine regions using the regionalization criterion of the Energy Information Administration (EIA) Census Division (see Table 7)[15] and identified the region to which each private account belongs. This division of the U.S. territory is that used by the EIA's National Energy Modeling System (NEMS) to account for nine local end-use demand modules.[16] Employing the same regionalization criterion, we

14. Regarding the potential underestimation of brokerage, since EPA allows firms to design a representative to trade on their name (EPA, 1994), some "general accounts" that appear in the ATS as a name and a surname may indeed belong to small brokers.

15. See http://www.eia.doe.gov/.

16. An alternative is to use the regionalization of the Electricity Market Module (see www.eia.doe.gov/oiaf/aeo/supplement/supmap.pdf). We consider this alternative to be less satisfying since it would include indistinct changes in local demand for electricity and changes in the wholesale electricity market structure over time.

Table 5: Regional and national Volume/10.000 tons

	Intraregional trade					
	b Volume	%	m Volume	%	p Volume	%
1995	0.0000	0	0.0074	0	753.4639	48
1996	0.0000	0	0.2051	0	328.2033	69
1997	0.0000	0	0.8500	0	341.6997	42
1998	0.0000	0	0.0002	0	350.6834	57
1999	0.0000	0	51.7021	23	550.0722	62
2000	0.0000	0	34.1704	10	1063.428	58
2001	0.0004	0	2.2700	3	797.8148	43
2002	0.0001	0	38.8426	27	674.5595	36
2003	0.0002	10	38.9572	27	637.8758	48
2004	0.0000	0	32.3942	17	587.0621	49
2005	0.2500	1	30.1862	19	848.4953	57
Total	0.2507	0	229.5854	11	6933.358	50
	National trade					
	b Volume	%	m Volume	%	p Volume	%
1995	4.7619	100	32.8688	100	802.2061	52
1996	0.0257	100	127.9883	100	148.9105	31
1997	1.0045	100	226.8563	100	465.6727	58
1998	0.0487	100	351.1904	100	265.4571	43
1999	12.4783	100	172.4268	77	331.3347	38
2000	40.5355	100	292.6028	90	763.8830	42
2001	52.9931	100	77.6243	97	1046.9052	57
2002	4.9379	100	106.4390	73	1211.2285	64
2003	0.0018	90	103.8867	73	686.9142	52
2004	1.7791	100	159.3920	83	607.2429	51
2005	43.6470	99	129.2377	81	631.2187	43
Total	162.2135	100	1780.5131	89	6960.9736	50

% is the percentage calculated for each alternative

also identified the degree of localization of each professional trader.[17] Second, we collected data on the monthly average retail electricity price at the regional level to account for local shocks affecting the supply/demand of electricity and, more generally, for unobserved local heterogeneity as determinants of counterpart choice. We created a 10th region to which all firms operating nationwide or those that, by definition, are not localized to a single region (specifically market makers) belong. Naturally, there are large groups that operate more than one utility across more than one region but not nationwide (e.g., SOCO[18] or AEP[19]). In this case we assign "units account" to the region to which it belongs and "general accounts" to the headquarters region. When the information regarding the owner of the unit account is unavailable it appears in our data as non-intragroup trade that will be controlled in our estimation and is most probably under-estimated.

Comparing Table 1 with 2 it seems that the average transaction size is higher when the counterpart chosen is a market maker, which in our case is captured by the variable $qasc^i$ (summary statistics in Table 8, together with variables *difdifpos* and *difdifneg* constructed as explained in previous section).

17. Usually, market makers trade nationwide while brokers only trade across selected regions.
18. SOCO stands for Southern Company. For further details, see http://www.southerncompany.com/aboutus/about.aspx
19. AEP stands for American Electric Power. See http://www.aep.com/about/

Table 6: Regional and national number of transactions.

Intraregional trade						
	b		m		p	
	Trans.	%	Trans.	%	Trans.	%
1995	0	0	2	2	172	44
1996	0	0	3	2	396	61
1997	0	0	3	1	522	68
1998	0	0	2	1	569	55
1999	0	0	14	7	870	44
2000	0	0	22	4	1054	36
2001	1	1	3	2	2069	50
2002	1	3	15	13	2332	42
2003	1	14	13	6	1929	53
2004	0	0	19	8	2493	59
2005	1	1	43	15	2822	62
Total	4	1	139	6	15228	51
National trade						
	b		m		p	
	Trans.	%	Trans.	%	Trans.	%
1995	4	100	82	98	215	56
1996	2	100	141	98	251	39
1997	3	100	223	99	251	32
1998	4	100	189	99	470	45
1999	35	100	194	93	1108	56
2000	70	100	521	96	1856	64
2001	101	99	191	98	2104	50
2002	29	97	98	87	3179	58
2003	6	86	221	94	1691	47
2004	41	100	210	92	1752	41
2005	104	99	236	85	1702	38
Total	399	99	2306	94	14579	49

Notes as in Table 5

Table 7: United States Census Division

States included in each region								
R1	R2	R3	R4	R5	R6	R7	R8	R9
CT	NJ	IL	IA	DC	AL	AR	AZ	AK
MA	NY	IN	KS	DE	KY	LA	CO	CA
ME	PA	PA	MN	FL	MS	OK	ID	HI
NH		MI	MO	GA	TN	TX	MT	OR
RI		OH	ND	MD			NV	WA
VT		WI	NE	NC			NM	
			SD	SC			UT	
				VA			WY	
				WV				

R# stands for region #
Source: EIA

During Phase I, only the 263 dirtiest generating units were subject to the Acid Rain program and another 111 units voluntarily opted into this phase. These 374 units belonged to 110 generators spread across the U.S.. Phase II introduces two fundamental changes in the SO_2 market: *(i)* nearly all fossil-fuel generators in the U.S. are now included in the Acid Rain program, which increases the number of buyers and the number of private counterparts, and *(ii)* the cap on emissions

Table 8: Summary statistics for price and quantity variables

Variable	mean	SD	min	Max
difdifpos	0.38	0.76	0.00	4.13
difdifneg	0.38	0.37	0.00	1.62
qasc	0.52	2.23	0.00	185.10

SD stands for standard deviation

becomes more stringent. In fact, the number of transactions with private counterparts increased substantially after the beginning of Phase II (see Table 2). During Phase II, beginning in 2000, all fossil-fired generating units greater than 25 MW^e were subject to the SO_2 cap, regardless of historical emission rates, which explains the increase in participation. This results in a total of nearly 4000 units being subject to the program during Phase II (see Ellerman, 2003 for details). We observe that the total volume of trades doubled during the first year of Phase II, reaching nearly 22 million allowances annually (Table 1) and that the Phase II average annual volume of allowances traded always exceeds 13 million, much higher than the average annual volume of allowances traded during Phase I. Similarly, the number of transactions increased steadily over time (Table 2). The change in market structure in terms of number of participants and the distribution of a fixed amount of allowances among a larger number of firms may have provoked an important change in market structure that influenced preferences regarding the choice of counterparts. This is captured by the variable ph^i. As mentioned, Table 3 reports summary statistics for variable *particip* on an annual basis[20], regarding all unit accounts belonging to the same company as accounts belonging to a single agent. Additionally, Tables 9 and 10 detail the bimonthly variation for participation in Phase I and II, respectively. We observe an increase in the volume of transactions during the two months prior to the allowance surrender date, March 1 and that, during Phase I, the number of transactions completed with private counterparts is higher during the first two months, whereas in Phase II, the number of transactions completed during these months are with market makers. This effect is captures in variables jf^i and $jfph2^i$ that account for this compliance date effect during Phase I and Phase II, respectively.

The emission reduction required during Phase II is greater (9 million tons), but the number of allowances available did not decrease significantly relative to Phase I because 30% of allowances distributed between 1995 and 1999 were banked (i.e., saved), and according to Ellerman and Montero (2005), only one-third of these where used to cover emissions in excess of the number of new vintage allowances issued between 2000 and 2002.

4. RESULTS

The results for the unrestricted model specification of the trading counterpart conditional logit (CL) model are reported in Table 11-M1. The results for the baseline model are in Table 11-M2. In Table 12-M3 we present an alternative specification that also incorporates interactions between some variables. We also performed tests for different groups of explanatory variables (not reported for brevity but available upon request). Multiple test results show that Models 1 and 3 outperform other comparable specifications, particularly Model 1. Moreover, the coefficients and odds ratios do not change significantly across specifications and consistently exhibit the expected signs, meaning that the estimation is robust to changes in specification. The values of the parameters also do not change in the case of Model 4 in Table 12-M4 in which we control for the effect that transactions

20. Overall, we consider 2011 distinct allowance accounts belonging to non-professional traders.

Table 9: Number of transactions per bimester during Phase I

Transactions per bimester Phase I				
	Bimester	b	m	p
1995	1	1	4	98
	2	0	9	86
	3	2	18	23
	4	0	14	54
	5	0	12	41
	6	1	27	85
1996	1	1	32	343
	2	0	22	20
	3	0	18	26
	4	0	19	82
	5	0	24	44
	6	1	29	132
1997	1	0	31	386
	2	0	21	25
	3	1	50	73
	4	0	37	56
	5	1	37	62
	6	1	50	171
1998	1	1	36	464
	2	0	24	78
	3	1	25	103
	4	1	24	112
	5	0	25	100
	6	1	57	182
1999	1	0	16	343
	2	3	25	263
	3	6	24	161
	4	10	59	206
	5	4	35	356
	6	12	49	649

Notes as in Table 1

Table 10: Number of transactions per bimester during Phase II

Transactions per bimester Phase II				
	Bimester	b	m	p
2000	1	8	86	720
	2	3	92	333
	3	10	105	384
	4	17	81	320
	5	9	63	412
	6	23	116	741
2001	1	22	49	1916
	2	21	23	589
	3	17	45	296
	4	19	32	353
	5	11	27	321
	6	12	18	698
2002	1	22	48	2368
	2	5	14	916
	3	0	17	558
	4	1	7	725
	5	0	9	443
	6	2	18	501
2003	1	5	57	2207
	2	1	36	257
	3	1	26	192
	4	0	27	279
	5	0	44	282
	6	0	44	403
2004	1	37	52	2733
	2	0	44	258
	3	0	37	240
	4	2	37	305
	5	2	29	248
	6	0	30	461
2005	1	18	54	2694
	2	3	34	344
	3	1	50	346
	4	2	36	441
	5	11	55	282
	6	70	50	417

Notes as in Table 1

within the same group may have on our results. For this purpose, Model 4 is estimated after dropping all transactions completed between privates that share the same general account (i.e., 2259 observations).

4.1 Market participation

The coefficients and odds ratios reported in Tables 11 and 12 show the importance of each explanatory variable in the choice of counterparts. Regarding the number of possible counterparts in each category ($particip^i_j$), which is a proxy for the search costs associated with each alternative, the results highlight that as the number of brokers increases, the utility derived form trading with them increases significantly, whereas the participation of an additional private counterpart in the market

Table 11: Conditional Logit Models

Variable	M1: Unrestricted				M2: Baseline			
	Coef.		SE	Odds Ratio	Coef.		SE	Odds Ratio
asc_b	–3.74	**	0.68	0.02	–4.18	**	0.69	0.02
asc_m	0.58	*	0.32	1.79	0.39		0.28	1.47
ytrend_b	–0.22		0.14	0.80	–0.20		0.14	0.82
ytrend_m	–0.33	**	0.05	0.72	–0.31	**	0.04	0.74
ytrendsq_b	0.01	*	0.01	1.01	0.01	*	0.01	1.01
ytrendsq_m	0.03	**	0.00	1.03	0.03	**	0.00	1.03
particip_b	0.35	**	0.03	1.41	0.33	**	0.03	1.39
particip_m	–0.12	**	0.05	0.88	–0.13	**	0.05	0.88
particip_p	0.00	**	0.00	1.00	0.00	**	0.00	1.00
ph_b	1.24	**	0.30	3.47	1.63	**	0.29	5.10
ph_m	0.64	**	0.12	1.90	0.90	**	0.11	2.46
jf_b	–1.23	**	0.59	0.29	–0.79	**	0.12	0.45
jf_m	–0.73	**	0.12	0.48	–1.12	**	0.06	0.33
jfph2_b	1.31	**	0.60	3.71				
jfph2_m	0.24	*	0.13	1.27				
qasc_b	–0.09		0.06	0.92				
qasc_m	0.02	**	0.01	1.02				
samer_b	–4.72	**	0.51	0.01				
samer_m	–2.78	**	0.10	0.06				
difdifpos_ b	0.35		0.22	1.42				
difdifpos_m	0.55	**	0.09	1.73				
difdifneg_ b	1.25	**	0.28	3.49				
difdifneg_m	0.12		0.12	1.12				
rbl_b	0.31		0.98	1.37	1.33	**	0.63	3.79
rbl_m	–0.79	*	0.42	0.45	0.78	**	0.25	2.19
rb2_b	0.43		0.67	1.54	0.41		0.60	1.50
rb2_m	0.17		0.28	1.18	0.47	**	0.22	1.61
rb3_b	0.44		0.63	1.55	0.28		0.60	1.32
rb3_m	0.69	**	0.26	2.00	0.12		0.22	1.13
rb4_b	0.09		0.65	1.09	0.62		0.61	1.86
rb4_m	0.35		0.27	1.41	0.15		0.23	1.16
rb5_b	–0.40		0.64	0.67	–0.06		0.61	0.95
rb5_m	–0.01		0.26	0.99	–0.16		0.23	0.85
rb6_b	–1.54	**	0.74	0.21	–0.53		0.65	0.59
rb6_m	–0.13		0.30	0.88	–0.24		0.24	0.79
rb7_b	0.39		0.63	1.48	0.50		0.61	1.65
rb7_m	0.32		0.27	1.37	0.34		0.24	1.41
rb8_b	0.28		0.63	1.33	0.36		0.61	1.43
rb8_m	0.57	**	0.26	1.77	0.34		0.23	1.41
rb9_b	–0.76		1.01	0.47	–0.43		0.74	0.65
rb9_m	–0.98	**	0.40	0.38	–0.40		0.28	0.67

** indicates significance at 5%; * indicates significance at 10%

has almost no effect on the utility derived from trading with private counterparts. Since private counterparts' participation is very high relative to that by other types of counterparts, the marginal utility derived from an increase in their market participation is very low with respect to the marginal utility derived from an increase in broker participation. This is because the agent's probability of finding a suitable match among private counterparts is already high (search costs are low).

Additionally, we find an odds ratio associated with the market participation of market makers that is smaller than one. This suggests that agents prefer a relatively small number of market makers rather than many market makers (possibly with each having fewer available permits). This is in line with Miao (2006), who based on a search model, finds that monopolistic market making may improve social welfare with respect to competitive market making because it partially internalizes

Table 12: Alternative especifications

	M3: Interactions				M4: Non-intragroup				
Variable	Coef		SE	OR	.	Coef		SE	OR
asc_b	–3.25	**	0.37	0.04		–3.77	**	0.68	0.02
asc_m	1.10	**	0.20	3.02		0.51		0.32	1.67
ytrend_b	–0.28	*	0.13	0.76		–0.22		0.14	0.80
ytrend_m	–0.33	**	0.04	0.72		–0.31	**	0.05	0.73
ytrendsq_b	0.02	**	0.01	1.02		0.01	*	0.01	1.01
ytrendsq_m	0.04	**	0.00	1.04		0.03	**	0.00	1.03
particip_b	0.36	**	0.03	1.44		0.35	**	0.03	1.41
particip_m	–0.12	**	0.05	0.89		–0.13	**	0.05	0.88
particip_p	0.00	**	0.00	1.00		0.00	**	0.00	1.00
ph_b	1.39	**	0.29	4.01		1.23	**	0.30	3.41
ph_m	0.69	**	0.12	1.99		0.64	**	0.12	1.90
jf_b	–1.22	**	0.59	0.30		–1.23	**	0.59	0.29
jf_m	–0.62	**	0.12	0.54		–0.76	**	0.12	0.47
jfph2_b	1.17	**	0.60	3.22		1.33	**	0.60	3.77
jfph2_m	0.12		0.14	1.13		0.29	**	0.14	1.34
qasc_b	–0.05		0.05	0.95		–0.08		0.06	0.92
qasc_m	0.01	**	0.01	1.01		0.05	**	0.01	1.05
samer_b	2.50	**	0.63	12.24		–4.58	**	0.51	0.01
samer_m	2.30	**	0.32	9.96		–2.66	**	0.10	0.07
difdifpos_b	0.25	**	0.07	1.29		0.36	*	0.22	1.44
difdifpos_m	0.12	**	0.03	1.12		0.57	**	0.09	1.76
difdifneg_ b	0.38	**	0.16	1.47		1.23	**	0.28	3.44
difdifneg_m	–0.18	**	0.08	0.84		0.12		0.12	1.12
rxbl_b	–21.74	**	0.68	0.00	*rblb*	0.28		0.99	1.32
rxbl_m	–5.15	**	0.67	0.01	*rblm*	–0.82	*	0.43	0.44
rxb2_b	–21.11	**	0.64	0.00	*rb2b*	0.43		0.67	1.54
rxb2_m	–3.60	**	0.33	0.03	*rb2m*	0.16		0.28	1.17
rxb3_b	–21.11	**	0.63	0.00	*rb3b*	0.45		0.63	1.57
rxb3_m	–22.56	**	0.32	0.00	*rb3m*	0.70	**	0.26	2.01
rxb4_b	–21.27	**	0.64	0.00	*rb4b*	0.10		0.65	1.10
rxb4_m	–22.44	**	0.32	0.00	*rb4m*	0.35		0.27	1.42
rxb5_b	–21.25	**	0.63	0.00	*rb5b*	–0.38		0.64	0.68
rxb5_m	–22.32	**	0.32	0.00	*rb5m*	0.00		0.26	1.00
rxb6_b	–21.48	**	0.66	0.00	*rb6b*	–1.51	**	0.74	0.22
rxb6_m	–22.18	**	0.33	0.00	*rb6m*	–0.10		0.30	0.90
rxb7_b	–5.58	**	1.19	0.00	*rb7b*	0.43		0.63	1.53
rxb7_m	–22.28	**	0.32	0.00	*rb7m*	0.36		0.27	1.43
rxb8_b	–21.09	**	0.63	0.00	*rb8b*	0.30		0.63	1.35
rxb8_m	–22.59	**	0.32	0.00	*rb8m*	0.58	**	0.26	1.78
rxb9_b	–21.42	**	0.64	0.00	*rb9b*	–0.79		1.01	0.46
rxb9_m	–22.96	**	0.32	0.00	*rb9m*	–1.00	**	0.41	0.37

Notes as in Table 11; OR are Odds Ratio; *rxblb* = *samer* * *rblb*

the externalities of bid–ask prices on the decentralized market. In this sense, in our model, agents make their choice to maximize their utility while accounting for this effect.

4.2 Size

How quantity ($qasc^i$) influences the choice of the counterpart is irrelevant when agents choose between a broker and a private counterpart. The coefficient is not significant at standard levels. However, there is a shift in preferences from private counterparts to market makers as quantity increases.

A possible explanation, borrowed from Barclay et al. (2003) and Bessminder and Kaufman (1997), is that when placing orders of a large size, agents wish to avoid disaggregating a single order into several transactions. This explanation underlines the role of market makers in reducing transaction costs for large transactions.

4.3 Regional electricity markets

The estimates show that the SO_2 market inherits a strong regional component from the electricity market. The estimates associated with the variable $samer^i$ show that, when choosing a private counterpart, agents prefer to trade within their region. In fact, for brokers, the odds ratio associated with $samer^i$ shows that, when switching from a counterpart in another region to a counterpart in its own region, the preference for brokers declines such that private counterparts are instead favored. The preference for market makers relative to private counterparts also declines when trading within their region. The existence of long-term business relationships in the local electricity market allows generators to reduce search costs when trading allowances among one another and generates economies of scope through the use of well established communication channels. Additionally, information regarding the counterpart and allowance market conditions is more important when trading within a region.

When the difference between a given regional electricity price and the national average is lower than the mean difference between regional and national prices, this indicates the presence of a negative electricity price shock, and we expect a local abundance of all inputs used for electricity production, in particular SO_2 allowances. In such cases, agents may prefer buying permits within their region rather than in the nationwide market. Instead, when the difference between the regional and national price is higher than the mean difference, i.e., in the presence of a positive electricity price shock, it is reasonable to imagine that agents prefer to buy permits outside of their region, where permits are less scarce. Regarding the change in the preference for brokers due to these electricity price changes, we find that the estimate associated with the variable $difdifpos^i$ is not significantly different from zero in most regressions. Instead, the estimate associated with $difdifneg^i$ respects the previous intuition, i.e. it shows that, when there is a negative electricity price shock in the region, the preference for broker increases relative to the preference for private counterparts. This may be because, when the shock is negative and therefore firms have incentives to trade within their region, they trade with brokers to reduce search and information costs.

Regarding the preference for market makers, the estimate associated with $difdifneg^i$ is non-significant, but the odds ratio associated with $difdifpos^i$ shows that, if the difference between the regional electricity price in the buyer's region and the national average is lower than the mean difference between regional and national prices, the preference for market maker increases by more than one and a half times with respect to the preference for private counterparts. This strong preference for market makers in the presence of incentives to buy permits from outside the region suggests that agents consider the counterpart risk in the nationwide market for SO_2 to be higher than that in the local market.

To account for regional heterogeneity and capture region-specific agent preferences, we control for the agent's main business location. Most regional dummies are not significant, meaning that there is no heterogeneity in the preferences of agents belonging to different regions.

To better understand agents' preferences with respect to the regional dimension, in Table 12-M3 we account for the interaction between $samer^i$ and the regional dummies $rb\#^i$. On the one hand, if a generator belongs to a region in which the number of private counterparts is high, we expect him to perceive no informational advantage from trading inside his own region due to the large scale of the local market. On the other hand, greater participation by private counterparts facilitates finding a private counterpart to meet his demand. The aim is to assess which of these forces prevails and to control for heterogeneity in local trading across regions. Model 3 shows that these variables are all very significant but not very different from one another. This means that in all regions, firms prefer to trade with private counterparts over other types of counterparts when trading within the same region and that this preference is stable across regions.

Many large firms operate more than one utility or generation plant in a given region. As an example, SOCO owns utilities in region 5 and region 6 of our regionalization criterion. When accounting for transactions between accounts belonging to the same group, the importance of the regional dimension could be overestimated. To assess the importance of intragroup transactions as determinants of our results, we estimate Model 4 after dropping those transactions. As shown in Table 12-M4, the results remain unchanged after dropping intragroup transactions, and no coefficient changes significantly.[21]

4.4 Market development

The coefficient associated with ph^i accounts for possible changes in preferences due to the institutional and regulatory changes introduced in Phase II. In all specifications, our results suggest that during Phase II, agents are approximately twice as likely to prefer market makers over private counterparts than in Phase I (and 3 times as likely to prefer brokers over private counterparts than in Phase I). The increase in the preference for market makers may be due to the increase in counterpart identification costs as the market develops. By contrast, the increase in the preference for brokers may suggest the increasing need to split a single purchase order into several transactions due to the increase in the number of participants that now hold low stocks of allowances. This may also be because those new participants are smaller and have less experience in trading.

The odds ratios associated with jf^i show that, in Phase I, the preference for trading with brokers or market makers decreases during these months. The contrary is the case during Phase II.[22] During these two months, many buyers enter the market under a tight schedule (rather than for hedging or ordinary portfolio management). Private counterparts holding stocks may enter the market expecting to obtain a better deal during these two months than what they could negotiate during the rest of the year. This increase in the supply of private counterparts relative to brokers and market makers may be the reason for the increase in the preference for private counterparts during Phase I. In fact, during Phase I, the marginal profitability of an increase in the number of private counterparts is higher than that in Phase II. Moreover, during January and February, immediacy is more important than during the rest of the year. The importance of immediacy could be a reason for the preference for market makers or brokers over private counterparts. This, together with the increase in the search costs in Phase II, may explain the preference for brokers and market makers compared to private counterparts in the latter Phase.

To account for the changes in preferences across alternatives as the market develops on an annual basis, we include specific non-linear time trend ($ytrend_j$, $ytrendsq_j$ with intercept asc_j). We expect to find an increase in the role of market makers due to the increase in counterpart risk as the complexity of the market and the number of market participants increases. The unrestricted

21. We also use specification tests to compare the models (see Table 16).

22. This can be observed by examining the sum of the odds ratios associated with *jfb+jfbph2* and *jfm+jfmph2,* respectively.

Table 13: Hausman Test for IIA

	Ho: Odds are independent of other alternatives.			
	Chi-squared	DF	p>Chi-squared	Result
b	0.909	19	1	for Ho
m	–1.58	18	1	for Ho

Alternatives in the regression's dependent variable are {*p*, *b*, *m*}

Table 14: Analysis of the effect of Enron's banckrupcy

	M5: Before 01			M6: After 01			M7: Without 00-01		
Variable	Coef.		SE	Coef.		SE	Coef.		SE
asc_b	–5.33	**	1.37	16.51	*	9.32	–7.17	**	0.93
asc_m	–1.53	**	0.45	–33.90	**	3.70	–2.02	**	0.46
ytrend_b	0.02		0.39	–6.22	**	2.04	–0.95	**	0.18
ytrend_m	0.35	**	0.12	5.05	**	0.90	–0.93	**	0.07
ytrendsq_b	0.03		0.04	0.35	**	0.10	0.02		0.01
ytrendsq_m	–0.07	**	0.02	–0.25	**	0.05	0.06	**	0.00
particip	0.00		0.00	–0.01	**	0.00			
particip_b							0.90	**	0.15
particip_m							–0.21	**	0.07
particip_p							–0.01	**	0.00
ph_b							–6.57	**	0.88
ph_m							–7.70	**	0.73
jf_b	–0.54	**	0.20	0.60	**	0.16	–1.04	*	0.60
jf_m	–0.46	**	0.08	–0.80	**	0.09	–0.83	**	0.12
jfph2_b							1.54	**	0.62
jfph2_m							0.08		0.15
qasc_b	–0.01		0.04	–0.31		0.25	–0.25		0.16
qasc_m	0.02	**	0.01	0.19	**	0.05	0.06	**	0.01
samer_b	–5.19	**	1.00	–4.54	**	0.61	–4.72	**	0.60
samer_m	–3.47	**	0.16	–2.17	**	0.12	–2.70	**	0.11
difdifpos_ b	0.14		0.45	0.34		0.26	0.31		0.26
difdifpos_m	0.50	**	0.15	0.43	**	0.13	0.57	**	0.11
difdifneg_ b	0.49		0.41	2.84	**	0.41	1.85	**	0.34
difdifneg_m	0.40	**	0.17	0.58	**	0.25	0.33	**	0.14

Notes as in Table 11

model suggests that, as the market develops, there is a modest decrease over time in the preference for brokers over private counterparts. This suggests that, all else being equal, the preference for brokers does not change substantially over time. In the case of the preference for market makers, we observe an increase over time, in particular at the end of the period. The market maker time trend is quite interesting: while it slowly decreases during Phase I, reaching a minimum in 2001, it exhibits an upward trend from 2002 until 2005. Indeed, activity by market makers reaches its minimum in 2001 due to the substantial increase in trade among private counterparts during that year (we further analyze this in Section 4.6). In general, we find that trade with private counterparts increased over time and trade with market makers increased even more during the last two years.

4.5 Counterpart differentiation

Finally, even if the Hausman test for IIA shows that a conditional logit model with three independent alternatives better fits our data than a conditional logit with two alternatives (see Table 13), for the sake of comparison, we also estimated two simple logit models (see Table 15). The Hausman test for IIA shows that the conditional logit specification with three independent

Table 15: Logit Models

	M8: N vs. m			M9: p vs. I		
Variable	Coef.		SE	Coef.		SE
asc	1.86	**	0.40	0.68	**	0.30
ytrend	–0.34	**	0.05	–0.31	**	0.05
ytrendsq	0.03	**	0.00	0.03	**	0.00
partic_N	0.00	**	0.00			
partic_m	–0.31	**	0.06			
partic_I				–0.06	**	0.02
particp				0.00	**	0.00
ph	–0.83	**	0.12	–0.36	**	0.09
jf	–0.74	**	0.12	–0.77	**	0.11
*jfph*2	0.22	*	0.13	0.38	**	0.13
same	–2.75	**	0.10	–2.92	**	0.09
qasc	0.02	**	0.01	0.02	**	0.01
difdifpos	0.54	**	0.09	0.57	**	0.09
difdifneg	0.06		0.12	0.26	**	0.11

Dependent variable is 1 for m in M8 and for I in M9
Notes as in Table 11

alternatives is adequate.[23] Indeed, our empirical model differs from the theoretical models on the choice between market makers and bilateral trade (see Rust and Hall, 2003 and Neeman and Vulkan, 2003), in that we focus on the counterpart choice based on given characteristics of the transaction (among others, the size of each alternative and of the transaction and time at which the transaction was realized) rather than explaining the choice of size and trading time.[24] The theory of centralized versus negotiated markets considers the alternatives of "broker" and "private" to be similar (see Neeman and Vulkan, 2003). However, financial market theory (see Barber and Odean, 2008) and behavioral economics (see Shapira and Venezia, 1998) contend that, in most markets, the relevant distinction is that between professional (brokers and market makers) and nonprofessional traders. The two types of intermediaries may be regarded as close alternatives if search costs are high or if agents wish to realize non-standard transactions in terms of size or type of contract (swaps, loans). Moreover, brokers and private counterparts may be viewed as close alternatives since both trade at negotiated prices. To be able to compare our results, which are obtained under the assumption that the three alternative counterparts as independent, with the literature just mentioned, we also estimated two simple logit models. The first considers brokers and private buyers as a joint alternative called "negotiated" (N) (see Table 15-M8). The second considers brokers and market makers as a joint category called "intermediaries" (I) (see Table 15-M9). The estimation method is similar to that detailed for the conditional logit model with the simplification that the set of choices is reduced in the first case to $J = \{N,m\}$ and in the second case to $J = \{I,p\}$. The results are in line with those of the conditional logit model. In particular, agents prefer bilateral trade to market makers when trading in the same region (see $same^i$), but when there are incentives to buy permits from outside the region (i.e., when there is a positive electricity price shock in their own region), they prefer to trade with market makers (see $difdifpos^i$). They also prefer market makers when placing large orders ($qasc^i$). Moreover, the time trends are also in line with our previous results. In this specification, the coefficient associated with $difdifneg^i$ is not statistically significant because the broker and private

23. For a discussion on how this result should be interpreted, see Cheng and Long (2007).

24. Their setting and objectives are very different from ours. Their main finding is that the buyers with the highest valuation of the homogeneous good trade with the market maker while the others search for better deals in the negotiated market. This result holds when the market maker has a marginal cost of executing transactions lower than the least efficient broker.

Table 16: Model comparison

	Obs	AIC	BIC
M1	97965	17162.01	17551.2
M2	97965	19753.74	20048.01
M3	97965	17487.93	17877.12
M4	91188	17407.54	17793.79
M5	41151	9760.38	10062.26
M6	56814	7401.629	7714.793
M7	73989	11953.47	12128.5
M8	32655	16431.66	16607.93
M9	32655	13935.92	14112.19

alternatives are now group as a single alternative *N*, which prevents this model from detecting the discrimination by buyers between these two options when there is a negative electricity price shock in their region (as we found in the case of the conditional logit specification).

In the case of Model 9, that represents a logit model in which intermediaries belong to the same alternative *I*, we find that the time trends and other coefficients are in line with what we found in the conditional logit specification. The AIC and BIC test reported in Table 16 favors Model 9 over Model 8. To further validate our results, we measured the goodness of fit of the conditional logit model in the Appendix.

4.6. Sensitivity analysis: Enron's behavior

The results discussed thus far, in particular the one regarding the time trend, may be biased by the abnormal behavior of the market maker Enron during the years 2000 and 2001 or by its bankruptcy at the end of 2001. The beginning of Phase II coincides with the last two years of Enron's activity in the SO_2 market. During these years, Enron was particularly relevant in terms of the volume and number of transactions, which could be due to fraudulent behavior. A large percentage of market makers' trade during these two years was attributable to Enron.[25]

To assess to what extent Enron's bankruptcy induced a change in preferences, we estimated the counterpart model on two subsamples (see Table 14), one considering transactions concluded before Enron's bankruptcy in December 2001 (the 1995–2001 subsample in Model 5) and another considering transactions from 2002 until 2005 (the 2002–2005 subsample in Model 6). We observe that the non-linear time trend for market makers is decreasing before Enron's bankruptcy and increasing afterwards. This is consistent with the results based on the full sample. With respect to the rest of the coefficients, there are no significant differences between the results of Model 5 and Model 6 or between these results and those based on the full sample. The greatest impact we observe in relation to Enron's bankruptcy is the important substitution of market makers by brokers in 2001 relative to 2000 (also shown in Tables 1 and 2). This substitution is in line with previous literature's results. In this regard, Jue et al. (2004) construct a model of oligopolistic competition between brokers (called middlemen) and market makers. They find that the exit of a market maker results in a shift of trade from the latter to brokers, but that after transition (approximately two months in their empirical application), trade volumes by alternative return to pre-exit levels. In line with Jue et al. (2004), we observe market makers being replaced by brokers immediately after Enron's bankruptcy.

25. We observe abnormal behavior by Enron during 2000 and 2001, both in terms of volume and in terms of number of transactions in Tables 1 and 2. Enron's abnormal behavior affects the weight of market makers' volume relative to other alternatives during the year 2000, and we observe a substitution of market makers for brokers in 2001. This phenomenon disappears after Enron's default in December 2001.

Similarly, to understand how Enron's abnormal activity during 2000 and 2001 may affect our results, we estimated the counterpart model excluding all transactions belonging to the years 2000 and 2001 (in Model 7). Again, we find that time trends are consistent with those found for the full sample but we also observe a significant change in coefficients[26]. In particular, the coefficients associated with ph^i suggests that, when excluding observations from the years 2000 and 2001, intermediaries are no longer preferred to private counterparts during Phase II. The results based on the full sample show that the preference for private counterparts increases during Phase II but that the preference for market makers increases to an even greater extent after 2002. In the estimation without the years 2000 and 2001, the increase in the number of private counterparts in 2000 could only be attributed to observations beginning in 2002. Consequently, the more than proportional increase in the preference for market makers over private counterparts previously found from 2002 on is no longer observed in this model specification.

5. CONCLUSIONS

The need to link CO_2 markets to create a global price for GHG emissions has been supported by the 2014 Nobel price winner, Jean Tirole, and many other economists (see Golier and Tirole, 2015). As the debate on how to implement such a link between regional markets remains open (see, e.g., Jaffe et al. 2009), it is important to understand that the determinants for buying or selling a certain amount of allowances in an emission trading market does not solely depend on the possibility of abating pollution at a lower marginal abatement cost. There are market conditions determining counterpart characteristics at different points in time, that have a direct influence on the utility derived from each specific transaction undertaken. Understanding the choice over types of counterparts as a function of market, individual and counterpart characteristics allows us to assess the fragmented structure of these markets and the important role of professional traders in linking local markets, reducing search and transaction costs, counterparty risks and, in general, increasing the information available. Additionally, we are able to understand how agents in this market consider counterpart choice, how this thinking evolves as the agents learn and to what extent it is influenced by changes in the market configuration provoked by market regulation. Ultimately, these results offer a broader perspective on how agents behave in emission trading markets and the link that those markets have with the polluting output market.

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26. The Hausman test for change in coefficients is significant. An alternative to this specification test would be the one suggested by Kohler et al. (2011) but its implementation for a clogit can be challenging with our data structure.

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APPENDIX: GOODNESS OF FIT OF THE MODEL

We simulate the utility derived from trading with each alternative for all transactions. To do this, we first compute the fitted utility using (Q)ML estimates. Then, under the distributional assumption stated in Section 2, we generate k(=200) draws[27] from a standard extreme value distribution and simulate the utility associated to each choice for all transactions. In each replication the selected choice is the one that maximizes utility in each transaction. Finally, given the distribution

27. We have performed several simulations of different sizes. Herein we show results for $k = 200$ but other simulations are available upon request.

of the choice for each transaction, we compute the median and 95% confidence band and compare this to the agents' actually observed choices. Figures 2,3 and 4 report the outcome for each choice respectively, aggregated on a monthly basis. In Figure 2 we observe that the all lines coincide, meaning that our estimations coincide with the true value. Even if there is more variability in Figures 3 and 4, the true value rarely falls outside the confidence interval. All in all, we observe that the aggregated true choice falls into the 95% confidence band for almost all cases, showing an adequate fitness of the model.

Figure 2: True versus Predicted utility derived from trading with another private

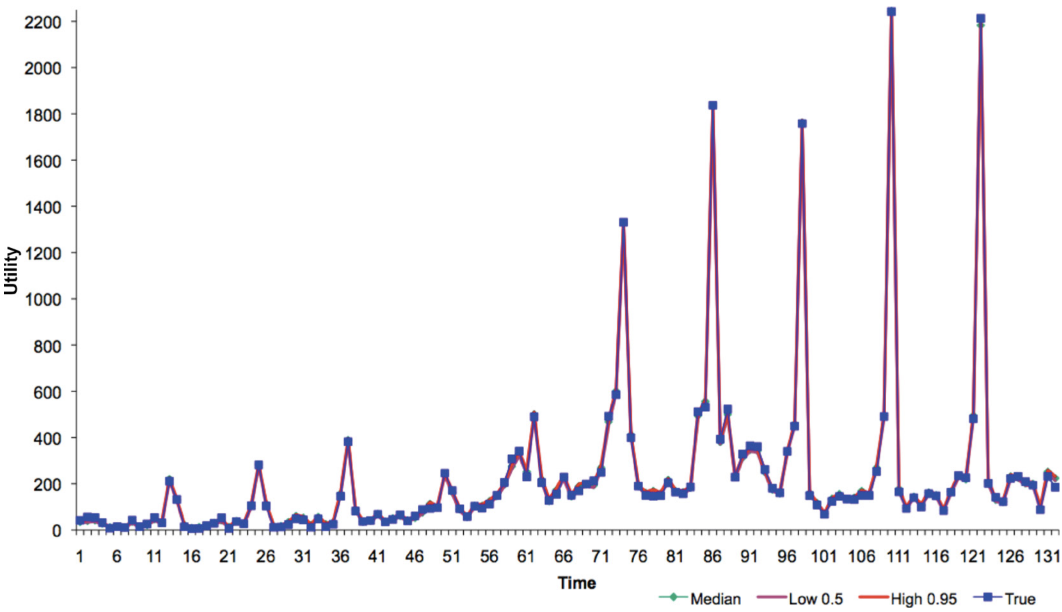

Figure 3: True versus Predicted utility derived from trading with a broker

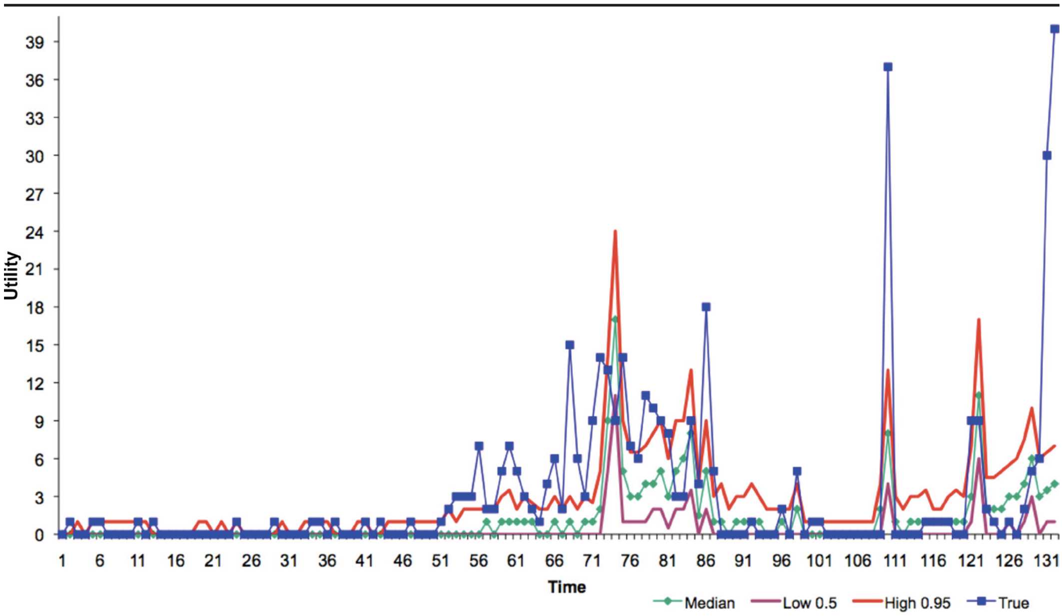

Figure 4: True versus Predicted utility derived from trading with a market maker