

# Estimating the Costs of Market Entry and Exit for Video Rental Stores

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## Abstract

This paper uses information on entry and exit to estimate jointly video rental stores' profits, entry costs and sell-off values. I find that the distribution of sell-off values first-order stochastically dominates that of entry costs, which suggests that the entry behavior in this industry cannot be well captured by a static model because such a model implicitly assumes that a potential entrant's entry cost and an incumbent's sell-off values are equal. I also find that the entry decision seems to be a one-shot decision where the option value of waiting plays little role.

## 1 Introduction

Retail industries experience market entry and exit that is relatively frequent. This paper uses information on entry and exit to jointly estimate retail stores' profits, entry costs and sell-off values. The idea is that stores enter into a market when they expect to be profitable, and stores choose to exit when they expect the sell-off value to be higher than the value of continuing the business. Entry and exit behavior therefore sheds light on the nature of profits, costs of entry, and sell-off values. This paper makes two points. First, a static model does not capture the entry and exit behavior well in the industry studied in this paper – video rental stores. Second, the paper compares two alternative models of potential entrants' entry decisions and concludes that the model assuming that potential entrants are short-run players (i.e, they just make a decision about whether to enter now or never) fits the data better.

Models of entry and exit have long been studied. Bresnahan and Reiss (1991) provide an entry model with all competitors in the market being identical. Richer versions of the Brenahan and

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Reiss model allow the competitors' profits to be different. Berry (1992), for example, allows for heterogeneity in both observed and unobserved costs. More recently, Seim (2006) and Mazzeo (2002) add one more strategy dimension to study jointly the decisions about entry and quality or location, respectively. All these models are either static or two-period models, and do not distinguish entry and exit. They implicitly assume incumbents and potential entrants of a market are identical in terms of facing the same opportunity costs (i.e., the costs of entry and sell-off values are equal).

Dynamic models, on the other hand, relax these assumptions and explicitly use the information on both entry and exit. This paper estimates a dynamic model of entry and exit in the video rental industry. I find that the distribution of sell-off values of video rental stores first order stochastically dominates the distribution of the cost of entry into the video rental market. This result is consistent with the intuition that the one-period cost of entry is likely to be smaller than the sell-off values that are related to the lifetime value of the stores. This result also indicates that the assumption of equal entry cost and sell-off values in a static entry model does not hold.

Moreover, this paper investigates whether potential entrants in this industry are long-run or short-run players. In a standard dynamic entry model, potential entrants are short-run players. If they decide not to enter a market, they will never enter again. In other words, a potential entrant either enters or perishes; and the value of waiting is zero. One exception is Fan and Xiao (2015), which treats potential entrants as long-run players. In their model, the potential entrant, in each period, compares the value of entry minus entry costs to the value of waiting when making a decision about whether to enter or wait. In this paper, we consider both alternative models. By estimating both models and comparing their fit to the data, I find that video rental stores' entry decision seems to be a one-shot decision. This is in contrast to Fan and Xiao (2015), which finds that local telephone firms are long-run players. One explanation for this difference in the findings is that video rental stores are generally smaller than local telephone firms, and the entry cost is also likely to be smaller. As a result, the video rental stores are more likely to make a simple decision on entry or not, rather than on the timing of entry.

The empirical context of this paper is video rental stores. Even though the video rental industry is declining, the following characteristics of this industry make the model described below particularly suitable: the products in this industry are relatively homogenous, and this industry experiences relatively frequent entry and exit, which helps identification.

By highlighting the importance of considering the dynamic behavior in an entry model and comparing two alternative dynamic entry model, this paper contributes to the literature on dynamic entry game estimation. Examples in this literature include Victor Aguirregabiria (2007), Bajari, Benkard and Levin (2007), Pakes, Ostrovsky and Berry (2007) and Pesendorfer and Schmidt-Dengler (2008).<sup>1</sup> The computation of a dynamic oligopoly model is quite burdensome. The straight-

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<sup>1</sup>Other examples include Ryan (2012), Collard-Wexler (2013) and Dunne, Klimek, Roberts and Xu (2013).

forward way would be to compute the equilibrium strategies for any given set of parameters, and search for the parameters to make the implications of the equilibrium strategies as close to the data as possible. To compute the equilibrium strategies of a dynamic game, however, one needs to know the value functions, which are in turn determined by the strategies played. Furthermore, the evolution of the markets is endogenous. Thus, computing a dynamic oligopoly model with a realistic number of competitors is prohibitive. This paper follows the estimation strategy provided by Pakes, Ostrovsky and Berry (2007) (henceforth, POB) to avoid this computation, and estimate the value functions directly for any given parameters.<sup>2</sup> But different from POB which relies on simulated data, this paper uses actual industry data and has to deal with – and thus provides solutions to – several practical issues.

The rest of the paper is organized as follows. Section 2 develops the dynamic entry and exit model. Section 3 describes the estimation procedure. The data are described in Section 4. The empirical results are presented in section 5. Section 6 concludes the paper.

## 2 Model

This section presents a dynamic model of entry and exit. The model presented here largely follows the one in POB. Let  $n_t$  be the number of video rental stores in the market at the beginning of year  $t$ , and  $m_t$  the market size that evolves exogenously according to a first-order Markov chain.<sup>3</sup> I assume stores in the market have the same profit function and the profits are determined solely by the number of incumbents and the market size. Furthermore, I assume that the one-period profit function has the following parametric form:

$$\pi(n, m; \eta, \theta) = \frac{m^\eta}{(1+n)^\theta},$$

where  $\eta$  and  $\theta$  are parameters to be estimated.

### 2.1 An Incumbent's Decision

In each period, each incumbent  $j$  observes its sell-off value of the video rental store, denoted by  $\phi_{jt}$ , which is incumbent  $j$ 's private information. Assume that  $\phi_{jt}$  is i.i.d. across  $j$  and  $t$ , and follows an exponential distribution with expectation  $\sigma$ . With the knowledge of  $\phi_{jt}$ , incumbent  $j$  has two choices: staying in business or exiting. I assume that upon exit, the store will not go back to business again. Let  $V^I(n, m, \phi; \eta, \theta)$  be the value of an incumbent with sell-off value  $\phi$  at state

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<sup>2</sup>Jofre-Bonet and Pesendorfer (2003) is another paper that uses the this idea to estimate the value function.

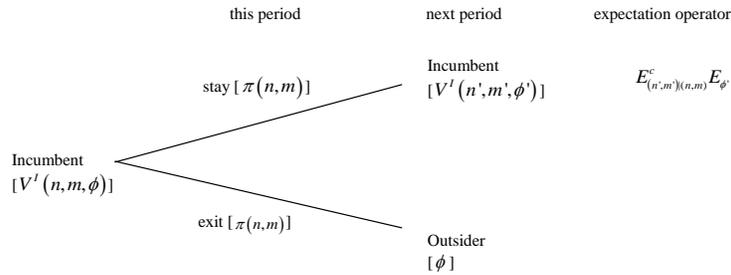
<sup>3</sup>In the empirical implementation, I will measure market size by population size.

$(n, m)$ . Then, the Bellman equation for a typical incumbent problem is

$$V^I(n, m, \phi; \eta, \theta) = \pi(n, m; \eta, \theta) + \beta \max \left\{ E_{(n', m')|(n, m)}^c E_{\phi'} V^I(n', m', \phi'; \eta, \theta), \phi \right\}, \quad (1)$$

where  $(n', m', \phi')$  denotes, respectively, the number of stores, the market size and the sell-off value next period. The expectation operator  $E_{(n', m')|(n, m)}^c$  denotes the incumbent's expectation of  $(n', m')$  conditional on itself *continuing* at state  $(n, m)$ , and  $E_{\phi'}$  is the expectation over  $\phi'$ . The stores discount future profit at discount rate  $\beta$ . The problem for incumbents is summarized by Figure 1.

Figure 1: Incumbent's problem



## 2.2 A Potential Entrant's Decision

I now turn to a potential entrant's entry decision. I assume that there are  $\varepsilon$  potential entrants in each market, which is common knowledge among potential entrants and incumbents. Potential entrant  $j$  observes the cost of entry  $\varphi_{jt}$  at the beginning of period  $t$ . Like the sell-off value  $\phi_{jt}$ , the entry cost  $\varphi_{jt}$  is also assumed to be private information to  $j$ , and identically and independently distributed across potential entrants and time. If  $j$  decides to enter the market, it has to pay the cost of entry  $\varphi_{jt}$  to set up the business, and starts earning profits next period. Therefore, the value of entry is the expected value of being an incumbent next period. The potential entrant's decision is based on the comparison of this value of entry net of entry cost with the value of waiting. I now describe two alternative models to capture a potential entrant's decision.

### 2.2.1 A Potential Entrant's Decision (Model 1)

In this model, I assume that potential entrants are short-run in the sense that once they decide not to enter into the market, they stay outside forever, that is, the value of not entering is then zero. Therefore, the Bellman equation is

$$V^P(n, m, \varphi; \eta, \theta) = \max \left\{ -\varphi + \beta E_{(n', m')|(n, m)}^c E_{\phi'} V^I(n', m', \phi'; \eta, \theta), 0 \right\}, \quad (2)$$

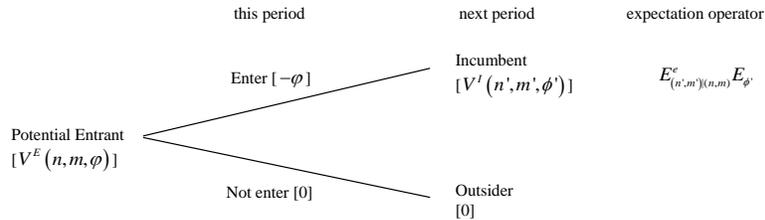
where  $V^P(n, m, \varphi; \eta, \theta)$  is the value of a potential entrant, and  $E_{(n', m')|(n, m)}^e$  is the potential entrant's expectation of  $(n', m')$  conditional on itself entering at state  $(n, m)$ .

In this model, I assume that the density of the distribution of entry fees is given by

$$f(z) = \lambda^2 \left( z - \frac{1}{\lambda} \right) \exp \left[ -\lambda \left( z - \frac{1}{\lambda} \right) \right] \quad (3)$$

for  $z \geq \frac{1}{\lambda}$ . This is a gamma distribution with one parameter fixed at 2. Here,  $\frac{1}{\lambda}$  is the boundary of the support for the entry cost  $\varphi$ .<sup>4</sup> This implies that the value of entry has to be high enough for there to be any entry. This model of potential entrants can be summarized by Figure 2.

Figure 2: Potential Entrant's Problem (Model 1: Short-run Player)



### 2.2.2 A Potential Entrant's Decision (Model 2)

Alternatively, if the potential entrants are long-run players and the timing of entry is a consideration, the value of waiting is the expected value of being a potential entrant next period, and the Bellman equation becomes

$$V^P(n, m, \varphi; \eta, \theta) = \max \left\{ -\varphi + \beta E_{(n', m')|(n, m)}^e E_{\varphi'} V^I(n', m', \varphi'; \eta, \theta), \right. \quad (4) \\ \left. \beta E_{(n', m')|(n, m)}^w E_{\varphi'} V^P(n', m', \varphi'; \eta, \theta) \right\},$$

where  $E_{(n', m')}^w$  is the potential entrant's expectation conditional on itself *waiting*. Note the difference of the value functions and the expectation operators in the first term and the second term in (4). Since the value of waiting for a long-run player is the expected value of being a potential entrant next period, the expectation is taken over the distribution of next period's entry cost  $\varphi'$  and over the state next period  $(n', m')$  conditional on itself waiting.

In Model 1, I impose a lower bound on the entry cost so that the value of entry needs to be high enough for there to be any entry. In Model 2, because the value of waiting is no longer zero, I do not need to impose such a lower bound anymore. In other words, the density function of the

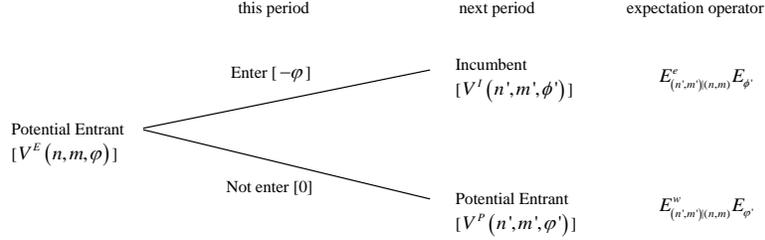
<sup>4</sup>Following POB, I assume the lower bound of the support is  $\frac{1}{\lambda}$ , instead of introducing an additional parameter.

entry cost is now

$$f(z) = \lambda^2 z \exp(-\lambda z) \quad (5)$$

Figure 3 summarizes this model of long-run potential entrants.

Figure 3: Potential Entrant's Problem (Model 2: Long-run Player)



### 3 Estimation

The estimation follows the procedure described in POB. Similar to POB, even though there might be multiple equilibria in this model, I assume that in the data generating process, all markets play the same equilibrium. Different from POB, which deals with simulated data and does not specify how to deal with states without incumbents and those with no entry, these cases do occur in my data. I describe a way to apply their procedure analogously.

#### 3.1 Value Functions in Vector Form

To estimate the model parameters, it is convenient to rewrite equation (1) in vector form. The state in this model is a pair  $(n, m)$ . I arrange the states ascendingly according to  $n$  first and then  $m$ , and denote the  $i$ th state by  $(n_i, m_i)$ . Let the vector  $VC(\eta, \theta)$  be the continuation value for incumbents. Its  $i$ th element is the expected value of being an incumbent conditional on continuing at state  $(n_i, m_i)$ , i.e.,  $E_{(n', m')|(n_i, m_i)}^c E_\phi V^I(n', m', \phi; \eta, \theta)$ . We also analogously define the vectors  $\pi(\eta, \theta)$  and  $p^x$  as the profit and the probability of exit. Then, applying the expectation operator to both sides of equation (1), we have that the value of continuation satisfies the following equation in vector form:

$$\begin{aligned} VC(\eta, \theta) &= M^c [\pi(\eta, \theta) + \beta E_\phi \max\{VC(\eta, \theta), \phi\}] \\ &= M^c [\pi(\eta, \theta) + \beta VC(\eta, \theta) + \beta \sigma p^x], \end{aligned} \quad (6)$$

where  $M^c$  is a matrix whose  $ij$ -element is the transition probability from  $(n_i, m_i)$  to  $(n_j, m_j)$  conditional on an incumbent continuing, and the second equation holds because the entry cost  $\phi$

follows an exponential distribution with expectation  $\sigma$ .

Analogously to the incumbent's problem, let  $VE(\eta, \theta)$  be the vector of entry value, whose  $i$ th element is  $E_{(n', m')|(n_i, m_i)}^e E_{\phi'} V^I(n', m', \phi'; \eta, \theta)$ . Note that the value of entry  $VE(\eta, \theta)$  and the value of continuation  $VC(\eta, \theta)$  differ only in the expectation operators. Therefore, we have

$$VE(\eta, \theta) = M^e [\pi(\eta, \theta) + \beta VC(\eta, \theta) + \beta \sigma p^x], \quad (7)$$

where  $M^e$  is a matrix whose  $ij$ -element is the transition probability from  $(n_i, m_i)$  to  $(n_j, m_j)$  conditional on a potential entrant entering.

Finally, in Model 2, we also need to compute the value of waiting. Let the vector  $VW(\eta, \theta)$  be the value of waiting. Its  $i$ th element is  $E_{(n', m')|(n_i, m_i)}^w E_{\varphi'} V^P(n', m', \varphi'; \eta, \theta)$ . Applying the expectation operation  $E_{(n', m')|(n_i, m_i)}^w E_{\varphi'}$  to both sides of (4) yields

$$\begin{aligned} VW(\eta, \theta) &= M^w \{p^e [-E(\varphi|\varphi < \beta VE(\eta, \theta) - \beta VW(\eta, \theta)) + \beta VE(\eta, \theta)] \\ &\quad + (1 - p^e) \beta VW(\eta, \theta)\}, \end{aligned} \quad (8)$$

where  $M^w$  is a matrix whose  $ij$ -element is the transition probability from  $(n_i, m_i)$  to  $(n_j, m_j)$  conditional on a potential entrant waiting, and  $p^e$  is the vector of the probability of entry.

### 3.2 Estimation of the Transition Probability Matrices

To estimate  $VC(\eta, \theta)$ ,  $VE(\eta, \theta)$  and  $VW(\eta, \theta)$ , I need consistent estimates of the transition matrices  $M^c, M^e, M^w$  and the probabilities  $p^x$  and  $p^e$ . I use their empirical counterparts. In the empirical implementation below, each observation is a market-year in the data. Let  $K(n, m) = \{k : (n_{(k)}, m_{(k)}) = (n, m)\}$  be the set of market-years with the same  $(n, m)$ , and  $n_{(k)}$ ,  $m_{(k)}$  and  $x_{(k)}$  are the number of incumbents, the market size, and the number of exits in market-year  $k$ , respectively.<sup>5</sup> The estimate of the transition probability conditional on an incumbent continuing is

$$\hat{M}_{ij}^c = \frac{\sum_{k \in K(n_i, m_i)} (n_i - x_{(k)}) 1 \{(n_{(k+1)}, m_{(k+1)}) = (n_j, m_j)\}}{\sum_{k \in K(n_i, m_i)} (n_i - x_{(k)})}, \quad (9)$$

where  $(n_{(k+1)}, m_{(k+1)})$  is the state in the same market, but one period after market-year  $k$ ,<sup>6</sup> and  $1\{\cdot\}$  is an indicator function. Since  $M^c$  is an incumbent's belief conditional on itself continuing, I weight the transition probability from state  $(n_i, m_i)$  by the number of incumbents who actually continue in those market-years at this state. However, if for some state  $(n_{i^o}, m_{i^o})$ , all the incumbents in all the market-years in  $K(n_{i^o}, m_{i^o})$  exit, then  $\sum_{k \in K(n_{i^o}, m_{i^o})} (n_i - x_{(k)}) = 0$  and the above estimate is

<sup>5</sup>From now on, the subscripts in the parentheses denote the market-years, and those without parentheses are indices of the states.

<sup>6</sup>If  $(n_i, m_i)$  is only observed in the last year, I impute the transition probability from  $(n_i, m_i)$  by taking the average of the transition probabilities from the states nearby.

not valid. In this case, the estimate is

$$\hat{M}_{i^o j}^c = \frac{\sum_{k \in K(n_{i^o}, m_{i^o})} 1 \{e_{(k)} = n_j - 1, m_{(k+1)} = m_j\}}{\#K(n_{i^o}, m_{i^o})}, \quad (10)$$

where  $e_{(k)}$  is the number of entrants in market-year  $k$ . Since the estimate of the probability of exit at  $(n_{i^o}, m_{i^o})$  is 1 in this case, the incumbent believes that all other incumbents will exit. Conditional on itself continuing, the probability of transiting to state  $(n_j, m_j)$  equals the probability of  $e = n_j - 1$  and  $m' = m_j$ .<sup>7</sup>

Similarly, the estimate of a potential entrant's belief about the state next period conditional on itself entering is

$$\hat{M}_{ij}^e = \frac{\sum_{k \in K(n_i, m_i)} e_{(k)} 1 \{(n_{(k+1)}, m_{(k+1)}) = (n_j, m_j)\}}{\sum_{k \in K(n_i, m_i)} e_{(k)}}. \quad (11)$$

I weight the transition probability by the number of potential entrants who actually enter.

If at some state  $(n_{i^o}, m_{i^o})$ , no store enters in any market-year in  $K(n_{i^o}, m_{i^o})$ , then the estimate is

$$\hat{M}_{i^o j}^e = \frac{\sum_{k \in K(n_{i^o}, m_{i^o})} 1 \{x_{(k)} = n_{i^o} + 1 - n_j, m_{(k+1)} = m_j\}}{\#K(n_{i^o}, m_{i^o})}. \quad (12)$$

The idea is similar to the one leading to (10): when the entrant expects itself to be the only one entering, the probability of transiting from state  $(n_{i^o}, m_{i^o})$  to state  $(n_j, m_j)$  conditional on itself entering equals the probability of  $n_{i^o} - x + 1 = n_j$  and  $m' = m_j$ .<sup>8</sup>

Finally, the estimate of the transition probabilities conditional on waiting  $M^w$  is given by

$$\hat{M}_{ij}^w = \frac{\sum_{k \in K(n_i, m_i)} (\varepsilon - e_{(k)}) 1 \{(n_{(k+1)}, m_{(k+1)}) = (n_j, m_j)\}}{\sum_{k \in K(n_i, m_i)} (\varepsilon - e_{(k)})}. \quad (13)$$

The weight used here is the number of potential entrants who did not enter.

As for the exit probability and the entry probability at state  $(n, m)$ , their estimates are, respectively,

$$\hat{p}^x(n, m) = \frac{1}{\#K(n, m)} \sum_{k \in K(n, m)} \frac{x_{(k)}}{n}, \quad (14)$$

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<sup>7</sup>Another way to obtain this is to explicitly write down the conditional transition probability. The probability of transiting from state  $(n_i, m_i)$  to state  $(n_j, m_j)$  is  $\sum_{(e, x) \text{ s.t. } n_j = n_i + e - x} b^x(x, n_i - 1 | n_i, m_i) b^e(e, \varepsilon | n_i, m_i) \Pr(m_j | m_i)$ ,

where  $b^x(x, n_i - 1 | n_i, m_i)$  is the probability of  $x$  out of  $(n_i - 1)$  incumbents exiting at state  $(n_i, m_i)$ , and  $b^e(e, \varepsilon | n_i, m_i)$  is the probability of  $e$  out of  $\varepsilon$  potential entrants entering at state  $(n_i, m_i)$ . When the probability of exit is 1 at state  $(n_{i^o}, m_{i^o})$ ,  $b^x(x, n_{i^o} - 1 | n_{i^o}, m_{i^o}) = 0$  for  $x < n_{i^o} - 1$  and  $= 1$  for  $x = n_{i^o} - 1$ . So, the transition probability is reduced to  $b^e(n_j - 1, \varepsilon | n_{i^o}, m_{i^o}) \Pr(m_j | m_{i^o})$ . And the empirical counterpart of it is exactly the RHS of equation (10).

<sup>8</sup>Again, this expression can be obtained mathematically by noting that this conditional probability of transiting is  $\sum_{(e, x) \text{ s.t. } n_j = n_i + e - x} b^x(x, n_i | n_i, m_i) b^e(e - 1, \varepsilon - 1 | n_i, m_i) \Pr(m_j | m_i) = b^x(n_i + 1 - n_j, \varepsilon | n_i, m_i) \Pr(m_j | m_i)$  when the probability of entering is zero.

and

$$\hat{p}^e(n, m) = \frac{1}{\#K(n, m)} \sum_{k \in K(n, m)} \frac{e_{(k)}}{\varepsilon}. \quad (15)$$

### 3.3 Estimates of the Value Functions

With consistent estimates of the transition probability matrices and the entry and exit probabilities, I get consistent estimates of the value functions by replacing  $M^c, M^e, M^w, p^x$  and  $p^e$  in (6), (7) and (8) by their estimates. The estimates of the value functions are

$$\begin{aligned} \widehat{VC}(\eta, \theta) &= (I - \beta \hat{M}^c)^{-1} \hat{M}^c \pi(\eta, \theta) + \beta (I - \beta \hat{M}^c)^{-1} \hat{M}^c \hat{p}^x \sigma \\ &= \hat{A} \pi(\eta, \theta) + \hat{a} \sigma, \end{aligned} \quad (16)$$

where  $\hat{A} = (I - \beta \hat{M}^c)^{-1} \hat{M}^c$  and  $\hat{a} = \beta \hat{A} \hat{p}^x$ , and

$$\begin{aligned} \widehat{VE}(\eta, \theta) &= \hat{M}^e \left[ \pi(\eta, \theta) + \beta \widehat{VC}(\eta, \theta) + \beta \hat{p}^x \sigma \right] \\ &= \hat{B} \pi(\eta, \theta) + \hat{b} \sigma, \end{aligned} \quad (17)$$

where  $\hat{B} = \hat{M}^e (I + \beta \hat{A})$  and  $\hat{b} = \beta \hat{M}^e (\hat{a} + \hat{p}^x)$ . Note that I calculate  $\hat{A}, \hat{B}, \hat{a}$  and  $\hat{b}$  from the data, and need to do it only once in the estimation procedure.

One more detail to notice is that  $\hat{M}_{ij}^e$  and  $\hat{M}_{ij}^c$  may not have the same dimensions. Potential entrants can enter a market with no incumbent, but trivially, incumbents exist only in markets with at least one incumbent. Let  $\mathbb{S}$  and  $\mathbb{S}_1$  be the set of all states observed in the data and the set of states with a positive number of incumbents, respectively, and let  $S$  and  $S_1$  be the corresponding cardinalities of the two sets. Note that  $M_{ij}^e = 0$  for  $j$  such that  $n_j = 0$  because this transition matrix is the one conditional on the potential entrant itself entering and the number of incumbents next period is therefore at least one. All elements in the first  $(S - S_1)$  columns of  $M^e$ , which are the transition probability to states with  $n = 0$ , are all 0. So, I can just augment the  $S_1 \times 1$  vector  $VC(\eta, \theta)$  to a  $S \times 1$  vector by filling the first  $(S - S_1)$  elements by any constant and the rest by  $S_1 \times 1$  vector  $VC(\eta, \theta)$ . Then, the dimensions of the matrices in (17) are compatible. Similarly, I can augment the  $S_1 \times 1$  vector  $\hat{p}^x$  to a  $S \times 1$  vector.

To obtain the estimate of  $VW(\eta, \theta)$ , note that the RHS of equation (8) is a contraction mapping of  $VW(\eta, \theta)$  because  $\varphi$  is assumed to be a log concave random variable (with gamma distribution) and therefore,  $0 \leq \frac{\partial E(\varphi|\varphi < d)}{\partial d} \leq 1$  (see Proposition 1 of Heckman and Honore (1990)). So, I can obtain the consistent estimate of  $VW(\eta, \theta)$  by replacing  $M^w$  and  $VE(\eta, \theta)$  in (8) by their estimates, and solve the equation by iteration.

### 3.4 Moment Conditions

I estimate four parameters – profit function parameters  $(\eta, \theta)$  and distribution parameters  $(\sigma, \lambda)$  – using four moment conditions. The first two conditions make the model predictions of the entry and exit probabilities as close as possible to the frequencies observed in the data as possible. The third and fourth conditions posit that prediction errors are uncorrelated with market sizes.

Specifically, let the prediction error of entry and exit at state  $(n, m)$  be

$$\begin{aligned} Xerror(n, m) &= \hat{p}^x(n, m; \eta, \theta, \sigma) \cdot n - \frac{1}{\#K(n, m)} \left( \sum_{k \in K(n, m)} x^{(k)} \right), \\ Error(n, m) &= \hat{p}^e(n, m; \eta, \theta, \lambda) \cdot \varepsilon - \frac{1}{\#K(n, m)} \left( \sum_{k \in K(n, m)} e^{(k)} \right), \end{aligned}$$

where the model prediction of the exit probability  $\hat{p}^x(n, m; \eta, \theta, \lambda) = \Pr(\phi \geq \widehat{VC}(\eta, \theta); \sigma)$ , and the model prediction of the entry probability  $\hat{p}^e(n, m; \eta, \theta, \lambda)$  is  $\Pr(\varphi \leq \beta \widehat{VE}(\eta, \theta); \lambda)$  in Model 1 and  $\Pr(\varphi \leq \beta \widehat{VE}(\eta, \theta) - \beta \widehat{VW}(\eta, \theta); \lambda)$  in Model 2.

Using the denotations  $Xerror(n, m)$  and  $Error(n, m)$ , the empirical counterparts of the four moments can be written as

$$\frac{1}{S} \sum_{(n, m) \in \mathbb{S}} Error(n, m) = 0 \quad (18)$$

$$\frac{1}{S_1} \sum_{(n, m) \in \mathbb{S}_1} Xerror(n, m) = 0 \quad (19)$$

$$\frac{1}{\#M} \sum_{m \in M} \left( \frac{1}{\#N(m)} \sum_{n_i \in N(m)} Error(n_i, m) \right) \cdot m = 0 \quad (20)$$

$$\frac{1}{\#M} \sum_{m \in M} \left( \frac{1}{\#N_1(m)} \sum_{n_i \in N_1(m)} Xerror(n_i, m) \right) \cdot m = 0 \quad (21)$$

where  $N(m) = \{n : (n, m) \in \mathbb{S}\}$  is the set of incumbent numbers that are observed in the data for a given  $m$ ,  $N_1(m) = \{n : (n, m) \in \mathbb{S}_1\}$  is the set of positive numbers of incumbents that are observed in the data for given  $m$ , and  $M = \{m : (n, m) \in \mathbb{S}\}$  is the set of market sizes observed in the data.

## 4 Data

The data for the number of incumbents, entrants and exits are taken from the National Establishment Time-Series Database (California). This data is designed to describe the dynamics of the U.S. economy. It keeps track of the birth, death and relocation of all the establishments that were ever in business in California between 1990 and 2004. This dataset is therefore ideal for studying the issue

of entry and exit.<sup>9</sup> Population data in 1990 and 2000 come from the decennial census. Population data in the years between 1991 and 1999 is from the estimates provided by the Population Division of Department of Finance in California. Population after 2000 comes from the estimates from the Population Division of U.S. Census Bureau.

The National Establishment Time-Series Database has data for the years between 1990 and 2004. But since I do not have complete information about exits in the last year, the sample I use for estimation is between 1990 and 2003. More specifically, the sample is constructed as follows.

Markets in this paper are Census places. I choose this definition of market mainly because of data availability. For years without a census, the smallest geographic unit with population estimates is Census place. There are 428 places in California with population data in all the years between 1990 and 2003 and having video rental stores in at least one of the years. However, cities as large as Los Angeles and San Diego obviously cannot be considered as just one market for the video renting industry. Due to the high transportation cost relative to the price of renting videos, video rental stores at either end of the large cities would rarely be in a direct competition with each other. According to an annual report of the Video Software Dealers Association, the average customer travels only 3.2 miles in total for a round trip to a video rental store. With this concern, I restrict the markets in this study to be places with a population smaller than 150,000 and leave out 29 places with a population larger than that. Furthermore, I leave out 8 cities which have a number of video rental stores larger than 20 in at least one of the years. Including these 8 cities in the sample would increase the number of possible states the state variables can obtain by 23, and 13 of them have been observed only once in the data. I leave them out in order to reduce sampling error. So, the data used in this study is panel data with 391 markets in 14 years.

The number of incumbents in market  $c$  at time  $t$  is the number of establishments with the first four digits of the Primary Standard Industrial Classification (SIC) code at time  $t$  equal to “7841”, which is the SIC code for “Video Tape Rental” industry. Number of entrants in market  $c$  at time  $t$  is the sum of the followings three: (i) the number of establishments that started business as video stores in market  $c$  at time  $t$ ; (ii) the number of establishments that switched from other business to video rental store at time  $t$ , and was in market  $c$  at time  $t$ ; (iii) the number of establishments that moved from other places to market  $c$  at time  $t$  and were video rental stores after moving, no matter whether they were video stores before moving. Similarly, an establishment is considered as an exitor in market  $c$  at time  $t$  if it falls into one of the following three categories: (i) video stores in market  $c$  whose last year in business was  $t$ ; (ii) video stores in market  $c$  that switched to another business at time  $t$  (the first four digits of the SIC code in year  $t$  are 7841 and those in year  $t + 1$

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<sup>9</sup>One caveat of the dataset is that it does not provide information on whether a store is a company-owned chain store, which may be different from other stores in terms of profitability or entry costs. During the sample period of 1990 – 2004, there were two main video rental chains, Blockbuster and Hollywood Video. Their stores, including both the franchised ones and the company-owned ones, account for about 7% of all video rental stores ever in the sample, implying that “independent” stores do play an important role in this industry.

are not); (iii) video stores in market  $c$  that moved out of the market, no matter whether they were video stores after moving.

Table 1 shows the frequencies of entry and exit. It indicates that there is frequent entry and exit in the video rental store industry. The percentage of markets that witnessed at least one entry during the sample period (i.e., between 1990 and 2003) is as high as 95%. This percentage is 94% for exit. Similarly, the percentage of market/year combinations that experienced some entry is 35%; and this percentage is 33% for exit. Table 1 also suggests that entry and exit often coexist. The percentage of markets that have ever experienced both entry and exit in the same year is 64%. Similarly, the percentage of market/years that saw both entry and exit is 16%. Table 2 describes the number of entrants, the number of exits and the exit rate. The average number of entrants and the average number of exits in a market/year are, respectively, 0.55 and 0.47. The average exit rate is 10%. The entry rate depends on the assumption of the number of potential entrants, and is therefore not reported in this table.

Table 1: Number of markets/market-years with entry and exit

	Number	Ratio in sample
Sample size	391	1
Markets with entry <sup>a</sup>	374	95.65%
Markets with exit	366	93.61%
Markets with both entry and exit in the same year	251	64.19%
Market/years	5474 <sup>b</sup>	1
Market/years with entry	1934	35.33%
Market/years with exit	1821	33.27%
Market/years with both entry and exit in the same year	880	16.08%

<sup>a</sup> Market with entry in at least one of the years between 1990 and 2003.  
<sup>b</sup>  $C \times T$ , where  $C=391$  is the number of markets in the sample and  $T=14$  is the length of time series.

Table 2: Descriptive statistics, number of entrants and exits, exit rate

	Mean	Minimum	Maximum
Number of entrants	0.5451	0	7
Number of exits	0.4677	0	6
Exit rate <sup>a</sup>	0.0971	0	1

<sup>a</sup>Exit rate at time  $t$  is defined as  $\frac{x_t}{n_t}$ , where  $x_t$  and  $n_t$  are the numbers of exits and incumbents at  $t$ .

## 5 Empirical results

The discount rate used in the estimation is given by 0.8, following Jofre-Bonet and Pesendorfer (2003). A state in this study is a pair  $(n, m)$ , where  $n$  is the number of incumbents and  $m$  is the market size. The number of incumbents,  $n$ , varies from 0 to 20 in the sample. I discretize population by dividing the population data into a grid of 40 bins with the same number of observations in each bin and use the median of each bin as  $m$ .<sup>10</sup> Standard deviations of the estimates are obtained by bootstrap.

Table 3 presents the estimation results based on Model 1 where a potential entrant is a short-run player. The four columns show the estimation results for the model with different numbers of potential entrants, which varies from 7 to 10. Table 3 indicates that the results are robust to the number of potential entrants. In what follows, I focus on the results with 7 potential entrants.

Table 3: Estimation result

	$\varepsilon = 7$		$\varepsilon = 8$		$\varepsilon = 9$		$\varepsilon = 10$	
$\eta$	0.377	(0.038)	0.360	(0.038)	0.361	(0.039)	0.370	(0.042)
$\theta$	0.521	(0.016)	0.489	(0.017)	0.501	(0.015)	0.524	(0.017)
$\sigma$	1.626	(0.116)	1.697	(0.118)	1.661	(0.113)	1.600	(0.109)
$\lambda$	0.495	(0.023)	0.465	(0.022)	0.461	(0.021)	0.465	(0.022)

Notes: Standard deviations are in the parentheses. They are obtained by 1000 bootstrap simulations for models with  $\varepsilon=7$  and  $\varepsilon=10$ , 200 parametric bootstrap simulations for models with  $\varepsilon=8$  and  $\varepsilon=9$ .

The elasticity of profit to market size is  $\hat{\eta} = 0.377$ , and that to  $(1 + n)$  is  $\hat{\theta} = 0.521$ . Figure 4 plots the profits at the states observable in data, together with the values of entry and continuation at these states. The states are sorted by the number of stores first and then by market size. From the figure, we can see the comovement of the values of entry and continuation, with the latter slightly higher at most states. However, these values do not always move in the same direction as profit. This is likely due to expectations about the evolution of the market. For example, a small number of competitors implies that the current profit is higher than that in a market with the same market size and a larger number of competitors. But it also means the number of entrants might be higher. As a result, the discounted value of cash flows, i.e., the values of entry or continuation, might be even lower than that in market with a slightly larger number of competitors. A static model typically implicitly assumes that the expectation about the evolution of the market equals the current state. This result (i.e., the entry and continuation values and the profit do not always move in the same direction) indicates that such an assumption made in static models is not valid at least in the empirical context studied in this paper.

Figure 5 plots the probabilities of entry, exit and continuation, i.e.,  $\Pr(\varphi \leq \beta VE)$ ,  $\Pr(\phi \geq VC)$

<sup>10</sup>The estimates are robust to different methods of discretization.

and  $\Pr(\phi \leq VC)$ . When the discounted value of entry (i.e.,  $\beta VE$ ) is small, there is no entrant. As it increases, the probability of entry increases. Also, the line of the probability of continuing is always above that of entry, indicating that the distribution of sell-off values first-order stochastically dominates that of the costs of entry. This is consistent with the intuition that the one-period cost of entry is smaller than the sell-off values that are related to the lifetime value of the stores. This is again evidence that a static model is not good for this kind of investigation because it does not distinguish incumbents from potential entrants and thus implicitly assumes that the distributions of entry cost and sell-off values are the same.

In Figure 6, I plot the ratio of the average entry cost for entrants (the stores who did enter the market) to the profit of the incumbents at each state, i.e.,  $E(\varphi|\varphi < \beta VE(n, m)) / \pi(n, m)$ . The ratio varies between 2.22 and 7.18. On average (across all states with entry), the entrants pay 4.36 times the incumbents' per-period profits to enter the market. For incumbents (see Figure 7), the ratio of the average sell-off values to the profit they earn in the period they exit (i.e.,  $E(\phi|\phi > VC(n, m)) / \pi(n, m)$ ) is in the range of 4.60 and 16.03.

Figures 8 and 9 show how well the model fits the data. Specifically, Figure 8 compares the average number of entrants for each state from the data to that from the estimation. Figure 9 does the same for the number of exits. From these figures, we can see that the model overall fits the data well, except that it somewhat overestimates the number of entrants when there are few incumbents in the market, and underestimates the number of entrants when there are more incumbents.

When I switch to Model 2, where a potential entrant is considered to be a long-run player, however, the fit gets worse. Specifically, I re-estimate the model using Model 2, simulate the number of entrants and the number of exits in each state according to the estimated model, and compare them to their counterparts directly from data. I show these comparisons in Figure 10 for the number of entrants and in Figure 11 for the number of exits. These two figures indicate that the model with long-run potential entrants is worse at fitting the data compared to Model 1. Model 2 does a particularly bad job at fitting the number of entrants: it over-predicts the number of entrants in states where the number of incumbents is small by more than around 6 new entrants and under-predicts it in states where the number of incumbents is large by 2 to 4 new entrants. This is probably because the elasticity of profit with respect to the number of incumbents is over-estimated in this model. According to Model 2, this elasticity with respect to  $(1 + n)$  is 6.850, implying that a firm's profit decreases by 94% if the number of firms in a market increases from 1 to 2. In contrast, according to Model 1, this elasticity is -0.521, implying that when a market changes from a monopoly market to a duopoly market, the profit of a firm decreases by 19%, which is a much more reasonable amount. Overall, the comparison of the fit to the data across Model 1 and Model 2 suggest that potential entrants in this industry are short-run players. They simply decide whether to enter or not all, rather than the timing of entry. This result is in contrast to the finding in Fan and Xiao (2015). Fan and Xiao (2015) find that, in the local telephone market,

potential entrants are long-run players. This difference in results is likely explained by the fact that video rental stores are smaller businesses than telecommunications companies. As a result, they may tend to make simpler decisions.

## 6 Conclusion

In this paper, I jointly estimate the profit function and the distributions of the costs of entry and the sell-off values for video rental stores. I find that the distribution of sell-off values of video rental stores first order stochastically dominates the distribution of the cost of entry into the video rental market. Entrants on average spend 2 to 7 times of incumbents' profit to enter a market, depending on the state of the market when they enter. The stores who exit the market on average get 4 to 16 times of the profit they earn in each period when they sell off their stores. These results indicate that a static model which assumes equal entry costs and sell-off values will not capture the entry decision in this industry well. Moreover, by comparing two alternative models of potential entrants' behavior, I find that the entry decision seems to be a one-shot decision. Potential entrants do not decide on entering now or later. They just make a decision about whether to enter now or never. This is probably because the potential entrants in this industry are relatively small business owners.

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Figure 4: Value functions and profit function

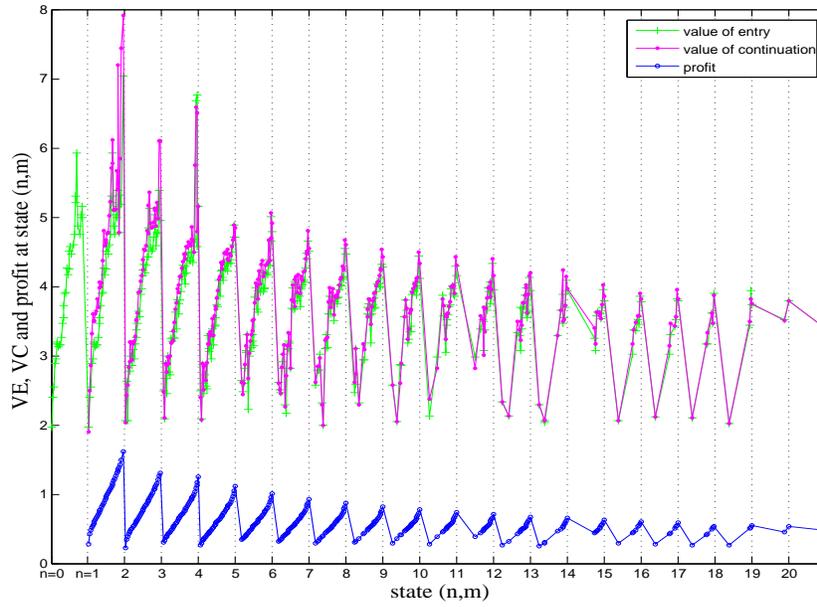


Figure 5: Probabilities of entry, exit and continuing

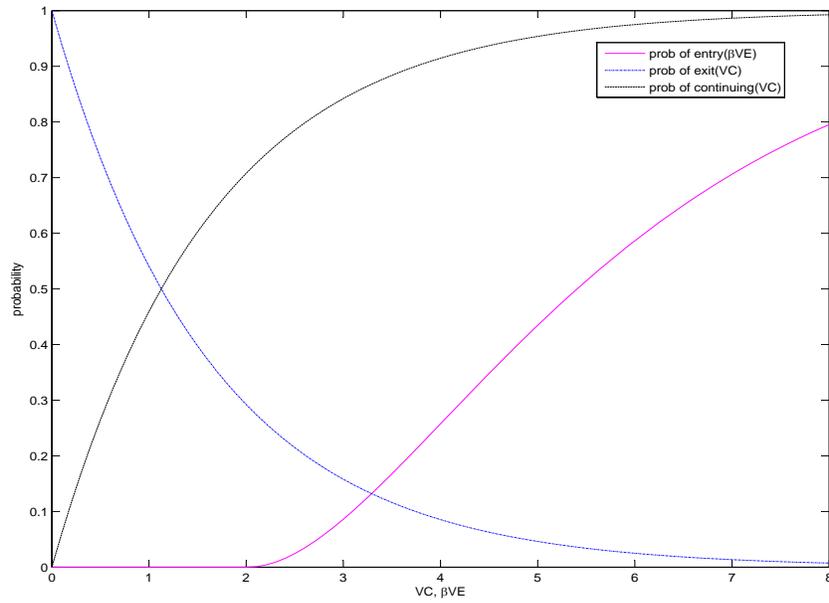


Figure 6: Ratio of the average entry cost for entrants to the profit of the incumbents

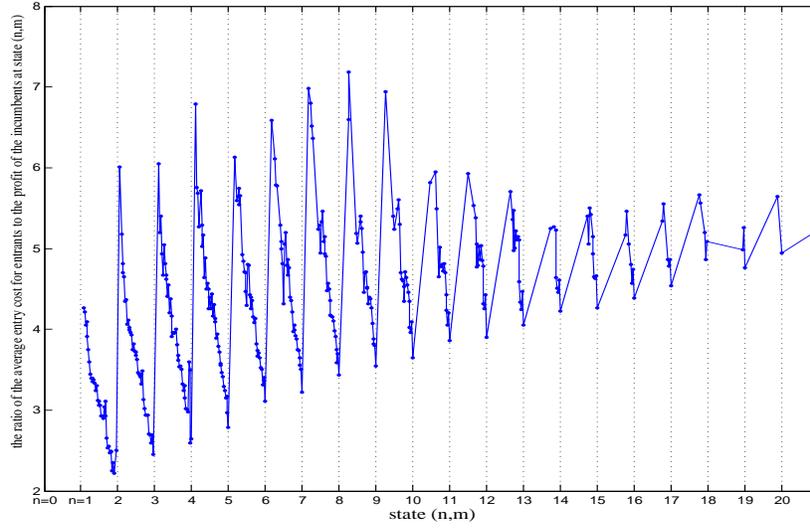


Figure 7: Ratio of the average sell-off values for exitors to their profits

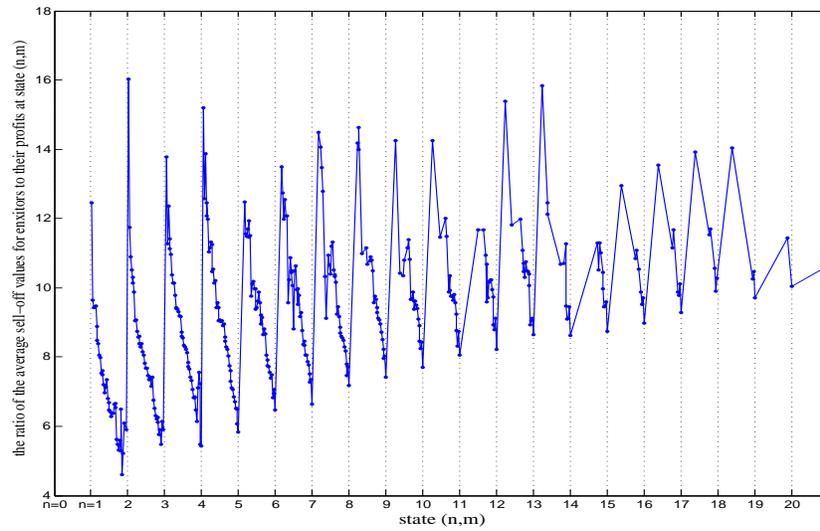


Figure 8: Fitting of the number of entrants

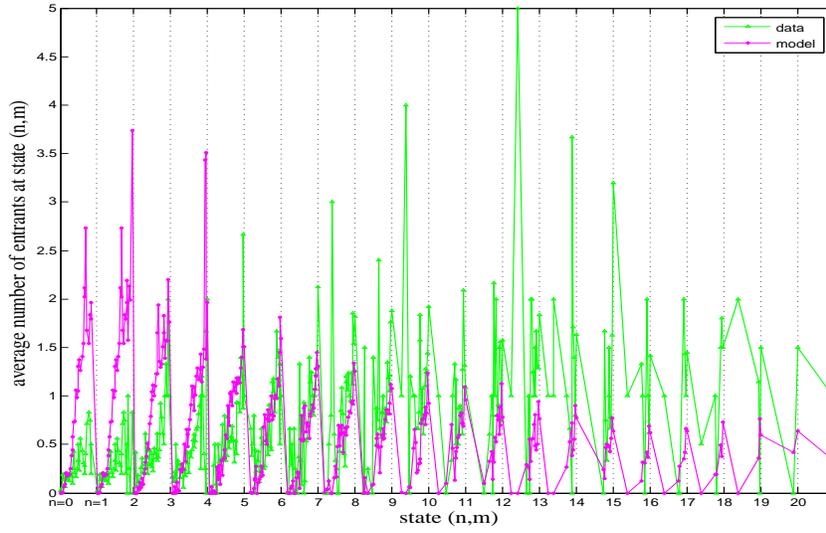


Figure 9: Fitting of the number of exits

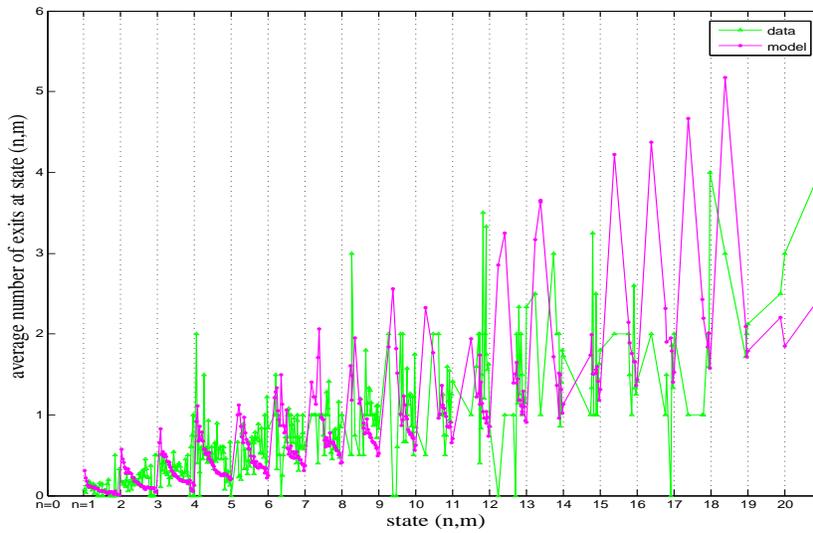


Figure 10: Fitting of the number of entrants (long-run potential entrants)

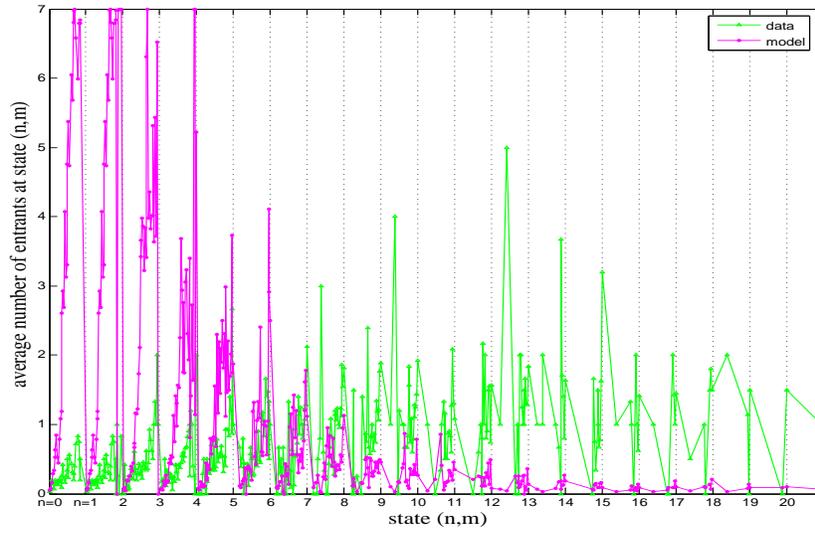


Figure 11: Fitting of the number of exits (long-run potential entrants)

