Entry and Exit in a Price Regulated Industry: Gasoline Retailing in Québec

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April 21, 2008

Abstract

The goal of this paper is to empirically examine the effect of price floor regulations on firms' entry and exit decisions. In particular I study the dynamic decisions of gasoline stations using a structural econometric approach. I measure the impact of a specific price floor regulation by observing firms' behavior before and after the implementation of the policy. The data used to estimate the model is a panel of local markets in Québec between 1991 and 2001. Strategic interaction between local competitors is modeled as a dynamic game between neighboring stations. I estimate the parameters of the model using the conditional choice probability estimator of Hotz and Miller [1993], as suggested by the recent literature on the estimation of dynamic discrete games. I then evaluate the effects of the policy by computing the difference between the continuation values of firms with and without the regulation. The results show that the price regulation had a significant impact on a firm's option value of staying in the market. A consequence of this is a lower exit probability, which led to a slower re-organization of the industry. Moreover, the impact of the policy is shown to have a larger positive impact on weaker stations (i.e. smaller stations using an older technology).

KEYWORDS: Entry and Exit; Policy Evaluation; Retail Markets.

1 Introduction

In many markets, prices are constrained by explicit or implicit floors which are aimed at protecting a group of firms from intense price competition. Agricultural price controls provide insurance to local producers against low prices. Similarly, the Galland Law in France states that no retailer can set the price of a product below its "effective wholesale price", which excludes discounts from the supplier based on the volume sold. Anti-dumping regulations and voluntary export restrictions are also aimed at protecting local producers by forbidding foreign firms to set prices below average variable costs.

The advocates of these regulations typically associate periods of low prices with predatory behavior from a group of firms toward smaller independent retailers. For instance, many U.S. states and Canadian provinces have either implemented or at least examined price control regulations or "divorcement" acts in gasoline retail market, on the basis of alleged predatory pricing practice by major retailers.

However, to the extent that firms face significant sunk entry or exit costs, evidence of prices below long run average costs (e.g. during a price war) are not sufficient to conclude that firms are colluding on a predatory strategy. In fact, as discussed extensively in the real option literature (e.g. Dixit and Pindyck (1994)), the normal exit threshold (i.e. the price under which a firm would exit) is typically well below the long run average cost. In those circumstances, fixing a price floor above this normal exit threshold will have important consequences on the entry and exit decisions of firms, by raising the option value of being active in the industry.

In this paper I empirically examine the effect of a price floor regulation on firms' entry and exit decisions by measuring the change in firms' incentives to stay active and enter the industry. In addition, using a structural econometric approach, I will infer a measure of firm welfare gain (or loss) associated with the price floor regulation. As outlined below, this research methodology departs significantly from the previous literature on the evaluation of price floor regulations that compared the price setting behavior of firms with and without a price floor.[1]

The empirical analysis will be conducted using a panel of gasoline stations in five cities of the province of Québec between 1991 and 2001. Starting in 1997, the provincial government implemented a price floor regulation which fixes weekly a minimum price close to the estimated wholesale price. The regulation also defines a minimum margin of \$0.03 which can be added to the floor if it is proven that a station has set its prices close to the floor level for a long enough period of time. The motivation and design of the regulation are thus

[1] See for instance Barron and Umbeck (1984), Anderson and Johnson (1999), Gagné et al. (2003)

very similar to an anti-dumping trade policy.

The model is a dynamic entry/exit game between local players in spatially differentiated locations. The model assumes that firms located in the same geographic cluster interact strategically only with their close neighbors. This restriction reduces the dimension of the problem and enables the study of entry and exit decisions in medium and large urban markets. By doing so, the proposed methodology departs from the previous literature on entry and exit, which has typically been restricted to small isolated markets (see for instance Bresnaham and Reiss (1991), and Mazzeo (2001)). Beresteanu and Ellickson (2005) study the dynamics of retail markets using a similar methodology but look at the problem from the perspective of chains rather than the individual stores.

The estimation of the model uses the conditional choice probability estimator of Hotz and Miller (1993) as suggested by the recent literature on the estimation of dynamic discrete games (see Aguirregaberia and Mira (2004), Pakes, Ostovsky and Berry (2004), Pensendorfer and Schmidth-Dengler (2003), and Bajari, Benkard and Levin (2004)).

The policy's impact is estimated by comparing the estimated continuation values of firms before and after the occurrence of the price floor regulation. A similar strategy, using an observed policy change in a dynamic model, has been used in the past by among others Rust and Rothwell (1995) to study the impact of a regulation change in the Nuclear Power industry. More recently, Ryan (**?**) uses an observed environmental regulation change to identify the increase in the operation costs due to more stringent environmental requirements.

The results indicate that the regulation had a significant impact on the decisions of firms to enter and exit the market. In particular, firms are less likely to enter and more likely to stay active in the industry. These results indicate that incumbent firms are benefiting from this regulation, which acts as a barrier to entry. Furthermore, the regulation has a bigger impact on less efficient stations compared to stations who use a more recent technology. These results imply that the price floor successfully protected weaker stations, at the expense of a slower reorganization of the industry.

The rest of the paper is organized as follows. Section 2 discusses the recent trends and

Table 1: Changes in the number of stations in Québec

	1989/1995	1995/1998	1998/2001	2001/2003
%Δ stations	-8.45	-10.38	-9.10	-7.41

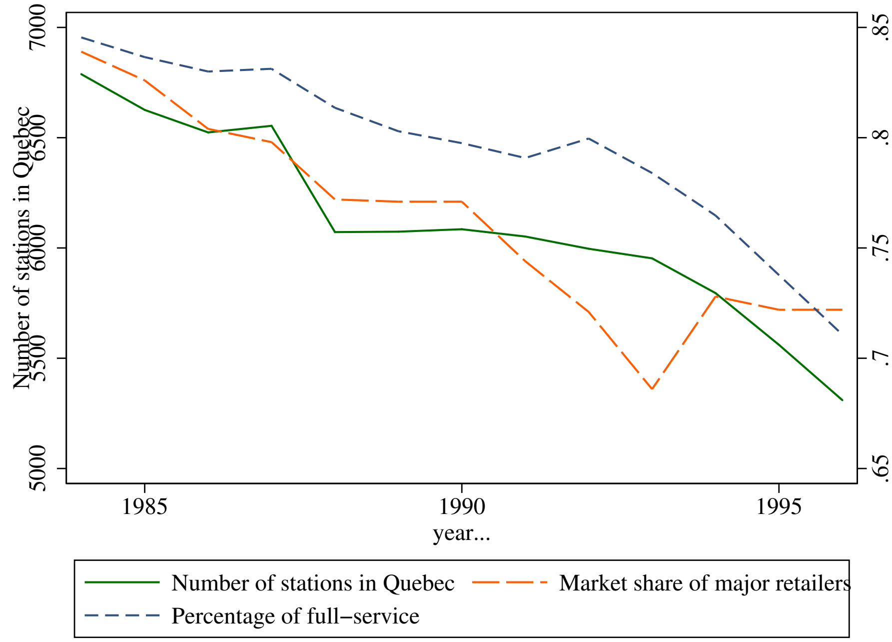
organization of the gasoline retail industry. Section 3 provides more details on the Québec regulation. Sections 4 and 5 present the model and the estimation strategy. Section 6 presents the empirical analysis. The final section discusses the results and future avenues of research.

2 Recent Trends in the Industry

Over the 1980s and the 1990s, the structure of the North-American gasoline retail industry has evolved toward fewer, larger scale stations. While this trend is common to most retail sectors, it has been particularly pronounced in the gasoline sector in part because of the two oil shocks in the 1970s. The industry started the 1980s with an excess capacity that had to be reduced to allow individual stations to cover their fixed operation costs. Table 1 and Figure 1 illustrate these changes for the province of Québec. In Canada there has been two important waves of exit: $1985 - 1989$ and $1993 - 1996$. Between $1989 - 1995$, the number of stations fell by 25%. In Québec during the same period, the number of stations dropped by only 8.45%, while it has reduced by nearly 30% between 1995 to 2003. The reduction in the number of stations was thus delayed in Quebec compared to the rest of Canada.

In addition, the industry has changed over the last 20 years in terms of the types of stations. The traditional gasoline station offering pump services and an automobile repair-shop has been replaced by self-service stations offering complementary services (e.g. convenience stores). This tendency reflects the change in the needs of consumers for car repair (from independent to dealer garages), as well as the fact that consumers are becoming more sensitive to price variations (since self-service stations typically charge lower prices). Over the 80s, this benefitted mainly to the independent retailers who were selling unbranded gasoline at lower prices. Consequently, until the mid-90s their market share increased steadily relative

Figure 1: Trends in Québec Gasoline Retail Industry Between 1985 − 1997



to major brand retailers. Figure 1 shows the evolution of the independents market shares between 1984 and 1996.

Finally, a more recent trend in the market is the entry of large scale self-service stations. These new stations can store 8 to 10 times the volume of a typical station, through multiple service bays and larger tanks. They typically sell unbranded gasoline, and are often associated with hyper-mart retailers like Wal-Mart or Costco. In the United States the number of independent high volume retailers was estimated to be 4411, while the number of hyper-marts offering gasoline was close to $2,434$. In 2002, the market share of the hyper-marts was 5.4% of the total consumption of gasoline in the United States. In Canada, Loblaws, Wal-Mart, Costco and Safeway are already present in the market with high volume stations. In Québec however, Costco has so far opened only one high volume store and Loblaw has just recently entered the market.

A consequence of the lack of new entry and slower reorganization of the Québec industry is that the average sales volume of stations is lower in the province than in rest of Canada.

Table 2: Average annual sales volume per station in Québec and Ontario

Years	Québec			Ontario	Difference
	Independent ML/Y	Majors ML/Y	Total ML/Y	ML/Y	ML/Y
1992			$1,58$		
1995			$2,0$	$3,5$	1.5
1998	$1,338$	$2,837$	$2,34$	$4,22$	$1,88$
2002	$1,455$	$3,259$	$2,64$	$4,78$	$2,14$

Source: CAA and Option Consommateur report (2002)

Table 2 presents evidence of the gap between the average sales volume of stations from Québec and Ontario. These differences are mainly due to the fact that there are more gasoline stations per capita in Québec, and that their capacity is smaller on average.

3 Description of the Regulation

The *law on petroleum products* was implemented in the summer of 1997 and administrated by the Régie de l'énergie du Québec (hereafter the "Board"). This followed the occurrence of an important price war during the summer of 1996, which was interpreted as evidence of predatory pricing behavior by the major retailing chains.[2] The mandate of the Board is threefold:

1. Monitor the gasoline industry, and gather information on prices;

2. Determine a weekly floor price or Minimum Estimated Price (MEP);

3. Prevent the occurrence of price wars by having the authority impose a 3 cents minimum margin in designated geographic markets.

The MEP approximates the average marginal cost of selling gasoline in each local market as follows:

$$MEP_{mt} = (w_t + tc_{mt} + T_{mt})(1 + t_t),$$

[2]This accusation was later rejected by the Competitive Bureau of Canada, which has never found evidence of predatory pricing behavior in Canada.

where w_t is the minimum wholesale price at the pipeline terminal, tc_{mt} is an estimate of the cost to deliver gasoline from the refinery to market m, T_{mt} is the sum of federal and provincial excise taxes, and t_t is the sum of the provincial and federal consumption taxes. The MEP is calculated and posted on the website of the board every Tuesday.

The role of the MEP is to set a floor price under which firms can sue their competitors for financial compensation on the basis of excessive and unreasonable commercial practices. This new feature of the civil law facilitates suing procedures between competitors in the market, in a fashion similar to anti-dumping laws.

In cases where companies repeatedly fail to respect the MEP, the regulation provides the Board the ability to impose an additional minimum margin to the MEP. It allows the board to add \$0.03 to the calculation of the MEP in a specific region after the occurrence of a period of low enough prices. The minimum margin serves two purposes. It first establishes an implicit (or long run) price floor, under which the Board considers that stations are not covering their fixed operating costs. It also enables the Board to compensate stations after a price war.

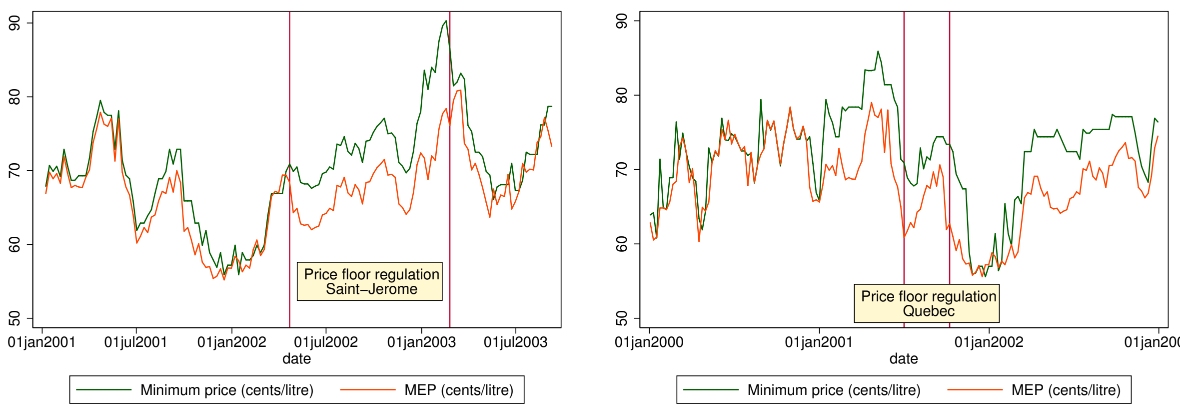
The technical working of this policy is as follows. First, after the occurrence of a long enough low price period, a gasoline retailer can ask the Board to investigate evidence of price anomalies. The Board then conducts a formal consultation of different interest groups (retailers, consumer protection groups) in order to evaluate the credibility of the accusation. If the board is convinced of the accusation, it can add \$0.03 to the calculation of the MEP for a certain period of time in a specific geographic zone where the price war occurred. In practice the Board considers a price predatory if the margin (price minus the MEP) is below \$0.03 for a long period of time (more than a month).

This minimum margin approximates the average operating cost of a representative station in the province.[3] The geographic zone typically includes all local markets which suffered from the price war. Similarly, the length of time for which the minimum margin is applicable is proportional to the length of time of the price war.

[3]After public consultations, the Board decided that the representative station is a self-service station operating a convenience store, and having an annual sales volume of 350 million liters

This minimum margin regulation has been imposed three times in two markets, St-Jérome and Quebec city. In St-Jérome (a city north of Montréal), it was added to the MEP from April 23, 2002 to February 25, 2003, and again from the December 9, 2003 to June 6, 2005. The imposition of this price floor followed the entry of Costco in St-Jérome in 2000, which drove the market price to the MEP level for more than a year. In Québec City, it was added to the MEP from July 3, 2001 to October 10, 2001. Its imposition followed a severe price war in the Québec City metropolitan area during the fall of 2000. Figures 3(a) and 3(b) show the evolution of the minimum surveyed price in both cities before and after the imposition of the minimum margin regulation.

Figure 2: Imposition of the 3 Cents Minimum Margin Regulation



(a) Gasoline prices in St-Jerome before and after the 3 cents minimum margin

(b) Gasoline prices Québec city before and after the 3 cents minimum margin

4 A model of Entry and Exit into Spatially Differentiated Locations

4.1 Market Environment

The relevant market definition is defined as a metropolitan area or city. Each market c is further divided into a set independent locations $l_c \in \{1, ..., L_c\}$, characterized by a major intersection or a street segment.[4] The definition of a location attempts to capture the fact that stations are typically clumped together along a street or at an intersection. From the customers point of view, stations within the same location are homogeneous in terms of their spatial characteristics. The profitability of a location l is characterized by a discrete state variable z_{lt} affecting all the stations active in l. Let $Z_t = \{z_{1t}, ..., z_{Lt}\}$ be the distribution of $z's$ across locations.

As discussed in section 2, the period studied covers an important reorganization of the industry. This reorganization is associated with a large exit rate from traditional stations, and fewer entries. In addition, most of the reorganization is associated with a change in the type of stations active in the market: from conventional stations with service bays, to large capacity self-service stations associated with a convenience store. Since demand for gasoline has been slowly increasing over the period, a model with homogeneous firms will not be able to reproduce the nonstationarity in the entry and exit rates. To capture this fact, I include two types of competing technologies in the environment, and model the reorganization as a switch from one dominant technology to the other. The two technologies are a conventional type indexed by c and gas-bar type indexed by g. The conventional type refers to a full-service station offering car-repair services as a complementary product. Gas-bar stations refer to larger capacity stations which do not have service bays, but sell complementary products through a convenience store and/or a car-wash. Let $M_t = \{n_{clt}, n_{glt}\}_{l=1}^{L}$ be the distribution of firms across locations.

Finally the description of the market state is completed by the regulation variable R_t, which is equal to one if the government has implemented the price floor. The regulation change is assumed to be unanticipated and permanent.

4.2 Individual Firm's Problem

The entry and exit decisions closely follows Ericson and Pakes (1995), and Pakes, Ostrovsky and Berry (2004). In particular, the game is such that local players decide to enter, stay in, or exit from each location independently of each other. In other words, as in Bresnahan

[4]The market c index will be dropped hereafter.

and Reiss (1991) or Mazzeo (2001), the model abstracts from any chain or network effects on the decision of a station to exit or enter a specific location. This assumption will not hold if the entry and exit decisions are made solely at the chain level. In the Canadian gasoline market, the reality is likely to lie in between the two extremes since about 20% of stations are owned and operated by national chains. A model in which global players (i.e. major chains) compete with local players would be more demanding in terms of data and computation and is beyond the scope of the present paper.

As in Ericson and Pakes (1995), the entry process is anonymous, in the sense that a fixed number of potential entrants are "born" each period. The following assumption describes this process:

Assumption 1. *In every period there is a fixed number of potential entrants ($\mathcal{E}$) who can enter each location. Furthermore, every new entrant enters the industry as a type g firm.*

This assumption states that there is a fixed number of potential entrants specific to each location. A more general specification would include an intermediate entry stage where firms decide in which location to become a potential entrant, but would add significant complexities to the model. See Seim (2004) for an example of a static location model in which firms simultaneously decide where to locate in a city.

The last part of Assumption 1 states that potential entrants can enter only with the "new" technology. This restriction is justified by the data, since we do not observe firms entering as type c stations.

Potential entrants and incumbents privately observe the realization of the set-up cost and the scrap value of their equipments respectively. This simplifies estimation and ensures existence of Bayesian Nash equilibrium in a pure strategies. See Doraszelski and Satterthwaite (2005) for a formal proof, and Seim (2004) for a related application of this property.

Assumption 2. *Each potential entrant privately observes the cost of setting up a station, labeled κ. This cost is drawn independently over time and across firms from a cdf F^{κ}.*

Assumption 3. *An incumbent of type $i \in \{g, c\}$ who chooses to exit form the market at the end of the period, receives a scrap value (net of cleaning costs) equal to ν. The scrap value is privately observed, and drawn independently from a cdf F_i^ν.*

Furthermore, a station is considered to exit if it chooses to physically close, or if it switches technology.

Assumption 4. *Incumbent firms cannot change their type.*

Under these assumptions, an incumbent firm of type $i \in \{c, g\}$ solves a dynamic program. The state vector at location l consists of the private value ν, and the aggregate state vector $S = \{Z, M, R\}$. Bellman's equation for the program is:

$$v_{il}^I(\nu, S) = \max_{\chi \in \{in, out\}} \Big\{ \pi_{il}(S) - FC_i + \delta E\big(v_{il}(\nu', S')\big) \quad , \quad \pi_{il}(S) - FC_i + \delta \nu \Big\}, \tag{1}$$

where $\pi_{il}(S)$ represents the reduced form profit function, FC_i is the fixed operation cost, and δ is the common discount factor. The solution to this problem is characterized by a decision rule, such that a firm exits ($\chi_{il}(\nu, S) = out$) if the scrap value ν is larger than the expected continuation value.

The state vector in the dynamic program of a potential entrant at location l includes the set-up cost κ and S:

$$v_l^E(\kappa, S) = \max_{\chi^e \in \{in, out\}} \Big\{ -\kappa + \delta E\big(v_{gl}(\nu', S')\big) \quad , \quad 0 \Big\}. \tag{2}$$

The firm will enter ($\chi^e(\nu, S) = in$) if the set-up cost is lower than the expected value of incumbency next period (i.e. $\delta E\big(v_{gl}(\nu', S')\big)$).

The expected continuation values in equations 1 and 2 involve an expectation over the equilibrium distribution of active firms M', and the distribution of local demand states Z'. Since this problem is not tractable in a large markets, the next section proposes an approximation method to reduce the dimensionality of the problem.

4.3 Aggregation Assumptions

An important limitation of the model is that firms take into account the evolution of the market level state variables Z_t and M_t when making their entry/exit decisions. Since these variables are distributions over spatial locations, the problem quickly becomes intractable when L is large. This difficulty is similar to the problem described by Krusell and Smith (1998) in a dynamic macro-economic model with heterogeneous agents. In this class of models, agents need to keep track of the aggregate distribution of assets in the economy in order to forecast future level of prices. The solution proposed by Krusell and Smith (1998) is to reduce the dimension of the state space by having agents track only the first few moments of the aggregate distribution (typically only the mean). In the same spirit, I approximate the full model by imposing the following two assumptions:

Assumption 5. *Firms behave strategically only with respect to their immediate neighbors active in the same location.*

Assumption 6. *The contribution of the variables Z and M in the reduced form payoff function can be accurately approximated by two single dimension variables z_l and m_l.*

Assumption 5 redefines the strategy space to be the set of players' actions in the same location, while Assumption 6 reduces the dimension of the aggregate state to two. The variable m equals the average number of firms active in other locations, weighted by the distance from location l. Similarly, z_l equals the weighted average of location-specific demand shocks. Weighting locations by distances approximates the substitution between locations (i.e. the weights are decreasing in distance). More details on the construction of these variables are provided in the empirical section.

I assume that firms use the following AR(1) model to form expectations about the future state variables:

$$\begin{aligned} [z_{lt+1}, m_{lt+1}]' &= \mu_0 + \mu_1 R_t + A[z_{lt}, m_{lt}]' + \varepsilon_{lt+1} \\ \text{where,} \qquad & A = \begin{pmatrix} a_z & 0 \\ 0 & a_m \end{pmatrix}. \end{aligned} \tag{3}$$

The regulation state enters the forecasting equations, so that the stationary distribution of the variables can be affected by the regulation. Let $\{G_r\}_{r=0,1}$ be the discretized Markov transition matrices describing the transition of the aggregate state variables.

Finally, the payoff relevant aggregate state vector is given by $s = \{n_c, n_g, z, m\}$. The static payoff function for a firm of type i in state s is approximated by:

$$\pi_i(s) = \theta_{iz} z + \theta_{ir} R + \theta_{ii} \log(n_{-i} + 1) + \theta_{i-i} \log(n_{i'} + 1) + \theta_{im} m, \tag{4}$$

where $n_{-i} = n_i - 1$, and $n_{i'}$ is the number of firms of type $i' \neq i$ in the same location. Similar reduced form payoff functions have been used in the empirical literature on entry games following the work of Bresnahan and Reiss (1991), as well as more recently by Aguirregabiria and Mira (2004) to study the entry and exit decisions of Chilean retailers.

4.4 Equilibrium Definition

Given the previous set of assumptions, the timing of the game is described as follows:

1. At the beginning of each period, potential entrants and incumbents observe the realization of their private shocks κ and ν.

2. The state of the location $\{n_{cjt}, n_{gjt}, z_{lt}, m_{jt}\}$ is revealed, and the regulation state R is announced.

3. Incumbents and potential entrants simultaneously choose their action:

   - If a firm chooses to enter, it pays the set up cost κ and becomes active in the following period.

   - If an incumbent chooses to exit the market, it stays active in the market until the end of the period and receives the scrap value of its equipment at the beginning of the following period.

4. Profits are realized, and the period ends.

Following the literature the strategy space is restricted to the set of symmetric Markov strategies. This removes calender time and conditions strategies only on payoff-relevant state variables (Maskin and Tirole (1988)). The main advantage of this assumption is that it reduces considerably the strategy space, by eliminating open loop strategies (i.e. strategies that condition on the full history of moves). Firms condition their strategy on the state of the local market $s = \{n_g, n_c, z, m, R\}$, their privately observed shock κ or ν, their type $i \in \{c, g\}$, and their activity state (i.e. incumbent (I) or potential entrant (E)).

Given a set of beliefs $\tilde{p} = \left\{\tilde{p}_i^a\right\}_{a\in\{I,E\},i\in\{g,c\}}$ measuring the subjective probability that the other firms in the market will be active next period, the decisions of an incumbent and a potential entrant are characterized by the following Bellman equations:

$$\begin{aligned} V_i^I(s,\nu|\tilde{p}) &= \max_{\chi_i=\{out,in\}} \Big\{\pi_i(s) + \delta\nu \quad , \quad \pi_i(s) + \\ &\qquad \delta \int \sum_{s'} V_i^I(s',\nu'|\tilde{p}), \text{ for } i \in \{g,c\} \Pr(s'|s,\tilde{p},\chi_i = 1) dF_i^{\nu}(\nu')\Big\} \qquad (5) \\ V^E(s,\kappa|\tilde{p}) &= \max_{\chi^e=\{out,in\}} \Big\{0 \quad , \quad -\kappa + \\ &\qquad \delta \int \sum_{s'} V_g^I(s',\nu'|\tilde{p}) \Pr(s'|s,\tilde{p},\chi^e = 1) dF_g^{\nu}(\nu')\Big\}. \qquad (6) \end{aligned}$$

Using the symmetry and iid properties of ν and κ, the state transition probabilities take the following forms:

$$\Pr(s'|s,\tilde{p},\chi_i = 1) = \sum_{(x_g,x_c,e)\in\mathcal{S}_{i,I}} \begin{array}{l} b(x_i, n_i - 1|s, \tilde{p}_i^I) b(x_{-i}, n_{-i}|s, \tilde{p}_{-i}^I) b(e, E|s, \tilde{p}^E) \\ \times g(z', m'|z, m) \end{array} \qquad (7)$$

$$\Pr(s'|s,\tilde{p},\chi^e = 1) = \sum_{(x_g,x_c,e)\in\mathcal{S}_{g,E}} \begin{array}{l} b(x_g, n_g|s, \tilde{p}_g^I) b(x_c, n_c|s, \tilde{p}_c^I) b(e, E-1|s, \tilde{p}^E) \\ \times g(z', m'|z, m) \end{array} \qquad (8)$$

where

$$\mathcal{S}_{i,a} = \left\{ \begin{array}{c|l} x_g & n_g' = n_g + e - x_g - \mathcal{I}(i = g, a = I) \\ x_c & n_c' = n_c - x_c - \mathcal{I}(i = c, a = I) \\ e & (x_g, x_c) \geq 0 \quad \& \quad 0 \leq e \leq E - \mathcal{I}(a = E) \end{array} \right\} \qquad (9)$$

$$b(r, n|s, \tilde{p}) = \binom{n}{r} \tilde{p}(s)^r \big(1 - \tilde{p}(s)\big)^{n-r}$$

and $\mathcal{I}(\cdot)$ is the indicator function, x_j is the number of type j firms who choose to exit, and e is the number of new entrant. Because the state space is discrete, the conditional transition probabilities can be written in matrix form. Let Γ_{ia} be this Markov transition matrix for type i in activity state a. The dimension of this matrix depends on the form of the payoff function because the potential number of firms active in the market is not restricted by the model. However, using the results of Ericson and Pakes (1995), one can show that as long as the profits are bounded, there exists a value $\bar{n}_i$ such that the probability of transiting in states with $n_i > \bar{n}_i$ is zero in equilibrium.

Let $\{\chi_i(s,\nu|\tilde{p}), \chi_i^e(s,\kappa|\tilde{p})\}$ be the optimal threshold decision rules solving the DDP problems in equations 5 and 6. These decision rules are the best-response actions given beliefs $\tilde{p}$. Alternatively the action of players can be represented in terms of their best-response choice probabilities. That is, the probability of entering or staying in the market, given beliefs $\tilde{p}$ about the opponents choice probabilities. This representation is obtained by integrating over the private values in the decision rules:

$$\begin{aligned}
\Delta_i^I(s|\tilde{p}) &= \int \mathcal{I}\Big(\nu < E\big[v_i^I(s',\nu'|\tilde{p})|s,\chi_i = 1\big]\Big) dF_i^\nu(\nu) \\
&= F_i^\nu\Big(E\big[v_i^I(s',\nu'|\tilde{p})\big|s,\chi_i = 1\big]\Big), && (10) \\
\Delta^E(s|\tilde{p}) &= \int \mathcal{I}\Big(\kappa < \delta E\big[v_g^I(s',\nu'|\tilde{p})|s,\chi^e = 1\big]\Big) dF^\kappa(\kappa) \\
&= F^\kappa\Big(\delta E\big[v_g^I(s',\nu'|\tilde{p})\big|s,\chi^e = 1\big]\Big). && (11)
\end{aligned}$$

Similarly, integrating the private shocks out of the value functions, the *ex-ante* value functions are given by:

$$\begin{aligned}
v_i^I(s|\tilde{p}) &= \int V_i^I(s,\nu,\tilde{\phi}|\tilde{p}) dF_i^\nu(\tilde{\phi}) \\
&= \pi_i(s) + \big(1 - \Delta_j^I(s|\tilde{p})\big)\delta E\big(\nu|\chi_i = 0\big) + \Delta_i^I(s|\tilde{p})\delta \sum_{s'} v_j^I(s'|\tilde{p})\Gamma_{iI}(s,s') \\
&= \pi_i(s) + \big(1 - \Delta_j^I(s|\tilde{p})\big)\delta E\big(\nu|\chi_i = 0\big) + \Delta_i^I(s|\tilde{p})\delta E v_i^I(s|\tilde{p},\chi_i = 1) && (12) \\
v^E(s|\tilde{p}) &= \int V^E(s,\tilde{\kappa}|\tilde{p}) dF^\kappa(\tilde{\kappa}) \\
&= \Delta^E(s|\tilde{p})\Big[-E(\kappa|\chi^e = 1) + \delta \sum_{s'} v_g^I(s'|\tilde{p})\Gamma_E(s,s')\Big] \\
&= \Delta^E(s|\tilde{p})\Big[-E(\kappa|\chi^e = 1) + \delta E v_g^I(s|\tilde{p},\chi^e = 1)\Big]. && (13)
\end{aligned}$$

These equations represent the continuation values as functions of the best-response choice probabilities and beliefs about the action of other players. The following definition characterizes a Markov Perfect (Bayesian) Nash equilibrium (MPE).

Definition 1. *A MPE is a set of probability functions* $p = \big\{p_i^a\big\}_{i=\{c,g\},a=\{I,E\}}$ *which solves the individual agent problem as defined in equations 5 and 6, and are consistent with the other* *players action. Alternatively, a MPE is a fixed point of the best-reply probability mapping:*

$$\mathbf{p} = \begin{pmatrix} \Delta_g^I(p) \\ \Delta_c^I(p) \\ \Delta^e(p) \end{pmatrix} = \Delta(\mathbf{p}) = \begin{pmatrix} F_g^\nu\big(Ev_g^I(p, \chi_g = 1)\big) \\ F_c^\nu\big(Ev_c^I(p, \chi_c = 1)\big) \\ F^\kappa\big(\delta Ev_g^I(p, \chi^e = 1)\big) \end{pmatrix} \tag{14}$$

A MPE is guaranteed to exist but there is no guarantee it is unique. The method used to recover parameters of interest under multiplicity of equilibrium is discussed below.

5 Estimation Strategy

The model generates conditional probabilities of exit and entry. The data includes observed entry and exit rates $Y_{tl} = \left\{e_{tl}, x_{jtl}\right\}_{j=g,c}$, and the observable state vector $X_{tl} = \{n_{gtl}, n_{ctl}, z_{tl}, m_{tl}, R_t\}$. It is also assumed that the econometrician has a consistent estimate of the transition probability matrix $\{G_0, G_1\}$ and the discount factor δ. The remaining parameters, $\theta = \{\theta_\pi, \theta_F\}$, can then be estimated either using a short panel on a large number of locations, or a long time series on a few locations.[5]

Recently a number of authors have suggested using the conditional choice probability (CCP) estimator developed by Hotz and Miller (1993) and Hotz et al. (1994) to get around the identification problem associated with the multiplicity of equilibria.[6] The starting point of the CCP estimator is the insight that for any dynamic discrete choice model with an additive unobserved utility shock, there exist a one-to-one mapping between the choice probabilities and the value function (i.e. relative to one alternative). Therefore, an unbiased estimate of the value function can be obtained using a consistent first stage estimate of the choice probabilities and the state transition matrix. This permits the computation of the choice probabilities predicted by the model without repeatedly solving the dynamic programming problem. Aguirregabiria and Mira (2002) proposed a K-step version of the CCP that sequentially updates the choice probability vector using the previous step estimates.

[5] Aguirregabiria and Mira (2004) estimate an entry/exit model using a short panel (5 years) of small cities in Chili, while Pensendorfer and Schmidt-Dengler (2003) estimate a similar model using quarterly data on two cities in Austria over a 20 years period.

[6] Those papers are: Aguirregabiria and Mira (2004), Bajari, Benkard and Levin (2004), Pakes, Ostrovsky and Berry (2004), and Pensendorfer and Schmidt-Dengler (2003).

In a multi-agent framework, this methodology has the advantage of avoiding the multiple equilibria problem. To do so, the following assumption is required:

Assumption 7. *The observed sample is the outcome of a single pure strategy equilibrium.*

Under this assumption, a consistent conditional choice probability estimator will provide the correct decision rules and equilibrium beliefs used by agents when making their decisions.

To illustrate the details of the estimating algorithm, one also needs to parameterize the distribution of private-valued shocks. I follow Pakes, Ostrovsky and Berry (2004) and assume that the scrap values and set-up cost are exponentially distributed with mean $\bar{\nu}_c$ and $\bar{\nu}_g$ respectively for the type c and g firms and mean entry cost $\bar{\kappa}$. This functional form assumption has the advantage of providing a closed form expression for the conditional expectation of the scrap value:

$$E\big(\nu|\nu > Ev_i^I(p)\big) = Ev_i^I(p) + \bar{\nu}_i.$$

Using these assumptions and the linearity of the payoff function (i.e. equation 4), the continuation values can be written in matrix form as a function of the unknown parameters $\theta = \{\theta_\pi, \bar{\nu_g}, \bar{\nu}_c, \bar{\kappa}\}$:

$$\begin{aligned}
Ev_i^I(p, \chi_i = 1|\theta) &= \big(I - \delta p_i^I \Gamma_{iI}\big)^{-1} \Gamma_{iI} \Big[S_i \theta_{\pi_i} + (1 - p_i^I)\bar{\nu}_i\Big] \\
Ev_g^E(p, \chi^e = 1|\theta) &= \Gamma_{gE} \Big[S_g \theta_{\pi_g} + (1 - p_g^I)\bar{\nu}_g + p_g^I \delta Ev_g^I(p, \chi_g = 1|\theta)\Big] \\
\text{where} \qquad & S_i = \big(R \quad z \quad \log(n_{-i}+1) \quad \log(n_{i'}+1) \quad m \quad -\mathbf{1}\big).
\end{aligned}$$

As discussed, θ is estimated in two steps. First, the conditional choice probabilities are consistently estimated using a reduced-form estimator. Let $\hat{\mathbf{p}} = \{\hat{p}_g^I, \hat{p}_c^I, \hat{p}^e\}$ be the matrix of first-stage estimates. Conditional on these first-step estimates, the model predicts a vector of choice probabilities using the best-response probability mapping:

$$\Delta(\hat{\mathbf{p}}|\theta) = \begin{pmatrix} 1 - \exp\Big(-\frac{1}{\bar{\nu_g}} Ev_g^I(\hat{p}, \chi_g = 1|\theta)\Big) \\ 1 - \exp\Big(-\frac{1}{\bar{\nu_g}} Ev_g^I(\hat{p}, \chi_c = 1|\theta)\Big) \\ 1 - \exp\Big(-\frac{1}{\bar{\kappa}} \delta Ev_g^E(\hat{p}, \chi^e = 1|\theta)\Big) \end{pmatrix}. \tag{15}$$

Second, the structural parameters are recovered by minimizing the difference between the predicted choice probabilities and the observed choice probabilities. This task can be performed either by maximizing a pseudo-likelihood function, or minimizing a quadratic loss function. As argued by Pesendorfer and Schmidt-Dengler (**?**), the least-square estimator is potentially more efficient than the PML, because it uses the full set of Nash equilibrium conditions (i.e. equation 14) to estimate the parameters. More specifically, the least-square estimator θ_{LS} solves the following problem:

$$Q(\theta_{LS}) = \min_{\theta} \Big(\hat{\mathbf{p}} - \Delta(\hat{\mathbf{p}}|\theta)\Big)' \Lambda \Big(\hat{\mathbf{p}} - \Delta(\hat{\mathbf{p}}|\theta)\Big), \tag{16}$$

where Λ is a positive definite weighting matrix. Pensendorfer and Scmidt-Dengler (**?**) derived the optimal asymptotic weighting matrix. I use an inefficient weighting matrix, and conduct inference using a parametric bootstrapping methodology.

5.1 Policy Impact

To measure the impact of a price control regulation on the welfare of incumbents and potential entrants in the market, I compute the value of being an incumbent and a potential entrant before and after the regulation change:

$$D_i^I \equiv v_i^I(R=1)/v_j^I(R=0),$$

$$D^E \equiv v_j^E(R=1)/v^E(R=0).$$

6 Empirical Analysis

6.1 Main Source of Data

The entry and exit decisions of gasoline retailers are examined using a panel of gasoline stations for five cities in the province of Québec: Québec City, Trois-Rivières, Sherbrooke, Chicoutimi, and Drummondville. Québec City, the largest of the group, includes between 200 and 300 stations, while the three others (excluding Drummondville) are middle size cities with between 60 and 100 stations (population between $100,000$ and $150,000$). Drummondvillle is the smallest city of the group (population $40,000$), and has approximately 40 stations.

The data are collected by Kent Marketing Consulting, which surveys every urban gasoline market in Canada. This data-set includes information on sales volume of all active stations in the surveyed markets, as well as station characteristics (i.e. location, type of amenities, brand, capacity) for an eleven year period between 1991 and 2001. For all cities except Québec, the information is available for the fourth quarter of each year (a 90 days period). For Québec City, the information is available bimonthly (a 60 days period). For the purpose of the empirical analysis, the sales information is converted to an average daily sales, and only annual information is used. The final unbalanced panel includes 6012 observations, i.e. at most 783 stations for 11 years.

6.2 Definition of Local Markets

A major issue is the definition of local markets in which firms are competing. The issue is particularly complicated in the case of large spatial markets because each station's demand is affected by the action of all other firms in the same city. Modeling the joint entry and exit decisions of all stations in a city of firms would be infeasible. To get around this problem, empirical studies of the gasoline industry have used different definitions of local markets. For instance, Slade (1987) studied the duration of price wars in a single local market in Vancouver, defined as a street segment. Pinske and Slade (1999) studied the distribution of ownership contracts between stations of Vancouver assuming various definitions of local markets. Their results suggest that the "best" definition of local market (i.e. used in the construction of a spatial weighing matrix) is one in which firms are competing only with their immediate neighbors along a street. More recently, Hastings (2004) used a definition of local markets such that "a station competes with any station within one mile along a surface street or freeway". One problem with the previous definitions is that the set of firms defining a local market is not closed, so that firms can be competing in two markets. This property implies that we cannot define meaningful strategies based solely on the actions of local players. Therefore, to be in line with the previous literature, and be able to define proper strategies, a local market must satisfy the three following properties:

1. The distance between stations must be small,

2. Two stations are in the same local market if they have at least one street in common,

3. A location must be a close set of firms (i.e. each firm is in only one local market), and the locations cannot geographically overlap.

The first two properties ensure that firms within a location share similar spatial characteristics, and offer homogeneous products. The last one ensures that the game between stations in the same location is defined properly. Iyer and Seetharaman (2004) used a similar definition of local markets, constructed by visually clustering gasoline stations into local markets.

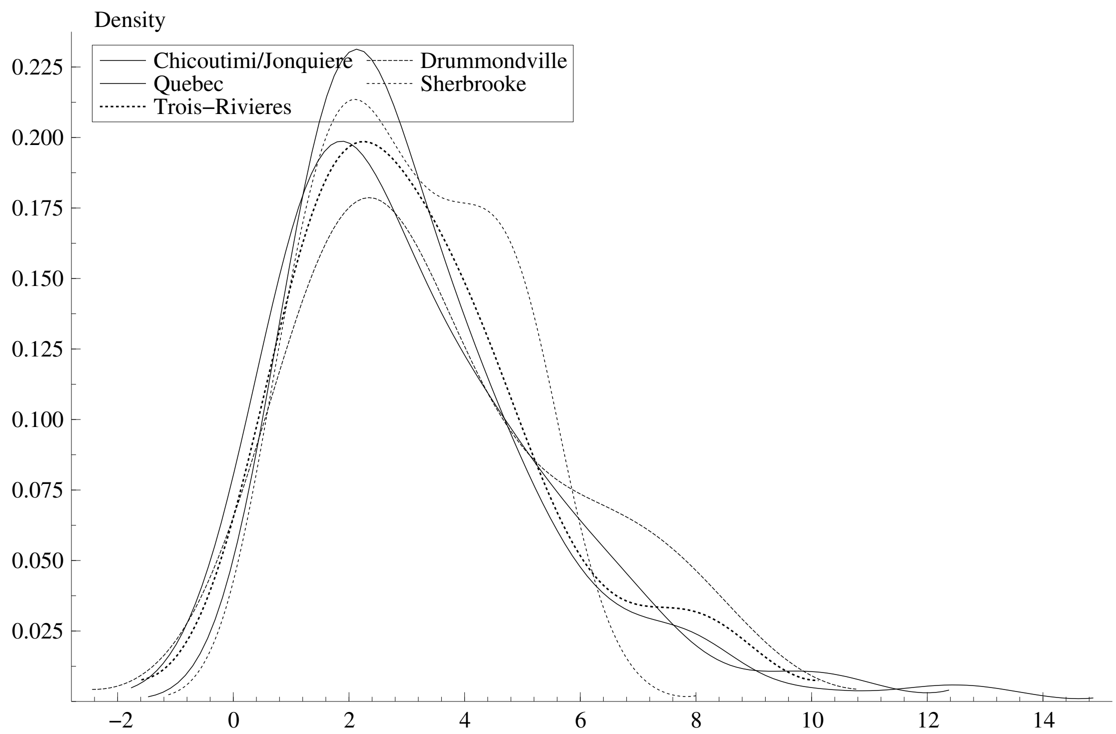
In order to implement a definition which meets these properties, I use a clustering algorithm which group stations according to two criteria: distance and connectivity. In particular, the algorithm iterates on the classification such that the distance between each station and the center of its local market is no greater than 1 mile, and stations share at least one street with the others (i.e. the stations are connected). The actual distance criteria can easily be varied to create larger or smaller markets. Note that this market definition is time invariant because it uses the total sample of stations who were active in the five cities at some point between 1991 and 2002.[7] In the chosen configuration, the average number of firms per local market is slightly above 3, with a maximum of 15. Figure 3 presents the distribution of firms in those local markets for the five cities.

6.3 Definition of the State Variables

Recall that the state of a location includes the regulation R_t, the number of stations of each type active in the location $\{n_{glt}, n_{clt}\}$, the market structure in neighboring locations m_{lt}, and the profitability of the location z_{lt}.

[7]Information after 2001 was obtained from the Québec Ministry of Energy, who is responsible to emit gasoline station permits.

Figure 3: Kernel density of the number of firms by local market



To construct the last two variables, one must choose an appropriate weighing matrix W, which weights more heavily closer locations. The choice of the weights is aimed at approximating the elasticity of substitution between two locations. A popular choice in the spatial econometrics literature is to use a Gaussian weighting function with bandwidth b (e.g. Fotheringham et al. (2002)):

$$w_{ij} = \begin{cases} \exp(-1/2(d_{ij}/b)^2) & \text{if } i \neq j \\ 0 & \text{otherwise,} \end{cases}$$

where d_{ij} is the distance between locations i and j. The weights are decreasing in d according to a Gaussian curve (i.e. the weights are decreasing at a faster rate when $d_{ij} > b$). Since the markets studied are different in terms of population density, I standardized the weights such that the sum of weights for each location is equal to one. That is:

$$w_{ij} = \frac{\exp(-1/2(d_{ij}/b)^2)}{\sum_{j=1..L} \exp(-1/2(d_{ij}/b)^2)}. \tag{17}$$

Table 3: State of Demand Results (GLS)

	Coefficients	**Std-Error**
TRADE	0.08786	0.01664
POP	0.03791	0.01265
n_g	1.432	0.02717
n_c	0.5879	0.02407
λ	0.7392	
R^2	0.6352	
K	65	
Nb. Obs.	2856	

To construct z_{lt} a regression of log sales at the location (q_{lt}) was run on a set of demographic characteristics:

$$\begin{aligned} q_{lt} &= A_t + B_1 \log(\text{POP}_{lt}) + B_2 \log(\text{TRADE}_l) \sum_{i=1}^{\#\text{AREA}} C_i \mathcal{I}(l \in \text{AREA}_i) + \\ & \quad D_1 \log(n_{glt} + 1) + D_2 \log(n_{clt} + 1) + \varepsilon_{lt} \qquad (18) \\ & \quad \text{where, } \varepsilon_{lt} = \lambda W_t \varepsilon_{lt} + \mu_{lt}. \end{aligned}$$

AREA is the area's type (i.e. highway, residential, and/or commercial). POP is the population of the census tract of location l. TRADE is the average number of retailing establishments (excluding gasoline retailers) in the postal-code group (i.e. FSA) of location l between 1999 and 2001.[8]

Equation 18 was estimated using an iterative GLS procedure (see Anselin (1988) for more details). The choice of the bandwidth b in the computation of the weights was set to 2 miles. At this level, the fit of the model (i.e. R^2) is maximized, and the estimated spatial correlation coefficient is lower than 1. Selected results from the regression are given in Table 3.

[8]FSA or Forward Sortation Area is defined as the first three components of the postal codes. This variable was constructed using the Small Area Retail Trade Estimate (or SARTRE) survey, conducted by Statistics Canada. This survey measures the number of retail establishments and the sales for all postal-code groups in Canada on an annual basis. Unfortunately, the data prior to 1999 are not publicly available from Statistics Canada.

Table 4: Descriptive Statistics

	Mean	**Std.Dev.**	**Maximum**	**Minimum**
# Entrants	0.03937	0.2088	3	0
# Exits type g	0.05122	0.2304	2	0
# Exits type c	0.04706	0.2177	2	0
Regulation	0.4545	0.4979	1	0
n_g	1.459	1.211	7	0
n_c	0.6156	0.8955	6	0
Demand state (z)	7.526	0.5881	9.233	3.475
Weighted N ($\tilde{m}$)	2.101	0.462	4.094	0.5394

Using these estimates, $\hat{z}_{lt}$ is defined as:

$$\hat{z}_{lt} = q_{lt} - \widehat{D}_1 \log(n_{glt}) - \widehat{D}_2 \log(n_{clt}). \tag{19}$$

For markets with no active stations, q_{lt} is not observed. In these cases z_{lt} is imputed using the observed characteristics and the estimated shocks ε_{lt} from the neighboring local markets (weighted by $\hat{\lambda}W$).

The second state variable m_{lt} equals the weighted number of active stations in neighboring locations:

$$m_{lt} = \sum_{l' \neq l} w_{ll'}(n_{cl't} + n_{gl't}). \tag{20}$$

Summary statistics of the variables used in the estimation are presented in Table 4 below. Table 5 also presents the distribution of new entrants, exits, and incumbents over the 11 years.

6.4 First-Stage Estimation Results

Table 6 reports the estimates of equation 3, the VAR (z,m). The variables were discretized into 5 grids each (i.e. total of 25 states). Following Tauchen (1986) these results were used to compute the Markov transition probability matrices (G_0, G_1) (i.e. before and after the implementation of the regulation).

Figure 4 presents the kernel smoothed densities of the two aggregate state variables for four years. The average of z_{lt} is slightly increasing over time, reflecting the favorable business

Table 5: Number of active firms, entrants, and exits per year

Year	Entrants	Exits (g)	Exits (c)	Incumbents (g)	Incumbents (c)
1991	20	18	24	437	265
1992	15	19	24	439	241
1993	19	13	19	435	217
1994	11	24	15	441	198
1995	7	13	16	428	183
1996	17	23	11	422	167
1997	8	11	10	416	156
1998	8	8	10	413	146
1999	6	15	9	413	136
2000	9	8	9	404	127
2001	6	9	4	405	118

Table 6: VAR(1) Results for the Aggregate State Variables

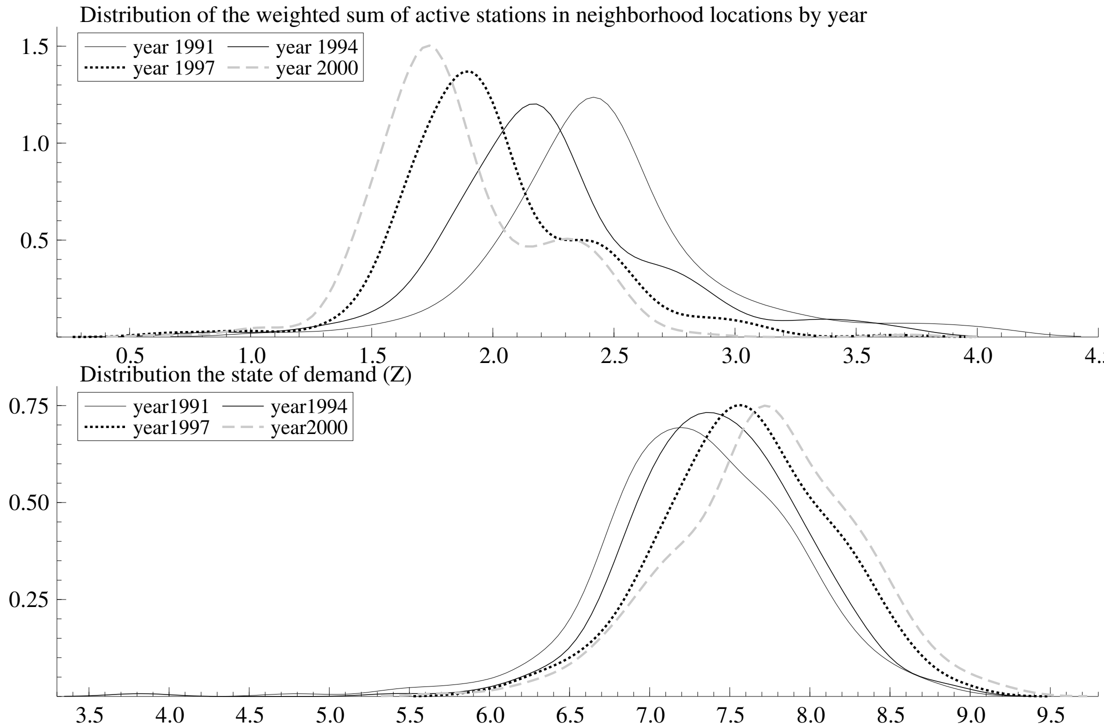
$$\begin{array}{rcccccccc} z_{lt} = & 0.934 & + & 0.015R_t & + & 0.879z_{lt-1} & + & \epsilon_{lt}^{z} \\ & (0.067) & & (0.0104) & & (0.009) & & (0.275) \\ m_{lt} = & 0.0275 & + & 0.016R_t & + & 0.953m_{lt-1} & + & \epsilon_{lt}^{m} \\ & (0.0086) & & (0.003) & & (0.003) & & (0.0837) \end{array}$$

Standard-errors are in parenthesis.

cycles. The distribution of the weighted number of stations (m_{lt}) is clearly decreasing, reflecting the reorganization of the industry.

Next, the entry and exit probabilities were estimated using a simple linear probit model. This approach was chosen, over a non-parametric spell frequency estimator, because the entry/exit decisions are not observed at every discrete states. This is an important limitation in this case because the non-parametric estimator would not yield an estimate of the continuation values at every state. Similar reduced form estimators of the conditional choice probabilities have been used by among others Aguirregaberia and Mira (2004) and Ryan (**?**) to estimate dynamic entry/exit games.

Figure 4: Kernel density of the aggregate state variables



Given a matrix of observed entry and exit choices $Y = \{e_{lt}, x_{glt}, x_{clt}\}$ and a matrix of observed states $X = \{R_t, \log(n_{glt}+1), \log(n_{clt}+1), z_{lt}, m_{lt}\}$, the reduced form choice probabilities are based on the parameters $\hat{\beta}$ that solves the following maximum likelihood problem:

$$\begin{aligned} l(Y|X,\hat{\beta}) \quad = \quad & \max_{\beta} \sum_t \sum_l \Bigg\{ e_{lt} \log\big(\Phi(X_{lt}\beta_e)\big) + (E - e_{lt}) \log\big(1 - \Phi(X_{lt}\beta_e)\big) + \\ & \sum_{i=c,g} \Big[(n_{ilt} - x_{ilt}) \log\big(\Phi(X_{lt}\beta_i)\big) + x_{ilt} \log\big(1 - \Phi(X_{lt}\beta_i)\big) \Big] \Bigg\}, \end{aligned}$$

where $\Phi()$ is the standard normal cdf, and the E the number of potential entrants in each location. E was set at 3 in the estimation, the maximum number of new entrants observed in the data. The results of this first-stage choice probability estimation are reproduced in Table 7.

Table 7: Probit Results for the Entry/Exit Decisions

	Entry	**Stay (g)**	**Stay (c)**
Intercept	-2.763	-2.15	0.3086
	(0.5418)	(0.5657)	(0.6567)
Regulation	-0.3294	0.1703	0.1837
	(0.0823)	(0.811)	(0.1021)
$\log(n_g + 1)$	-0.1476	-0.2012	-0.0491
	(0.0703)	(0.1006)	(0.0083)
$\log(n_c + 1)$	-0.08434	0.1526	0.03438
	(0.0767)	(0.0803)	(0.1322)
z_{lt}	0.1027	0.5076	0.1228
	(0.0642)	(0.0686)	(0.0764)
m_{lt}	0.01332	0.1566	0.06794
	(0.08325)	(0.0824)	(0.1062)
Nb. Obs.	3124		
LLF	-1816		

Standard-errors are parenthesis.

The results suggest that the regulation had a significant impact on the continuation and entry probabilities. In particular, the price regulation reduced the entry probability and increased significantly the exit probability for the two types of firms. Also, the number of type g stations reduces significantly the entry probability but not the number of type c stations. Interestingly, the continuation probability of the type g firms is negatively correlated with the number of active firms of type g but positively correlated with the number of type c firms. This reinforces the perception that the gas-bar type (g) is a superior technology, with smaller marginal cost or higher value. The coefficient associated with z_{lt} has the anticipated sign (positive) in all three equations. For the type c firms, it appears however that the exit probability is much less correlated with the profitability of the locations z_{lt}. This reflects the fact that these stations earn a large fraction of their revenue from other services (e.g. car repairs), which are less correlated with gasoline demand. The market variable m_{lt} is not significant and positive (instead of negative) in all three equations. So it appears that aggregate state variable z_{lt} would be sufficient to explain the profits of firms.

6.5 Second-Stage Estimation

The remaining parameters are estimated by minimizing the distance between the vector of predicted choice probabilities and the first-step estimated choice probabilities. The scale of the profit parameters cannot be separately identified from exits and entries only. Only relative payoffs matter. Therefore, I normalized the average scrap values to 1, and expressed the continuation values relative to the scrap value of each type. The parameters to be estimated include those entering the profit functions for both types ($\theta_\pi = \{\theta_r, \theta_i, \theta_{-i}, \theta_z, \theta_m, FC\}_{i=c,g}$), and the average set-up cost ($\bar{\kappa}$). Note also that the fixed cost is not separately identified from a constant in the profit function. The value of this parameter should thus be interpreted as the fixed operating cost, net of the average profits from other services and products offered.

Various methods have been proposed to estimate the parameters. I report the results from the non-linear least-square (NLS) approach proposed by Pesendorfer and Schmidth-Dengler (**?**), and the GMM estimator suggested by Pakes, Ostrovsky and Berry (2004). The theoretical and empirical moment conditions for the later approach are given by:

$$E(\hat{p}_s - \Delta(\theta, \hat{p})|Z_s) = \frac{1}{\#S}\sum_s Z_s(\hat{p}_s - \Delta_s(\hat{p}, \theta)) = 0. \tag{21}$$

The results reported below use the vector of state variables as instruments. The Monte-Carlo results presented in Pakes, Ostrovsky and Berry (2004) suggest that the GMM approach is more reliable in small samples, because it is less sensitive to bias from the first-stage choice probability estimates.

In both cases, inference is conducted using a parametric bootstrap approach. More specifically, given a set of estimates $\hat{\theta}$, B bootstrap samples were generated by drawing independent private value shocks (ν_c, ν_g, κ) for each active firm and potential entrant in the sample. The estimated parameters are then used to predict the entry and exit decisions at each observed state. This procedure generates confidence intervals and bootstrap standard-errors which take into account the randomness generated by the first-stage choice probability estimates.

Table 8: Estimated Parameters (NLS)

	Estimates	**Std-Error**	5% / 95%
Type g			
θ_R	0.01243	0.01338	[−0.001 ,0.042]
θ_i	−0.02404	0.01708	[−0.045 ,0.011]
θ_{-i}	0.05207	0.02433	[−0.016 ,0.065]
θ_z	0.2914	0.03959	[0.047 ,0.17]
θ_m	0.07586	0.03657	[−0.023 ,0.099]
FC	2.251	0.3292	[0.28 ,1.3]
Type c			
θ_R	0.03576	0.02177	[0.005 ,0.074]
θ_i	0.003003	0.02874	[−0.045 ,0.048]
θ_{-i}	−0.008963	0.02473	[−0.05 ,0.03]
θ_z	0.06354	0.03828	[−0.046 ,0.088]
θ_m	0.03417	0.0425	[−0.059 ,0.083]
FC	0.5252	0.3329	[−0.42 ,0.76]
κ	17.6	1.239	[16 ,20]
Nb. Bootstrap	499		
Policy iterations	1		
Nb. Observations	3124		
Nb. States	798		

Note also that the parameters can be affected by the choice of the state space used to estimate the model. More specifically, although the state space is potentially unbounded (i.e. there is no maximum number of firms active in each location), the model predicts the existence a recurrent subset of the state space, such that the probability of transiting from a state in this subset to a state outside is zero (see Ericson and Pakes (1995) for more details). Empirically, one needs to assume that the observed sample is drawn from the recurrent set, and make further assumptions about the relevant state space. Pakes, Ostrovsky and Berry (2004) suggest defining the recurrent state space as the union of all visited states. The state space is thus all combinations of (z, m, n_c, n_g) observed in the data.

Table 8 presents the results using the NLS estimation method, and Table 9 presents the GMM results. For each, the number of states used in the estimation is 798, and 499 bootstrap replications have been performed.

Table 9: Estimated Parameters (GMM)

Type g	**Estimates**	**Std-Error**	5% / 95%
θ_R	0.0123	0.01439	[-0.0022 ,0.041]
θ_i	-0.02386	0.01615	[-0.043 ,0.011]
θ_{-i}	0.05223	0.0238	[-0.012 ,0.066]
θ_z	0.2944	0.03621	[0.058 ,0.17]
θ_m	0.07679	0.0342	[-0.024 ,0.1]
FC	2.275	0.2919	[0.4 ,1.3]
Type c			
θ_R	0.03576	0.02096	[0.0084 ,0.074]
θ_i	0.002989	0.02583	[-0.035 ,0.056]
θ_{-i}	-0.008944	0.0256	[-0.055 ,0.024]
θ_z	0.06366	0.03703	[-0.051 ,0.071]
θ_m	0.03422	0.04117	[-0.056 ,0.084]
FC	0.5262	0.3223	[-0.47 ,0.63]
κ	17.46	1.56	[15.811 ,19.494]
Nb. Bootstrap	499		
Policy iterations	1		
Nb. Observations	3124		
Nb. States	798		

The parameter estimates are very similar under both estimation methods. For the type c stations, all parameters except θ_R are not different from zero according to the bootstrap confidence interval. For the type g stations, the two competition variables (i.e. θ_i and θ_{-i}), the constant, and the effect of the demand state variable are more precisely estimated, although not all are significantly different from zero. The average sunk cost of entry is very precisely estimated and large.

The sign and magnitude of the point estimates provide interesting insights into this market. The profits of type g firms are negatively affected by the number of competitors of the same type, and positively affected by the number of type c stations. However, for conventional stations the effect of more competition from their own type is close to zero, while the effect of the number of type g competitors is negative. This suggests that type c firms are weak competitors, either because they have higher marginal costs, or provide low-value services for consumers.

Furthermore the effect of the demand state variable z_{lt} is positive in both equations, but is much larger in magnitude for stations of type g. Similarly, the constant in type g's profit function is negative and significantly different from zero (i.e. positive fixed cost). This is not the case for type c firms. This indicates that type g stations have much higher fixed operation costs, and that contrary to type c stations, their profits are closely related to gasoline market conditions (as measured by z_{lt}). This is reasonable since type g firms are self-service stations using the most recent technology, and generally have large storage capacity. It is thus plausible that most of their labour costs are fixed, and that their equipment is more expensive to operate. Moreover, they offer complementary products and services directly related to the volume of gasoline sold (e.g. convenience store products or car-wash). Conventional stations on the other hand are typically full-service stations offering car-repair services. An important fraction of their revenues is therefore more or less independent of the volume of gasoline sold, while their labour costs are in a large part variable. These two factors contribute to lower the estimate of the fixed-cost for type c stations.

The entry cost is also estimated to be quite large relative to the other parameters. This indicates that there are significant barriers to entry in this market, a result also found by Aguirregabiria and Mira (2004) using Chilean data on gasoline local markets.

As suggested by the reduced form estimation, the market variable m does not have a significant impact on firms' profits, and the point estimates have a positive sign (instead of negative). Finding a more appropriate measure of conditions in related markets is left for later versions of this paper.

The realization of the price floor has a positive impact on profits for both types of stations, but it is significantly different from zero only for type c firms. Table 10 presents the average change in the continuation values for type c and type g firms. The changes are measured in percentage. The mean and the quantiles are over all states. On average, the regulation raised the continuation value of firms in the market by about 10% for the type g firms and by 13% for the type c firms. Since the continuation values are the option value of staying

Table 10: Estimated Policy Impact (NLS)

	Mean	5% **quantile**	**Median**	95% **quantile**
$\Delta^{\%}V_g$	0.1016	0.06503	0.1021	0.1552
$\Delta^{\%}V_c$	0.1319	0.1165	0.1306	0.1466

active in the market, this result suggests that incumbents are less likely to exit the market under the regulation state. The fact that the regulation benefited more the conventional stations implies that the policy effectively protected the smaller and less efficient firms in the market. Since these stations are not using the more recent technology, it also means that the regulation has contributed to the slower reorganization of the Québec industry.

7 Conclusion

In this chapter, I estimate a dynamic entry/exit model applied to gasoline stations. Using data before and after the implementation of a price floor regulation, I evaluate the impact of price controls on firms' decisions to exit and enter the market.

One contribution is a method to study dynamic entry/exit games in large urban markets, by considering the strategic interaction of players in small homogeneous local markets. A clustering algorithm groups firms into independent locations based on distance and connectivity through the road network. Although more work needs to be done to determine the appropriate form of aggregation which defines the sate variables and their transition probabilities, this approach could be applied to study a wider class of retailing markets.

The results suggest as hypothesized the dynamic behavior of gasoline stations differs greatly by type. In particular, gas-bar stations face a higher opportunity cost of staying in the market when conditions are not favorable. This reflects higher fixed operation costs, and lower profits from independent sources of revenues. Furthermore, the entry cost is very high relative to profits, which explains the slow reorganization of this industry. The threshold variable profits over which stations enter the market must be significantly higher than the average variable cost, causing firms to delay their entry decisions.

The price regulation introduced in 1997 increased profits of both types of stations and lead to higher continuation values and lower exit probabilities. The impact was larger on the value of conventional stations. Since these stations are associated with the older inefficient technology, this implies that the regulation protected weaker firms more. This result is consistent with the fact that the Québec gasoline retail industry has been slower to re-organize than other North-American gasoline markets.

References

Aguirregabiria, V. and P. Mira (2002). Swapping the nested fixed point algorithm: A class of estimators for discrete markov decision models. *Econometrica 70*(4), 1519–1543.

Aguirregabiria, V. and P. Mira (2004). Sequential estimation of dynamic discrete games. Forthcoming, Econometrica.

Anderson, R. W. and R. N. Johnson (1999). Antitrust and sales-below-cost laws: The case of retail gasoline. *Review of Industrial Organization 14*, 189–204.

Anselin, L. (1988). *Spatial Econometrics: Methods and Models.*

Bajari, P., L. Benkard, and J. Levin (2004). Estimating dynamic models of imperfect competition. forthcoming, Econometrica.

Barron, J. and J. Umbeck (1984). The effects of different contractual arrangements: The case of the retail of gasoline market. *Journal of Law & Economics 27*, 313–328.

Beresteanu, A. and P. B. Ellickson (2005, October). The dynamics of retail oligopoly. working paper, Duke University.

Bresnahan, T. F. and P. C. Reiss (1991). Entry and competition in concentrated markets. *Journal of Political Economy 99*(5), 977–1009.

Dixit, A. K. and R. S. Pindyck (1994). *Investment under uncertainty.* Princeton University Press.

Doraszelski, U. and M. Satterthwaite (2005). Foundations of markov-perfect industry dynamics: Existence, purification, and multiplicity. mimeo, Harvard University.

Ericson, R. and A. Pakes (1995). Markov-perfect industry dynamics: A framework for empirical work. *The Review of Economic Studies 62*(1), 53–82.

Fotheringham, A. S., C. Brunsdon, and M. Charlton (2002). *Geographically Weighted Regression.* Wiley.

Gagné, R., S. Van Norden, and B. Versaevel (2003, September). Testing optimal punishment mechanisms under price regulation: The case of the retail market for gasoline. working paper, HEC Montréal.

Hastings, J. (2004). Vertical relationships and competition in retail gasoline markets: Empirical evidence from contract changes in southern california. *American Economic Review*.

Hotz, V. J. and R. A. Miller (1993). Conditional choice probabilities and the estimation of dynamic models. *The Review of Economic Studies 60*(3), 497–529.

Hotz, V. J., R. A. Miller, S. Sanders, and J. Smith (1994). A simulation estimator for dynamic models of discrete choice. *The Review of Economic Studies 61*(2), 265–289.

Iyer, G. and P. Seetharaman (2004, February). Quality and location in retail gasoline markets. working paper, Haas School of Business, University of California at Berkeley.

Krusell, P. and J. Smith, Anthony A. (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of Political Economy 106*(5), 867–896.

Maskin, E. and J. Tirole (1988). A theory of dynamic oligopoly, ii: Price competition, kinked demand curves, and edgeworth cycles. *Econometrica: Journal of the Econometric Society 56*(3), 571–599.

Mazzeo, M. (2001). Product choice and oligopoly market structure. *Rand Journal of Economics*.

Pakes, A., M. Ostrovsky, and S. Berry (2004). Simple estimators for the parameters of discrete dynamic games (with entry / exit examples). mimeo, Harvard University.

Pesendorfer, M. and P. Schmidt-Dengler (2003). NBER Working Paper 9726.

Pinkse, J. and M. Slade (1999). Contracting in space: an application of spatial statistics to the discrete choice model. *Journal of Econometrics 85*, 125–154.

Rust, J. and G. Rothwell (1995). Optimal response to a shift in regulatory regime: The case of the us nuclear power industry. *Journal of Applied Econometrics 10*(Special Issue: The Microeconometrics of Dynamic Decision Making), S75–S118.

Seim, K. (2004). An empirical model of firm entry with endogenous product-type choices. forthcoming, Rand Journal of Economics.

Slade, M. E. (1987). Interfirm rivalry in a repeated game: An empirical test of tacit collusion. *The Journal of Industrial Economics 35*(4, The Empirical Renaissance in Industrial Economics), 499–516.

Tauchen, G. (1986). Finite state markov-chain approximation to univariate and vector autoregressions. *Economics Letters 20*, 177–181.