Demand Uncertainty, Dynamic Learning and Exit in Competitive Markets

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August, 2014

Abstract

Incidences of firm exit are common in a market full of uncertainty. We consider two sources of uncertainty that may affect a firm's exit decision. One is the uncertainty about consumers' preference toward its own product. The other is the uncertainty toward the demand for the competitors' products. These uncertainties are gradually resolved as a firm continues to gather information by staying in the market. Exit occurs when a firm learns that it is of low competitiveness. We model firms' optimal exit decisions under demand uncertainty in competitive markets using a dynamic game. Specifically, firms use the sales in each period to update their beliefs on the true types of themselves as well as their competitors in a Bayesian fashion. The optimal decision on whether and when to exit a market depends on the expected value of additional learning, the fixed cost of operation, and the expected actions of the competitors. We estimate the model using data from China's evolving microwave oven industry. We then perform counterfactual simulations to evaluate how different factors affect individual firms' optimal exit decisions and the industry evolution path.

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Keywords: demand uncertainty; Bayesian learning; entry and exit; dynamic oligopoly game

1 Introduction

In June 2012, HTC, the world's fifth largest smartphone brand by shipment, announced that it was pulling out of the Brazilian market after observing the struggling sales numbers. Despite the fact that Brazil was a growing market with 8.9 million smartphone users in 2011 and was predicted to become the world's fourth most important market by 2016, HTC decided to exit with a falling market share that registered at 0.11%, far behind its competitors such as Samsung, Apple and Sony.[1]

Firms' exit decisions are often related to the uncertainty of operating in a market and such uncertainty could be multi-folded. One fundamental uncertainty lies in the potential demand for a firm's own product. Moreover, a firm could be uncertain about consumers' perception toward the competitors' products. In other words, there is uncertainty about the relative competitiveness of one's own product to the competing products in the same market. Such uncertainty may in fact attract many firms to enter a new market or a new industry to learn about their true types. The uncertainty is resolved over time as firms continue to operate in the market. Eventually those revealed to be the low types exit. In many manufacturing industries, the number of producers often declines by 50% or more during the introductory period of the industry evolution (Gort and Klepper, 1982). How do firms make optimal exit decisions in an uncertain and competitive environment? How do market characteristics, competition structure and the level of uncertainty about one's own product and the competing products affect the timing of exit?

Investigating the exit decision is important. In fact, having the option to exit at any point in time increases the net present value of market entry (Dixit and Pindyck, 1994). The idea is that firms can gather more information about the profitability in a new market through delaying exit. Following this stream of literature, we model the exit decision in a dynamic industry as a "learning and selection" process (Javanovic, 1982). By staying in the market, a firm can gradually resolve the uncertainty through performance signals. Different from the previous literature that focuses on the learning of one's own demand or cost, we model two types of learning: (1) Learning about self. We assume that a firm is uncertain about demand and learns about consumers' intrinsic preference toward its

[1] Adapted from news articles "HTC Shuts Brazil Office As It Focuses Elsewhere" (*Wall Street Journal*, June 25, 2012, page B2) and "Struggling HTC to exit Brazilian market" (http://www.tech-ex.net/2012/06/struggling-htc-to-exit-brazilian-market.html).

product using product sales as signals.[2] (2) Learning about competitors. We assume that there is also uncertainty about consumers' preference toward the rivals' products and a firm needs to learn the competitiveness of other firms.[3] Again, we assume that the sales of competing products signal their true demand.

A firm's exit decision is based on the learning of oneself as well as the competitors in the same market. If a firm chooses to stay, it can expect to receive more information and to have a better understanding of the true demand for its own product and for competing products. However, there is a fixed cost of staying in the market and learning. In addition, a firm's strategy also depends on the possible actions from the rivals. The competition landscape would be different if more or fewer firms decide to exit. A firm's optimal exit decision depends on the expected value of additional information gathering, the cost of stay, and the expected behavior of the competitors. We use a dynamic game to capture firms' dynamic learning and exit decisions under demand uncertainty and oligopolistic competition.

We estimate the model using panel data from China's evolving microwave oven industry from 2000 to 2008 across 20 major cities. This industry started in mid 1990s and the demand for microwave oven kept growing during our study period. However, we observe in the data that more than half of the brands exited the market (see Figure 1). Typically a brand was sold in multiple cities in the beginning and exited an increasing number of markets over the years. Our model allows the true demand, or consumers' intrinsic preference toward a brand, to vary across markets. Learning of the local preference for one's own product and for competing products in the same market determines the optimal timing of exit from that market. Through empirical analysis, we can assess the role of demand uncertainty and competition on firms' optimal exit decisions. In addition to understanding individual firms' exit decisions, another objective of our empirical analysis is to examine the impact of uncertainty and learning on the evolution path of the industry.

Our results indicate that, with higher demand uncertainty on firms' own products or on competing products, firms would possess stronger incentives to stay in the market and

[2] We focus on demand uncertainty because the industry we examine in the paper has mature and standard production technology where learning about cost is less of a concern.

[3] The idea can be related to Fudenberg and Tirole (1986). In their duopoly model, they assume that each firm knows its own cost but not that of the rival and exit timing is the only strategic variable. The non-exit decision of the opponent essentially signals low cost of that firm. In our model, firms learn the true demand for its own product and for competitors' products through sales signals.

learn about the true demand. As a result, higher uncertainty would cause the number of firms in the market to decline at a slower rate. During the process, even weak firms have incentives to delay exits in order to collect more information and resolve the demand uncertainty, despite incurring losses in the short term. Such experimentation can be costly to the industry. Through simulations we find that, without any demand uncertainty at the beginning of our study period, the total profit of the industry could have been higher by 2.65 million Chinese yuan. Also, uncertainty about competitors is equally important to uncertainty about own demand in firms' exit decisions and in the industry evolution.

Our findings extend the existing literature on firms' exit behavior and industry shakeout, mostly related to technological changes. Jovanovic and MacDonald (1994) attribute an industry shakeout to firms' failure in implementing a major innovation developed outside the industry, or losing the game of "implementation race". Klepper and Graddy (1990) interpret shakeout as part of a gradual evolution process driven by technological changes. In another theory, shakeout is attributed to the emergence of a dominant design of the product in an industry (Abernathy and Utterback, 1978; Utterback and Suárez, 1993). However, as noted by Klepper and Simons (2005), it is difficult to find evidence of technological milestones in many industries. Also, technological changes may not explain the fact that the same firm can be successful in certain markets but can fail in others. In our model, exit is a result of learning and selection when the uncertainty on own demand and on competitors gradually resolves. We see our explanation as complementary to the existing theories and applicable to product categories that experience shakeout with no clear technological triggers. Our model also provides a natural explanation to why exit decisions may differ across markets for the same firm. There is also a stream of literature that explains shakeout as the result of overshooting an equilibrium number of firms due to coordination failure among potential entrants (e.g. Dixit and Shapiro, 1986; Cabral, 1993), or as the result of irrational entry (e.g. Camerer and Lovallo, 1999). While Ghemawat and Nalebuff (1990) and Lieberman (1990) study exit patterns in a declining industry, we instead focus on exit decisions in an emerging industry where demand uncertainty is prominent.

This paper is closely related to a few papers that use a structural approach to study optimal exit decisions with learning. Dixit and Chintagunta (2007) propose a learning model embedded in a logit framework in investigating the exit behavior of discount airlines. Airlines use the realized market demand to update their belief on the intrinsic attractiveness of a market. The model is static in the sense that it does not account for the option of waiting and exiting in future. Abbring and Campbell (2004) study firms' survival of the first year by estimating a structural model of learning and survival under monopolistic competition. They find that fixed cost plays a larger role in determining exit behavior than entrepreneurs' learning. Hitsch (2006) uses a dynamic model to examine a firm's optimal product launch and scrap decisions under demand uncertainty in the ready-to-eat breakfast cereal industry. A firm learns the true demand for its new product from observed sales. The unique feature of our model, compared to the previous literature, is that we explicitly model the learning about competitors in addition to the learning about one's own demand and allow for strategic interactions among firms. Our results indicate that learning about competitors also plays a significant role in driving the exit patterns.

More broadly our work stems from the literature on applications of Bayesian learning models in marketing and economics. A large number of work has used Bayesian learning model in studying individual choices since Erdem and Keane (1996).[4] For example, Mehta, Rajiv and Srinivasan, 2004) propose a model that accounts for forgetting in consumer learning. Erdem, Keane and Sun (2008) focus on learning product quality from different information sources. Chan, Narasimhan and Xie (2013) examine learning on multiple product attributes. Ching (2010) studies firms' entry and pricing behavior in the prescription drug market, assuming that both patients and firms learn about product quality through consumer experiences. Excess entry can happen in this setup due to the fact that entry costs are paid before a random government approval process, giving each firm the chance to become the first entrant and earn sizable profits. In our empirical setting, we abstract away from consumer learning of product quality and focus on firms' exit decisions and how their exit decisions connect to their learning of consumer preference toward their own and competitors' products in a local market.

The rest of paper proceeds as follows. We first Introduce the dynamic model of learning and exit. Next, we describe the data from China's microwave industry and estimate the proposed model using this dataset. We then present the counterfactual analysis that assess the role of demand uncertainty and other factors in determining the exit timing. We conclude with a discussion of the limitations of our work and suggest future research avenues.

[4]See Ching, Erdem and Keane (2013) for a recent review.

2 Model Development

We present a general model that allows for both entry and exit yet the focus is on firms' decisions of whether and when to exit a market. It corresponds to the stage of industry evolution that most of the firms have already entered the market and the critical decision is whether to stay or exit. Additional entry may occur under certain conditions as discussed below.

To be consistent with our empirical application, we motivate the model as a firm making exit decisions at city level, i.e., whether to exit a city in each time period. A firm or a brand has presence in one or many cities and each city is considered as a separate market with potentially different sets of competitors and different consumer preference. In this setup we use 'firm' and 'brand' interchangeably because each firm has only one brand in our dataset.

Firms are uncertain about consumers' preference, or the perceived quality of their brands, in a local market upon entry. We use α_{jm} to denote brand j's perceived quality in city m. A brand may have different perceived quality across markets. The prior belief on α_{jm} at the beginning of period t can be characterized by a normal distribution that we will discuss in more detail below. Brand j's sales in city m in each period provide some information about the perceived quality α_{jm} that is unobservable to firms. High sales suggest that it is likely that the local consumers have a high intrinsic preference toward the brand. However, high sales in one period could also be driven by temporary demand shocks. Therefore, sales are noisy indicators of true demand in the market. A firm utilizes the sales signals to update its belief in a Bayesian fashion.

At the same time, we assume that firms are uncertain about the true demand for their competitors' products as well but can learn through the sales of those products. Uncertainties around a brand and its competitors are gradually resolved as a firm continues to operate in the market. A firm has the option to delay exit and gather more information about product demand in the market, but it incurs a fixed cost in each period while staying active. Thus optimal exit decisions depend on the learning of oneself and the competitors, the fixed cost, and the expected actions from the competitors.

A new entrant incurs a sunk cost to enter a market and starts to sell products in the period following entry. Given our main focus on the exit decision, we assume that there is only one potential entrant in each market and each period.[5] This assumption is generally supported by the fact that very few new entries are observed when the industry starts the shakeout process (Agarwal and Gort, 1996; Klepper and Simons, 2005).

The timing of the game is as follows. At the beginning of each time period, each incumbent observes privately its cost of operating in the market in that period and simultaneously decides whether to exit or stay. If a firm decides to exit, it leaves the market forever. If a firm decides to stay, it sets the optimal price for the current period knowing that a Bertrand pricing game is played among the active incumbents in the same market. After the sales of the period are realized, firms update their beliefs on themselves as well as on competitors. Meanwhile, a potential entrant gets a draw of entry cost and decides whether to enter a local market. If it decides to enter, entry cost is paid and the firm is active in the next period.

2.1 Product Demand

We first specify the demand function. We assume that in market m, a household h's indirect utility from purchasing brand j at time t can be expressed as:

$$U_{hjmt} = \alpha_{jm} + \beta_h p_{jmt} + \xi_{jmt} + \varepsilon_{hjmt}. \tag{1}$$

α_{jm} is the perceived quality of brand j by the consumers in market m. Consumers in different market may have different perception toward the same brand. For example, consumers living in the area where a brand originated may have a higher intrinsic preference toward the brand than consumers in other regions (Bronnenberg, Dubé and Dhar, 2007). p_{jmt} is the product price and the coefficient β_h reflects the price sensitivity that varies across households.[6] ξ_{jmt} is the market specific and brand specific demand shock. Finally, ε_{hjmt} is an idiosyncratic demand shock that follows independent standard Gumbel distributions. This setup gives rise to a random coefficient logit demand model that has been widely used to model consumers' discrete choices among a set of competing options (e.g. Berry, Levinsohn and Pakes, 1995; Nevo, 2001).

The heterogeneity in price sensitivity across households is specified as follows:

$$\beta_h = \beta + \boldsymbol{\gamma_1} D_h + \gamma_2 \tau_h \tag{2}$$

[5] The model can be extended to allow for many potential entrants at the cost of additional complexity.

[6] Other product characteristics can enter the utility function in a similar fashion.

D_h is a vector describing household h's demographic information such as household income. The term τ_h captures any unobserved heterogeneity that contributes to the variation in price sensitivity. It is assumed to follow a standard normal distribution.

The indirect utility of the no-purchase option is normalized to have a zero mean. The market share of brand j in market m at period t can be written as:

$$s_{jmt} = \int \frac{exp(\alpha_{jm} + \beta_h p_{jmt} + \xi_{jmt})}{1 + \sum_k exp(\alpha_{km} + \beta_h p_{kmt} + \xi_{kmt})} dF(\beta_h) \tag{3}$$

Note that the integration of the random coefficient β_h is over both the distribution of household demographics and the distribution of the unobserved factor τ_h.

Following Berry, Levinsohn and Pakes (1995), one can invert the demand system to infer the mean utility of each product in the market, $\varphi_{jmt} = \alpha_{jm} + \beta p_{jmt} + \xi_{jmt}$, by equating the predicted market shares with the observed market shares. After adjusting for the price effect, the sum of α_{jm} and ξ_{jmt} becomes the noisy signal of the perceived quality. Because the demand shock ξ_{jmt} is not perfectly observable to firms, it is not separable from the perceived brand quality.

2.2 Learning about Self

A firm is uncertain about the true demand for its product in a local market. However, the firm can learn about the consumer preference over time as sales in each period reveal some information of the perceived quality of its product. The sales signal of firm j in market m at period t can be written as

$$\delta_{jmt} = \alpha_{jm} + \xi_{jmt} \tag{4}$$

As mentioned above, this can be obtained by inverting the demand system.[7] We assume that ξ_{jmt} is i.i.d normally distributed with mean 0 and variance σ_ξ^2. The assumption suggests that any correlation between the sales signals in different periods is driven by the underlying product quality, α_{jm}. The variance σ_ξ^2 indicates how precise the sales signals are in revealing a firm's true type and is assumed to be the same across firms. Therefore, the demand signal in each time period follows a normal distribution:

$$\delta_{jmt} \sim N(\alpha_{jm}, \sigma_\xi^2) \tag{5}$$

[7] The implicit assumption here is that firms know the price coefficient which enables the demand inversion. The information on price elasticity may be extracted from other established home appliance. We assume that the main uncertainty is around consumers' intrinsic preference toward the product instead of the price sensitivity.

The prior belief about α_{jm} at the beginning of period t can be characterized by a normal distribution as well:

$$\alpha_{jmt} \sim N(\mu_{jmt}, \sigma^2_{jmt}) \tag{6}$$

The firm (conditional on not exiting at period t) updates its belief based on the signal received in the period, δ_{jmt}, in a Bayesian fashion:

$$\mu_{jm,t+1} = \frac{\sigma^2_\xi \mu_{jmt} + \sigma^2_{jmt}\delta_{jmt}}{\sigma^2_{jmt} + \sigma^2_\xi}; \tag{7}$$

$$\sigma^2_{jm,t+1} = \frac{\sigma^2_\xi \sigma^2_{jmt}}{\sigma^2_{jmt} + \sigma^2_\xi}. \tag{8}$$

It is clear that if the sales signals are not informative (i.e. σ_ξ is large), then the firm would rely more on the prior belief and the learning is slow. If the sales signals are precise (i.e. σ_ξ is small), then the updating would rely more the sales signals received and the uncertainty would be resolved faster.

We assume that the prior belief in the initial period follows a normal distribution with mean μ_{jm0} and variance σ^2_{jm0}, where μ_{jm0} is drawn from a normal distribution $N(\alpha_{jm}, \sigma^2_{jm0})$. In other words, the prior belief on product quality is assumed to be unbiased. How fast the uncertainty is resolved depends on both how diffuse the prior belief is and how accurate the sales signals are.

2.3 Learning about Competitors

The profitability of a brand depends on consumers' preference towards the brand relative to its competing brands. Therefore, it is also important for a firm to learn about the competitors. Theoretically, a firm can track each individual competitor and update its belief on each competitor following the same Bayes rule described by equations (7) and (8). However, it is computationally infeasible to solve the oligopoly game with dynamic learning and strategic interactions given a large number of firms in the market. To address this issue, we make an assumption of bounded rationality under which firms only track the most important summary statistics in making exit decisions, specifically the group average and the total number of competitors, instead of tracking each competitor individually. In essence a firms keeps track of its competitive position in relation to the average strength of its competitors. As the industry evolves and stabilizes, a firm can obtain a more and more accurate understanding of its competitive position.[8]

Let N_{mt} be the total number of incumbents in market m at period t. Firm j updates its belief on competing firms in the same market by using the average sales signal of these firms, $\bar{\delta}_{-jmt} = \frac{1}{N_{mt}-1}\sum_{(-j)} \delta_{imt}$, where δ_{imt} is the sales signal of competitor i in market m. The prior belief on an average competitor at the beginning of period t can be characterized by a normal distribution:

$$\bar{\alpha}_{-jmt} \sim N(\bar{\mu}_{-jmt}, \bar{\sigma}^2_{-jmt}). \tag{9}$$

Given the average sales signal, the prior belief is updated in the Bayesian fashion:

$$\bar{\mu}_{-jm,t+1} = \frac{\bar{\sigma}^2_{\xi}\bar{\mu}_{-jmt} + \bar{\sigma}^2_{-jmt}\bar{\delta}_{-jmt}}{\bar{\sigma}^2_{-jmt} + \bar{\sigma}^2_{\xi}}; \tag{10}$$

$$\bar{\sigma}^2_{-jm,t+1} = \frac{\bar{\sigma}^2_{\xi}\bar{\sigma}^2_{-jmt}}{\bar{\sigma}^2_{-jmt} + \bar{\sigma}^2_{\xi}}. \tag{11}$$

$\bar{\sigma}^2_{\xi}$ represents the variance of the average sales signal for other firms from firm j's perspective. We allow the precision of the average signal for other firms ($\bar{\sigma}^2_{\xi}$) and the signal for the focal firm (σ^2_{ξ}) to be different. We assume that the prior belief on the average competitor in the initial period is unbiased and follows a normal distribution $N(\bar{\alpha}_{-jm}, \bar{\sigma}^2_{-jm0})$. The variance of the initial belief reflects the prior uncertainty about the competitors in the market.

2.4 The Profit Function

We assume that active firms engage in price competition. Firm j's profit in period t from operating in market m can be expressed as:

$$\pi_{jmt} = (p_{jmt} - c_j)Q_{jmt}(\mathbf{p}_{mt}) - F_{jmt} = \tilde{\pi}_{jmt} - F_{jmt} \tag{12}$$

[8] This idea resembles the concept of oblivious equilibrium introduced in Weintraub, Benkard and Van Roy (2008) where each firm makes decision based on its own state and the average industry state. The authors show that the oblivious equilibrium can closely approximates the Markov perfect equilibrium when the market is not dominated by a few firms. The difference is that in an oblivious equilibrium, firms ignore the current information on competitors' states and only focus on the long-run average state, whereas in our model, firms still track rivals' information in each period although rivals' information is summarized into the number of rivals and their average state. The equilibrium concept used here is still Markov perfect equilibrium.

where c_j is the marginal cost and is assumed to be time invariant for simplicity.[9] Q_{jmt} is firm j's sales, given by the product of the market share in equation (3) and the total market size of city m, denoted by M_m, i.e. $Q_{jmt} = M_m s_{jmt}$. It is a function of the prices of all the competing products in the same market, summarized by the price vector $\mathbf{p}_{mt}$. F_{jmt} is the fixed cost of operating in the local market in each period, which may include costs associated with maintaining shelf space and marketing expenditures.

We further assume that the fixed cost can be decomposed into a deterministic component and a stochastic component:

$$F_{jmt} = \tilde{F}_m + \omega_{jmt}; \quad \omega_{jmt} \sim N(0, \sigma_\omega^2). \tag{13}$$

The recurring component $\tilde{F}_m$ is allowed to vary across markets, reflecting the fact that the operating cost may differ across different cities. The random component ω_{jmt} incorporates any instantaneous shocks to the fixed cost in the current period. It follows a normal distribution with mean 0 and variance σ_ω^2.

At period t, firm j sets a price p_{jmt} to maximize the single period profit. Note that the optimal pricing depends on the vector $\boldsymbol{\delta}_{\mathbf{mt}}$, with each element $\delta_{jmt} = \alpha_{jm} + \xi_{jmt}$. Given the assumption that firm j learns the average competitor instead of tracking each individual firm, element i $(i \neq j)$ in the vector $\boldsymbol{\delta}_{\mathbf{mt}}$ can be written as $\delta_{imt} = \bar{\alpha}_{-jm} + \bar{\xi}_{-jmt}$. There are three layers of uncertainties to be considered, including the uncertainty on the perceived quality of the firm's own brand, α_{jm}, and the uncertainty on the competing brands, α_{-jm}. In addition, there are demand shocks in each period. Therefore a firm maximizes the expected profit in the current period, given its belief on the true demand of all the staying firms as well as their pricing strategies. Calculating the expected profit involves integrating out all layers of uncertainties.

2.5 The Exit and Entry Decision

At the beginning of each time period in market m, an incumbent needs to decide whether to stay or exit. We assume that the random component of the fixed cost, ω_{jmt}, is realized before the decision. Although the distribution of this random component is common knowledge, a firm only observes its own cost realizations but not those of its competitors.

[9] It can be extended to capture cases with time varying cost. For the microwave industry that we study, the production technology is relatively mature and we do not find clear pattern of declining cost from our empirical estimation.

If the firm decides to stay, it receives the profit from selling its product in the current period less the fixed cost, as well as the expected future value. If it decides to exit, it does so at the beginning of the period and the decision is irreversible (re-entry is not allowed). The exit value is normalized to be zero. The firm takes the optimal action so the value function satisfies

$$V(S_{jmt}, \omega_{jmt}) = max\{E[\tilde{\pi}_{jmt}(S_{jmt})] - (\tilde{F}_m + \omega_{jmt}) + \theta E[V(S_{jm,t+1}, \omega_{jm,t+1})|S_{jmt}],\ 0\} \tag{14}$$

S_{jmt} is the state vector: $S_{jmt} = [\mu_{jmt}, \sigma^2_{jmt}, \bar{\mu}_{-jmt}, \bar{\sigma}^2_{-jmt}, N_{mt}, Z_m]$. The first two variables in the state vector characterize the mean and variance of firm j's belief on its own product at the beginning of period t in market m. The next two variables characterize its belief on the average perceived quality of competing brands in the same market. N_{mt} is the number of firms in the market that evolves endogenously with entry and exit. Z_m summarizes the characteristics of market m such as the market size and market specific fixed cost.

The term $E[\tilde{\pi}_{jmt}(S_{jmt})]$ corresponds to the firm's expected profit from operating in the current period (before accounting for fixed cost). The expectation is taken over the following: (1) the number of active competitors in this period after firms make simultaneous entry and exit decisions; (2) the current belief on the perceived quality of one's own brand and competing brands; and (3) the demand shocks. The sum of $\tilde{F}_m$ and ω_{jmt} represents the fixed cost that the firm would incur by remaining active in this period. θ is a discount factor. The expectation on future value $E[V(S_{jm,t+1}, \omega_{jm,t+1})|S_{jmt}]$ is taken over the evolving number of firms as well as over the updated belief on the firm's own brand and competing brands.

Firm j would choose to exit in the current period if and only if the fixed cost is greater than the value of continuation, that is

$$\tilde{F}_{jm} + \omega_{jmt} > E[\tilde{\pi}_{jmt}(S_{jmt})] + \theta E[V(S_{jm,t+1}, \omega_{jm,t+1})|S_{jmt}]. \tag{15}$$

Given the distributional assumption on ω_{jmt}, the exit probability can be written as:

$$Pr(exit)_{jmt} = 1 - \Phi(\frac{E[\tilde{\pi}_{jmt}(S_{jmt})] - \tilde{F}_m + \theta E[V(S_{jm,t+1}, \omega_{jm,t+1})|S_{jmt}]}{\sigma_\omega}). \tag{16}$$

The above exit rule has a few implications. First, it is clear that a firm is less likely to exit if $\tilde{F}_m$ is lower. In other words, a firm would delay exit if the cost of experimenting with the product and getting additional information is relatively low in a market. Second, a firm is less likely to exit if the expected current profit and future value are high, e.g.

when its perceived product quality is higher than others, or when the expected number of competitors in future is low. The expected future value critically depends on the updating of the belief on the true types of oneself and competitors. Thus a firm is less likely to exit immediately if the degree of uncertainty is high. Intuitively, the value of gathering additional information through operating in the market is higher when the uncertainty is higher. Compared to the case with lower demand uncertainty (either on its own product or on competing products), in case of higher demand uncertainty we should observe exits occurring later. The key factor is that the option value of waiting is higher in this latter case.

Although very few new entries are observed in the shakeout stage of industry evolution, our model allows for the possibility of entry but restricts to one potential entrant in each time period in each market. We further assume that the potential entrant is short-lived, i.e., either chooses to enter now or never. So the potential entrant in market m at period t solves the following problem:

$$V^o(S_{jmt}, \kappa_{mt}) = max\{-\kappa_{mt} + \theta E[V(S_{jm,t+1}, \omega_{jm,t+1})|S_{jmt}],\ 0\} \tag{17}$$

If the potential entrant decides to enter, it needs to pay the entry cost κ_{mt} now, which is a random draw from a uniform distribution on the interval $[\underline{K},\ \overline{K}]$. The entrant is uncertain about its true type upon entry and learns through sales signals over time. The true type of the entrant is assumed to be a random draw from the quality distribution of all firms. The entrant becomes active in the next period and forms expectation on future value as other incumbents. On the other hand, if the potential entrant decides not to enter, it receives 0 payoff and the never comes back. Therefore, the entry probability can be expressed as:

$$Pr(enter)_{jmt} = \frac{\theta E[V(S_{jm,t+1}, \omega_{jm,t+1})|S_{jmt}]) - \underline{K}}{\overline{K} - \underline{K}} \tag{18}$$

As expected, a potential entrant is more likely to enter if the entry cost is low and the expected future value is high.

2.6 Equilibrium

The equilibrium of the dynamic game can be characterized as the fixed point of the best response mapping in probability space (e.g. Aguirregabiria and Mira, 2007). First, we focus on the value function of incumbents and let $\bar{V}(S_{jmt}) = \int V(S_{jmt}, \omega_{jmt})dF(\omega_{jmt})$ be the expected value function after integrating out the private shock in the fixed cost.

To make the presentation succinct, we drop the subscript and abbreviate S_{jmt} as S and $S_{jm,t+1}$ as S'. Let P^s denote the probability that firm j would stay in market m at period t. We have

$$\begin{aligned}\bar{V}(S) &= P^s\{E[\tilde{\pi}(S)] - \tilde{F} + \theta E[\bar{V}(S')|S]\} - P^s E[\omega|\omega < E[\tilde{\pi}(S)] - \tilde{F} + \theta E[\bar{V}(S')|S]] \\ &= P^s\{E[\tilde{\pi}(S)] - \tilde{F} + \theta E[\bar{V}(S')|S]\} + \sigma_\omega \phi(\Phi^{-1}(P^s)) \qquad (19)\end{aligned}$$

The second step in equation (19) is derived from the assumption that the random shock ω follows a normal distribution, with $\phi(\cdot)$ and $\Phi(\cdot)$ denoting the density function and cumulative distribution function of the standard normal distribution and Φ^{-1} the inverse function of Φ.[10] Since $E[\bar{V}(S')|S] = \bar{V}(S) \cdot T(S'|S)$, where $T(S'|S)$ is the matrix of transition probability, by rearranging the above equation, the integrated value function $\bar{V}(\cdot)$ can be written as:

$$\bar{V}(S) = [I - \theta P^s T(S'|S)]^{-1}\{P^s E[\tilde{\pi}(S)] - P^s\tilde{F} + \sigma_\omega \phi(\Phi^{-1}(P^s))\} \qquad (20)$$

The transition of the state vector S is determined by the learning process and firms' exit and entry probabilities. The evolution of the belief on one's own product is characterized by equation (7) and (8), while the evolution of the belief on competing products is characterized by equation (10) and (11). The number of firms in the market evolves according to $N' = N - N^x + N^e$, where N^x and N^e indicate the number of exiting firms and new entrants respectively. So the transition of N depends on both the exit and entry probabilities.

Now the expected value function is expressed as a function of choice (i.e. exit and entry) probabilities and model parameters. Given a set of parameters, we can compute the expected value function associated with an arbitrary vector of choice probabilities following equation (20). On the other hand, both the entry and exit probabilities are functions of the expected value function, as indicated by equation (16) and (18).[11] Thus, an equilibrium is achieved if one can find a fixed point in the probability space, or equivalently a vector of choice probabilities that simultaneously satisfies equation (16), (18) and (20).

[10] Please see Appendix for the derivation details.

[11] More precisely, the exit probability expressed by equation (16) and the entry probability by equation (18) depend on the expected value function after integrating out the private draws of fixed cost and entry cost.

3 Data and Industry Background

The empirical context for this study is China's microwave oven industry. The industry started to grow in the mid 1990s but the growth was slow initially due to limited household income and high prices at the time. The market penetration started to accelerate from late 1990s as prices decreased while household income increased. By year 2001, the penetration rate of microwave oven reached 21.9% in urban areas but was still virtually zero in rural areas, according to the National Bureau of Statistics of China. Despite that there seems to be ample room for the industry to grow, the number of producers started to drop from early 2000. On average, we observe the number of brands dropped by more than 50% in each city during our study period from 2000 to 2008 (see Table 1). The industry is suitable for our study because there was no significant technological innovation in this industry during our study period. Also, as the shakeout progresses the aggregate demand for the industry is still growing, suggesting that the industry shakeout is not a result of shrinkage in demand.

Our data came from a major market research firm in China. We have information on the yearly unit sales and average prices for each microwave oven brand in 20 major cities of mainland China from year 2000 to year 2008.[12] Year 2000 is the first year that the research firm systematically monitored the microwave industry at the brand level. Table 1 shows the number of brands in each city in year 2000, 2004 and 2008 respectively. Because we observe unit sales instead of the actual exit decisions, we have to determine what constitutes an exit. For example, we may assume that a brand exits the market after operating in period t if we observe zero sales thereafter. However, given quite a few observations in the data that a brand has single digit sales for a couple of years before completely disappearing, we treat these single digit sales in the final years as stock clearance after the brand has already decided to withdraw from the market. Therefore, we assume that a brand exits in year t if the sales of the brand dropped below 10 units ever since that year.[13]

We treat each city as a separate market and investigate a firm's decision of whether and when to exit a city. We do not consider cross-market learning in our model. Instead, we allow the local preference to differ across cities and the learning is about each specific market. Allowing for correlation in learning across markets would significantly increase

[12] We adjusted the prices for inflation so that all prices are in 2005 Chinese yuan.

[13] We also experimented with other cutoff numbers and our results are qualitatively the same.

the complexity of the model estimation and is left for future research.

The data indicate significant heterogeneity among the competing brands. Galanz, LG and Midea were market leaders in almost all the cities during the study period and in total accounted for more than half of the market share across all the markets. Other brands are relatively small in terms of market share, and shakeout occurs among this group of smaller firms. For our empirical analysis below, we classify the firms into two tiers. The first tier includes Galanz, LG and Midea. All the other firms are in the second tier and are significantly smaller in size.

In addition to the data described above, we also collected information on the number of households and average household income for each city from the China City Statistical Yearbook 2000-2008. The information will be used in our empirical estimation, as we describe below.

4 Model Estimation

We are interested in how the demand uncertainty on a firm's own product and on its competing products drives the exit patterns that one observes in China's microwave industry across different cities. In principle, our model could allow for learning and tracking the perceived quality of each individual brand. However, as discussed earlier, keeping track of every single brand would increase the dimension of the problem and render the empirical estimation infeasible, given the fact that there are typically 10 to 20 microwave brands in a city. To reduce the dimension of our dynamic model, we leverage on the observed market structure in the microwave industry. Because the three major brands (namely Galanz, LG and Midea) are clearly in a separate tier from the other smaller and relatively more homogeneous brands, we assume that the true types of the three major brands are common knowledge to all firms since the beginning of our study period. In other words, firms do not need to learn about the true quality of the top three brands through sales signals. The rest of the brands need to learn their true demand as well as other small brands. For these smaller brands, we assume that a good approximation can be obtained by tracking the average quality without tracking each brand individually.

We use a two-stage estimation approach similar to Hitsch (2006). In the first stage, we estimate the parameters in the random-coefficient logit demand system. The demand estimation generates several key variables that we use as input to our second-stage estimation.

In the second stage, we follow the learning process and solve the dynamic oligopoly game to compute firm's exit probabilities under different parameter values. We then match the predicted exit probabilities with the observed exit decisions to estimate the structural parameters governing firms' exit decisions, including the degree of initial demand uncertainty at the beginning of our study period, the precision of the sales signals, and the fixed cost of operating in a market.

4.1 Estimation Strategy: First Stage

The data we use for the first-stage estimation is the panel data on the yearly sales and average prices for each brand in each of the 20 major cities from 2000 to 2008. Recall that we allow for consumer heterogeneity in price sensitivity as described in equation (2). Specifically, we model price coefficient β_h as a function of household income I_h: $\beta_h = \beta + \gamma_1 I_h + \gamma_2 \tau_h$. We expect the households with higher income to be less price sensitive than the families with lower income. Given the aggregate nature of our data, we draw I_h from a log-normal distribution specific to each city.[14]

Following Berry, Levinsohn and Pakes (1995), we estimate the demand parameters using a GMM framework. Given any guess on the parameters that determine individual price sensitivity, $\theta_r = [\gamma_1, \gamma_2]$, one can invert the demand system to obtain the mean utility of each product, $\varphi_{jmt} = \alpha_{jm} + \beta p_{jmt} + \xi_{jmt}$, by equating the predicted market share in equation (3) and the observed market share of each brand. We then obtain the following residual:

$$\hat{\xi}_{jmt}(\theta_d) = \varphi_{jmt}(\theta_r) - (\alpha_{jm} + \beta p_{jmt}). \tag{21}$$

The vector of demand parameters θ_d includes the fixed effect of each brand in each city α_{jm}, the mean price coefficient β, and the heterogeneity parameters θ_r. One can consistently estimate θ_d from the moment conditions that interact the residuals defined above and a set of appropriate instruments. Since product prices can be potentially endogenous (Villas-Boas and Winer, 1999), following Hausman (1996) and Nevo (2001) we use the average price of the same brand in other cities as well as the number of competing brands

[14]The mean household income for each city comes from the China Statistical Yearbook. The variance of the household income distribution comes from Duan and Chen (2010), in which the authors report the household income dispersion for urban areas and rural areas in each province. Without more detailed data on the income distribution specific to each city, we use their estimates for the urban areas in the province where a city locates as an approximation.

in the local market as instruments.[15] The GMM estimator is defined as

$$\hat{\theta}_d = \underset{\theta_d}{\text{argmin}}\ \xi'_{jmt} Z W^{-1} Z' \xi_{jmt} \tag{22}$$

where Z is the vector of instruments and W is a consistent estimate of $E[Z'\xi\xi'Z]$.

The estimation results allow us to recover the "signals" that firms receive and use to update their beliefs on themselves and competitors. While a firm can not directly observe the perceived product quality α_{jm}, it receives a noisy signal in each period that contains some information about α_{jm},

$$\delta_{jmt} = \varphi_{jmt}(\theta_r) - \beta p_{jmt} = \alpha_{jm} + \xi_{jmt} \tag{23}$$

which is the mean utility adjusted for price. The estimated signals for each brand in each city at each time period become part of the data used for the second-stage estimation.

Given the demand estimates θ_d, we can compute the marginal cost of each brand in each city based on the first order conditions of the profit maximization. We then calculate the average marginal cost for the second-tier firms in each city, which will be used in the second-stage estimation. We still use the individual cost estimates for each brand in the first tier.

4.2 Estimation Strategy: Second Stage

The objective of the second stage is to estimate the parameters associated with the fixed cost distribution, the initial variances and signal variances for updating firms' beliefs on their own products and competing products. The data used for the estimation in this stage include two parts. The first part is the series of sales signals of each brand in each market derived from the first-stage estimation. The second part is the actual exit decisions observed in each market over time. The parameters in the profit function are obtained from the first-stage estimation. We assume a discount factor of 0.92, corresponding to an annual interest rate of 8%.

As discussed earlier, a firm's initial belief on its own brand can be characterized as a normal distribution with mean μ_{jm0} and variance σ_0^2, where μ_{jm0} is drawn from $N(\alpha_{jm}, \sigma_0^2)$.

[15] The endogeneity arises when a firm knows the demand shock ξ_{jmt} and incorporates the information to the pricing p_{jmt}. Recall that in our model, firms cannot separate the true brand quality α_{jm} and the demand shock ξ_{jmt} but rather take the whole as a signal in learning. However, the pricing decision could be correlated with the signal even though the firm does not perfectly know ξ_{jmt}. We therefore use IV to correct the potential endogeneity issue.

The initial variance σ_0^2 indicates the degree of uncertainty on one's own brand at the beginning of our data period.[16] The signal variance σ_ξ^2 indicates the accuracy of the sales signals in revealing the firm's true type. These two variance parameters determine the evolution of demand uncertainty on one's own type. Similarly, the initial belief on other (second-tier) firms in market m follows a normal distribution with mean $\bar{\mu}_{-jm0}$ and variance $\bar{\sigma}_0^2$, where $\bar{\mu}_{-jm0}$ is drawn from $N(\bar{\alpha}_{-jm}, \bar{\sigma}_0^2)$. The initial variance $\bar{\sigma}_0^2$ and signal variance $\bar{\sigma}_\xi^2$ determine the learning process on the true type of competitors.

Because new entry is very rare in our data, we do not consider entry in the dynamic game estimation and focus on the exit decision instead.[17] For the fixed cost, we allow the mean to vary across cities as a function of the average household income in a city. We expect the fixed cost to be higher in cities with higher household income or richer cities. Specifically,

$$F_{jmt} = \nu_0 + \nu_1 \bar{I}_m + \omega_{jmt}; \quad \omega_{jmt} \sim N(0, \sigma_\omega^2). \tag{24}$$

In summary, The parameters to be estimates in this stage are $[\sigma_0^2, \sigma_\xi^2, \bar{\sigma}_0^2, \bar{\sigma}_\xi^2, \nu_0, \nu_1, \sigma_\omega^2]$.

As described in Section 2.5, the state space contains the following dimensions: $S_{jmt} = [\mu_{jmt}, \sigma_{jmt}^2, \bar{\mu}_{-jmt}, \bar{\sigma}_{-jmt}^2, N_{mt}, Z_m]$. According to the Bayes rule, both σ_{jmt}^2 and $\bar{\sigma}_{-jmt}^2$ are functions of time period t given the initial variances and signal variances. Therefore, we can trace the time period t in place of both σ_{jmt}^2 and $\bar{\sigma}_{-jmt}^2$. This enables us to reduce the number of dimensions by one, i.e., $S_{jmt} = [\mu_{jmt}, \bar{\mu}_{-jmt}, N_{mt}, t, Z_m]$.[18] Any time-invariant market characteristics are captured by the state vector Z_m. We solve for the equilibrium for each city individually.

Given a set of parameter values, we use backward induction to solve the dynamic game for a specific city. Start with a T that is big enough such that the uncertainty on the perceived quality of one's own brand and competing brands becomes extremely small and additional learning is not necessary.[19] We compute the equilibrium value function and exit

[16] The degree of prior uncertainty could potentially be a function of market experience and other firm characteristics. Since we do not have additional firm-specific information such as initial entry year in a market, we assume the prior uncertainty to be the same across the second tier firms at the beginning of our data period.

[17] For papers that focus on the equilibrium entry decisions across markets, see for example, Bresnahan and Reiss (1990), Seim (2006) and Zhu and Singh (2009).

[18] The state variable μ_{jmt} and $\bar{\mu}_{-jmt}$ are continuous. Each variable is discretized into 10 grid points in estimation.

[19] We verify this condition after an equilibrium is obtained. In practice we set T = 20 in the estimation. Ching (2010) also assumes that there is a terminal period that the uncertainty of the product is completely

probability in time period T with no learning going forward, and then use it to compute the value function and exit probability in time period $T-1$. We keep going backward in time until we solve for the equilibrium value function and exit probability for all time periods.

The equilibrium in each period is the fixed point of the best response mapping in the space of firms' choice probabilities. Specifically, we solve for the equilibrium in period t in the following steps:

1. Given the discretized state space, calculate the expected single-period profit for each state. It involves integrating the uncertainties in the demand function and solving a Bertrand pricing game between different types of competitors in the market.[20]

2. Given the initial guess of exit probabilities P_t^0, calculate the transition matrix $T(S'|S)$. Given the expected single-period profit, the transition matrix, and the value function in period $t+1$, calculate the value function of the current period following equation (19).

3. Given the calculated value function, update the policy function to obtain P_t^1 following equation (16).

4. Repeat step 2 by replacing P_t^0 with P_t^1, and repeat step 3 to update P_t^1. Continue the procedure until $|P_t^1 - P_t^0|$ approaches 0.

5. Save the equilibrium value function and policy function to be used in period $t-1$.

For a specific set of parameter values, we can compute the equilibrium exit probabilities for all time periods in all markets and then calculate the likelihood of any exit pattern. The objective is to find the set of parameter values that maximizes the likelihood of the observed exit pattern in our dataset. Let θ_g be the structural parameters in the dynamic model. Then

$$\hat{\theta}_g = \max_{\theta_g} \prod_m \prod_j \prod_t Pr(exit_{jmt}|\theta_g)^{Y_{jmt}}[1 - Pr(exit_{jmt}|\theta_g)]^{1-Y_{jmt}} \tag{25}$$

where $Pr(exit_{jmt}|\theta_g)$ is the equilibrium probability of exit from city m in period t by firm j under the parameter vector θ_g. Y_{jmt} is actual observation on exit, which takes the value 1 if firm j exits from city m in period t and 0 otherwise.

resolved and solves the dynamic programming problem backwardly.

[20]Recall that there are three layers of uncertainties: uncertainty of one's own demand, uncertainty of the average type of competitors and the temporary demand shocks. To solve for the optimal price, one has to first integrate out the layers of uncertainties. We use numerical integration method here.

4.3 Identification

We briefly discuss the identification of the parameters in the dynamic model. The identification of the learning parameters are from their different effects on firms' exit patterns. The variance of the sales signals is identified by how fast firms learn about their true types and how fast they exit conditional on the initial uncertainty levels. The variance of initial beliefs on one's own and competitors' products can be identified by the observed exit patterns in the first period, given that firms make exit decisions at the beginning of a period before production and sales. Exit in the first period may indicate that the demand uncertainty is low to start with.

The separation of the belief variances on firms' own products versus competitors' products comes from their different implications on firms' exit decisions. As can be seen from the counterfactual analysis below, the option value of waiting is different when removing the uncertainty on one's own product or competitors' products while retaining the other. By maximizing the likelihood of the observed exit patterns, we can determine the levels of these variance terms.

Finally, the parameters associated with the fixed cost are mainly identified from the cross-sectional feature of the data. Similar firms facing similar set of competitors in different markets may exit in different time periods, suggesting difference in fixed cost across markets. Such observations help identify the fixed cost parameters.

4.4 First-stage Estimation Results

The main estimation results of the random-coefficient logit demand model are presented in Table 2. The baseline price coefficient is negative as expected and highly significant. To allow for consumer heterogeneity, we interact price with household income. The positive effect of the interaction term suggests that households with higher income are less price sensitive. The brand and market specific fixed effects ($\hat{\alpha}_{jm}$) were not individually reported. The mean perceived quality for Galanz is 0.8 across markets and it is -0.5 and -0.7 for Media and LG respectively. The mean perceived quality for the second tier firms is -3. For brands in this tier with presence in multiple cities, there is significant difference in perceived quality across markets with an average standard deviation of 1.92 across brands. Such difference in local demand explains the non-uniform exit decision for the same brand.

As discussed earlier, based on the demand estimates we can recover the marginal costs from the first order condition of the profit maximization problem. Given the cost estimates, we calculate the gross margins for each brand in each market throughout our study period. The average gross margin across brands and markets is 8.89%. Even the top brands, such as Galanz, Midea and LG, have gross margins around 10%. The low gross margin reflects the fierce competition in China's microwave industry. The competition and the low profit margin eventually drive unprofitable firms to exit.

4.5 Second-stage Estimation Results

The estimation results in the second stage are displayed in Table 3. The results indicate that both the uncertainty around one's own brand and the uncertainty around the competing brands are present at the beginning of our data period. Moreover, the uncertainty about competitors is of larger magnitude and more persistent than the uncertainty of own demand in this industry. The standard deviation of a firm's initial belief toward one's own product is 0.5862, while the standard deviation of the initial belief toward competitors is 1.1928. It suggests that the uncertainty about competitors is much higher than the uncertainty about one's own product. Moreover, the standard deviation of a firm's own sales signals (0.9336) is smaller than that of the sales signals on competitors (1.3275). In other words, the sales signals that a firm received about its own product are more precise or more informative in revealing its true type than the sales signals about other firms. A couple of factors may contribute to this difference: (1) A firm uses the average sales signals of competing products to learn about the mean quality level of competing products. Such learning is relatively coarse compared with learning about a specific firm. (2) A firm may have less access to accurate information about the demand for competitors than for its own product.

We also find that the standard errors around the parameter estimates that govern the process of learning of others are larger than those around the parameter estimates for self learning. It suggests that there may be substantial variation across markets in the importance of learning about competitors relative to learning about self in determining the exit patterns.

According to the fixed cost estimates, the average fixed cost $\tilde{F}_m$ (without the random component) per period across markets is 157,000 Chinese yuan, which is consistent with the low labor and rental cost in China during our study period. The coefficient for the average household income is positive and significant, indicating that the fixed cost is indeed higher in cities with higher wage.

5 Discussion

With the model estimates, we can now examine how various factors affect firms' exit decisions and in turn the market evolution pattern. The focus is on the role of demand uncertainty on firms' exit timing and on industry shakeout. First, we study an individual firm's optimal exit policy and how it depends on the perceived product quality and the uncertainty involved. Next we simulate the industry evolution to see how the number of firms evolves over time in a market. We show that the aggregate evolution pattern is affected by the fixed cost of operating in the market, and the demand uncertainty for a firm's own product and for the competing products.

5.1 Optimal Exit Decision

First, we examine the factors driving firms' optimal exit decisions. As discussed previously, a firm's expected future value of staying in the market and its exit probability depend on the state variables $S_{jmt} = [\mu_{jmt}, \sigma^2_{jmt}, \bar{\mu}_{-jmt}, \bar{\sigma}^2_{-jmt}, N_{mt}, Z_m]$. In particular, we are interested in the impact of the perceived product quality and the degree of uncertainty of both one's own product and the competing products, which are the first four elements of the state vector.

Although firms are uncertain about the true demand for their own products and the competing products, their current beliefs on the perceived quality of these products are still critical in determining whether a firm would exit or stay in the market. If a firm believes that the demand for its product is likely to be high, it has less incentive to exit. However, if a firm believes that competing products are probably of higher quality, it is more likely to exit. This intuition is consistent with the value function and exit policy depicted in Figure 2, which is based on the Beijing market with 14 second-tier brands at the beginning of our study period.

Figure 2 shows how expected future value and probability of stay in the first period vary according to different values of the perceived product quality of one's own product (μ_{jm0}) and of competing products ($\bar{\mu}_{-jm0}$). It is clear that as a firm's perceived product quality becomes higher, holding the perceived quality of competing products constant, the expected future value is higher and so it the probability of stay. On the other hand, when the perceived quality of competing products is higher, holding one's own product quality constant, then the expected future value and probability of stay are both lower. In comparison, the value function and exit policy are more sensitive to the perceived quality of one's own product than to that of competing products.

In Figure 2, we hold the uncertainty around the initial belief at the estimated level, and examine the implications of varying perceived quality. Next we fix the perceived product quality and investigate the role of uncertainty. Specifically, in this exercise we fix the mean perceived quality of a firm's own product and of competing products at the same level of -3, and vary the degree of prior uncertainty associated with its own product (denoted by σ_0) and with competing products (denoted by σ_0^c). The case of $\sigma_0 = \sigma_0^c = 0$ corresponds to no uncertainty on any product in the market. When σ_0 or σ_0^c goes up from 0, there is higher degree of uncertainty on one's own type or on competitors' types.

As indicated in Figure 3, the degree of uncertainty associated with the prior belief has a significant effect on the expected future value and probability of stay. Both the uncertainty on oneself and on others lead to higher expected future value and higher probability of stay. In other words, firms are more likely to stay in the market when there is higher degree of uncertainty, especially when the uncertainty toward one's own type is high. This is consistent with the finding in Hitsch (2006) that, under higher demand uncertainty, the option value of staying and learning can be potentially high, while the risk is limited because firms can always stop operating at any time and cut the losses. The uncertainty on the competitors side provides further incentive to stay and learn. Together they explain the observation in our data that many firms choose to stay in the market despite losing money in the current period.

5.2 Market Evolution Pattern

The factors driving firms' exit decisions will in turn have an impact on how a market evolves over time. Now we conduct a series of simulations to study the market evolution pattern according to our model and estimates.

In order to simulate the evolving number of firms over time in a specific market, we start with the observed set of firms in year 2000. For each of these firms, we draw the initial beliefs according to $\mu_{jm0} \sim N(\alpha_{jm}, \sigma_0^2)$ and $\bar{\mu}_{-jm0} \sim N(\bar{\alpha}_{-jm}, \bar{\sigma}_0^2)$. At the beginning of each period, firms decide whether to stay or exit according to their private draw of the fixed cost from the estimated distribution. The firms that choose to stay then engage in price competition and operate in the market. At the end of the period the remaining firms draw sales signals and update their beliefs.

Following the above procedure we simulate the number of firms over time. We can repeat the procedure for a large number of times and obtain the average number of firms over time as our simulated market evolution path. In Figure 4 we plot the simulated evolution path for Beijing and Shanghai market and compare it with the respective observed path. Our simulated paths resembles closely to the observed ones.

Next, we vary the fixed cost and the degree of demand uncertainty to see how the market evolution pattern reacts to such variations. Unless stated otherwise, all subsequent simulations are based on the Beijing market.

5.2.1 Impact of fixed cost

Firms incur a fixed cost in each period if they stay in the market. The magnitude of fixed cost affects not only the profit in the current period, but also the expected future value indirectly. Facing a higher fixed cost of operating in the market, a firm would receive a lower profit in the current period, and in addition would expect the future value of staying to be lower as well. Both would result in a higher exit probability. Therefore, we would expect the shakeout to become faster at a higher fixed cost.

In Figure 5, we plot the predicted market evolution path under the assumption that the fixed cost would be increased or decreased by 10% or 20% respectively. As expected, when the fixed cost is lower, firms tend to stay in the market longer; and when the fixed cost is higher, firms exit faster. By year 2004, the middle of our study period, the predicted exit rate at the current fixed cost is about 66%. The exit rate would have been 62% if the fixed cost were 20% lower, and predicted exit rate would have been 72% if the fixed cost were 20% higher. The more rapid shakeout under higher fixed cost is driven by the fact that staying in the market to collect additional information becomes more costly.

5.2.2 Impact of demand uncertainty

The model estimates reveal the presence of demand uncertainty for firms' own products as well as for competing products. Therefore firms learn in both aspects. To better understand how different aspects of demand uncertainty affect the exit patterns, we simulate the market evolution under the following scenarios: (1) We assume that firms have perfect knowledge on the quality of their own products but are uncertain about the quality of their competitors. In other words, firms "shut down" learning about themselves but keep learning about others. (2) We assume that firms actively engage in learning the demand for their own products but not for the competing products. In other words, the learning of self is present but not the learning of competitors. (3) There is no demand uncertainty for any product in the market, and no learning is necessary in this case.

The simulation results are presented in Figure 6. The model prediction with full learning is the same as in Figure 4 (a). Compared to scenario with full learning, other scenarios lead to faster exits and more rapid industry shakeout. Intuitively, if there is less uncertainty on the profitability for a firm, then there is less value of waiting to gather additional information. Therefore, we expect to see faster exit with less demand uncertainty. Indeed the scenario with no uncertainty and no learning leads to the most rapid industry shakeout, while the evolution paths generated from the other two scenarios with partial learning are somewhere between the predictions of full learning and no learning. In addition, we find that in this market the simulated path with learning about competitors only is closer to the true path than the simulated path of learning about self only, which suggests that ignoring the uncertainty from the competitors can bias the predictions on exit timing.

5.2.3 Value of information

Under demand uncertainty, it is optimal for even a weak firm to delay exit and collect more information to learn about the true demand for its product and competitors. Such experimenting behavior could be costly to firms, however, as a weak firm may continue to incur losses until it decides to exit eventually. The higher the uncertainty, the longer a weak firm might stay, and hence the deeper losses. If the uncertainty could be removed or reduced, weak firms would exit faster and avoid the losses associated with the expensive learning process. Therefore, the industry benefit from information that could remove or reduce prior uncertainty.

In Figure 6, we simulate the market evolution assuming different levels of uncertainty in the market. With no uncertainty, weak firms would exit faster and incur smaller losses than they would under full uncertainty. Therefore we expect the scenario of no uncertainty to generate higher profit for the industry than the scenario of full uncertainty. The difference in total profit can be regarded as the value of information that removes the uncertainty.

We calculate the total profit for the industry in each scenario. We find that compared to the scenario with full uncertainty and hence full learning, the total profit would have been approximately 1 million Chinese yuan higher if the uncertainty around one's own product can be removed. The total profit would have been 0.82 million higher if there is no uncertainty about competitors. And the total profit would have been 2.65 million higher if all uncertainty can be removed.

The increase in total profit associated with lower uncertainty comes from two possible sources. First, with lower uncertainty, weak firms would exit faster and avoid incurring excessive losses. Second, strong firms also benefit from the faster exits of weak firms due to less competition in the market. Taking together, the industry may be better off if the uncertainty can be reduced, which suggests the value of acquiring information.

6 Conclusion

In this paper, we develop a dynamic model to study firms' exit decisions under demand uncertainty and competition. Our model accounts for the learning of one's own product as well as the learning of the competitors'. Our estimation results show that there is significant uncertainty around the competing products and learning on both sides is important. Through simulations, we examine how the industry evolution pattern can be affected by different aspects of market characteristics and learning process. Higher demand uncertainty for a firm's own product and for its competing products gives the firm stronger incentive to stay in the market and learn about the demand, resulting in slower industry shakeout. Higher fixed cost, on the other hand, renders a firm to shorten experimentation and triggers faster exit.

Our proposed model provides an explanation for the empirical observation that the same brand present in multiple markets selectively exit some. Potential demand for the same brand may vary across markets. In addition, the number and type of competitors are different in difference markets. Even with the same competitors, the local preference towards their products can be uncertain. Therefore, learning of a local market is necessary. A brand chooses to exit in those markets where evidences suggest a weak competitiveness. Recall the HTC case introduced in the beginning of the paper. While it exited the Brazilian market due to weak performance, it had a strong presence in Asian markets such as China and Japan. Other explanations of exit at the firm level, such as technological change and acquisition, are less applicable in market level exit.

There are a few avenues worth pursuing for future research. First, given very few observations on entry we choose to focus on firms' exit decisions especially in the empirical part. With appropriate data it would be more interesting to estimate an integrated model of entry and exit, so that we can trace firms' paths from the beginning and investigate how the uncertainty resolves through learning.

When integrated with the entry stage, the model can be further extended to allow for additional types of learning. For example, potential entrants can learn about the aggregate potential demand through the early movers' performance, and decide whether to enter the market (Horvath, Schivardi and Woywode, 2001; Yang, 2012). Therefore, in addition to the uncertainty about the quality of different products, the uncertainty about the aggregate market size could be important in the early stages of a new industry.

The model can also be extended to study the evolution of different industries, and potentially provide an explanation to why some industries exhibit earlier and dramatic shakeout, while some others see it much later. According to the model, the former could be driven by low uncertainty or fast learning while the latter could be a result of high prior uncertainty or slow updating. We can examine the industry characteristics that affect the initial uncertainty and speed of learning, or affect the industry shakeout pattern directly. Thus estimating the model using cross-industry data may generate insights about how industry characteristics influence the shakeout pattern and timing.

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Appendix

Here we elaborate on the details to derive the second line in equation (19). Note that the value function is

$$\bar{V}(S) = P^s\{E[\tilde{\pi}(S)] - \tilde{F} + \theta E[\bar{V}(S')|S]\} - P^s E[\omega|\omega < EVC]$$

where $EVC = E[\tilde{\pi}(S)] - \tilde{F} + \theta E[\bar{V}(S')|S]$ is the expected value of continuation. Given the assumption that the random component of fixed cost ω_{jmt} is normally distributed with mean 0 and variance σ_ω^2, the probability of stay is

$$P^s = Pr(\omega_{jmt} < EVC) = \Phi(\frac{EVC}{\sigma_\omega}). \tag{26}$$

Using properties of a normal distribution, one can show that, for $x \sim N(\mu, \sigma^2)$ and any constant a,

$$E(x|x < a) = \mu - [\frac{\frac{1}{\sigma}\phi(\frac{a-\mu}{\sigma})}{\Phi(\frac{a-\mu}{\sigma})}]\sigma^2. \tag{27}$$

Using this result, we can express the conditional expectation in the second part of the value function above as:

$$P^s E[\omega_{jmt}|\omega_{jmt} < EVC] = -\sigma_\omega \phi(\frac{EVC}{\sigma_\omega}) = -\sigma_\omega \phi(\Phi^{-1}(P^s)).$$

The last step is a transformation into the inverse of the cumulative distribution function. The purpose is to express the term as a function of the exit policy, which facilitates the policy iteration in computing the equilibrium.

Figures and Tables

Table 1: Number of Brands across Cities

City	2000	2004	2008
Beijing	17	9	6
Changsha	13	7	5
Chengdu	12	8	6
Chongqing	12	8	6
Dalian	11	7	6
Fuzhou	11	6	6
Guangzhou	12	8	6
Hangzhou	12	9	6
Harbin	10	8	6
Kunming	10	7	6
Nanjing	15	8	6
Qingdao	10	9	6
Shanghai	19	9	7
Shenyang	8	8	6
Shenzhen	10	9	6
Tianjin	13	9	6
Wuhan	18	8	6
Wuxi	14	9	6
Xiamen	12	7	5
Xian	12	7	5

Table 2: Estimates for the Demand Model

	Est.	Std. Err.
Price (β)	-0.0423	0.0003
$\times$ Income (γ_1)	0.0082	0.0018
$\times$ Unobserved factor (γ_2)	0.0075	0.0040
Number of Observations	1525	

Table 3: Estimates for the Dynamic Exit Game

	Est.	Std. Err.
Learning of self		
initial prior std. (σ_0)	0.5862	0.0680
signal std. (σ_ξ)	0.9336	0.0648
Learning of others		
initial prior std. ($\bar{\sigma}_0$)	1.1928	0.4891
signal std. ($\bar{\sigma}_\xi$)	1.3275	0.4400
Fixed cost		
baseline (ν_0)	0.0344	0.0296
Income (ν_1)	0.0025	0.0007
std. (σ_ω)	0.0891	0.0352
Number of Observations	787	
Log likelihood	-376.15	

Figure 1: The Industry Evolution

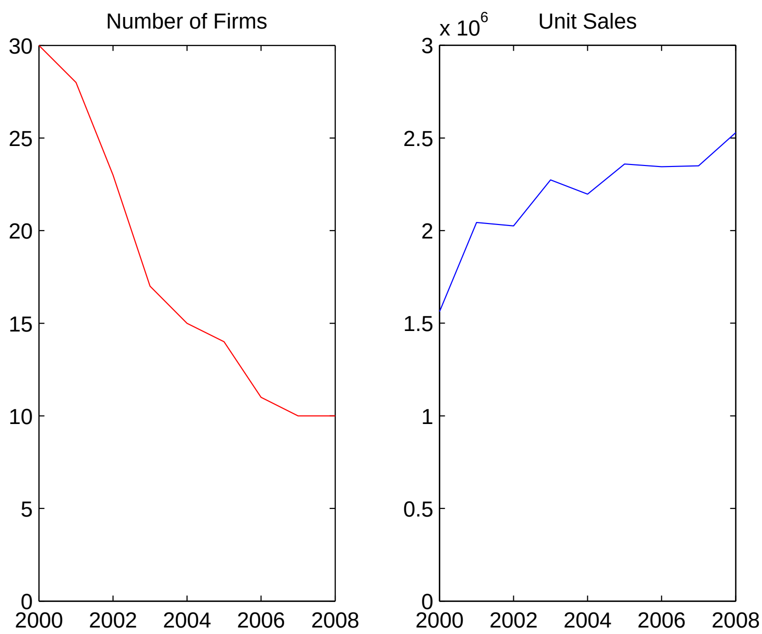


Figure 2: Expected Future Value and Probability of Stay on Product Quality

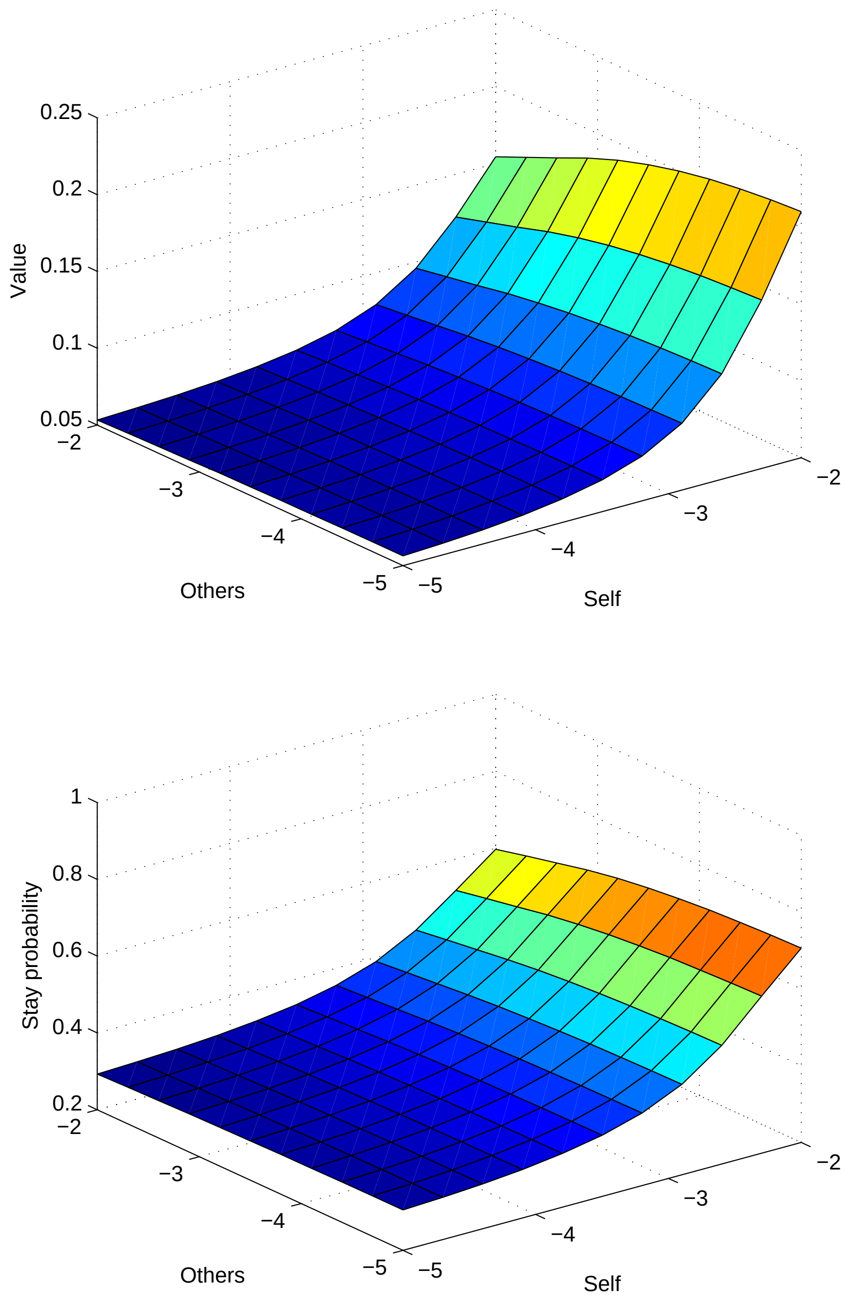
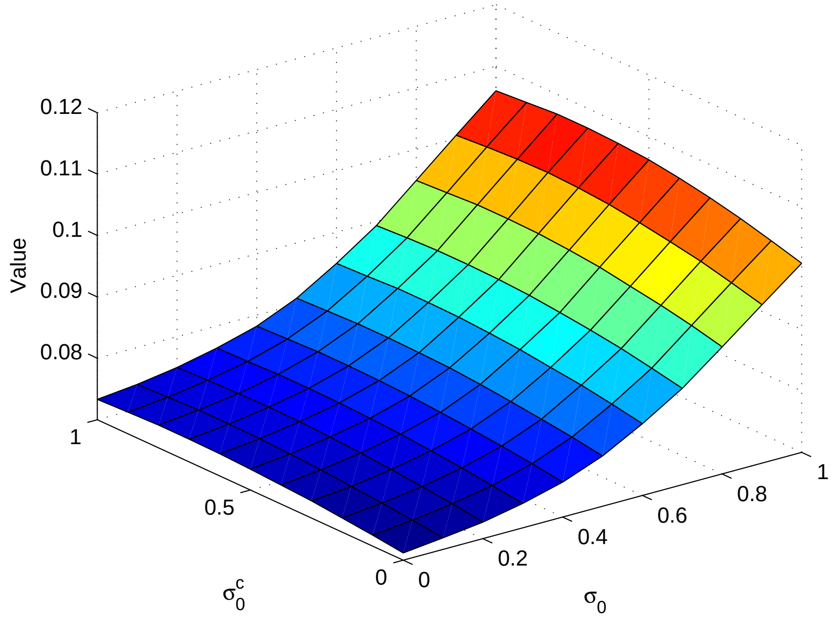


Figure 3: Expected Future Value and Probability of Stay on Demand Uncertainty



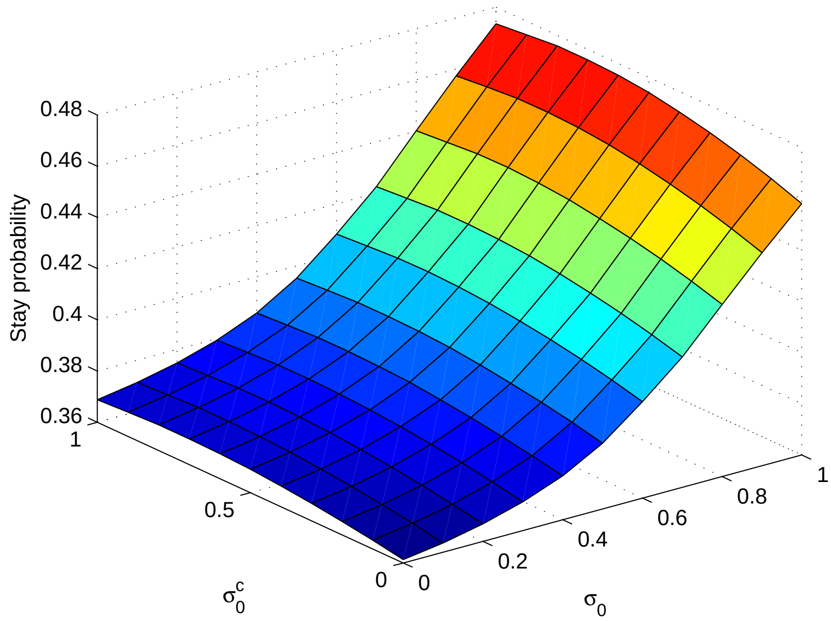
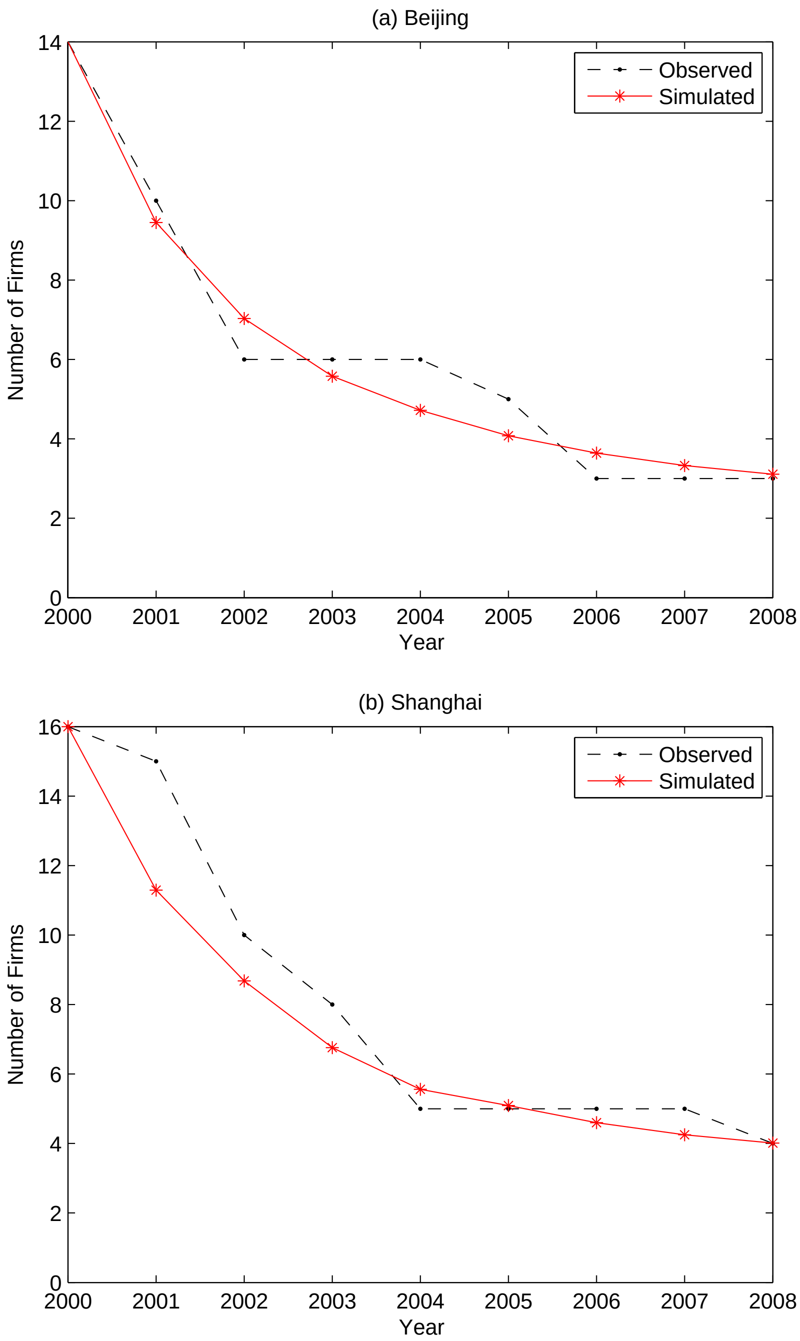


Figure 4: Actual vs. Simulated Exit Paths*



*The number of firms depicted in the figure include the second-tier firms only.

Figure 5: Market Evolution and Fixed Cost

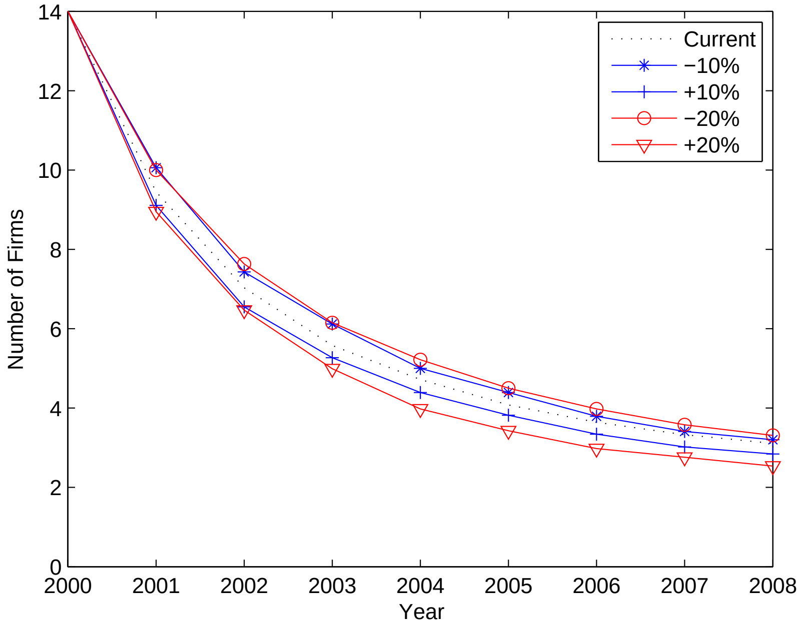


Figure 6: Market Evolution and Demand Uncertainty