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Abstract: In this paper we study the determinants of the counterpart choice in the U.S. market for SO2 allowances. Counterparts can be chosen among three alternatives proved to be independent: market makers, brokers or private. Privates are mostly U.S. electricity generators. We find that the SO2 allowances market, as the electricity market, is regionalized. The national dimension only appears when there are local imbalances that give incentives to search for a better price outside of the region. Additionally, our results suggest that agents like counterpart differentiation i.e. they value positively the presence of few market makers, possibly with large stocks but they also value positively the presence of many brokers (and privates). In line with previous literature results, we also find agents prefer market makers when placing large size orders and that the preference for market makers increases on time due to the increase in the counterpart risk. Finally, we also identify the influence of the regulatory framework, i.e. the division in phases and the chosen allowance surrender date, in the counterpart choice. The previous results are robust to Enron's abnormal behavior during 2000-2001 and its posterior bankruptcy.

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1 Introduction

Sulfur dioxide (SO_2) emission allowances are property rights that have been introduced as part of the environmental regulation supported by the U.S. Environmental Protection Agency (EPA) to reduce the SO_2 emissions produced by fossil fueled electricity generators. The creation of a tradable property rights coinciding with the preestablished pollution reduction target is generally called cap-and-trade regulation and, in this case, is commonly known as the "Acid Rain Program". Its name refers to the acid rain provoked in certain areas of the U.S. due to SO_2 emissions. The cap is reflected in the total amount of allowances created and allocated by the EPA. These allowances are allocated for free[1] on a yearly 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 the 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 (and across time), equalizing marginal abatement costs to the unique allowance price. To this end, generators hold an inventory of SO_2 allowance 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).

When a private agent (an electricity generator) in the SO_2 allowance market wants to place an order, he must choose between three mutually exclusive type of trading counterparts (from now on simply counterparts or alternatives). Those alternatives are: "broker", "market maker", or another "private" counterpart. In this paper we investigate the determinants of this choice. In particular, we focus on the way agent's characteristics, transaction's characteristics and each alternative's characteristics impact on the counterpart choice. The intuition behind this is the following: when choosing a counterpart from which to buy a certain amount of allowances, the agent searches for the lowest allowance price and the lowest costs (and risks) associated to the transaction. In this paper we only account for the latter motivation due to the lack of price information. Then, depending on the market conditions at each point in time (i.e. local scarcity of allowances, the time left before the next allowances 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

[1] Table A of the U.S. Clean Air Act lists allowance allocations.

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), agents prefer one alternative over the other. To this end, we are able to understand which are the characteristics of each counterpart that agents value the most and how this preference may change with the specific characteristics of transactions. Market microstructure literature underlines the difficulty of studying and regulating decentralized markets since each transaction is unknown to other market participants (O'Hara, 1995). By means of understanding the determinants behind agents' counterpart choice, we are able to throw some light on some issues of crucial importance for regulatory policy, namely: (i) how the structure of the underlying electricity market influences agents' trading behavior in the permits market; (ii) how the rules imposed by the environmental regulation (e.g. having different number of agents entering the market in subsequent phases or having a fixed allowance surrender date) impact on the number (and type) of agents entering the market[2] and consequently on market evolution; and (iii) which is the role of professional traders as the market evolves and if their presence has an impact on the environmental regulation's efficiency.

A broker is experienced in the negotiation of standard and non-standard volumes, as well as in the negotiation of trading and credit 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 desegregate 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 an agent. A fixed brokerage fee must be paid to trade with a broker.

A market maker, instead, trades on his own behalf and for this reason he holds allowances stocks. Holding stocks force market makers to have a 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 where transactions are discontinuous due to the small number of participants and their 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 to each transaction also increases.

Besides trading with professional traders, another possibility is to

[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.

trade with a private counterpart, most likely an electricity generator that operates in one or more of the U.S. states subject to the Acid Rain Program. The market for electricity, rather than national, is a regional market. According to Joskow (1997), in 1997 retail consumers still had to buy their electricity from the legal monopoly supplier, generally vertically integrated. In this line, Joskow (2005) explains how the efforts to introduce competition in the electricity market and to connect local electricity grids to create a competitive nation-wide market have not succeeded so far. Such regional dimension might be reflected in the SO_2 market. Local electricity market conditions are likely to drive the local supply/demand of SO_2 allowances as they are an input for electricity production, and electricity generators are the main actors in the SO_2 market. Furthermore, generators operating in the same region are likely to be partners/competitors in the local electricity market and linked by well established commercial relationships. The existence of long term business relationships allows them to reduce search costs when trading allowances among each other, and generate scope economies by using well established communication channels. Additionally, the information regarding the counterpart and the allowances market conditions are grater within their own region, which may influence the counterpart choice.

To study the determinants of the trading counterpart choice, we have obtained[3] a database that collects all transactions registered in the Allowance Tracking System (ATS) of the EPA between January 1995 and December[4] 2005. From the database we selected all transactions in which a private agent appears as a buyer. We extracted those transactions because we are only interested in private counterpart's choice. We have checked that, if we had considered transactions that have a private agent as a seller instead of a buyer, results would mirror the results stated hereafter. To account for the regional dimension and the link between the SO_2 market and the electricity market we have completed our database with data on local electric market conditions. Firstly, we have divided the U.S. in nine regions using the regionalization criterion of the Energy Information Administration[5] (EIA) Census Division. Then, we have identified the region to which each generator belongs. Within the same regionalization criterion we have also identified the localization of each professional trader. Usually, market makers trade nation-wide while brokers just trade across more than one region. Secondly, we have

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

[4]We have excluded auction data as well as compensation and surrender allowance transfers.

[5]See http://www.eia.doe.gov/.

collected data on the monthly average retail price at a regional level to be able to account for local shocks in the supply/demand of electricity, and in general for unobserved local heterogeneity as determinants for the counterpart choice.

We find evidence to support the hypothesis that the SO_2 market inherits the local dimension from the electricity market and that this determines the way agents choose their trading counterpart. This finding may be important from a regulatory perspective. As mentioned before, the principle behind the creation of this market is creating the possibility of abating emissions at the lowest marginal cost nationwide. If trade among privates takes place mostly regionally, the main objective of the creation of this market would not be completely fulfilled. Instead, the national dimension prevails when there are local imbalances in the supply or demand of allowances, which also influences agent's preferences with respect to each type of trading counterpart. We find that, in average, generators prefer to trade within their own region with other generators or brokers. On the other hand, when there is a shock in the local electricity market that makes SO_2 allowances locally scarce, our results show that generators are more likely to buy allowances from market makers. These results suggest that the counterpart risk is perceived as higher in the nation-wide market. Additionally, this suggests that professional traders, in particular market makers, by posting a single allowance (bid-ask) price, serve as a link between local allowance markets making it possible to equalize marginal abatement costs nationwide, i.e. increasing the efficiency of the environmental regulation itself.

Rust and Hall (2003) and Neeman and Vulkan (2003) rely on dynamic models to investigate the reasons behind the coexistence of centralized options (i.e. market makers) and negotiated trade[6] (i.e. bilateral trade and brokered trade). In this sense, Rust and Hall (2003) and Neeman and Vulkan (2003) consider the alternatives "broker" and "private" as equivalent since both trade at negotiated prices. On the other hand, the financial market theory (see Barber and Odean, 2008) and behavioral economics theory (see Shapira and Venezia, 1998) consider that, in most markets, the relevant distinction is the one between professional (brokers and market makers) and non-professional traders. In this paper we consider the three counterpart alternatives as independent[7] finding

[6]Their setting is very different from ours as well as their objetives. Their main finding is that buyers with the highest valuation for 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.

[7]We validate the assumption using the Hausman test for independence of irrelevant alternatives (IIA) (Hausman, 1978) as well as the Small-Hsiao specification

that each explanatory variable influences the preference for each type of counterpart quite differently. This is the case, for example, of market participation. Intuition suggests that as the number of participants of a certain type, say brokers, increases, the utility derived from trading with a counterpart of that type also increases due to lower search cost associated with that alternative. In fact, our findings with respect to brokers are in line with this intuition. Additionally, we find that the marginal utility derived from an increase in the number of private counterparts is positive but very low with respect to the marginal utility derived from an increase in broker's market participation. This is the case because private participation is already very high in relation to the participation of brokers (search costs related to that alternative are already low). On the contrary, we find that agents derive a positive marginal utility from a decrease in the number of market makers. This result suggests that generators prefer the presence of a relatively small number of market makers of a larger size to the existence of a large number of market makers, each with smaller stocks available. This is in line with Miao (2006) who, based on a search model of centralized versus decentralized trade, shows that, unlike competitive market making, monopolistic market-making may improve social welfare because it partially internalizes the externalities of bid–ask prices on the decentralized market[8].

In relation to the transaction's size, we find that agents prefer to trade with market makers as the size increases, whereas size makes no difference when choosing among private and brokers. This result may be due to the difficulty in finding a single counterpart to fulfill big orders. These results regarding alternatives' market participation and transactions' size suggest that agents value positively counterpart diversification. Then, the presence of market makers and brokers increase the utility derived from trading in the SO_2 market.

In relation to market conditions given by the regulation, we investigate how the counterpart choice is influenced, firstly, by the need of immediacy and the increase of private participants when the allowance surrender date is approaching, and secondly, by the change in the market configuration when passing from Phase I to Phase II. We find that, during Phase II, agents are more likely to prefer professional traders. This result is due to the increase in the counterpart identification costs and on the increasing need of disaggregating each order in multiple transactions due to the small size of the new market participants. Finally,

test (see Small and Hsiao, 1985 and Cheng and Long, 2007). Results of both tests support the IIA hypothesis.

[8]This is the case of the monopolistic specialists system on the New York Stock Exchange (NYSE).

we account for changes in preferences across alternatives as the market develops. We find that trade with private counterparts increases with time (as more firms are covered by the regulation) but trade with market makers increases even more the last two years considered. Additionally, we find there is no significant change in the preference for brokers with time.

Enron's activity 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 market activity, measured in terms of volume and in terms of number of transactions, was most likely due to fraudulent behavior. Therefore, it might be the case that our results are affected by this abnormal behavior. A first approach to assess this possibility consists in removing from our data all transactions concluded during the years 2000 and 2001, when Enron's activity was particularly relevant. Our results in this case are in line with those obtained using the full sample, suggesting that our results are robust to Enron's behavior during these years.

Another concern is that Enron's disappearance may cause a dramatic change in agent's preferences with respect to the counterpart choice. With respect to this last point, Jue et al. (2004) build 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 (roughly 2 months in their empirical application) trade volumes by alternative go back to pre-exit levels. To account for the change in preferences after Enron's disappearance we consider two subsamples, before Enron bankruptcy (from 1995 to 2001) and after (from 2002 to 2005). We find that the results based on the full sample still hold in the two subsamples even if, in line with Jue et al., (2004), immediately after Enron's bankruptcy we observe a substitution of market makers by brokers.

As far as we know this is the first attempt to study the counterpart choice in an emission allowance market. Similar empirical papers have been written on the choice of competing trading platforms (see Hendel et al., 2007 and Bernheim and Meer, 2008 for applications to the housing market). Both Hendel et al. (2007) and Bernheim and Meer (2008) show that agents using a broker find a counterpart quicker than the ones selling bilaterally. Additionally, Hendel et al. (2007) find that bilateral trade is associated with agents that are either better bargainers or in need of less immediacy. In this sense, Hendel et al. (2007) show how individual characteristics and platform characteristics influence the choice between bilateral trade and brokered trade. This "differentiation" between platforms 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. (2007) claim that it might be socially efficient to have multiple platforms (in our case alternatives), offering different service levels, catering to different type of houses and sellers (in our case transactions and agents).

Finally, other related literature is 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 go to the centralized market since multiple transactions are needed to fulfil a single order of large size.

In Section 2 we describe our data and provide some descriptive statistics. In Section 3 we introduce our trading counterpart choice model. In Section 4 we discuss identification assumptions. In Section 5 we present the estimation results and in Section 6 we assess the goodness of fit of the model. In Section 7 we conclude.

2 Stylized facts and data description

The creation of the market for emissions has established the SO_2 allowances as an additional electricity production input. The net short or long position in SO_2 allowances depends on each period's difference between the allowances that a generator needs for production and the number of allowances received, yearly, from the EPA. In our data, we observe that each generator enters the market more than once a week and, in some cases, more than once a day. This frequency suggests that firms enter this market to optimize their allowance holdings. Once they decided to enter the market, generators choose their trading counterparts for each transaction depending on the transaction characteristics, on the information they have regarding each alternative (and the associated search costs) and on market conditions both of the SO_2 market and of the underlying electricity market.

2.1 Trading data

The data regarding transaction and alternative's characteristics as determinants for the counterpart choice is extracted from the Allowance Tracking System (ATS) of the EPA. We consider all transfers registered in the ATS between January 1995 and December 2005 after excluding auction data as well as compensation and surrender allowance transfers. This gives a database accounting for 32.655 transactions over 10 years.

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 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. Electricity generators generally hold "unit accounts" from where the verified emissions by generating unit are deducted and a "general account" to trade SO_2 allowances. By contrast, professional traders just 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[9]. We consider as market makers all professional traders that hold stocks by that time.

The ATS is the primary source of allowance-trading data. However it will 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 the 1st, date when EPA deduces from unit accounts the amount of allowances needed to cover the previous year SO_2 emissions. Consequently, no measure based on the ATS can be certain of including 100 percent of transactions. This will probably make our model underestimate brokerage's importance: brokers, as they do not hold stocks for themselves, do not necessarily need to open a general account in the ATS. In this sense, transaction originally negotiated through a broker may appear in our database as one or many transactions between private counterparts. However, Joskow et al. (1998) express that, to their understanding, prompt recording of transactions was the rule rather than the exception and that transactions registered as "private transfers" in the ATS are the best available lower-bound estimate of transactions between privates, market makers and brokers.

2.2 Transactions' characteristics and market conditions imposed by regulation

We observe differences in the characteristics of transactions undertaken with different type of counterparts, as well as, differences in the trading behavior as market conditions change (both inside the year and as time goes by) due to the rules imposed by the environmental regulation. Figure 4 shows that the average transaction size is higher when the counterpart chosen is a market maker. This could be the case because, when placing orders of a large size, agents wish to avoid disaggregating a single order in several transactions. Figure 5 shows an increase in the number

[9]If some profesional trader holds less than 1000 allowances at the end of each period but in the following months the stock holding tends to zero it is also considered as broker.

of transactions during the two months prior to the allowance surrender date, March the 1st. The change in counterpart preferences during these two months can be learnt from Table 3 for Phase I and from Table 4 for Phase II. We observe that in Phase I the number of transactions done with private counterparts is higher during the first bimester whereas, in Phase II, also the number of transactions done with market makers increases during these two months.

During Phase I, only the 263 dirtiest generating units were subject to the Acid Rain program and another 111 units voluntary opted into this phase. These 374 units belonged to 110 generators spread over the US territory. During Phase II, beginning in 2000, all fossil-fired generating units greater than 25 MW^e were subject to SO_2 cap, regardless of historical emission rates. This results in a total of nearly 4000 units subject to the program in Phase II (see Ellerman, 2003 for details). Table 5 shows each type of agents participating in the market yearly[10] considering all unit accounts belonging to the same company as accounts belonging to a single agent. This table shows the important increase of private agents' participation starting in 2000.

The emission reduction required in Phase II is stronger (9 million ton), but the number of allowances available did not decreased significantly since 30% of allowances distributed between 1995 and 1999 where banked (i.e. saved) and, according to Ellerman and Montero (2005), only one third where used to cover emissions in excess of the number of new vintage allowances issued between 2000 and 2002. We observe that the total volume of trade doubles the first year of Phase II reaching almost 22 million allowances a year (see Table 1) and that the Phase II average yearly volume of allowances traded is always higher than 13 million, much higher than the average yearly volume of allowances traded during Phase I (see Figure 6). Similarly, the number of transactions increased steadily over time (see Figure 8). The change in market structure in terms of number of participants as well as the distribution of a fixed amount of allowances among a larger number of firms may provoke an important change in market structure influencing the preference for counterparts.

2.3 Counterpart characteristics

The larger the number of agents belonging to a specific group the lower the search costs associated to that group. Participation of each type of counterpart in terms of volume and in terms of number of transactions can be seen in Figures 6-9. We have intentionally separated Enron's par-

[10] Overall, we consider 2.011 distinct allowance accounts belonging to non-professional traders.

ticipation from the other market makers since we observe an abnormal behavior of Enron during 2000 and 2001, both in terms of volume and in terms of number of transactions (see for example the evolution of the number of transactions in Figure 9). Enron's abnormal behavior affects the weight of market maker's volume in relation to other alternatives during the year 2000 and we observe a substitution of market makers for brokers in 2001 (see Figure 9 and Figure 11 in comparison with Figure 10). This phenomena disappears after Enron's default in December 2001. Hereafter we account for the possible impact of Enron's behavior on our estimation results.

2.4 Local market conditions

We cross-reference the ATS transactions data with data on local electric market conditions. Since we are interested in capturing how differences in local demand/supply for electricity may impact agents' trading behavior in the SO_2 market, we divide the U.S. in nine regions according to the Energy Information Administration[11] (EIA) Census Division (see Table 2). This division of the U.S. territory is the one used by the EIA's National Energy Modeling System (NEMS) to account for nine local end-use demand modules[12]. We have created a 10th region to which all firms operating nationwide or by definition without a single localization (for instance some market makers) belong. The number of agents belonging to each region in our data is summarized in Table 2. Naturally, there are big groups that operate more than one utility across more than one region but not yet nation-wide (e.g. SOCO[13] or AEP[14]). In this cases we assign each "unit account" to the region it belongs and the "general account" to the headquarter's region. We will control for the effect that intragroup transactions may have in our estimation.

There is no U.S. national market for electricity. Then, the regional structure of the electricity market may be reflected in the SO_2 market. 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 at their locations and at prices approved by the state regulatory commission. Most of these utilities had historically been vertically integrated operating the four primary elec-

[11] See http://www.eia.doe.gov/.

[12] 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 indistinctly changes in local demand for electricity and changes in the wholesale electricity market structure across time.

[13] SOCO stands for Southern Company. For more details see http://www.southerncompany.com/aboutus/about.aspx

[14] AEP stands for American Electric Power. See http://www.aep.com/about/

tricity supply functions: generation, transmission, distribution and retailing. In late 1999 the Federal Energy Regulatory Commission (FERC) started moving towards the introduction of institutional change in the wholesale electricity market with the intension of connecting local grids and increasing competition. This stopped 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 in local markets 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. Most likely, this represents an informational advantage when trading SO_2 allowances with each other. In such case we expect to observe a larger amount of intra-regional private trade. Tables 6 and 7 show the importance of intra-regional trade. We observe that most brokers and market maker's trade is national whereas most of private transactions are local.

3 Trading counterpart model

From the point of view of the estimation method, our model is similar to the ones used by the labor selection theory (see for example Boskin, 1974). Similarly to an agent that must choose a job according to his skills and the benefits offered by the employer, when an agent enters the market to buy a certain amount of SO_2 allowances, he faces the problem of choosing a counterpart depending on his characteristics, on those of the transaction, on market characteristics and on counterpart characteristics. We assume that agents maximize their utilities (or profits) independently of what they have chosen in previous transactions. Then, they maximize:

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

where i indexes each transaction[15] and j indexes possible counterparts of 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 part which is a function of observable characteristics and ε_j^i denotes the stochastic part which represents the unobserved characteristics. To implement the model we must specify a functional form for the deterministic component of the utility function as well as 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

[15] Notice that we consider buy contracts placed by private agents.

market of each alternative -in number of participants per year- (denoted $particip_j^i$) as a proxy for the supply of each type of counterpart (see summary statistics in Table 5); *(ii)* a component ($samer^i$) that reflects the utility (due to an informational advantage) derived from trading with a counterpart that is located in the same region as opposed to a different region (see Table 8).; *(iii)* two components that capture shocks in the supply/demand in the local electricity market ($difdifpos^i$ and $difdifneg^i$); *(iv)* a dummy variable that accounts for the allowance verification period as opposed to the rest of the year (jf^i); *(v)* a dummy component capturing the utility derived from trading during Phase II as opposed to Phase I (ph^i); *(vi)* a group of dummies accounting for regional heterogeneity ($rb\#^i$) that take the value one for the region where 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 consider the interaction between some of these components.

The construction of the variables ($difdifpos$ and $difdifneg$) is worth a few words. Figure 12 shows there are some regions where the monthly retail electricity price is systematically below or systematically above the national average. This is due to the fact that some regions have more resources for electricity production than others. On the other hand, Figure 12 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) as compared to the rest of the territory, 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 (subtract) it with the mean annual difference between those prices ($mean_a(p_{r\#} - p_n)$). That is, we define $difdif = p_{r\#} - p_n - mean_a(p_{r\#} - p_n)$. 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. Summary statistics for the latter variables are reported in Table 9.

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 an alternative of reference, in our case alternative private (p), and differences in utilities are computed with respect to the utility of choosing the alternative of reference. This normalization is common practice in conditional logit models as the one used herein (see McFadden, 1973 for details, McFadden, 1974 for an example and Manski, 2001 for a summary on the estimation method).

Under the previous assumptions the deterministic part of the utility function for each choice can then be expressed as

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

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

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

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

In the case of the SO_2 market, the three alternatives appear to be 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 belonging to the same local electricity market. Also, professional traders seem to be very different one from another in the SO_2 market: by holding stocks and standing ready to buy or sell, market makers reduce the counterpart risk whereas brokers just reduce search costs and customize transaction. Then, the three mutually exclusive alternatives seem to be independent. We therefore use a conditional logit model and, to validate this intuition, we apply the Hausman test for independence of irrelevant alternatives (IIA) (see Hausman, 1978 and Cheng and Long, 2007).

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

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

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 extreme value distribution with constant variance (McFadden, 1973), the probability that alternative $k \in J$ is chosen can be expressed as:

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

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

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 other, the size of each alternative and of the transaction and the moment in which the transaction was realized) rather than explaining the choice of size and time to trade.

As stated in Section 1, the theory of centralized versus negotiated markets considers the alternatives "broker" and "private" as similar (see Neeman and Vulkan, 2003) whereas the financial market theory (see Barber and Odean, 2008) and behavioral economics theory (see Shapira and Venezia, 1998) considers that, in most markets, the relevant distinction is the one between professional (brokers and market makers) and non-professional traders. Both type of intermediaries may be viewed 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). On the other side, brokers and private counterparts may be viewed as close alternatives since both trade at negotiated prices. To be able to compare our results when considering three alternative counterparts as independent with the literature just mentioned, we have also estimated two simple logit models. The first one considers brokers and private as a joint alternative called "negotiated" (N). The second one considers brokers and market makers as a joint category called "intermediaries" (I). The estimation method is similar to the one 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 $J = \{I, p\}$.

4 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 think that this assumption is suspect for the variable that accounts for the participation of each alternative trading counterpart ($particip_j^i$) in the market. This variable accounts for the number of brokers, market makers and privates that participate in the market each year, and enters the equation considering one year lag. In fact, even if the number of market makers and brokers does not change significantly with time, the number of transactions as well as the volume of transactions suffer important changes (compare values in Table 1 with Table 5) suggesting the non-endogeneity of the variable $particip_j^i$.

We compute robust standard errors estimation for all model specifications to ensure homoskedasticity.

5 Estimation results

The results for the unrestricted model specification of the trading counterpart conditional logit (CL) model are reported in Table 12-M1. Results for the baseline model are in Table 12-M2. The LR test comparing the unrestricted model with the baseline model proves the difference to be significant (p lower than 0.0001), favouring the unrestricted model (see Table 16). Model 3 in Table 13-M3 shows an alternative specification where interactions between some variables are taken into account. We have performed log-likelihood ratio (LR) tests for different groups of explanatory variables (not reported for shortness but available upon request). Test results show that Models M1 and M3 outperform all the others. Moreover, coefficients and odds ratio do not change significantly across specifications and have always the expected signs meaning that estimation is robust to changes in specification. The stability in the value of the parameters also applies to the case of Model 4 in Table 13-M4 where we control for the effect that transactions between utilities of the same group may have on our results. With this purpose Model 4 is estimated after dropping all transactions done between accounts that belong to the same group (i.e. 2.259 observations).

The Hausman test for IIA in Table 11 shows that the conditional logit specification with three independent alternatives is adequate (for a discussion on the way this result should be interpreted see Cheng and Long, 2007).

For ease of comparison to previous literature we also estimate two alternative models, one where brokers and private belong to a single alternative called "negotiated" (N) (see Table 15-M8), and another one where market makers and brokers are merged into a category called "intermediaries" (I) (see Table 15-M9).

Finally, since it is reasonable to suspect that the abnormal behavior of Enron during 2000 and 2001 may affect our results, we estimate our model on a sample where years 2000 and 2001 have been excluded (see Table 14-M7). Additionally, to account for the change in preferences that the bankruptcy of Enron may have produced, we have estimated the model on two subsamples considering the period before and after Enron bankruptcy, respectively (see Table 14-M5 and M6). We want to check that estimations are not biased with respect to the relevance of market makers when including 2000 and 2001 and to control for the possible change in counterpart preferences in 2001, after Enron's bankruptcy.

5.1 Market participation

Coefficients and odds ratios reported in Tables 12 and 13 show the importance of each explanatory variable in the buyer's choice of counterparts. Regarding the number of possible counterparts in each category ($particip_j^i$), which is a proxy of the search costs associated to 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 trader in the market has almost no effect in the utility derived from trading with privates. Since privates' participation is very high in relation to the 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's participation. This is the case because the agent's probability of finding a suited match of the type private is already high (search costs are low).

Additionally, we find an odds ratio associated to the market participation of market makers smaller than one. This suggests agents prefer a relatively small number of market makers rather than many market makers, possibly each with smaller stocks available. 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 the externalities of bid–ask prices on the decentralized market. In this sense, in our model agents make their choice to maximize their utility taking this effect into account.

From the study of the relevance of the variable $particip_j^i$ on the counterpart choice, we learn that agents value positively the existence of counterparts with a clear differentiation in their characteristics.

5.2 Transaction size

The way the quantity ($qasc^i$) influences the choice of the counterpart has no relevance when agents discriminate between a broker and a private. The coefficient is not significant at standard levels. However, there is a shift in preferences from private to market maker as quantity increases. A possible explanation, borrowed from Barclay et al. (2003) and Bessminder and Kaufman (1997), would be the need to desegregate a single order into multiple transactions when the size of the order is large. This explanation underlines the role of market makers in reducing transaction costs for large transactions. In fact, Barclay et al. (2003) and Bessminder and Kaufman (1997) find that agents seeking to trade large quantities usually go to the centralized market to avoid doing multiple transactions to fulfil a single order. This result is also in line with what we observe in Figure 4: the average volume per transaction is higher in the case of market makers than in the case of brokers and private counterparts.

5.3 The regional dimension

The estimates show that the SO_2 market inherits from the electricity market a strong regional component. The estimates associated to the variable $samer^i$ show that, when choosing a private counterpart, agents prefer to trade inside their region. In fact, when looking at brokers, the odds ratio associated to $samer^i$ shows that, when switching from a counterpart in another region to a counterpart in his own region, the preference for brokers reduces in favor of private. When looking at market makers, the preference for market makers in relation to private also reduces when trading inside their region. This suggests that the fact that generators know each other and are able to use well established communication channels reduces search and information costs, reduces counterpart risk and uncertainty in the local permits market, and increases the probability of privates to be chosen as counterparts.

When the difference between the regional electricity price and the national average is lower than the mean difference between them[16] we are in the presence of a negative electricity price shock and we can expect local abundance of inputs used for electricity production, in particular SO_2 allowances. In such cases, agents may prefer to buy permits inside their region rather than in the nationwide market. Instead, when the difference between regional and national price is higher than the mean difference, i.e. when we are in the presence of a positive electricity price shock, it is reasonable to think that agents may prefer to buy permits outside of their region where permits are less scarce. When looking at the change in the preference for brokers due to these electricity price changes, we find that the estimate associated to the variable $difdifpos^i$ is not significantly different from zero in most regressions. Instead, the estimate associated to $difdifneg^i$ shows that, when there is a negative electricity price shock, the preference for broker increases with respect to private. This may be due to the fact that, in the presence of an unusual event, agents prefer to rely on professional traders that reduce search and information costs. When the shock is negative having incentives to trade inside their region, they trade with brokers.

When looking at the preference for market makers, the estimate associated to $difdifneg^i$ is non-significant but the odds ratio associated to $difdifpos^i$ shows that, if the difference between the regional electricity price in the buyer's region and the national average is lower than the

[16] The latter can be interpreted as a systematic difference between regional and national prices.

mean difference between them, the preference for market maker increases more than one and a half times with respect to private. This strong preference for market makers when having 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 in the local market.

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

To better understand agents' preferences with respect to the regional dimension, in Table 13-M3 we account for the interaction between $samer^i$ and the regional dummies $rb\#^i$. On the one hand, if an agent belongs to a region in which the number of private counterparts is high, we could 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, the larger participation of privates makes it easier to find a private counterpart to match his demand. The aim is to assess which of these forces prevails and to control for heterogeneity in terms of local trading among regions. Model 3 shows that these variables are all very significant but not very different one from the other. This means that in all regions firms prefer to trade with privates over other type of counterparts when trading in the same region, but this preference is stable across regions.

Many big firms operate more than one utility or generation plant in the same 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 13-M4 results remain unchanged after dropping intragroup transactions and no coefficient changes significantly.

5.4 Changes in preferences as the market develops

As mentioned in Section 2, Phase II introduces two fundamental changes in the SO_2 market: (i) almost all fossil-fuel generators in the U.S. territory are now included in the Acid Rain program, which increases the number of buyers as well as the number of private counterparts, and (ii) the cap on emissions becomes more stringent. In fact, the number of transactions with private counterparts largely increased from the beginning of Phase II (see Figure 8). The coefficient associated to ph^i

accounts for the possible change in preferences due to the institutional an regulatory changes introduced in Phase II. In all specifications, our results suggest that during Phase II agents are about twice more likely to prefer market makers over private counterparts than in Phase I (and more than 3 times for brokers). The increase in the preference for market makers may be due to the increase in the counterpart identification costs. Instead, the increase in the preference for brokers may suggest the increasing need to desegregate a single purchase order in several transactions due to the increase in the number of participants that now hold few stocks (Figure 4 shows the decrease in the average volume of allowances per transaction). It may also underline the reduced trading experience of the firms included in Phase II.

Our model also includes the variables jf^i and $jfph2^i$ that account for the compliance period effect (January-February trade increase detected in Figure 5) during Phase I and Phase II, respectively. The odds ratio associated to jf^i show that, in Phase I, the preference for trading with brokers or market makers decreases during these months. The contrary happens when considering Phase II[17]. During these two months a lot of buyers enter the market on a tight schedule (rather than for hedging or ordinary portfolio management). This increase in allowance's demand may attract private counterparts holding stocks, since they expect to get 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 in relation to brokers and market makers may be the reason for an increase in the preference toward privates during Phase I. In fact, during Phase I the marginal profitability from an increase in the number of private counterparts is higher than 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 preferring market makers or brokers to private counterparts. This, together with the increase in the search costs in Phase II, may explain the preference towards brokers and market makers with respect to privates after the year 2000.

To account for the changes in preferences across alternatives as the market develops on a yearly basis, we include an alternative 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 model suggest that, as the market develops there is a modest decrease over time in the pref-

[17]This may be understood by looking at the sum of the odds ratio associated to *jfb+jfbph2* and *jfm+jfmph2,* respectivelly.

erence for brokers with respect to private counterparts. This suggests that, all the rest being equal, preference for brokers do not change much over time. In the case of the preference for market makers, we find an increase with time, in particular at the end of the period. The market maker time trend is quite particular: while it slowly decreases during Phase I reaching a minimum in 2001, it shows an upward trend from 2002 until 2005. This results could be thought off as counterintuitive if looking at Figure 9. Instead, market maker's activity reaches a minimum in 2001 due to the spectacular increase of trade among privates during that year, as shown in Figure 8. In general, we find that trade with private counterparts increased with time and trade with market makers increased even more the last two years considered in the data.

5.5 The relevance of Enron

The results discussed may be biased by the abnormal behavior of Enron during the years 2000 and 2001 or by its bankruptcy by 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 volume and number of transactions, which could be due to fraudulent behavior. In fact, a big percentage of market maker's trade during these two years was due to Enron's trade (see Figure 7).

To assess to which extent Enron's bankruptcy induces a change in preferences we have estimated (see Table 14), on the one hand, the counterpart model on a subsample considering transactions concluded before Enron's bankruptcy in December 2001 (see Model 5) and, on the other hand, the counterpart model on a subsample considering transactions from 2002 until 2005 (in Model 6). We observe that the non-linear time trend for market makers is decreasing before Enron's bankruptcy (considering subsample 1995-2001 in Model 5) and increasing afterwards (considering the subsample 2002-2005 in Model 6). 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 in Model 5 and Model 6 as well as between these and the results based on the full sample.

The biggest impact we observe in relation to Enron's bankruptcy is the important substitution of market makers by brokers in 2001 in comparison to 2000, as shown in Figure 7 and 8 (see also Figure 10 and 11 for a monthly detail). This substitution is in line with Jue et al. (2004). The latter find that the exit of a market maker results in a shift of trade to brokers, but that after transition trade volumes by alternative go back to pre-exit levels.

In the same line, to understand how Enron's abnormal activity during

2000 and 2001 may affect our results, we have estimated the counterpart model excluding all transactions belonging to years 2000 and 2001 (in Model 7). Once more we find that time trends are consistent with the trends found for the full sample. The only coefficients that change significantly[18] with respect to results based on the full sample model are the ones associated to ph^i. This result suggest that, when excluding observations from years 2000 and 2001, during Phase II intermediaries are no longer preferred to private. The results based on the full sample show that the preference for privates increases in Phase II but that the preference for market makers increases even more after 2002. In the estimation without the years 2000 and 2001 the increase in the number of privates in 2000 is only accounted for from 2002. Then, the more than proportional increase in the preference for market makers over privates produced from 2002 on can no longer be appreciated.

5.6 Relevance of counterpart differentiation

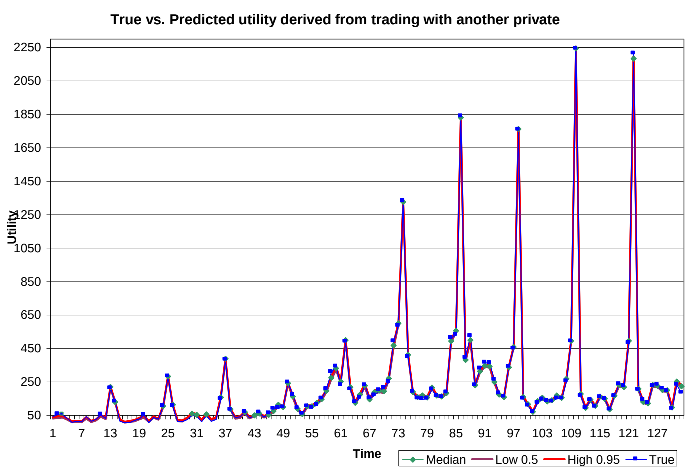
Finally, even if the Hausman test for IIA shows that a conditional logit model with three independent alternatives is superior to fit our data than a conditional logit with two alternatives (see Table 11), for the sake of comparison we have also estimated two simple logit models (see Table 15). Model 8 shows the results for the estimation when considering negotiated trade (private and brokers) as a single alternative. The results are in line with the results 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 having 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, time trends are also in line with our previous results. In this specification, the coefficient associated to $difdifneg^i$ is not statistically significant because the alternatives broker and private belong to the same alternative N, which prevents this model to detect the discrimination buyers do between these two options when there is a negative electricity price shock in their region (as we have found in the case of the conditional logit specification).

Model 9 shows the results for a logit model where intermediaries belong to the same alternative I. Once more we find that time trends as well as other coefficients are in line with what we found in the conditional logit specification.

[18] We test: $\frac{\beta_{ph_{jFULL}} - \beta_{ph_j}}{\sqrt[2]{\left(Var(\beta_{ph_{jFULL}}) - Var(\beta_{ph_j})\right)}}$ and compare it with a normal distribution $N(0,1)$.

6 Goodness of fit of the model

All LR tests[19] performed favor the unrestricted model over any other alternative specification. To further validate our results, we measure the goodness of fit of the model. To this end, we simulate the utility derived from trading with each alternative for all transactions (and therefore the probability of each counterpart of being chosen). To do this, we first compute the fitted utility using (Q)ML estimates. Then, under the distributional assumption stated in Section 3, we generate $k(= 200)$ draws 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 of the choice for each transaction, we compute the median and 95% confidence band and compare this to the agents' observed choices. The following three figures report the outcome for each choice respectively, aggregated on a monthly basis. We observe that the aggregated true choice falls into the 95% confidence band for almost all cases, showing an adequate fitness of the model.



Utility from trading with privates

[19] See Table 16 for the pseudo log likelyhood value of each specification.

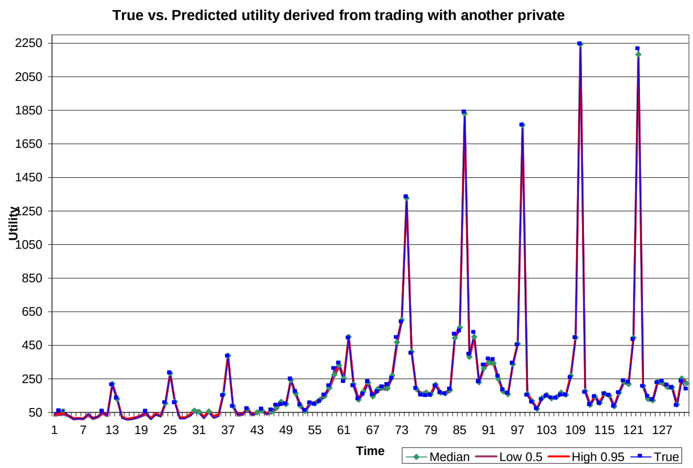


FIG. 1 Utility from trading with privates

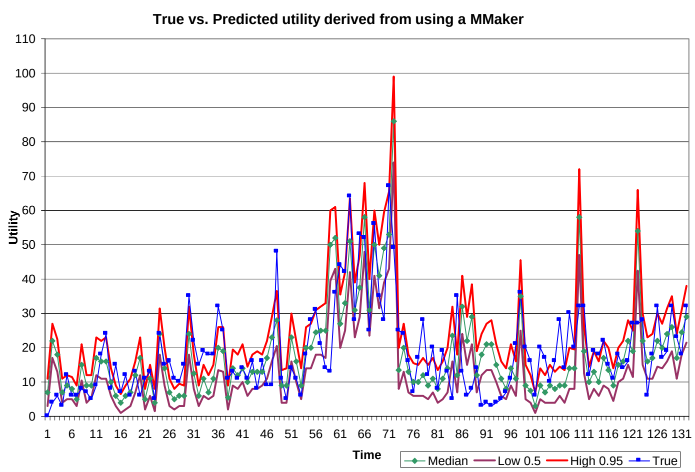


FIG. 2 Utility from trading with market makers

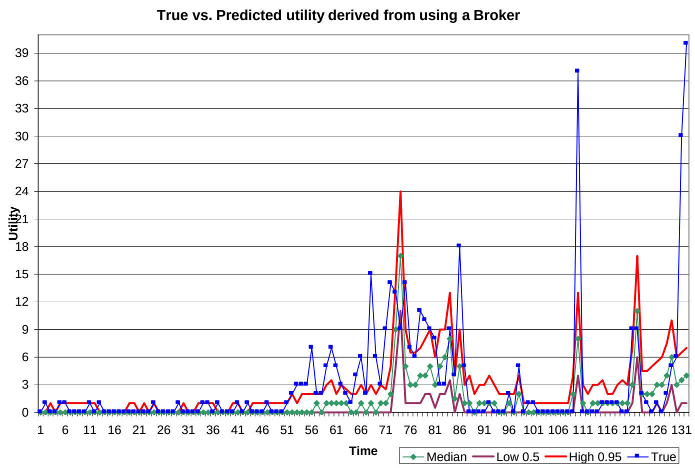


FIG. 3 Utility from trading with brokers

7 Concluding remarks

The utility of buying or selling a certain amount of allowances in an emission trading market does not only relies on the possibility of abating pollution at a lower marginal abatement cost. There are market conditions and counterpart characteristics that have direct influence on the utility derived from each specific transaction undertaken. Understanding the preference over types of counterparts as a function of market, individual and counterpart characteristics allows us to assess the fragmented structure of this market and the important role of professional traders in linking local markets, reducing search and transaction costs, counterpart risks and, in general, increasing the information available. Additionally, we are able to understand the way agents in this market think about the counterpart choice, how this thinking evolves with agents learning and to which extent it is influenced by changes in the market configuration provoked by market regulation. All in all, these results give a wider view of the way agents behave in emission trading markets.

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8 Appendix

	Volume of trade /10.000 tons			Number of trans.		
Year	B	M	P	B	M	P
1995	4.762	32.876	1555.670	4	84	387
1996	0.026	128.193	477.114	2	144	647
1997	1.005	227.706	807.372	3	226	773
1998	0.049	351.191	616.141	4	191	1039
1999	12.478	224.129	881.407	35	208	1978
2000	40.536	326.773	1827.311	70	543	2910
2001	52.994	79.894	1844.720	102	194	4173
2002	4.938	145.282	1885.788	30	113	5511
2003	0.002	142.844	1324.790	7	234	3620
2004	1.779	191.786	1194.305	41	229	4245
2005	43.897	159.424	1479.714	105	279	4524
Total	162.464	2010.099	13894.332	403	2445	29807

B stands for broker, M for market maker and P for private

Table 1: Total number of transactions and volume/10.000 of allowances traded per year

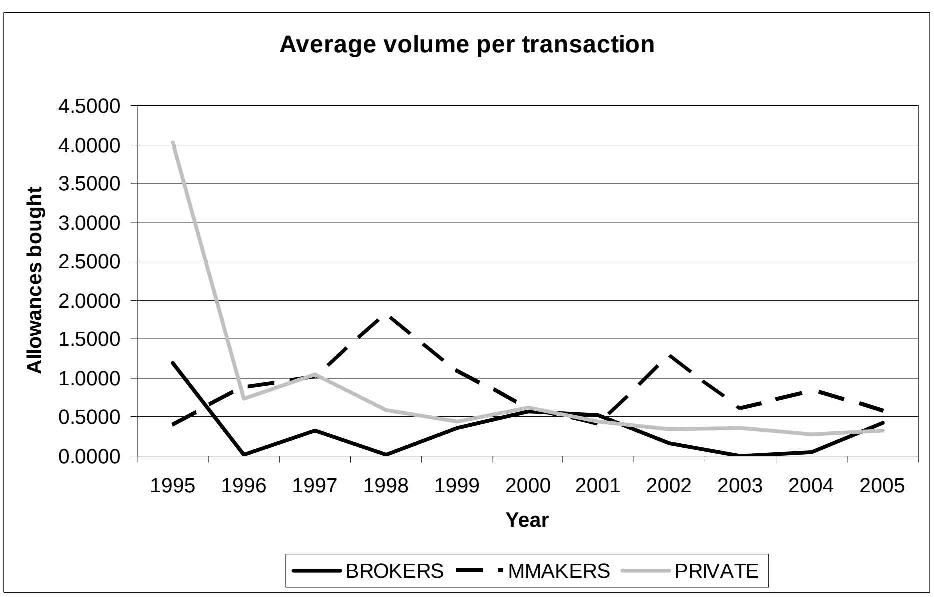

FIG. 4 Average size per transaction

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

R# stands for region #
Source: EIA

Table 2: United States Census Division

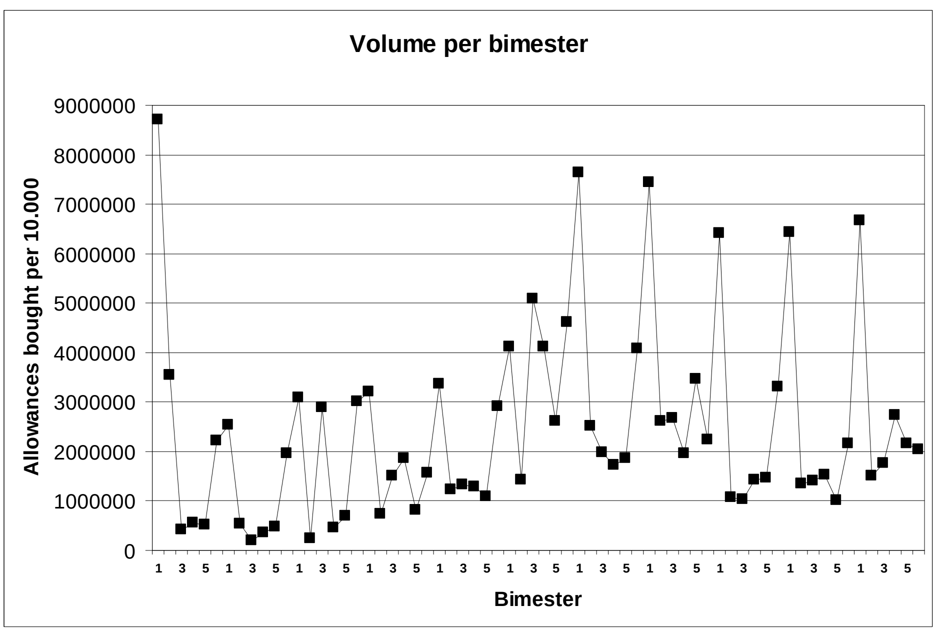

FIG. 5 Volume/10.000 allowances per month

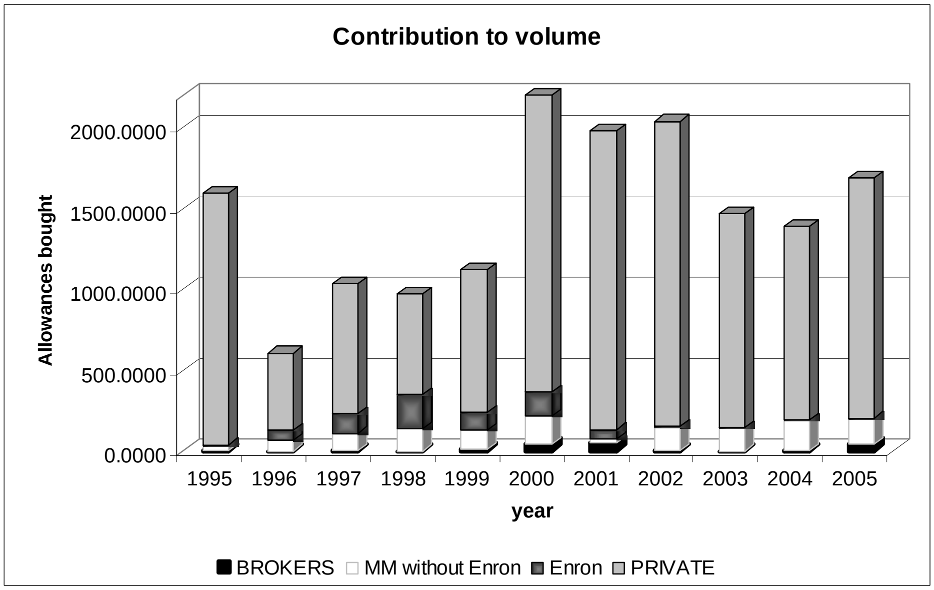

FIG. 6 Counterpart's contribution to trade /10.000

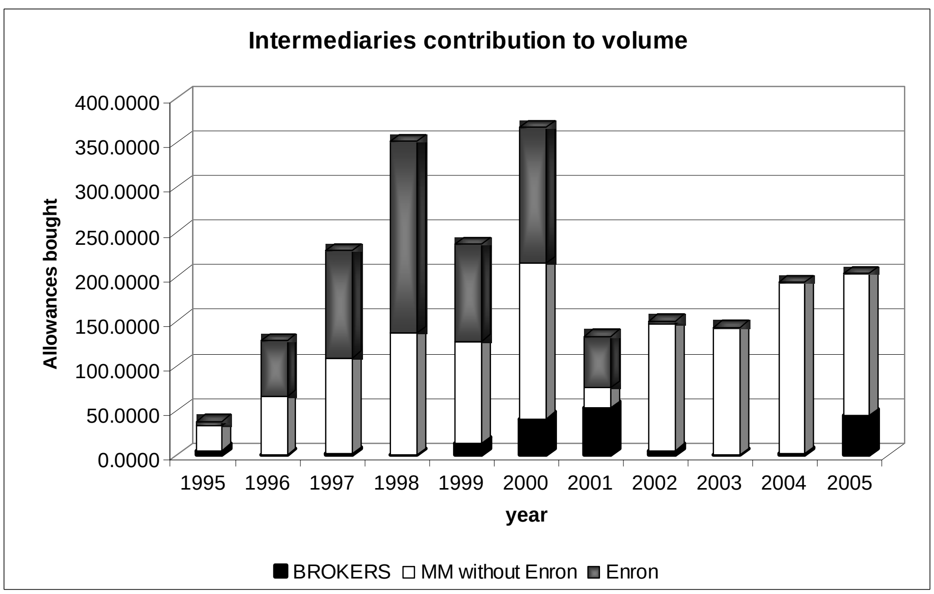

FIG. 7 Intermediaries contribution to volume/10.000 of trade

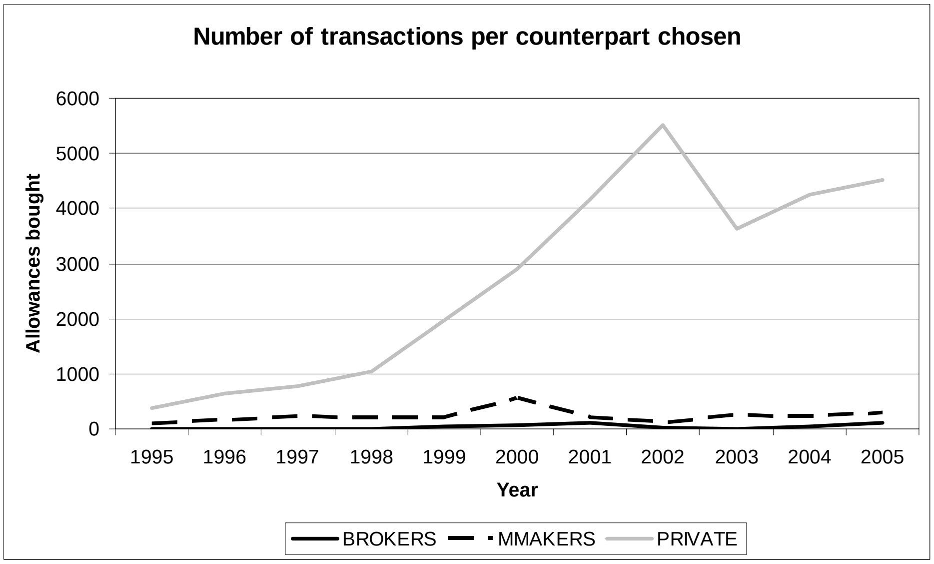

FIG. 8 Yearly number of transactions

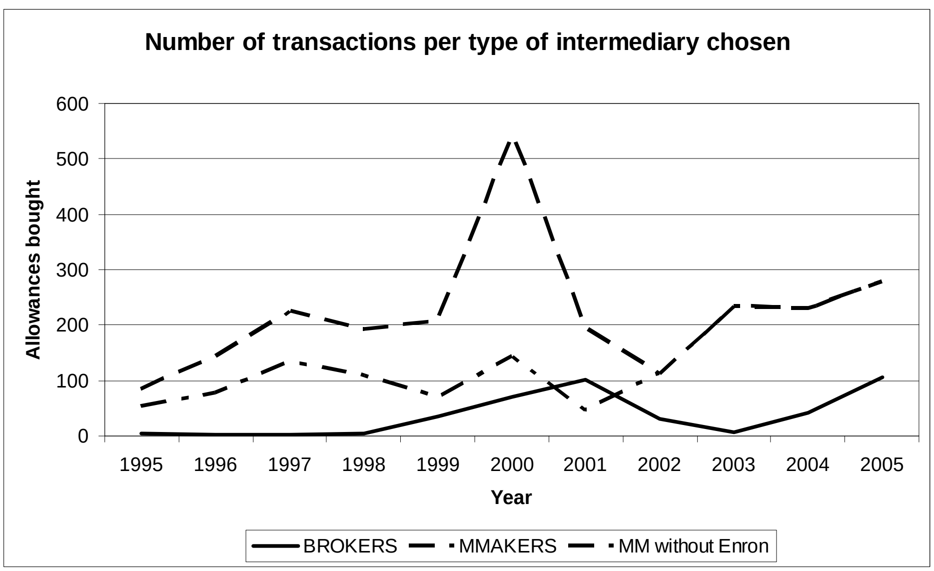

FIG. 9 Transactions per type of intermediary

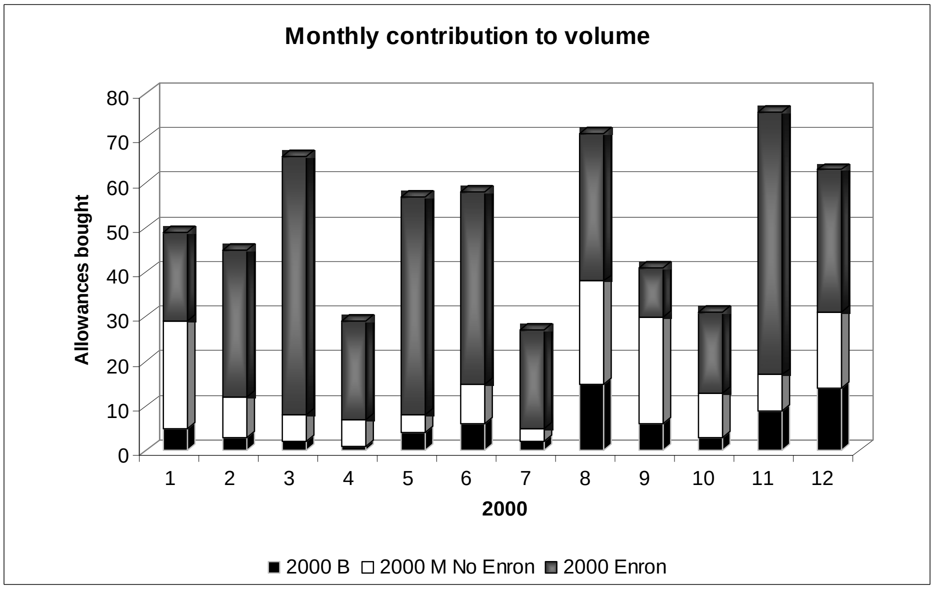

FIG. 10 Monthly contribution to volume in 2000

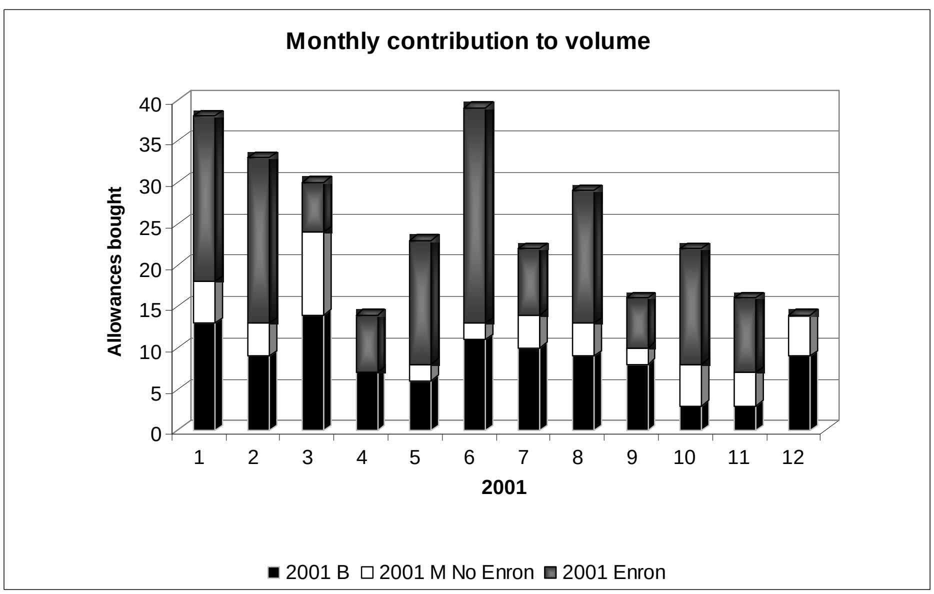

FIG. 11 Monthly contribution to volume in 2001

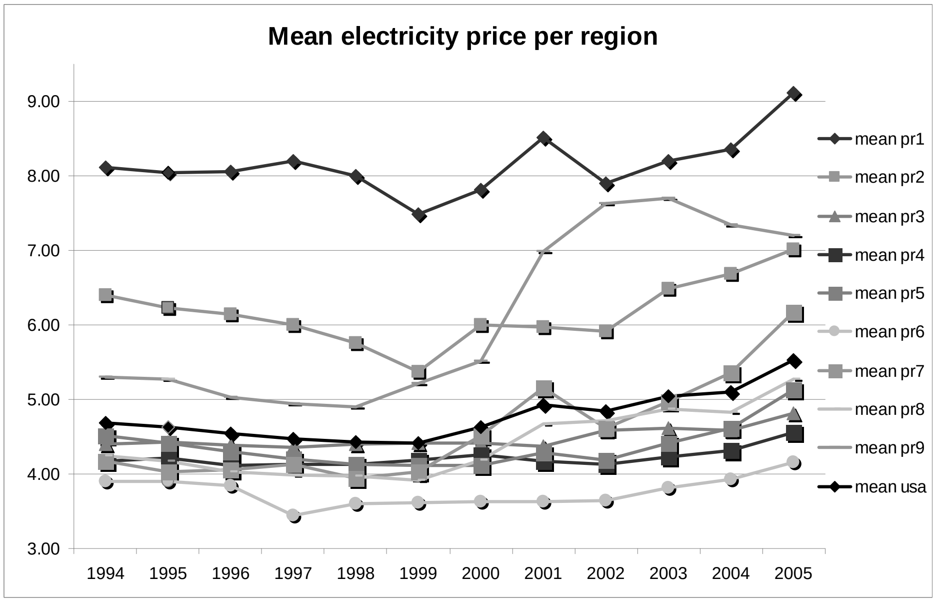

FIG. 12 Comparison of retail electricity prices

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 3: Number of transactions per bimester during Phase I

	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

Table 4: Number of transactions per bimester during Phase II

	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

Table 5: Summary statistics for variable *particip*

Intraregional trade						
Year	B		M		P	
	Volume	%	Volume	%	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		M		P	
Year	Volume	%	Volume	%	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

Table 6: Regional and national Volume/10.000 tons

Intraregional trade

	B		M		P	
Year	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	
Year	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 6

Table 7: Regional and national number of transactions.

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

Table 8: Transactions that take place inside the same region

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

Table 9: Summary statistics for price and quantity variables

R	freq.	%	cumul.
1	689	2.10	2.10
2	5775	17.53	19.62
3	8659	26.37	46.00
4	2566	7.81	53.81
5	6250	19.03	72.84
6	2466	7.51	80.35
7	2310	7.03	87.39
8	2942	8.96	96.35
9	910	2.77	99.12
USA	289	0.88	100

Notes as in Table 5

Table 10: Quantity of private buyers in each region

Ho: Odds are independent of other alternatives.

	Chi-squared	Dickey-Fuller	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 11: Hausman Test for IIA

	M1: Unrestricted				M2: Baseline			
Variable	Coef.		SE	Odds Ratio	Coef.		SE	Odds Ratio
$ascb$	-3.74	**	0.68	0.02	-4.18	**	0.69	0.02
$ascm$	0.58	*	0.32	1.79	0.39		0.28	1.47
$ytrendb$	-0.22		0.14	0.80	-0.20		0.14	0.82
$ytrendm$	-0.33	**	0.05	0.72	-0.31	**	0.04	0.74
$ytrendsqb$	0.01	*	0.01	1.01	0.01	*	0.01	1.01
$ytrendsqm$	0.03	**	0.00	1.03	0.03	**	0.00	1.03
$participb$	0.35	**	0.03	1.41	0.33	**	0.03	1.39
$participm$	-0.12	**	0.05	0.88	-0.13	**	0.05	0.88
$participp$	0.00	**	0.00	1.00	0.00	**	0.00	1.00
phb	1.24	**	0.30	3.47	1.63	**	0.29	5.10
phm	0.64	**	0.12	1.90	0.90	**	0.11	2.46
jfb	-1.23	**	0.59	0.29	-0.79	**	0.12	0.45
jfm	-0.73	**	0.12	0.48	-1.12	**	0.06	0.33
$jfbph2$	1.31	**	0.60	3.71				
$jfmph2$	0.24	*	0.13	1.27				
$qascb$	-0.09		0.06	0.92				
$qascm$	0.02	**	0.01	1.02				
$samerb$	-4.72	**	0.51	0.01				
$samerm$	-2.78	**	0.10	0.06				
$difdifposb$	0.35		0.22	1.42				
$difdifposm$	0.55	**	0.09	1.73				
$difdifnegb$	1.25	**	0.28	3.49				
$difdifnegm$	0.12		0.12	1.12				
$rb1b$	0.31		0.98	1.37	1.33	**	0.63	3.79
$rb1m$	-0.79	*	0.42	0.45	0.78	**	0.25	2.19
$rb2b$	0.43		0.67	1.54	0.41		0.60	1.50
$rb2m$	0.17		0.28	1.18	0.47	**	0.22	1.61
$rb3b$	0.44		0.63	1.55	0.28		0.60	1.32
$rb3m$	0.69	**	0.26	2.00	0.12		0.22	1.13
$rb4b$	0.09		0.65	1.09	0.62		0.61	1.86
$rb4m$	0.35		0.27	1.41	0.15		0.23	1.16
$rb5b$	-0.40		0.64	0.67	-0.06		0.61	0.95
$rb5m$	-0.01		0.26	0.99	-0.16		0.23	0.85
$rb6b$	-1.54	**	0.74	0.21	-0.53		0.65	0.59
$rb6m$	-0.13		0.30	0.88	-0.24		0.24	0.79
$rb7b$	0.39		0.63	1.48	0.50		0.61	1.65
$rb7m$	0.32		0.27	1.37	0.34		0.24	1.41
$rb8b$	0.28		0.63	1.33	0.36		0.61	1.43
$rb8m$	0.57	**	0.26	1.77	0.34		0.23	1.41
$rb9b$	-0.76		1.01	0.47	-0.43		0.74	0.65
$rb9m$	-0.98	**	0.40	0.38	-0.40		0.28	0.67

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

Table 12: Conditional Logit Models

M3: Interactions						M4: Non-intragroup			
Variable	Coef.		SE	OR		Coef.		SE	OR
$ascb$	-3.25	**	0.37	0.04		-3.77	**	0.68	0.02
$ascm$	1.10	**	0.20	3.02		0.51		0.32	1.67
$ytrendb$	-0.28	*	0.13	0.76		-0.22		0.14	0.80
$ytrendm$	-0.33	**	0.04	0.72		-0.31	**	0.05	0.73
$ytrendsqb$	0.02	**	0.01	1.02		0.01	*	0.01	1.01
$ytrendsqm$	0.04	**	0.00	1.04		0.03	**	0.00	1.03
$participb$	0.36	**	0.03	1.44		0.35	**	0.03	1.41
$participm$	-0.12	**	0.05	0.89		-0.13	**	0.05	0.88
$participp$	0.00	**	0.00	1.00		0.00	**	0.00	1.00
phb	1.39	**	0.29	4.01		1.23	**	0.30	3.41
phm	0.69	**	0.12	1.99		0.64	**	0.12	1.90
jfb	-1.22	**	0.59	0.30		-1.23	**	0.59	0.29
jfm	-0.62	**	0.12	0.54		-0.76	**	0.12	0.47
$jfbph2$	1.17	**	0.60	3.22		1.33	**	0.60	3.77
$jfmph2$	0.12		0.14	1.13		0.29	**	0.14	1.34
$qascb$	-0.05		0.05	0.95		-0.08		0.06	0.92
$qascm$	0.01	**	0.01	1.01		0.05	**	0.01	1.05
$samerb$	2.50	**	0.63	12.24		-4.58	**	0.51	0.01
$samerm$	2.30	**	0.32	9.96		-2.66	**	0.10	0.07
$difdifposb$	0.25	**	0.07	1.29		0.36	*	0.22	1.44
$difdifposm$	0.12	**	0.03	1.12		0.57	**	0.09	1.76
$difdifnegb$	0.38	**	0.16	1.47		1.23	**	0.28	3.44
$difdifnegm$	-0.18	**	0.08	0.84		0.12		0.12	1.12
$rxb1b$	-21.74	**	0.68	0.00	$rb1b$	0.28		0.99	1.32
$rxb1m$	-5.15	**	0.67	0.01	$rb1m$	-0.82	*	0.43	0.44
$rxb2b$	-21.11	**	0.64	0.00	$rb2b$	0.43		0.67	1.54
$rxb2m$	-3.60	**	0.33	0.03	$rb2m$	0.16		0.28	1.17
$rxb3b$	-21.11	**	0.63	0.00	$rb3b$	0.45		0.63	1.57
$rxb3m$	-22.56	**	0.32	0.00	$rb3m$	0.70	**	0.26	2.01
$rxb4b$	-21.27	**	0.64	0.00	$rb4b$	0.10		0.65	1.10
$rxb4m$	-22.44	**	0.32	0.00	$rb4m$	0.35		0.27	1.42
$rxb5b$	-21.25	**	0.63	0.00	$rb5b$	-0.38		0.64	0.68
$rxb5m$	-22.32	**	0.32	0.00	$rb5m$	0.00		0.26	1.00
$rxb6b$	-21.48	**	0.66	0.00	$rb6b$	-1.51	**	0.74	0.22
$rxb6m$	-22.18	**	0.33	0.00	$rb6m$	-0.10		0.30	0.90
$rxb7b$	-5.58	**	1.19	0.00	$rb7b$	0.43		0.63	1.53
$rxb7m$	-22.28	**	0.32	0.00	$rb7m$	0.36		0.27	1.43
$rxb8b$	-21.09	**	0.63	0.00	$rb8b$	0.30		0.63	1.35
$rxb8m$	-22.59	**	0.32	0.00	$rb8m$	0.58	**	0.26	1.78
$rxb9b$	-21.42	**	0.64	0.00	$rb9b$	-0.79		1.01	0.46
$rxb9m$	-22.96	**	0.32	0.00	$rb9m$	-1.00	**	0.41	0.37

Notes as in Table 12; OR are Odds Ratio; $rxb1b = samer * rb1b$

Table 13: Alternative especifications

	M5: Before 01			M6: After 01			M7: Without 00-01		
Variable	Coef.		SE	Coef.		SE	Coef.		SE
ascb	-5.33	**	1.37	16.51	*	9.32	-7.17	**	0.93
ascm	-1.53	**	0.45	-33.90	**	3.70	-2.02	**	0.46
ytrendb	0.02		0.39	-6.22	**	2.04	-0.95	**	0.18
ytrendm	0.35	**	0.12	5.05	**	0.90	-0.93	**	0.07
ytrendsqb	0.03		0.04	0.35	**	0.10	0.02		0.01
ytrendsqm	-0.07	**	0.02	-0.25	**	0.05	0.06	**	0.00
particip	0.00		0.00	-0.01	**	0.00			
participb							0.90	**	0.15
participm							-0.21	**	0.07
participp							-0.01	**	0.00
phb							-6.57	**	0.88
phm							-7.70	**	0.73
jfb	-0.54	**	0.20	0.60	**	0.16	-1.04	*	0.60
jfm	-0.46	**	0.08	-0.80	**	0.09	-0.83	**	0.12
*jfbph*2							1.54	**	0.62
*jfmph*2							0.08		0.15
qascb	-0.01		0.04	-0.31		0.25	-0.25		0.16
qascm	0.02	**	0.01	0.19	**	0.05	0.06	**	0.01
samerb	-5.19	**	1.00	-4.54	**	0.61	-4.72	**	0.60
samerm	-3.47	**	0.16	-2.17	**	0.12	-2.70	**	0.11
difdifposb	0.14		0.45	0.34		0.26	0.31		0.26
difdifposm	0.50	**	0.15	0.43	**	0.13	0.57	**	0.11
difdifnegb	0.49		0.41	2.84	**	0.41	1.85	**	0.34
difdifnegm	0.40	**	0.17	0.58	**	0.25	0.33	**	0.14

Notes as in Table 12

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

	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
particN	0.00	**	0.00			
particm	-0.31	**	0.06			
particI				-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 12

Table 15: Logit Models

	PseudoLL	PseudoR2	Obs.	Par.
M1	-8702.96	0.76	32655	41
M2	-9845.87	0.73	32655	31
M3	-8540.00	0.76	32655	41
M4	-8662.77	0.74	30396	41
M5	-4845.19	0.68	13717	35
M6	-3665.81	0.82	18938	35
M7	-5813.37	0.79	24663	41
M8	-6946.96	0.20	32655	20
M9	-7694.83	0.20	32655	20

Table 16: Fitness of the different especifications