

# Choosing between Order-of-Entry Assumptions in Empirical Entry Models: Evidence from Competition between Burger King and McDonald's Restaurant Outlets

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September 2, 2013

Forthcoming in *Journal of Industrial Economics*

## Abstract

We demonstrate how a non-nested statistical test developed by Vuong (1989) can be used to assess the suitability of alternate order-of-entry assumptions used for identification purposes in empirical entry models. As an example, we estimate an entry model of McDonald's and Burger King restaurant outlets in United States. The data set focuses on relatively small "isolated" markets. For these markets, the non-nested tests suggest that order-of-entry assumptions that give Burger King outlets a first-mover advantage are statistically preferred. Last, a Monte Carlo experiment provides encouraging results suggesting that the Vuong-type test yields reliable results within the entry model framework.

*Keywords:* Empirical Entry Model; Non-nested Statistical Test; Competition in Fast Food

*JEL Classification codes:* L13; L66; C1; C25

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We thank the editor, John Asker, and two anonymous referees for very helpful comments that significantly improved the quality of this paper. We thank Daru Zhang for her dedicated work in data collection and Zhuojie Huang for his specialty in GIS. The authors benefited from discussions with Linchun Chen, Kim P. Huynh, Felicia Ionescu, and Dean Scrimgeour. This paper was presented at the 2012 International Industrial Organization Conference in Washington, D.C., March 16, 2012, and in South China Normal University, Guangzhou, China. We thank Mark Manuszak, Mark Roberts, Rodrigo Moita, Hiau Looi Kee, Javier Elizalde, Brian Adams, Zhiqiang Dong, Yuan Liu, Jie Wang, Zhong Wang, and conference participants for their helpful comments. All remaining errors are ours.

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## 1. Introduction

Static econometric entry models with heterogeneous firms often pose estimation challenges due to the presence of multiple Nash equilibria. One way researchers have dealt with these challenges is to invoke one of many alternate equilibrium selection assumptions to render identification and estimation feasible. While econometrically convenient, such equilibrium selection assumptions are not always easy to justify. However, at a minimum it may provide more comfort to readers of this type of research if researchers provide statistical evidence that discriminate among alternative equilibrium selection assumptions. As such, the main contribution of this paper is to show how Vuong-type non-nested tests [see Vuong (1989)] can be used to choose between alternate equilibrium selection assumptions that are commonly made when using static entry models. To illustrate the implementation of non-nested tests, we use data on the presence of Burger King and McDonald's restaurant outlets in a cross-section of local markets in the United States. We also use the opportunity to provide inference on competition between Burger King and McDonald's restaurant outlets in the United States, which is another contribution of our paper.

Static entry models can be divided into two categories: (i) entry models of complete information; and (ii) entry models of incomplete information. The complete information assumption in entry models implies that all parts of each firm's profit function are common knowledge to rival firms. In contrast, an incomplete information assumption implies that part of each firm's profit function is private information for the firm. Multiple Nash equilibria in the entry game can occur irrespective of whether complete or incomplete information is assumed for

the profit functions of firms.<sup>1</sup> However, in this paper we focus on static entry games of complete information.<sup>2</sup>

Researchers have used various methods to deal with the challenges posed by multiple Nash equilibria in static entry models of complete information. For example, Bresnahan and Reiss (1991) proposed that the model be restricted to predict the total number of entering firms but not firm identities. However, a caveat with this approach is that the researcher will not be able to make use of information that captures the heterogeneity of firms. Berry (1992), Mazzeo (2002), Tamer (2003), Einav (2010), and Cleeren et al. (2010), among others,<sup>3</sup> provide an alternative method to obtain unique equilibrium while still allowing for firm heterogeneity. In particular, these papers exploit the fact that a unique equilibrium of the entry model can be obtained by assuming that firms enter the relevant market sequentially. Since first-movers preempt other players in an entry game, an order-of-entry assumption essentially is an equilibrium selection assumption when multiple equilibria differ based on the identity of firms that ultimately enter. It must be noted however, that while the sequential entry assumption may be used to obtain a unique equilibrium of the entry model, the order-of-entry assumption does not further imply that price and output determination follow this assumed order.

An alternative estimation strategy that can handle situations of multiple equilibria, and does not require invoking an order-of-entry assumption, is the “bounds-type” approach outlined in Ciliberto and Tamer (2009). However, the bounds-type estimation approach has its own challenges. For example, parameters might only be set identified rather than point identified

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<sup>1</sup> In a dynamic entry/exit game setting, Doraszelski and Satterthwaite (2010) argue that an equilibrium might not exist when firms are not allowed to choose mixed entry/exit strategies in an entry/exit game of complete information. The authors further show that, instead of allowing mixed strategies, an incomplete information assumption is an alternate way to guarantee that an equilibrium exists in the entry/exit game.

<sup>2</sup> For examples of entry models of incomplete information, see Seim (2006), Einav (2010) and Yang (2012).

<sup>3</sup> See Berry and Reiss (2007) for an excellent review of this literature.

when using the bounds-type estimation approach, but invoking an order-of-entry assumption approach makes it possible to point identify parameters. So some researchers may still opt to go the route of invoking an order-of-entry assumption to estimate parameters of the entry model. Our paper illustrates to these researchers one way to formally test competing order-of-entry assumptions if their preferred estimation strategy is to invoke an order-of-entry assumption.

First, we use the empirical entry model framework developed by Cleeren et al. (2010) to identify a unique equilibrium in a multi-player, multi-equilibrium, entry game. This framework easily allows for estimation of the entry model under alternate order-of-entry assumptions. We then focus on statistical selection of the most appropriate order-of-entry assumption for the entry model. The basic framework for the non-nested maximum likelihood statistical selection test is developed by Vuong (1989), but we implement it in the context of long-run strategic entry decisions of firms, while Gasmi, Laffont, and Vuong (1992) implement it to distinguish between different assumptions about the nature of short-run product market competition between firms.

Across the types of markets in the McDonald's-Burger King data set we use, we find that order-of-entry assumptions that give Burger King outlets first-mover advantage are statistically favored. Furthermore, there is evidence that order-of-entry assumptions matter for the resulting parameter estimates of the type of entry model we consider, which can prove crucial in settings where policy conclusions need to be drawn based on estimated parameters. In the data section we discuss the characteristics of markets present in our data set. We also run a small-scale Monte Carlo experiment to assess the power of the test in distinguishing between alternate order-of-entry assumptions. The experiment reveals that the test gives correct results in 77 out of 100 simulations.

Since our econometric analysis is applied to data on Burger King and McDonald's restaurant outlets in United States, it is instructive to briefly review previous work on the fast-food industry. Most papers in this literature conclude that there is significant difference between McDonald's and Burger King's response to various market characteristics and therefore these two chains are not considered perfectly substitutable. Some researchers such as Lafontaine (1995) and Kalnins and Lafontaine (2004) focus on the franchising feature of the industry. They identify different factors that affect franchisee and franchisor's decision-making. Graddy (1997) focuses on price discrimination within the fast-food industry, while Stewart and Davis (2005) are more generally concerned about price dispersion of different fast-food chains. Kalnins (2003) applies spatial econometrics to hamburger price data to assess the degree of substitutability of products and locations of spatially dispersed franchised chains. Thomadsen (2005) uses spatial econometric models to analyze how ownership structure and market geographic characteristics jointly influence the pricing decision of McDonald's and Burger King restaurant outlets and found that McDonald's outlets give a statistically significant higher utility to consumers than do Burger King outlets. Thomadsen (2007) examines the optimal product positioning decision of McDonald's and Burger King restaurant outlets and finds that the equilibrium depends crucially on market size.

Standard models of entry, which include the type of entry model we use in this paper, capture the competitive effects of entry, i.e. reduction in profits due to additional entry, but not the effects of learning. Toivanen and Waterson (2005) constructed an entry model designed to capture the effects of learning. Specifically, they design their entry model to identify a positive spillover effect between competitors when there is at least one store of the competing firm already present in the market. The authors estimate their model using panel data on the

presences of McDonald's and Burger King restaurant outlets in local markets in the United Kingdom (U.K.). They find that existing rival presence in a market increases the probability of entry by increasing expected market size. This result suggests that a potential entrant can learn about the profitability of a market by observing the existing rival's performance.

Yang (2012) uses the same dataset as Toivanen and Waterson (2005) and further explored the learning aspects of firms' entry strategy, but in contrast, Yang (2012) uses a framework in which firms have incomplete information about each other's profitability. The positive spillover effect result persists even under incomplete information. Importantly, Yang (2012) distinguishes between hidden information on cost or demand. He finds that significant positive spillover effects for both restaurant chains can only be found in the hidden cost specification, while a learning effect is significant and positive for Burger King under all specifications.

The rest of the paper is organized as follows: Section 2 outlines the econometric model as well as the non-nested test procedure used for selecting the appropriate order-of-entry assumption. In Section 3 we discuss our data and descriptive statistics. Section 4 presents estimation results from our model as well as results of the non-nested test. The last section concludes.

## 2. The Model

Let the numbers of McDonald's ( $M$  or MAC) and Burger King ( $B$  or BK) restaurant outlets in a market be denoted by  $N_M$  and  $N_B$ , respectively. Profit for an outlet of chain type  $f (= M, B)$  is given by a latent variable  $\Pi_f$  such that

$$\Pi_f(N_M, N_B) = \pi_f(N_M, N_B) - \varepsilon_f, \quad (1)$$

where  $\pi_f(N_M, N_B)$  is the deterministic part, and  $\varepsilon_f$  is the part that is unobservable to researchers but observed by all firms (complete information assumption) and therefore we assume this part of profit is random. We assume that outlets of the same brand/chain are homogeneous.<sup>4</sup>

Three standard assumptions are employed here for the deterministic part of restaurant outlets' profit:

#### ASSUMPTION 1

$$\pi_M(N_M + 1, N_B) < \pi_M(N_M, N_B)$$

$$\pi_B(N_M, N_B + 1) < \pi_B(N_M, N_B)$$

#### ASSUMPTION 2

$$\pi_M(N_M, N_B + 1) \leq \pi_M(N_M, N_B)$$

$$\pi_B(N_M + 1, N_B) \leq \pi_B(N_M, N_B)$$

#### ASSUMPTION 3

$$\pi_M(N_M + 1, N_B - 1) < \pi_M(N_M, N_B)$$

$$\pi_B(N_M - 1, N_B + 1) < \pi_B(N_M, N_B).$$

Assumptions 1 and 2 are derived from the fact that restaurant outlets within any particular market, either of the same chain or not, compete with each other and thus a new entrant lowers the profitability of existing outlets of either chain. Assumption 3 states that the negative profit impact due to the new entry of within chain restaurant outlet is greater than the negative profit impact due to entry of a different type chain outlet. In other words, intra-chain competition is more intensive than inter-chain competition. As mathematically shown and proven in Cleeren et

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<sup>4</sup>See Thomadsen (2005) for a discussion of the justification of this homogenous assumption.

al. (2010),<sup>5</sup> each of these three assumptions is needed to derive a generalized probability expression (see equation (3) below) that deals with all the possible cases in which multiple Nash equilibrium might arise. In other words, together, these three assumptions are necessary to ensure a well defined probability space on which to build the likelihood function.

With these assumptions, an observed market structure  $(n_M, n_B)$  is a Nash equilibrium if

$$\begin{aligned} \pi_M(n_M + 1, n_B) < \varepsilon_M \leq \pi_M(n_M, n_B) \\ \pi_B(n_M, n_B + 1) < \varepsilon_B \leq \pi_B(n_M, n_B) \end{aligned} \quad (2)$$

Conditions in (2) will admit multiple Nash equilibria without additional structure on the entry game. Furthermore, these conditions will yield a unique Nash if we assume that outlets enter according to a certain sequence. In addition, Cleeren et al. (2010) argue that when looking at a market structure with totally  $n$  competing firms, “only the number of players of each type during these first  $n$  moves matters, and their exact order of entry is otherwise irrelevant (p.462).”

Let  $\tilde{n}_M$  be the number of McDonald’s outlets during the first  $n$  moves in the assumed sequence of entry, the probability of observing market structure  $(n_M, n_B)$  as a Subgame Perfect Nash Equilibrium (SPNE) is given by:

$$\begin{aligned} & P(N_M = n_M, N_B = n_B) \\ &= \int_{\pi_M(n_M+1, n_B)}^{\pi_M(n_M, n_B)} \int_{\pi_B(n_M, n_B+1)}^{\pi_B(n_M, n_B)} \phi(u_M, u_B) du_M du_B \\ & - I(\tilde{n}_M - n_M) \int_{\pi_M(n_M+1, n_B)}^{\pi_M(n_M+1, n_B-1)} \int_{\pi_B(n_M+1, n_B)}^{\pi_B(n_M, n_B)} \phi(u_M, u_B) du_M du_B \\ & - I(n_M - \tilde{n}_M) \int_{\pi_M(n_M, n_B+1)}^{\pi_M(n_M, n_B)} \int_{\pi_B(n_M-1, n_B+1)}^{\pi_B(n_M, n_B+1)} \phi(u_M, u_B) du_M du_B \end{aligned} \quad (3)$$

where  $I(x)$  is an indicator function that takes the value 1 if  $x > 0$ , and 0 otherwise.  $\phi(\cdot)$

denotes the standardized bivariate normal density function specified as:

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<sup>5</sup> In Cleeren et al. (2010), see Assumptions 1, 2A and 2B on page 460, Claims 1, 2 and 3 and the discussion of these claims on page 461, as well as the formal proof of these claims in the Appendix.



$$\phi(u_M, u_B) = \frac{1}{2\pi\sigma_{u_M}\sigma_{u_B}\sqrt{1-\rho^2}} \exp\left[-\frac{1}{2}\left(\frac{u_M^2 + u_B^2 - 2\rho u_M u_B}{1-\rho^2}\right)\right], \quad (4)$$

where  $\rho$  is a parameter that measures the correlation of shocks across chain-type profits with  $-1 < \rho < 1$ . When  $\rho \neq 0$ , equations (3) and (4) together yield a bivariate ordered probit model with endogenous variables  $(n_M, n_B)$ . However, if we impose the restriction  $\rho = 0$ , then shocks to chain-type profits are assumed independent and the model reduces to two separate ordered probit models - one for each chain-type.

Suppose in a market there are two McDonald's outlets and two Burger King outlets. If the assumed sequence of entry for up to 6 outlets is given either by MBMBMB, MMBBMB, or BBMMMB, based on equation (3) the probability of observing market structure  $(n_M, n_B) = (2, 2)$  is given by the same expression,

$$P(N_M = n_M, N_B = n_B) = \int_{\pi_M(n_M+1, n_B)}^{\pi_M(n_M, n_B)} \int_{\pi_B(n_M, n_B+1)}^{\pi_B(n_M, n_B)} \phi(u_M, u_B) du_M du_B.$$

This is because for all three of these assumed entry sequences, there are exactly two McDonald's outlets in the first  $4 = n_M + n_B$  entries, i.e.  $\tilde{n}_M = 2$ , which implies that indicator function  $I(\bullet)$  in equation (3) yields the following:  $I(\tilde{n}_M - n_M) = I(n_M - \tilde{n}_M) = I(2 - 2) = 0$ .<sup>6</sup> However, for those same assumed sequences of entry, the probability of observing market structure  $(n_M, n_B) = (1, 1)$  is computed using a different expression in each case.

Considering market structure  $(n_M, n_B) = (1, 1)$  and assumed order-of-entry MBMBMB, there is only 1 McDonald's outlet in the first  $2 = n_M + n_B$  entries, which implies,  $\tilde{n}_M = 1$  and the indicator function  $I(\bullet)$  in equation (3) yields the following:

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<sup>6</sup> Since our exposition draws heavily from Cleeren et al. (2010), the reader is referred to that paper for additional examples and discussion.

$I(\tilde{n}_M - n_M) = I(n_M - \tilde{n}_M) = I(1-1) = 0$ . Therefore, assuming entry sequence MBMBMB, the appropriate probability expression for the  $(n_M, n_B) = (1, 1)$  market structure that is implied by equation (3) is:

$$P(N_M = n_M, N_B = n_B) = \int_{\pi_M(n_M+1, n_B)}^{\pi_M(n_M, n_B)} \int_{\pi_B(n_M, n_B+1)}^{\pi_B(n_M, n_B)} \phi(u_M, u_B) du_M du_B.$$

Considering market structure  $(n_M, n_B) = (1, 1)$  and assumed order-of-entry MMBBMB, there are 2 McDonald's outlets in the first 2 entries, which implies  $\tilde{n}_M = 2$ ;  $I(\tilde{n}_M - n_M) = I(2-1) = 1$ ; and  $I(n_M - \tilde{n}_M) = I(1-2) = 0$ . Therefore, assuming entry sequence MMBBMB, the appropriate probability expression for the  $(n_M, n_B) = (1, 1)$  market structure that is implied by equation (3) is:

$$\begin{aligned} & P(N_M = n_M, N_B = n_B) \\ &= \int_{\pi_M(n_M+1, n_B)}^{\pi_M(n_M, n_B)} \int_{\pi_B(n_M, n_B+1)}^{\pi_B(n_M, n_B)} \phi(u_M, u_B) du_M du_B \\ & - \int_{\pi_M(n_M+1, n_B)}^{\pi_M(n_M+1, n_B-1)} \int_{\pi_B(n_M+1, n_B)}^{\pi_B(n_M, n_B)} \phi(u_M, u_B) du_M du_B \end{aligned}$$

Last, considering market structure  $(n_M, n_B) = (1, 1)$  and assumed order-of-entry BBMMMB, there is 0 McDonald's outlet in the first 2 entries, which implies,  $\tilde{n}_M = 0$ ;  $I(\tilde{n}_M - n_M) = I(0-1) = 0$ ; and  $I(n_M - \tilde{n}_M) = I(1-0) = 1$ . Therefore, assuming entry sequence BBMMMB, the appropriate probability expression for the  $(n_M, n_B) = (1, 1)$  market structure that is implied by equation (3) is:

$$\begin{aligned} & P(N_M = n_M, N_B = n_B) \\ &= \int_{\pi_M(n_M+1, n_B)}^{\pi_M(n_M, n_B)} \int_{\pi_B(n_M, n_B+1)}^{\pi_B(n_M, n_B)} \phi(u_M, u_B) du_M du_B \\ & - \int_{\pi_M(n_M, n_B+1)}^{\pi_M(n_M, n_B)} \int_{\pi_B(n_M-1, n_B+1)}^{\pi_B(n_M, n_B+1)} \phi(u_M, u_B) du_M du_B \end{aligned}$$

Once the probability expression for each market structure is constructed, we can easily compile these market structure probabilities to construct a well-defined log likelihood function:

$$LL = \sum_{t=1}^T \sum_{n'_M=0, n'_B=0}^{n_M^{\max}, n_B^{\max}} \log \left[ P(N_M^t = n_M^t, N_B^t = n_B^t) \right]^{D_{N_M^t, N_B^t}^t}, \quad (5)$$

where superscript  $t$  indexes markets and  $D_{N_M^t, N_B^t}^t$  is a zero-one indicator variable that equals one if  $N_M^t = n_M^t$  and  $N_B^t = n_B^t$  but zero otherwise. Note that the log likelihood function in equation (5) is a function of the correlation parameter,  $\rho$ , via equations (3) and (4). Additional parameters will be introduced once the profit function is specified.

### *Specification of Profit Function*

For any given market with market structure  $(N_M, N_B)$ , the deterministic part of profit is specified as:

$$\pi_f(N_M, N_B) = \beta_f X + \sum_{i=1}^{N_f-1} \delta_{f,i} + \sum_{j=1}^{N_f} \gamma_{f,j}, \quad (6)$$

where  $X$  is a vector of market-specific characteristics including population and other socio-demographic variables, while  $\beta_f$  is the associated chain-specific vector of parameters that capture how the profit of a restaurant outlet of a given chain-type is affected by a marginal change in the relevant market-specific characteristic.  $\delta_f$  measures the marginal profit effect due to entry of same chain-type restaurant outlets (intra-chain competition), while  $\gamma_f$  measures the marginal profit effect due to entry of different chain-type restaurant outlets (inter-chain competition).  $\beta_f$ ,  $\delta_f$ , and  $\gamma_f$  are chain-specific parameters to be estimated.

Note that we assume  $\pi_f = 0$  when  $N_f = 0$ . Thus there are only  $N_f - 1$  intra-chain marginal competitive effect parameters starting from the second same chain-type restaurant outlet in the particular market. Also, from Assumptions 1-3, we must have,

$$\delta_f < 0; \gamma_f < 0; \delta_f < \gamma_f; \delta_{f,i} < \delta_{f,i+1}; \gamma_{f,i} < \gamma_{f,i+1}, (f = M, B).$$

In our estimation, we impose these restrictions.

Given the functional form specification of the profit function in equation (6) and the log likelihood equation in equation (5), we estimate the parameters of the model via Maximum Likelihood, that is, we estimate the parameters by solving the following optimization problem:<sup>7</sup>

$$\underset{\beta, \delta, \gamma, \rho}{\text{Max}} LL(X; \beta, \delta, \gamma, \rho). \quad (7)$$

### *Non-nested Test Procedure*

The non-nested test procedure we use in this paper is an application of tests developed by Vuong (1989). Gasmi, Laffont, and Vuong (1992) also applied the non-nested test procedures in a different setting. For each pair of assumed order-of-entry model specifications  $(S_p, S_q)$ , the likelihood ratio statistic is:

$$LR \equiv \sum_{t=1}^T (LL_t^p - LL_t^q), \quad (8)$$

where  $T$  is the total number of observations in the sample, while  $LL_t^p$  and  $LL_t^q$  are the optimal values at observation  $t$  taken by the log likelihood functions for order-of-entry model specifications  $S_p$  and  $S_q$  respectively. Vuong (1989) argues that the likelihood ratio statistic in equation (8) can be normalized by its variance:

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<sup>7</sup> We numerically optimize the log likelihood function over the parameter space using the fminsearch algorithm in the MATLAB computer software.

$$\omega^2 = \frac{1}{T} \sum_{t=1}^T (LL_t^p - LL_t^q)^2 - \left[ \frac{1}{T} \sum_{t=1}^T (LL_t^p - LL_t^q) \right]^2, \quad (9)$$

so that the following non-nested test statistic:

$$NNT = T^{-0.5} \frac{LR}{\omega}, \quad (10)$$

is asymptotically distributed standard normal under the null hypothesis of equal fit.<sup>8</sup>

A one-tale statistical test at the 5% significance level for the standard normal distribution has critical values  $\pm 1.64$ . If  $-1.64 < NNT < 1.64$  we conclude the data are unable to discriminate between the two order-of-entry models, and therefore the null hypothesis cannot be rejected. If  $NNT < -1.64$ , we conclude that order-of-entry specification  $S_q$  better explains the data compared to specification  $S_p$ , but if  $NNT > 1.64$ , we conclude that specification  $S_p$  better explains the data compared to specification  $S_q$ .

One of the very important features of this type of non-nested normalized likelihood ratio test is that, as noted by Gasmi, Laffont, and Vuong (1992), it can be used to test between two different models even though one or both of them are mis-specified. In other words, without committing to declare a “true” model, the test allows the researcher to conclude which, if any, of the two models being compared better fits the data.

### 3. Data

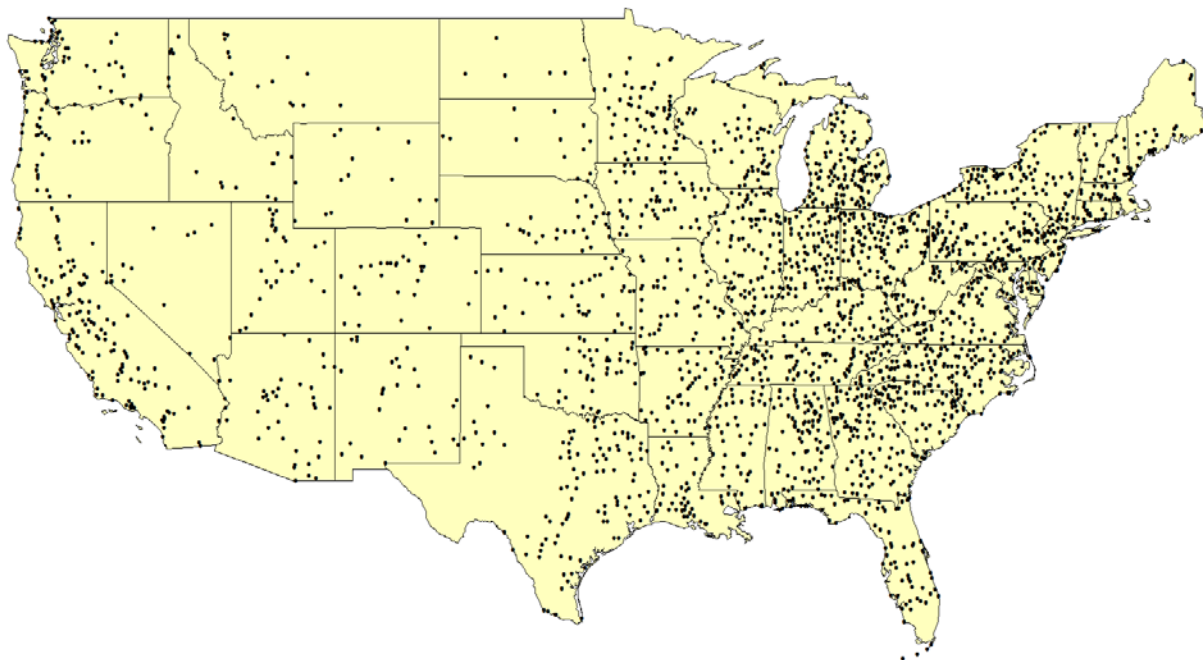
We obtained our dataset via the Internet in the spring of 2011. For store location information, we rely on McDonald’s and Burger King online restaurant locator on their homepage. We collect market structure data for the 48 contiguous states of the United States.

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<sup>8</sup> The equations used here for the LR statistic; the variance of the LR statistic; and the non-nested test statistic, correspond to equations (3.1), (4.2) and (5.6) on pages 312, 314 and 318 respectively in Vuong (1989).

Local “markets” are delineated at the city level. Socio-demographic characteristic data of each city are obtained from the U.S. Census Bureau Census 2000 Summary File 3. Google Map is used to ensure each city in our sample can reasonably be treated as a “single local market”. A single local market is defined as an “isolated city” that is more than 10 miles away from the closest neighboring city. It is well known in the literature that static entry models of the type we consider in this paper are better suited for data with a cross-section of individually “isolated markets”.

**Figure 1: Geographical Distribution of Markets**



In our data, we have included 2,506 isolated city areas. Figure 1 shows a geographical distribution of the cities/markets in our sample throughout the 48 contiguous states of the United States, where each market is designated with a black dot on the map. These cities each have at least one McDonald’s (MAC) or Burger King (BK) restaurant outlet, but neither restaurant chain

has more than 3 outlets. The total number of McDonald's restaurants in our sample is 3083, while the total number of Burger King restaurants is 2004.<sup>9</sup> The observed numbers of occurrences of each market structure in the data are reported in Table 1, while Table 2 presents definitions and simple descriptive statistics of all socio-demographic variables that we use in the analysis.

**Table 1: Observed Market Configurations**

Market Structure: ( $N_M, N_B$ )	Number of Markets	Percent of Total (%)
(1, 0)	728	29.05
(2, 0)	39	1.56
(3, 0)	7	0.28
(0, 1)	219	8.74
(1, 1)	924	36.87
(2, 1)	261	10.42
(3, 1)	99	3.95
(0, 2)	6	0.24
(1, 2)	34	1.36
(2, 2)	76	3.03
(3, 2)	70	2.79
(0, 3)	0	0
(1, 3)	1	0.04
(2, 3)	10	0.4
(3, 3)	32	1.28
Total	2506	100

Static entry models better fit industries that can reasonably be described as being in a long-run equilibrium state. According to the U.S. Securities and Exchange Commission (SEC)

<sup>9</sup> By year-end of 2011, McDonald's and Burger King have 14098 and 7204 outlets, respectively, in the United States. Thus our sample has 21.9% of all McDonald's outlets and 27.8% of all Burger King outlets in the U.S.

filings of McDonald's and Burger King, McDonald's outlets in the United States has gone from 13492 to 14157 between 2002 and 2012, an increase of less than 5% in 10 years, while Burger King outlets in the U.S. and Canada has gone from 7534 to 7476, a decrease of less than 1% in 6 years.<sup>10</sup> These numbers show that there are minimal changes in McDonald's and Burger King restaurant outlets over this 10-year period, and therefore it is reasonable to argue that during this period the industry in North America is approximately in a long-run equilibrium state.

**Table 2: Definition and Descriptive Statistics for Variables used in our Analysis**

<i>Name</i>	<i>Definition</i>	<i>Mean</i>	<i>Min</i>	<i>Max</i>	<i>S. D.</i>
Pop	Population (in 1K)	9.923	0.112	117.083	11.318
PCI	Per Capita Income (in 1K\$)	17.645	6.967	62.131	4.711
White	Percentage of Pop that is white (%)	83.16	1.67	100	18.15
Male	Percentage of Pop that is male (%)	47.71	33.51	68.62	2.87
Family <sup>a</sup>	Percentage of households reported as family (%)	65.91	27.47	97.25	7.96
BA	Percentage of population that has Bachelor's degree or above (%)	17.97	0.48	69.19	9.4

<sup>a</sup> From the definition of U.S. Census Bureau, "A family includes a householder and one or more other people living in the same household who are related to the householder by birth, marriage, or adoption... Thus, the number of family households is equal to the number of families." See documentation for Census 2000 Summary File 3 for detail.

Information in Table 1 provides some support for the three assumptions outlined in the model section of the paper. One challenge to those assumptions is the idea that restaurant outlets already present in a market can positively influence subsequent entry, an effect Toivanen and Waterson (2005) refer to as a positive spillover effect, which they found when analyzing the expansions of McDonald's and Burger King outlets in the United Kingdom. If there are strong

<sup>10</sup> The SEC filing documents are available only back to 2006 for Burger King when it first went IPO in that year. In addition, from 2006 to 2012, Burger King's K10 annual reports only provide numbers of outlets for U.S. and Canada combined.



positive spillover effects in our U.S. data set, we should expect the vast majority of markets to contain both McDonald's and Burger King outlets, and the correlation between outlets of both chain-types being in a given market should be high. However, only 60.14% of the markets in our sample contain both McDonald's and Burger King outlets. Moreover, the correlation between the presence of both in a given market is only 0.3618.<sup>11</sup> These characteristics of our data are appropriate for the model framework we use.

Judging from the standard deviations of the variables in Table 2, one can see that socio-demographic variations across our sample cities are not trivial. Not surprisingly, consistent with population density, Figure 1 shows that more markets are concentrated in the eastern and western regions of the United States compared to the central region.

We follow Mazzeo (2002) and transform socio-demographic variables in the following manner:

$$x_t^* = \ln \left[ x_t / \frac{1}{T} \sum_{t=1}^T x_t \right],$$

where  $T$  is the total number of observations of the full sample (2506 in our paper). This transformation implies that when the untransformed variable takes on a value equal to its mean, the associated transformed variable will take on a value of zero. These transformations should not affect the qualitative impact of variables since each variable's ordinal property is preserved. So for example, the transformed population variable still remains a valid index of market size. As discussed in Mazzeo (2002) and confirmed by our own experience, the advantage of such a transformation of the variables helps with making estimation of the nonlinear entry model easier.

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<sup>11</sup> After putting information in Table 1 into a 2506-by-2 matrix, we calculate the correlation of the two columns to obtain the correlation of 0.3618.

In Table 3, we present three reduced-form regression specifications in which number of McDonald’s restaurant outlets, number of Burger King restaurant outlets, and the total number of McDonald’s and Burger King restaurant outlets are dependent variables respectively. Table 3 demonstrates that the number of restaurant outlets is positively related to population, and negatively related to percentage of households reported as family. The variable “Highway” is a zero-one dummy variable that equals to 1 when a city/market is within 6 miles of driving distance to an interstate highway. Not surprisingly, locations close to inter-state highways attract both restaurants.

**Table 3: Reduced-form Regressions**

Variables	MAC	BK	MAC+BK
Constant	1.447** (0.226)	1.171** (0.207)	2.618** (0.315)
Pop	0.0391** (0.0023)	0.0289** (0.0018)	0.0680** (0.0036)
PCI	-0.0065 (0.0041)	-0.0018 (0.0039)	-0.0083 (0.0059)
White	-0.0711 (0.0963)	-0.274** (0.0904)	-0.345* (0.135)
Male	-0.0764 (0.414)	0.465 (0.360)	0.389 (0.563)
Family	-0.778** (0.180)	-1.080** (0.173)	-1.858** (0.257)
BA	0.232 (0.207)	-0.016 (0.193)	0.216 (0.299)
Highway	0.141** (0.0255)	0.174** (0.0230)	0.315** (0.0362)
Observations	2,506	2,506	2,506
R-squared	0.411	0.323	0.511

Notes: The reduced-form regressions are estimated using Ordinary Least Squares (OLS). We have included state dummies. Robust standard errors are in parentheses. \*\* indicates statistical significance at the 1% level; \* indicates statistical significance at the 5% level.

#### 4. Results

Recall that in our sample, there are maximum 3 McDonald’s and 3 Burger King restaurant outlets in any given market. Thus there could be up to 20 different possible entry

orders for these 6 restaurants. We begin by focusing on the following four order-of-entry specifications:

- (1) McDonald's outlets move first: MMMBBB
- (2) Burger King outlets move first: BBBMMM
- (3) Alternate moves starting with M: MBMBMB
- (4) Alternate moves starting with B: BMBMBM

In Table 4, we report profit function parameter estimates for both chain-type firms under each of the four distinct assumed entry orders. Several results can be drawn from these parameter estimates. First, among the socio-demographic variables we consider, the most robust determinants of entry are the size of population in a particular market (*Pop*), the percentage of family households (*Family*), and if city is within six miles of driving distance to an interstate highway (*Highway*). These results are consistent with those from the reduced-form regressions reported in Table 3. A location that is within six miles of the nearest interstate highway, which has a relatively large population and a small proportion of family households, appears to be most conducive for fast food entry. Both large local population and a nearby highway imply a larger market size. The positive signs from these two variables are consistent with previous literature. On the other hand, family households are more likely to cook on their own or go to a finer dining restaurant, which is suggested by the negative sign on the *Family* variable.

Second, intra-chain competitive effects ( $\delta_1$  and  $\delta_2$ ) are strong and statistically significant, while inter-chain competitive effects ( $\gamma_1$ ,  $\gamma_2$  and  $\gamma_3$ ) seem to be relatively weak. There could be several factors that contribute to these competitive effects results, one of which may be that differentiation across the chains are sufficiently strong and brand-loyal customers comprise a significant segment of the market. It is also possible that the weak inter-chain

competitive effects result could in part be due to some market characteristics that we the researchers cannot observe, and therefore cannot fully control for in the models.<sup>12</sup>

**Table 4: Estimation Results for the Static Entry Model**

	MMBBB		BBMMM		MBMBMB		BMBMBM	
	MAC	BK	MAC	BK	MAC	BK	MAC	BK
Constant	0.6401** (0.0581)	0.3868** (0.1085)	1.0072** (0.0675)	0.4214** (0.0793)	0.7182** (0.0730)	0.3662** (0.1153)	1.0298** (0.0644)	0.4187** (0.0742)
Pop	0.3664** (0.0210)	0.3593** (0.0266)	0.3772** (0.0209)	0.3702** (0.0250)	0.3763** (0.0207)	0.3664** (0.0247)	0.3803** (0.0201)	0.3795** (0.0231)
PCI	-0.1123 (0.0861)	0.0439 (0.0955)	-0.1093 (0.0749)	-0.0624 (0.0821)	-0.0808 (0.0862)	0.0492 (0.0961)	-0.1216 (0.0748)	-0.0500 (0.0843)
White	-0.0282 (0.0594)	-0.1536* (0.0599)	-0.0357 (0.0536)	-0.0893 (0.0527)	-0.0444 (0.0600)	-0.1593* (0.0585)	-0.0323 (0.0543)	-0.0998 (0.0534)
Male	-0.1712 (0.3034)	-0.2707 (0.3266)	-0.1284 (0.2840)	-0.1674 (0.3105)	-0.1343 (0.2981)	-0.2526 (0.3163)	-0.1380 (0.2847)	-0.2017 (0.3109)
Family	-0.6026** (0.1223)	-0.8639** (0.1301)	-0.5401** (0.1083)	-0.6879** (0.1171)	-0.6453** (0.1189)	-0.8876** (0.1273)	-0.5889** (0.1122)	-0.7523** (0.1163)
BA	0.0001 (0.0441)	-0.0467 (0.0461)	-0.0001 (0.0381)	-0.0288 (0.0400)	0.0016 (0.0451)	-0.0393 (0.0461)	-0.0041 (0.0386)	-0.0328 (0.0397)
Highway	0.1423** (0.0321)	0.1455** (0.0336)	0.0868** (0.0290)	0.0973** (0.0301)	0.1619** (0.0318)	0.1570** (0.0329)	0.1065** (0.0299)	0.1164** (0.0318)
$\delta_1$	-1.8296** (0.0666)	-1.5484** (0.0703)	-1.7625** (0.0730)	-1.5270** (0.0528)	-1.8511** (0.0790)	-1.4784** (0.0684)	-1.7883** (0.0695)	-1.5448** (0.0521)
$\delta_2$	-0.5825** (0.0326)	-0.7901** (0.0748)	-0.6490** (0.0354)	-0.8781** (0.0742)	-0.5862** (0.0554)	-0.8346** (0.0750)	-0.6576** (0.0345)	-0.8281** (0.0697)
$\gamma_1$	-0.0048 (0.0044)	-0.0001 (0.0986)	-0.4500** (0.0508)	-0.0001 (0.0783)	-0.0867* (0.0368)	-0.0001 (0.1166)	-0.4589** (0.0499)	-0.0001 (0.0737)
$\gamma_2$	-0.0001 (0.1019)	-0.0001 (0.1230)	-0.0001 (0.0546)	-0.1245 (0.0640)	-0.0001 (0.0713)	-0.0380 (0.1006)	-0.0001 (0.0546)	-0.1391 (0.0825)
$\gamma_3$	-0.0001 (21.3754)	-0.7901** (0.1160)	-0.2654* (0.1299)	-0.8781** (0.0670)	-0.0001 (42.9599)	-0.8346** (0.1129)	-0.1573 (0.1355)	-0.8281** (0.0885)
$\rho$	0.9687** (0.0123)		0.9887** (0.0027)		0.9741** (0.0092)		0.9841** (0.0032)	
Log likelihood	-3585.5543		-3493.7479		-3571.5353		-3500.7303	

Notes: Models are estimated using Maximum Likelihood. Standard errors are in parentheses. \*\* indicates statistical significance at the 1% level; \* indicates statistical significance at the 5% level.

<sup>12</sup> We thank an anonymous referee for suggesting this possibility.

Despite the relatively small values for most inter-chain competitive effects, two results stand out. First, the negative and statistically significant values of  $\gamma_3$  in BK profit functions suggest that the presence of a third MAC outlet has a distinctively negative impact on the profit of BK outlets. Second, when the assumed entry order is either BK moves first or alternate moves that begin with BK, i.e. either BBBMMM or BMBMBM, the presence of the first BK outlet has a distinctively negative impact on the profit of MAC outlets ( $\gamma_1$  in MAC profit function).

While the magnitudes of coefficients on population are consistent across order-of-entry specifications in Table 4, the magnitudes of other coefficients that are statistically significant vary across order-of-entry specifications. Interestingly, coefficients of “Family” and “Highway” are the largest for both chains under the entry order assumption MBMBMB, followed by MMMBBB, then BMBMBM, with BBBMMM the smallest. Such result shows that different entry order assumptions imply different types of response to changes in socio-demographic variables.

Both the magnitudes and statistical significance of intra and inter-chain competitive effects parameters vary across order-of-entry specifications. For example, the entry of a second McDonald’s outlet reduces the profit of the existing McDonald’s outlet by a larger amount under entry order MMMBBB ( $\delta_1 = -1.8296$ ) compared to BBBMMM ( $\delta_1 = -1.7625$ ). So there is evidence that order-of-entry assumptions matter for the resulting parameter estimates, which can prove crucial in settings where policy conclusions need to be drawn based on estimated parameters.

Overall, the intra and inter-chain competitive effects parameters seem more sensitive across order-of-entry assumptions compared to the sensitivity of parameters associated with the

demographic variables. This result makes sense since the order-of-entry assumptions directly relate to strategic interactions between the restaurant outlets.

Last, the unobserved portion of the profit function of McDonald's and Burger King are highly cross-correlated as indicated by the estimates of  $\rho$ . Note that the estimates of  $\rho$  are close to 1, but statistically different from 1.

As mentioned before, the non-nested likelihood ratio test can be used to test competing model specifications even if the models are mis-specified. The results of the test are reported in Table 5. The non-nested test statistics show that entry orders BBBMMM and BMBMBM are statistically indistinguishable at conventional levels of statistical significance, but each of these entry orders is statistically preferable to MMMBBB and MBMBMB. In addition, MBMBMB is statistically preferred to MMMBBB. In summary, among the four entry orders considered thus far, entry orders that give Burger King outlets first-mover advantage seem to be statistically preferable across the sample of markets in our data set.

**Table 5: Results of Non-nested Test**

$p \backslash q$	BBBMMM	MBMBMB	BMBMBM
MMMBBB	-5.2165	-2.4345	-5.4747
BBBMMM	-	3.7443	1.5503
MBMBMB	-	-	-3,8405

To further investigate whether the first-mover advantage of Burger King outlets persists across a comprehensive set of alternate entry order assumptions, we estimate the entry model under each of the possible order-of-entry assumptions and test them against each other.<sup>13</sup> There

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<sup>13</sup> We thank anonymous referees for pointing out the importance of estimating and testing all entry orders, as well as the Monte Carlo experiment below.

are a total of 20 entry orders when at most 3 MAC and 3 BK outlets are present in a given market. We report the results of these non-nested tests in Table A-1 in Appendix A.<sup>14</sup>

A positive number in Table A-1 suggests that the entry order assumption in the row is either statistically indistinguishable from the column entry order or statistically dominates the column entry order, while a negative number suggests that the column entry order is either statistically indistinguishable from the row entry order or statistically dominates the row entry order. An examination of the row that has the BBBMMM entry order reveals that BBBMMM is never dominated by any of the 19 alternate entry orders, and it strictly dominates 11 of the 19 alternate entry orders. In addition, MMMBBB is statistically dominated by BBBMMM; MBMBMB; BMBMBM; MBMMBB; MBBMMB; BMMMBB; BMMBMB; BMMBBM; BMBMMB; BBMMMB; and BBMBMM, each of which gives Burger King outlets better first-mover advantage than the MMMBBB entry order. In general, the results in Table A-1 suggest that entry orders that give Burger King outlets a first-mover advantage are most often statistically preferable.

As a cautionary note, the reader is reminded that our sample of markets exclude major metropolitan areas, as well as markets that cannot reasonably be considered as “isolated”. Therefore, we cannot say whether our findings extend to all markets in the United States. We can only claim that our results suggest Burger King outlets have a first-mover advantage over McDonald’s outlets in relatively small isolated markets.

Last, we use a small-scale Monte Carlo experiment to assess the power of the Vuong (1989) test within the context that we use it in this paper. Details on how we construct and

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<sup>14</sup> In the interest of space, we do not report the regression estimates of the entry model under the 20 different order-of-entry assumptions. However, we are happy to provide these estimates upon request.

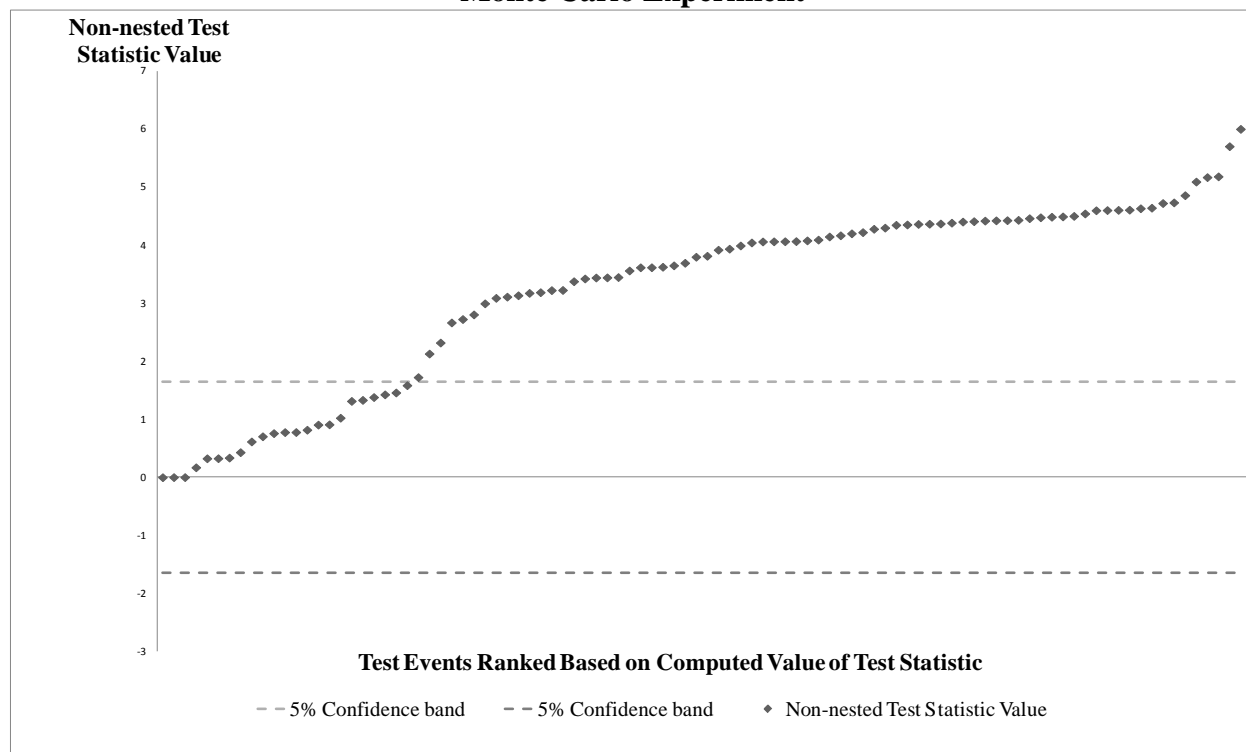
implement the experiment are provided in Appendix B. The following discussion only provides a “big picture” description of the experiment and its results.

We first generate 100 data sets, each containing 1000 markets. Similar to our real data set, we allow a maximum of three outlets of each type in each market of a simulated data set. Each simulated data set consists of simulated variables that capture market characteristics. In each simulated data set we use: (i) the simulated market characteristic variables; (ii) parameterized outlet profit functions; and (iii) a specific order-of-entry assumption, to generate the equilibrium number of outlets of each type that will be present in each simulated market. Therefore, the advantage we have with each simulated data set relative to the real McDonald’s-Burger King data set is that, we actually know the “true” order-of-entry that generate the equilibrium market structure in each simulated data set.

Each simulated data set is generated assuming the entry order is MMMBBB. For each simulated data set we econometrically estimate the entry model under MMMBBB, the “true” order-of-entry, as well as under MBMBMB, and then apply the non-nested test to see which of the two order-of-entry assumptions is statistically favored by the test. Given that there are 100 simulated data sets, this process produces 100 non-nested test statistic values. Figure 2 graphically illustrates the results of the non-nested tests.



**Figure 2: Plot of Computed Non-nested Test Statistic Values from Monte Carlo Experiment**



The vertical axis in Figure 2 measures the computed value of the non-nested test statistic for each of the 100 test events. On the horizontal axis we rank test events by their computed test statistic value. A positive test statistic value that is greater than 1.64 (one-tale cutoff value at the 5% level of significance) suggests that the MMMBBB order-of-entry assumption is statistically preferred to the MBMBMB order-of-entry assumption. Alternatively, a negative test statistic value that is less than -1.64 suggests that the MBMBMB order-of-entry assumption is statistically preferred to the MMMBBB order-of-entry assumption.

Among the 100 test events the results are clear that, at the 5% level of significance, MBMBMB is never statistically preferred to MMMBBB, but MMMBBB is statistically preferred to MBMBMB in 77 test events. Therefore, at a 5% level of statistical significance, the test reveals the correct order-of-entry entry assumption 77% of the time. A similar result is

obtained when MMMBBB is the order-of-entry used to generate simulation data sets, and tested against the BBBMMM order-of-entry assumption.<sup>15</sup>

## 5. Conclusion

In research that uses static empirical entry models of complete information, it is often convenient to assume that players enter sequentially, which makes it necessary to specify a suitable order of entry. In this paper, we show how a Vuong-type non-nested test can be used to statistically assess the suitability of entry order assumptions. As an example, we estimate and test alternate order-of-entry assumptions in our entry model on McDonald's and Burger King restaurant outlets. The data set we use focuses on relatively small "isolated" markets in the United States. In these markets, the results suggest that the more suitable assumption for the entry model is that Burger King outlets have a first-mover advantage over McDonald's. Furthermore, there is evidence that order-of-entry assumptions matter for the resulting parameter estimates of the type of entry model we consider, which can prove crucial in settings where policy conclusions need to be drawn based on estimated parameters.

We also conducted a small-scale Monte Carlo experiment to assess the reliability of the Vuong-type statistical test to reveal the most suitable order-of-entry assumption. Results from the experiment are encouraging, suggesting that at a 5% level of significance the test reveals the "true" order-of-entry 77% of the time.

The estimated entry model also provides some interesting results on the fast food burger industry. We find that, among the socio-demographic variables we consider, the most robust determinants of entry of either McDonald's or Burger King restaurant outlets are: (1) the size of

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<sup>15</sup> When testing MMMBBB against BBBMMM at the 5% level of statistical significance, 76 out of 100 test events reveal that MMMBBB dominates BBBMMM, while the remaining 24 test events suggest these two order-of-entry assumptions are statistically indistinguishable.

population in a particular market; (2) the percentage of family households; and (3) if the city is within six miles of driving distance to an interstate highway. We also find that intra-chain competitive effects are strong and significant, while most inter-chain competitive effects seem to be relatively weak. There could be several factors that contribute to these competitive effects results, one of which may be that differentiation across the chains are sufficiently strong and brand-loyal customers comprise a significant segment of the market. Future research may want to explore the robustness of these findings in other sample markets.





## Appendix B: Procedure of the Monte Carlo experiment

In an effort to assess the reliability of the non-nested test in our context, we have implemented a small-scale Monte Carlo experiment. The following discussion describes the procedure we use.

### *Simulated Market Characteristic Variables*

Our sample consists of 100 different simulated data sets. In each simulated data set there are 1000 markets. Each simulated data set contain three independent variables that measure market characteristics, and the values taken by these independent variables vary across the 1000 markets and across the 100 data sets. A uniform probability distribution is used to generate the values of our simulated independent variables. The minimum and maximum values taken by the three simulated independent variables respectively correspond to variables Pop, PCI and Male in our real McDonald's-Burger King sample markets. The simulated market characteristic variables are denoted: Pop\_sim; CPI\_sim; and Male\_sim.

### *Unobserved Part of Profit – Random Draws*

Similar to our real McDonald's-Burger King data set, we assume there are two types of competing outlets, denoted  $M$  and  $B$  respectively, which can populate a simulated market. Each outlet has a profit function of the form specified in equations (1) and (6), i.e.

$$\Pi_f(N_M, N_B) = \beta_f X + \sum_{i=1}^{N_f-1} \delta_{f,i} + \sum_{j=1}^{N-f} \gamma_{f,j} - \varepsilon_f \text{ for } f (= M, B), \text{ where } \varepsilon_f \text{ is the unobserved part of}$$

the profit function. Just as we did in our entry model, we continue to assume that the unobserved

parts of outlet profit  $(\varepsilon_M, \varepsilon_B)$  are distributed bivariate standard normal across outlets, with cross-correlation parameter  $\rho$ .

For each data set, we draw the unobserved part of outlets' profit from a bivariate normal distribution with  $\rho = 0.6$ , which yields a 1000-by-2 matrix of unobserved profit draws  $(\tilde{\varepsilon}_M, \tilde{\varepsilon}_B)$ . Each row of this matrix corresponds to a market in a simulated data set. Each simulated data set has a different 1000-by-2 matrix of unobserved profit draws.

### *Creating a Complete Simulated Data Set*

Given the simulated market characteristic variables  $\tilde{X} = (\text{Ones}, \text{Pop\_sim}, \text{CPI\_sim}, \text{Male\_sim})$ , the unobserved profit draws  $(\tilde{\varepsilon}_M, \tilde{\varepsilon}_B)$ , and the assumed profit function parameters in Table B-1  $(\tilde{\beta}_f, \tilde{\delta}_{f,i}, \tilde{\gamma}_{f,i})$ , we can use outlet profit functions to compute the equilibrium number of outlets of each type  $(\tilde{N}_M, \tilde{N}_B)$  that will be present in each simulated market under a specific order-of-entry assumption. In particular, let the simulated profit for outlet  $f$  be denoted by  $\tilde{\Pi}_f(\tilde{N}_M, \tilde{N}_B) = \tilde{\pi}_f(\tilde{X}, \tilde{\beta}_f, \tilde{\delta}_f, \tilde{\gamma}_f) - \tilde{\varepsilon}_f$ . Since outlets must have non-negative profits in equilibrium, we essentially solve for the vector of integer values  $(\tilde{N}_M, \tilde{N}_B)$  such that  $\tilde{\Pi}_f(\tilde{N}_M, \tilde{N}_B) \geq 0$ . To obtain a unique solution vector  $(\tilde{N}_M, \tilde{N}_B)$ , we impose the MMMBBB order-of-entry assumption. This specific order-of-entry assumption is imposed in all 100 simulated data sets that we create.

In the end each simulated data set has data on market characteristic variables, as well as number of outlets of each type in each market. Market structure configurations and their associated frequencies in a typical simulated data set are reported in Table B-2.

**Table B-1 Assumed Parameters**

	MAC	BK
Constant	0.85	3
Pop_sim	0.2	0.5
CPI_sim	0.8	2
Male_sim	0.6	0.06
$\tilde{\delta}_1$	-0.8	-2
$\tilde{\delta}_2$	-0.7	-1.8
$\tilde{\gamma}_1$	-0.2	-1.7
$\tilde{\gamma}_2$	-0.01	-0.06
$\tilde{\gamma}_3$	-0.005	-0.03
$\rho$	0.6	

**Table B-2 A Typical Simulated Data Set**

Mkt. Str.	0, 0	1, 0	2, 0	3, 0	0, 1	1, 1	2, 1	3, 1	0, 2	1, 2	2, 2	3, 2	0, 3	1, 3	2, 3	3, 3
Obs.	43	107	54	37	143	121	86	64	110	53	65	87	14	0	6	10

### *Econometric Estimation and Non-nested Test*

Once we have all 100 simulated data sets established, we econometrically estimate the entry model on each data set under each of two distinct order-of-entry assumptions, where one of the two order-of-entry assumptions is the “true” one used for generating the simulated data. In our experiment, the two distinct order-of-entry assumptions used for estimating the entry model are: (i) MMMBBB; and (ii) MBMBMB. As previously stated, the simulated data are generated under the MMMBBB order-of-entry assumption.

Once the entry model is econometrically estimated under each of the two order-of-entry assumptions for a given simulated data set, we then compute the non-nested test statistic according to equations (8), (9) and (10) in the paper. Since there are 100 simulated data sets, this process produces 100 computed non-nested test statistics. The number of cases in which the computed value of the non-nested test statistic suggests that MMMBBB is the statistically



preferred order-of-entry assumption reveals the percentage of times that the test will yield the correct answer on average.

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