The Effect of Quality Disclosure on Firm Entry and Exit Dynamics: Evidence from Online Review Platforms

Ying Bao* Limin Fang† Matthew Osborne‡

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Abstract

This paper develops a theoretical model that studies the impact of quality disclosure on the entry and exit dynamics of firms in an industry with many firms. We employ a novel dynamic oligopoly game framework and use the oblivious equilibrium concept to solve the game. We unravel two key forces through which quality disclosure drives market dynamics: (1) the direct effect, which is the change in consumers' preference for a product once they know the true quality, and (2) the competition effect, which is the change in the competitive environment due to quality disclosure. Depending on which force dominates, several scenarios are possible. In some cases, quality disclosure can drive competition to such a fierce level that high-quality firms are discouraged from entry. To test our model predictions, we use as a case study the impact of online reviews on the market dynamics of the restaurant industry in Texas. Using a unique dataset that tracks the entry and exit of restaurants and consumers' online review activities, we empirically test the effect of quality disclosure through online reviews. Results confirm the most common predictions of our model, where the direct effect dominates the competition effect: the penetration of online review platforms encourages the entry of high-quality independent restaurants and speeds up the exit of young low-quality independent restaurants. No significant impact is found for either chains or established independent restaurants.

*University of Illinois Urbana-Champaign, Gies College of Business. Email: ybao@illinois.edu.
†University of British Columbia, Sauder School of Business. Email: limin.fang@sauder.ubc.ca.
‡University of Toronto, Rotman School of Management. Email: matthew.osborne@rotman.utoronto.Ca.

1 Introduction

Information on product quality plays a critical role in consumer's purchase decisions. In the digital age, an abundance of resources is at consumers' fingertips to search for product information; for example, online reviews, videos and images from social media influencers, consumer reports, etc. Searching for quality information has become an integral part of consumers' shopping journey. According to statistica.com, over 90% of consumers read reviews before buying a product (van Gelder, 2023). Given the crucial role of quality information in consumers' decisions, policymakers are mandating quality disclosure in various domains, such as restaurant hygiene grade, automobile manufacturer fuel efficiency measure, and mortality rates for hospitals (Dranove and Jin, 2010). These phenomena have intrigued academic researchers to study the impact of quality disclosure on a number of market outcomes, including consumer learning (e.g. Fang, 2022; Luca, 2016; Wu et al., 2015), product sales (e.g. Chevalier and Mayzlin, 2006; Zhu and Zhang, 2010; Hollenbeck, 2018), firms' strategic voluntary disclosure decisions (e.g. Guo and Zhao, 2009; Jin, 2005; Oh and Park, 2019a) and quality improvement (e.g. Jin and Leslie, 2003). However, none of the existing research has systematically investigated the effect of quality disclosure on the entry and exit dynamics of firms in an entire industry. Knowing the change in industry dynamics is important because it helps policymakers and regulators to assess the welfare effect of quality disclosure. While existing research primarily focuses on how quality disclosure improves matches between consumers and products, the entry and exit dynamics of products is just as important (if not more) because it affects consumers' choice set.

To shed light in this understudied area, this paper develops a theoretical framework that models how quality disclosure affects the entry and exit dynamics of firms in an industry with many firms. This model builds on the dynamic oligopoly games under the Ericson and Pakes (EP) framework (Ericson and Pakes, 1995a). Using the oblivious equilibrium (OE) concept proposed by Weintraub et al. (2008), we characterize the properties of the equilibrium outcomes. Although the model does not yield closed-form equilibrium solutions, we are able to derive analytically comparative statics that generalize the effect of quality disclosure on equilibrium outcomes. Specifically, we highlight two main forces behind quality disclosure: the direct effect and the competition effect. On the one hand, quality disclosure exacerbates the gap between the perceived qualities of high- and low-quality firms, leading to a divergence in consumers' preferences over high- and low-quality products (the direct effect). On the other hand, quality disclosure can change the competition faced by firms by affecting both consumers' perceptions over quality of competing products and competitors' entry and exit behaviors (the competition effect). Depending on which effect dominates, the total effect of quality disclosure can go in different directions. For example, low-quality firms are likely to exit more with greater quality disclosure because consumers do not like low-quality products. Greater exits will result in fewer firms in the market and thereby weaken competition. Weaker competition in turn encourages the entry of all firms. In which direction the net effect should be is unclear.

The interplay between the two forces yields a number of interesting scenarios. First, although the direct effect is certain for high- and low-quality restaurants, the competition effect is not. It may increase or decrease. If high-quality restaurants enter more and exit less, then competition would increase. However, if the greater exits of low-quality restaurants significantly reduce the number of firms in the market, then competition could weaken. Second, for a given directional change in competition, whether the direct effect dominates the competition effect yields different equilibrium scenarios. For example, for high-quality firms, if competition increases and the competition effect dominates, then despite the benefit of higher perceived quality, these firms would not want to enter the market. This mechanism can generate the counter-intuitive outcome that quality disclosure reduces the entry of high-quality firms. Similarly, for low-quality firms, if competition declines and the competition effect dominates, then they would want to enter the market, which is another counter-intuitive result. Evidently if the direct effect dominates the competition effect, regardless of how competition changes, high-quality firms will be more likely to enter and less likely to exit, and the reverse would hold for low-quality firms. We characterize the various scenarios through a number of propositions and corollaries. To present these model predictions intuitively, we conduct numerical simulations to compute the equilibrium outcomes of the model for a wide range of parameters, and plot the difference in the outcomes with and without quality disclosure. We find that the parameter region with the direct effect being dominant is larger than those where the competition effect dominates. In addition, these simulations also illustrate how market factors such as entry cost or quality difference between high- and low-quality firms affects equilibrium outcomes.

A few other features of our model are worth noting. First, although our model focuses on the entry and exit dynamics, the profit function from product competition has a micro foundation in the form of the logit demand. Second, we include firms that are affiliated with chains, such that consumers' perception of their quality does not change with quality disclosure. Including these firms makes the model more realistic and helps the model generate empirically testable predictions. Last but not the least, even though our model's setting is the restaurant industry, it is general enough to apply to all retail industries with many firms.

To test our model predictions empirically, we use as a case study the effect of online reviews on the market dynamics of the restaurant industry in Texas. The restaurants industry is an excellent context for the empirical application because it features many differentiated firms in the market. We collected a unique dataset with a full record of the entry and exit timing of full-service restaurants in Texas from 1995 to 2016. To gauge consumers' usage of online reviews, we also gathered review information from three major platforms, including Google, Yelp and TripAdvisor. These online review platforms penetrated different regions in Texas during various periods of time. This variation allows us to tease out the effect of online review platforms on the entry and exit of restaurants. The empirical results confirm the most common scenario from the model predictions, where the direct effect dominates the competition effect. For entry, the penetration of online review platforms increases the entry of high-quality independent restaurants but has the opposite effect on low-quality restaurants. In terms of exit, the effect depends on a restaurant's quality, chain affiliation as well as age: young high-quality independent restaurants stay in the market longer, whereas young low-quality independent restaurants exit more quickly. No statistically significant effect is detected for either chain or established independent restaurants.

In this context, this paper makes several contributions to the literature. First, we develop a novel framework that models the effect of quality disclosure on the entry and exit dynamics of firms in an industry with many firms. We provide a complete picture of the effect by unravelling the interplay between the direct effect and the competition effect of quality disclosure. To the best of our knowledge, this paper is the first that studies these effects theoretically and systematically. Second, our paper generalizes the model predictions by providing analytical comparative statics in a dynamic oligopoly game. Dynamic oligopoly games under the EP framework is well known for lacking analytical close-form solutions. As a result, comparative statics are usually obtained through numerical simulations for a range of parameters (e.g. Besanko et al., 2014; Borkovsky et al., 2012). Our comparative statics, on the other hand, is derived analytically and thereby has the advantage of being able to characterize the model predictions in the entire parameter space, providing more generalized insights. Third, our model implements the solution concept of the oblivious equilibrium (OE) proposed by Weintraub et al. (2008). This equilibrium concept greatly simplifies the equilibrium solutions. Our application demonstrates the value of adopting the OE concept in solving games that may suffer from the curse of dimensionality. Finally, our empirical study provides support to our theoretical model, and it documents a number of new empirical facts. In particular, the effect of online reviews on firm entry has not been examined in the existing literature.

Our research has important implications for both firms and policymakers. It provides guidance to firms on how to choose markets with various degrees of mandatory quality disclosure. Mandatory disclosure is not always good for high-quality firms because it can greatly intensify competition. Therefore, high-quality firms may want to avoid some markets with mandatory disclosure. To policymakers, our study sheds light on when to mandate quality disclosure. As discussed earlier, mandatory disclosure policies have been implemented in many industries such as automobile, airlines, healthcare, etc. The main argument for these policies is that quality disclosure reduces information frictions, promotes market competition, and weeds out low-quality firms, all of which would improve consumer welfare. However, as shown by our model predictions, sometimes quality disclosure can reduce competition and give rise to market power of high-quality firms. In addition, in some cases, it could increase competition so much that it discourages the entry of high-quality firms. Therefore, mandatory quality disclosure is not necessarily always welfare improving. It should be implemented with caution.

The rest of the paper is organized as follows. In Section 2, we review the related literature. In Section 3, we set up the model and provide characterizations of the equilibrium solutions. In

Section 4, we develop and prove comparative statics and provide numerical examples. In Section 5, we empirically test our model predictions using the restaurant industry in Texas as a case study. In Section 6, we conclude and discuss future research areas.

2 Literature Review

This paper is closely related to several strands of literature. First, our paper contributes to the studies of quality disclosure and its impact on market outcomes. Hotz and Xiao (2013) builds a model of voluntary quality disclosure with differentiated products and heterogeneous consumers, and shows that disclosure will result in more elastic demand and more intensive price competition. Oh and Park (2019b) shows that quality disclosure can affect market competition. They show that a unique non-disclosure equilibrium can exist, in which the incumbent does not reveal its quality and prevents potential entrants from determining the profitable quality level, thereby deterring entry. They also show that mandatory disclosure law will increase potential entrants and the expected quality from the incumbent. Board and Meyer-ter Vehn (2013) models product quality as a function of past investments, with incentives depending on quality disclosure and consumer learning. When the market learns quality through good signals, a high-reputation firm has a lower investment incentive to improve quality, while a low-reputation firm has a higher incentive to make a breakthrough. Conversely, when the market learns quality through bad signals, incentives increase in the firm's reputation. Empirically, Jin and Leslie (2003) and Simon et al. (2005) support that restaurant hygiene disclosure has caused restaurants to make hygiene quality improvements and reduced foodborne disease in Los Angeles. Jin and Sorensen (2006) and Dafny and Dranove (2008) provide evidence that public rating increased the market share for higher-rated plans.Dranove and Sfekas (2008) derives a model of patient response to hospital report cards and structurally estimates the profit gain for higher-rated hospitals. They show that the effect is mainly due to patients shifting away from low-rated hospitals. Using online review platform as a quality disclosure mechanism, Farronato and Zervas (2022) empirically support that restaurant improve hygiene if they are more exposed to review platforms. In addition to revenue and quality change, consumer welfare is affected by quality disclosure. Charbi (2021) look at the welfare impact of quality reporting in Medicare Advantage. Wu et al. (2015) and Lewis and Zervas (2016) use structural models to estimate the welfare effects of review platforms. Using online review platforms as a quality disclosure enforcement, our paper has a novel contribution of modeling disclosure and subsequent impact on dynamic entry and exit, and studying its impact on welfare through a more complete framework.

Second, our paper contributes to the study of online reviews and their impact on market outcomes. Some literature study the impact of online reviews on sales revenue; for example,Chevalier and Mayzlin (2006), Zhu and Zhang (2010), Anderson and Magruder (2012), Luca (2016) and Hollenbeck (2018). Using the structural learning model, Zhao et al. (2013) estimate the impact of reviews on book sales using panel data of 243 consumers. In addition to estimating the revenue impact of online reviews on restaurants, our paper examines its impact on market structure through the heterogeneous effect on different types of restaurants. Fang (2022) studies the heterogeneous effect of online reviews and shows that high-rating restaurants in more touristy areas experience larger revenue increases caused by online reviews. Our project is closely related to Donati (2022), where he builds a model of consumer search with firms' endogenous quality decisions and estimates the impact of online reviews on the restaurant industry in Rome. He shows that the reduction of mobile internet data expenses causes the monthly exit rate among more touristy restaurants to increase by $0.11 - 0.16$ percentage points, which was mainly driven by low-rating restaurants. But the firm entry is only studied in the aggregate industry composition analysis, where the overall share of low-rating restaurants in tourist areas decreases by 2.5 percentage points. Newberry and Zhou (2019) uses a discrete choice demand model that incorporates Bayesian learning to find that the online review system has a larger impact on smaller local retailers on Alibaba's Tmall. Anenberg et al. (2019) show that online review platforms put a larger selective force on urban markets. In addition, Janetos and Tilly (2017) studies the impact of online review platforms on store exit by estimating a dynamic model of adverse selection, ratings, and optimal stopping. In equilibrium, sellers optimally exit the market, and market beliefs on quality are determined by the rating system and seller's actions. They compute the returns to reputation and use counterfactuals to show the impact of the review system on market structure. However, online review platforms will ultimately affect firm entry by reshaping the ex-ante beliefs and incentives, yet both theoretical and empirical evidence on how online reviews affect entry is scarce. Our research studies both entry and exit which allows a more complete and accurate estimate of the impact of online review platforms.

More broadly, this research contributes to the literature on the dynamic oligopoly game of entry and exit, in particular, the application of the oblivious equilibrium concept for Ericson and Pakes (1995a) type models. Weintraub et al. (2008) proposes an approximation method that bypasses the curse of dimensionality for analyzing Ericson and Pakes (1995a)-style dynamic models of imperfect competition. They define oblivious equilibrium, in which each firm makes decisions based only on its own state and long-run industry state while ignoring current competitors' states. They establish conditions under which oblivious equilibrium well approximates Markov perfect equilibrium asymptotically as the market becomes large. In Weintraub et al. (2010), they develop an algorithm for computing oblivious equilibrium and demonstrate its efficiency and accuracy by deriving its approximation error bounds. Benkard et al. (2015) further extends OE to applications in highly concentrated markets, by defining a partially oblivious equilibrium that allows a set of dominant firms. This extension accommodates richer strategic interactions but is still computationally light. A recent application is Chen and Xu (2023), where they develop a structural model of R&D investment and productivity for the Korean electric motor industry, and use OE approximation to estimate the R&D cost, knowledge spillovers and other dynamic parameters. Our model is a novel application of the oblivious equilibrium concept, where we are able to characterize the property of the model analytically, derive model comparative statics, and provide more generalized insights from the model predictions.

3 Model

Our model follows the framework from the seminal work by Ericson and Pakes (1995b) (EP), where firms are forward-looking and make entry and exit decisions every period, and they take into consideration their rivals' strategies that will affect their profits. Given that the restaurant industry features many small differentiated firms in one industry, we adopt the oblivious equilibrium concept proposed by Weintraub et al. (2008), who show that in a market with many small firms, the oblivious equilibrium approximates well the Markov perfect equilibrium. In our model, there are high- and low-quality restaurants as well as chain and independent restaurants. In addition, independent restaurants are divided into three age types: new, young, and established, based on how long they have been in the market. The age type of the independent restaurant matters because independent restaurants do not enter the market with a reputation, unlike chain restaurants. Consumers need to learn gradually the true quality of an independent restaurant. The longer an independent restaurant is in the market, the more likely consumers know of its true quality. The reputation built through consumers' own trials and word of mouth (WOM), such as reviews on online review platforms and recommendations from friends and family, will play a role in how fast consumers learn the true quality of independent restaurants. Although we develop the model in the restaurant-industry setting, our model is general enough to accommodate a wide range of industries where quality disclosure is important and there are many small firms in a market. For this reason, we use firms and restaurants interchangeably in this section. Below is the detailed setup of our model.

3.1 Firms, Actions, Profits and States

Every period potential entrants decide whether to enter the market or not. Entrants' types in terms of their quality type ($T \in \{H, L\}$) and chain affiliation ($D \in \{I, c\}$) are determined before entry. The quality (q) for both high-quality independent and chain restaurants is $\bar{q}$, and the quality for the low quality restaurants is $\underline{q}$. The quality q is also set before entry and does not change after entry. The numbers of potential entrants from each type are N_H for high-quality independent restaurants, N_L for low-quality independent restaurants, N_{Hc} for high-quality chain restaurants, and N_{Lc} for low-quality chain restaurants. Once potential entrants enter the market, they become incumbents.

Incumbent chain restaurants' quality is revealed to consumers as soon as they are in the market because they benefit from the chain's reputation. Incumbent independent restaurants, on the other hand, need time to reveal their true quality to consumers. New incumbent independent restaurants are perceived as having a quality at $\hat{q}_0$, which is assumed to be exogenously given. For simplicity, we set it at the average of those of the high- and low-quality restaurants:

$$\hat{q}_0 \equiv \frac{1}{2}(\bar{q} + \underline{q}), \tag{1}$$

This perceived quality represents an average quality perceived by all consumers in the market.

After being in the market for one period, a new restaurant becomes a young restaurant, and its perceived quality $\hat{q}_1$ becomes $\hat{q}_0 + (q - \hat{q}_0)\gamma, \forall q \in \{\underline{q}, \bar{q}\}$. $\gamma \in [0, 1]$ represents the amount of information available that consumers can use to learn about restaurant quality.[1] At one extreme, when $\gamma = 0$, there is no information, and the perceived quality of young independent restaurants stays at $\hat{q}_0$. At the other extreme, when $\gamma = 1$, information is so widely available such that the perceived quality is the true quality. In reality, γ is mostly likely somewhere in between. The larger γ is, the closer to the truth the perceived quality becomes.

After being in the market for two periods, a restaurant becomes established, and its true quality is fully revealed to consumers. This stage is an abstraction of the period when a restaurant has been in the market long enough, such that the restaurant's true quality is learned. Similar to this stage, the young stage is also a generalization of the learning period, where information on quality is only starting to accumulate. The learning period may be much longer than one period in the real world. Here we model it into one period as a way of simplification. At the extreme, the learning period may last forever. We discuss this case in an extension of the model at the end of this section.

At the established stage, once a restaurant's true quality is fully revealed, the perceived quality is the true quality for the remainder of the restaurant's life time until it exits. The time horizon of this dynamic game is infinite. If a restaurant never exits, it stays in the market for an infinite number of periods. We summarize how perceived quality evolves over different stages in Table C.1 of the Appendix.

Every period, an incumbent restaurant takes as given the market structure and consumers' beliefs on its quality and engage in a static product competition.[2] A restaurant's perceived quality affects its per-period flow profit in terms of both consumers' willingness to pay and its competitive position relative to other incumbents. In particular, the distribution of restaurants over perceived quality ($n(\hat{q})$) matters for a restaurant's flow profit, which has the following form:

$$\pi(q, \hat{q}(q, g, D, \gamma), M, N, f) = \frac{M \exp(\hat{q})}{\sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}') + 1} - C(q, D), \tag{2}$$

where $q \in \{\underline{q}, \bar{q}\}$ is the restaurant's true quality, and $\hat{q} \in \{\hat{q}_0, \hat{q}_1, q\}$ is the perceived quality, which is a function of a restaurant's true quality q, chain affiliation $D \in \{I, c\}$, age type g and γ. Here I

[1] This function form is consistent with the Bayesian learning process when taken at the population average. Fang (2022) provides detailed derivation of this functional form. (See equation (13) of Fang (2022).) Here, we abstract away from the effect of a restaurant's sales on its own perceived quality; that is, greater demand at a restaurant may generate more information on quality.

[2] This is a common assumption in the EP framework. That is, we abstract away from firms' dynamic considerations when choosing prices, such as predatory pricing or pricing low at the beginning in order to induce more consumers learn about their quality. Instead firms are myopic and choose prices only to maximize their current-period profits.

denotes independent and c chain. Let $\{0, 1, 2\}$ represent a restaurant age type of new, young, and established, respectively, then $g \in \{0, 1, 2\}$. Similar to $\hat{q}$, $\hat{q}' \in \{\hat{q}_0, \hat{q}_1, q\}$ represents any perceived quality that exists in the market. $n(\hat{q}')$ is the number of restaurants with perceived quality $\hat{q}'$. $\frac{\exp(\hat{q})}{\sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')+1}$ can then be seen as the market share of a restaurant with perceived quality $\hat{q}$. Here we abstract from equilibrium prices set in the static product competition, but rather use $\hat{q}$ to represent the "price-adjusted" quality; that is, the actual quality minus the price. This abstraction is reasonable as quality measures, especially those from online review platforms or magazines, are usually adjusted for prices. For example, a 5-star fine-dining restaurant does not have the same actual quality (in terms of either food or service) with that of a 5-star burger joint. The 5-star fine-dining restaurant is typically seen as having a much higher actual quality than the burger joint, but as being much more expensive as well. In this demand expression, we also assume that all firms have the same constant markup. This assumption follows directly from a logit demand model with many small firms that compete in prices.[3] The parameter M then represents the multiple of market size and the markup, and consequently, $\frac{M\exp(\hat{q})}{\sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')+1}$ summarizes the variable profit of a restaurant. The function $C(q, D)$ captures the fixed cost incurred by a restaurant each period, such as rent and the chef's salary. This cost depends on the restaurant's true quality and its chain affiliation. High-quality restaurants usually incur a higher cost than low-quality restaurants. Given a quality type, independent restaurants typically experience higher costs than chain restaurants, which benefit from economies of scale. Note that the cost function is affected by the true quality of a restaurant, not the perceived quality. For example, even though a new high-quality restaurant is perceived as having the same quality as a new low-quality restaurant, the high-quality restaurant incurs a higher cost. In addition, we assume that M is large enough, such that $\pi(q, \hat{q}(q, g, D, \gamma), M, N, f) > 0$ always.

The timing of events in this dynamic game is as follows:

1. At the beginning of each period, potential entrants from each quality type and chain affiliation type decide to enter the market or not. Let $a \in \{0, 1\}$ denote a firm's action, with 0 representing inactive in the market and 1 active.

2. If a firm decides to enter ($a = 1$), it incurs an entry cost of $\kappa(q, D) + \varepsilon$, where $\kappa(q, D) > 0$ is the average entry cost incurred by a restaurant with quality q and chain affiliation type D. $\varepsilon \sim U(-b_0, b_0)$ is a private random shock, and is independent and identically distributed (i.i.d.) across time and firms. The firm observes the shock first before making the entry decision.

3. Once a firm enters the market, it earns a profit as a new restaurant immediately.[4]

[3]See equation 3.5 of Berry et al. (1995). In a logit demand model with Bertrand competition, when the market share of a product is small, its markup is constant.

[4]The absence of time-to-build assumption does not affect the predictions of the model.

4. Consumers learn about restaurant quality over time. Restaurants make profits according to equation 2.

5. At the beginning of each period, an incumbent firm decides whether to exit the market. If it exits, it receives a scrap value of $\phi \sim U[-b_1, b_1]$, which is a private shock only known to the firm itself and is observed before the decision of exit. It is i.i.d. across time and firms. A firm that chooses to exit does not earn a profit in that period.

6. Once a firm exits, it stays out of the market permanently. A firm that is not in the market earns 0 profit.

Given the profit function in equation 2 as well as the shocks to entry cost and scrap value, a restaurant's payoff relevant state is $(q, g, M, \boldsymbol{n}, D, \varepsilon, \phi)$, where $\boldsymbol{n} = \{n(\hat{q}')\}$ is a vector that summarizes the long-run invariant distribution of the number of restaurants at each perceived quality level. Here for notation simplicity, we assign $g = 0$ to potential entrants as well as new restaurants. That is, restaurants with $g = 0$ are potential entrants at the beginning of the period; if they decide to enter the market, they become new restaurants. New restaurants do not have the option to exit until the beginning of next period after becoming young restaurants. Because we adopt the oblivious equilibrium (OE) concept, where firms do not track each individual firm's actions but take the long-run invariant distribution of firms as given, M and $\boldsymbol{n}$ can be omitted from a restaurant state. A restaurant can base its entry and exit action only on q, g, and D in addition to ε and ϕ. Let $s = (q, g, D)$ denote the state of a restaurant.

3.2 A Firm's Problem

A firm chooses a strategy (σ) of entry and exit every period in order to maximize the net present value of current and future profits. In particular, a firm discounts its future profits at a rate of $\beta \in (0, 1)$. Following the literature, we focus on symmetric Markov strategies of firms, such that the action at each period from the strategy is state-dependent and firms of the same type choose the same strategy. Let $\widetilde{V}(s, \varepsilon, \phi, a)$ denote the action-specific value function that accounts for the present value of a firm's profits from current and all future periods, then a firm solves the following maximization problem:

$$\max_a \widetilde{V}(s, \varepsilon, \phi, a | M, \boldsymbol{n}) = \Pi(s, \varepsilon, \phi, a) + (\mathbb{1}\{g = 0\} + a\mathbb{1}\{g > 0\}) \beta \mathbb{E}\left(\widetilde{V}(s', \varepsilon', \phi', a' | \sigma, s, a, M, \boldsymbol{n})\right), \tag{3}$$

where $\Pi(s, \varepsilon, \phi, a) \equiv a\pi(s, a) - a\mathbb{1}\{g = 0\}(\kappa + \varepsilon) + (1 - a)\mathbb{1}\{g > 0\}\phi$. The symbol ' denotes the next period. The law of motion for g is $g' = (g + a)\mathbb{1}\{g < 2\} + g\mathbb{1}\{g = 2\}$. The next period action $a' = \sigma(s', \varepsilon', \phi')$.

Given that ε and ϕ are private shocks, firms' strategies appear probabilistic to their rivals. Once we integrate over ε or ϕ, a firm's strategy can be represented by entry and exit probabilities.

In particular, let $P_\sigma^E(q, D)$ and $P_\sigma^X(q, g > 0, D)$ denote the entry and exit probabilities associated with the strategy σ respectively, then

$$P_\sigma^E(q, D) = \int \mathbb{1}\{\sigma(q, 0, D, \varepsilon) = 1\} \frac{1}{2b_0} d\varepsilon, \tag{4}$$

$$P_\sigma^X(q, g, D) = \int \mathbb{1}\{\sigma(q, g > 0, D, \phi) = 0\} \frac{1}{2b_1} d\phi \tag{5}$$

Let $V(s)$ denote an integrated value function such that $V(s) \equiv \int \tilde{V}(\boldsymbol{s}, \varepsilon, \sigma) \frac{1}{2b_0} d\varepsilon$ when $g = 0$ and $V(s) \equiv \int \tilde{V}(\boldsymbol{s}, \phi, \sigma) \frac{1}{2b_1} d\phi$ when $g > 0$. Then integrated value function can be expressed as a function of the entry and exit probabilities:

$$V(s; \mathbf{P}^\sigma) = \begin{cases} P_\sigma^E(s)\left(\pi(s) - \kappa - \mathbb{E}(\varepsilon|a = 1) + \beta V(q, 1, D; \mathbf{P}^\sigma)\right) + (1 - P_\sigma^E(s))\beta V(q, 0, D; \mathbf{P}^\sigma) & \text{if } g = 0, \\ (1 - P_\sigma^X(s))\left(\pi(s) + \beta V(q, 2, D; \mathbf{P}^\sigma)\right) + P_\sigma^X(s)\mathbb{E}(\phi|a = 0) & \text{if } g > 0, \end{cases} \tag{6}$$

where $\mathbf{P}^\sigma$ is a vector that summarizes the entry and exit probabilities at various states.

3.3 Oblivious Equilibrium

We use the concept of oblivious equilibrium (OE), which is defined as follows:

$$\max_\sigma V(s|\sigma, M, \boldsymbol{n}) \equiv V(s; \mathbf{P}^*|M, \boldsymbol{n}), \tag{7}$$

where $\mathbf{P}^* = (\mathbf{P^E}, \mathbf{P^X})$ is the oblivious equilibrium strategy and is a collection of the optimal P^E and P^X at various states.

It is important to note that in an OE, competitors' strategies are relevant for a firm's optimal strategy through the industry state $\boldsymbol{n}$, which is invariant over time in the long run. As shown in Weintraub et al. (2008), the OE approximates the Markov perfect equilibrium well if M is very large and if a number of assumptions and the "light-tailed" condition are satisfied. We provide in the Appendix the proof that our setting satisfies the assumptions for OE and the "light-tailed" condition. The light-tail condition means that there are many firms in the market such that not a single firm's action would have a large impact on any other firm's profit, or the probability that this happens is very small. This is why a firm does not need to keep detailed track of competitors' states in an OE. In our setting, when M is very large, the total number of firms in the market is very large. Regardless of each firm's individual entry and exit actions, the fraction of restaurants at any given perceived quality $n(\hat{q}) / \sum_{\hat{q}'} n(\hat{q}')$ remains constant.[5] In addition, the event when the industry is controlled by a few large firms has a very low probability of happening. Therefore, a firm's decision rule by simply taking into account the industry state $\boldsymbol{n}$ when making entry and exit decisions is a close-to optimal strategy.

[5] This is based on the law of large numbers.

An OE should satisfy the following conditions:

$$\pi(q,0,D) - \kappa - \varepsilon + \beta V(q,1,D|\mathbf{P}^*) > \beta V(q,0,D|\mathbf{P}^*), \tag{8}$$

$$\pi(q,g>0,D) + \beta V(q,2,D|\mathbf{P}^*) < \phi \tag{9}$$

These conditions 8 and 9 are based on firms' optimal decisions of entry and exit.

In addition, the invariant long-run distribution of firms $\boldsymbol{n}$ in an OE should satisfy the following conditions:

$$n(q,0,I,\gamma) = N(q,I)P^E(q,I,\gamma); \tag{10}$$

$$n(q,1,I,\gamma) = n(q,0,I,\gamma)(1 - P^X(q,1,I,\gamma)); \tag{11}$$

$$n(q,2,I,\gamma) = (n(q,1,I,\gamma) + n(q,2,I,\gamma))(1 - P^X(q,2,I,\gamma)); \tag{12}$$

$$n(q,c,\gamma) = N(q,c)P^E(q,I,\gamma) + n(q,c,\gamma)(1 - P^X(q,c,\gamma)) \tag{13}$$

where $N(q,D)$ is N_H if $q = \bar{q}$ and $D = I$, N_L if $q = \underline{q}$ and $D = I$, N_{Hc} if $q = \bar{q}$ and $D = c$, and N_{Lc} if $q = \underline{q}$ and $D = c$. These equations are based on the law of motion of $\boldsymbol{n}$.

Equations (10) to (12) show the numbers of independent restaurants at various levels of perceived quality. The age type of a restaurant is important for independent restaurants, but not relevant at all for chain restaurants. Therefore, we have three equations for independent restaurants, but only one for chain restaurants, and the number of chain restaurants is not a function of g. Furthermore, because the long-run distribution of restaurants over perceived quality is invariant, the number of restaurants at each perceived quality level must remain constant as well. This implies that the $n(q,2,I,\gamma)$ in equation (12) and $n(q,c,\gamma)$ in equation (13) will show up in both the left-hand side and the right-hand side of the equations.

The equilibrium conditions in equations (8) to (13) yield a system of non-linear equations, of which the solution $\mathbf{P}^*$ is a fixed point. For any given value of $\gamma \in [0,1]$, an equilibrium solution $\mathbf{P}^*$ exists. We provide the algebraic expressions of the solution $\mathbf{P}^*$ and $\boldsymbol{n}$ in Tables C.3 and C.4 in SectionC of Appendix. Note that there are no closed-form analytical solutions for these probabilities, although they can be solved numerically.

Despite the lack of closed-form solutions, we can still sign the directions of γ's effects on entry and exit probabilities for a wide range of parameters. In the next section, we discuss the comparative statics of the OE solutions. For notation simplicity, from the following section onward, we will convert (q,g,D) into subscripts. We also omit the subscript I for independent restaurants but use the "c" subscript to indicate chain. For example, $P^X(\bar{q},1,I)$ will be denoted as P^X_{H1}, and $P^X(\bar{q},g,c)$ denoted by P^X_{Hc}. We provide a detailed definition of each of these notations in Table A.1 of the Appendix.

Model Extension As mentioned previously, in reality, the learning period captured by the young stage of an independent restaurant can last much longer than one period. At the extreme, it could last forever. For example, at locations with mostly transient consumers, such as tourist areas or areas around highway exits, consumers are travellers and visit the stores only once. No matter how old the restaurants are at these locations, they are new to consumers because consumers never tried them before. Unless consumers have access to online reviews or recommendation from magazines, it is very difficult for consumers to discover the true quality of restaurants before trying them out. In Appendix F, we extend the model to a case with an extremely slow learning process. In this extension, the young stage of an independent restaurant lasts forever. We also provide the OE solution to the extended model, comparative statics, as well as a set of numerical analysis. The key difference in model behaviors between the baseline model in the main text and the extension is that information (as captured by γ) has a much stronger effect on equilibrium outcomes in the extended model. This is because information plays a role for a much longer period of a restaurant's life in the extension, instead of just one period.

4 Comparative Statics

The equilibrium outcomes of this model is the result of the interplay between two main forces: a direct effect and a competition effect. The direct effect comes from the fact that quality disclosure (γ) influences the perceived quality $\hat{q}$ and thereby affects the flow profit. The change in flow profits in turn alters firms' entry and exit dynamics, which influence the competition faced by each firm. This is the competition effect. Like the direct effect, the competition effect also affects the flow profit, but through the denominator of the flow profit, $\sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')$. The direct effect and the competition effect can work in the same direction for some types of restaurants, but can also work against each other for other types of restaurants. Which effect dominates determines the direction of the overall effect of quality disclosure (γ) on the entry and exit dynamics of firms. We first formally define the direct effect and the competition effect. Then we introduce an assumption of the parameter space to eliminate extreme cases. Next, we provide four propositions (Propositions 1-4) that characterise the directions of the effect of γ on entry and exit probabilities as well as the conditions under which they hold.

Definition 1. The direct effect (DE) of γ on $\mathbf{P^*_T}, \forall T \in \{H, L\}$ is $\frac{\partial \mathbf{P^*_T}}{\partial \pi_{T1}} \frac{\partial \pi_{T1}}{\partial M \exp(\hat{q}_{T1})} \frac{\partial M \exp(\hat{q}_{T1})}{\partial \hat{q}_{T1}} \frac{\partial \hat{q}_{T1}}{\partial \gamma}$, and 0 on $\mathbf{P^*_{Tc}}$.

In this definition, $\mathbf{P^*_T}$ is the vector of equilibrium probabilities of independent restaurants with quality level $T \in \{H, L\}$; for high quality, $\mathbf{P^*_H} = (P^E_H, P^X_{H1}, P^X_{H2})$ and for low-quality, $\mathbf{P^*_L} = (P^E_L, P^X_{L1}, P^X_{L2})$. Similarly defined, $\mathbf{P^*_{Tc}}$ is the vector of equilibrium probabilities of chain restaurants. This definition states that the direct effect is through the numerator of the flow profit function π. Because the numerator of neither π_{T0} nor π_{T2} changes with γ, the derivative is only with respect to π_{T1} and subsequently $\hat{q}_{T1}$. For chain restaurants, the numerators of the flow profits never change with γ; therefore, the direct effect for chain is 0.

Definition 2. The competition effect (CE) of γ on $\mathbf{P}^*_{\mathbf{T}}, \forall T \in \{H, L\}$ is $\left(\frac{\partial \mathbf{P}^*_{\mathbf{T}}}{\partial \pi_{T0}} \frac{\partial \pi_{T0}}{\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')} + \frac{\partial \mathbf{P}^*_{\mathbf{T}}}{\partial \pi_{T1}} \frac{\partial \pi_{T1}}{\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')} + \frac{\partial \mathbf{P}^*_{\mathbf{T}}}{\partial \pi_{T2}} \frac{\partial \pi_{T2}}{\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')}\right) \frac{\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')}{\partial \gamma}$, and the CE on $\mathbf{P}^*_{\mathbf{Tc}}$ is $\frac{\partial \mathbf{P}^*_{\mathbf{T}}}{\partial \pi_{Tc}} \frac{\partial \pi_{Tc}}{\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')} \frac{\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')}{\partial \gamma}$

This definition states that the competition effect is through the denominator of the flow profit function. The DE and CE together constitute the total effect of γ on equilibrium probabilities. Before introducing the propositions, we first discuss an assumption on the parameter space in order to eliminate extreme cases of the effect of γ. The assumption is not restrictive and easy to hold under the assumptions of OE.

Assumption 1. The market size M is large enough such that

1. $\left(1 + \frac{(\sqrt{b_1} - B_H)}{B_H} \exp(\bar{q} - \hat{q}_{H1})\right) \frac{-(n_{L1} \exp(\hat{q}_{L1}) - n_{H1} \exp(\hat{q}_{H1}))}{\sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}') + 1} < 1$ when $\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')/\partial \gamma > 0$;
2. $\left(1 + \frac{(\sqrt{b_1} - B_L)}{B_L} \exp(\underline{q} - \hat{q}_{L1})\right) \frac{n_{L1} \exp(\hat{q}_{L1}) - n_{H1} \exp(\hat{q}_{H1})}{\sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}') + 1} < 1$ when $\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')/\partial \gamma < 0$,

where $B_T = \sqrt{(b_1 - \beta b_1 - \beta \pi_{T2})}, \forall T \in \{H, L\}$.

Assumption 1 can easily hold when there are many firms in the market. This assumption is to eliminate cases where the number of restaurants from every type is going up (down) with γ, but $\sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')$ is going down (up). This assumption will be used in the proofs of Propositions 3 and 4.

Once we have the definitions of direct effect and competition effect, we can sign these effects. The signs for the direct effect are perfectly predictable and straightforward. Proposition 1 establishes this:

Proposition 1. The DEs on chain restaurants are 0, and the DEs on independent restaurants have the following signs:

$DE(P^E_H) > 0$, $DE(P^X_{H1}) < 0$, $DE(P^X_{H2}) = 0$,
$DE(P^E_L) < 0$, $DE(P^X_{L1}) > 0$, $DE(P^X_{L2}) = 0$.

In this proposition, $DE(\cdot)$ denotes the direct effect on each probability.[6] The proof of Proposition 1 is shown in the Appendix. The intuition behind the proof of Proposition 1 is very simple. The entry probability of an independent restaurant increases in the flow profit at the young stage, and the young-stage flow profit increases in its numerator, which grows in the perceived quality $\hat{q}_1$. Because the perceived quality increases with γ for high-quality restaurants, but decreases for low-quality restaurants, the signs of the direct effects for the entry probabilities are then easily determined. As for the exit probabilities, those at the young stage decrease in π_{T1}, and therefore the signs of the direct effects are the opposite as those for entry probabilities. The exit probabilities at the established stage do not change in γ because π_{T1} do not enter firms' decisions at this stage; as a result, the direct effects for them are 0.

[6]The functional form of $DE(\cdot)$ is the same as that in Definition 1; for example, $DE(P^E_H) = \frac{\partial P^E_H}{\partial \pi_{H1}} \frac{\partial \pi_{H1}}{\partial M \exp(\hat{q}_{H1})} \frac{\partial M \exp(\hat{q}_{H1})}{\partial \hat{q}_{H1}} \frac{\partial \hat{q}_{H1}}{\partial \gamma}$.

Proposition 2. Under certain conditions, the CE on any probability can be positive, zero or negative. The key determining factor is $\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')/\partial\gamma$. The conditions are

(1) when $\bar{F}_L + \bar{F}_H > 0$, $\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')/\partial\gamma > 0$;

(2) when $\bar{F}_L + \bar{F}_H = 0$, $\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')/\partial\gamma = 0$, and

(3) when $\bar{F}_L + \bar{F}_H < 0$, $\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')/\partial\gamma < 0$, where

$$\begin{aligned}
\bar{F}_L = N_L \Bigg[& \exp(\hat{q}_0)\frac{\partial P_L^E}{\partial\gamma} + \exp(\hat{q}_{L1})\left(\frac{\partial P_L^E(1-P_{L1}^X)}{\partial\gamma} + P_L^E(1-P_{L1}^X)\frac{(\underline{q}-\bar{q})}{2}\right) \\
& + \exp(\underline{q})\left(\frac{\partial P_L^E(1-P_{L1}^X)(1/P_{L2}^X-1)}{\partial\gamma} + \frac{N_{Lc}}{N_L}\frac{\partial P_{Lc}^E(1/P_{Lc}^X-1)}{\partial\gamma}\right)\Bigg] \qquad (14) \\
\bar{F}_H = N_H \Bigg[& \exp(\hat{q}_0)\frac{\partial P_H^E}{\partial\gamma} + \exp(\hat{q}_{H1})\left(\frac{\partial P_H^E(1-P_{H1}^X)}{\partial\gamma} + P_H^E(1-P_{H1}^X))\frac{(\bar{q}-\underline{q})}{2}\right) \\
& + \exp(\bar{q})\left(\frac{\partial P_H^E(1-P_{H1}^X)(1/P_{H2}^X-1)}{\partial\gamma} + \frac{N_{Hc}}{N_H}\frac{\partial P_{Hc}^E(1/P_{Hc}^X-1)}{\partial\gamma}\right)\Bigg] \qquad (15)
\end{aligned}$$

The proof is shown in the Appendix. For ease of interpretation, we refer to $\sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}'$ as competition in the remaining text. Proposition 2 says that a higher γ can potentially increase or decrease competition faced by firms. On the one hand, greater extent of quality disclosure can make higher-quality restaurants known to consumers and thereby increase competition. On the other hand, it can also encourage the exit of low-quality firms and subsequently reduce competition by decreasing the total number of competitors. The exact signs depend on which force overpowers the other. As shown in the expressions of $\bar{F}_L$ and $\bar{F}_H$ (equations 14 and 15 respectively), the effect on competition is mostly through the effect on entry and exit probabilities of firms. Proposition 2 allows us to sign the competition effect. The corollary below establishes that.

Corollary 1.

(1) When $\bar{F}_L + \bar{F}_H > 0$, $CE(P_T^E) < 0$, $CE(P_{T1}^X) > 0$, $CE(P_{T2}^X) > 0$, $CE(P_{Tc}^E) < 0$, $CE(P_{Tc}^X) > 0, \forall T \in \{H, L\}$.

(2) When $\bar{F}_L + \bar{F}_H = 0$, $CE(P_T^E) = 0$, $CE(P_{T1}^X) = 0$, $CE(P_{T2}^X) = 0$, $CE(P_{Tc}^E) = 0$, $CE(P_{Tc}^X) = 0, \forall T \in \{H, L\}$.

(3) When $\bar{F}_L + \bar{F}_H < 0$, $CE(P_T^E) > 0$, $CE(P_{T1}^X) < 0$, $CE(P_{T2}^X) < 0$, $CE(P_{Tc}^E) > 0$, $CE(P_{Tc}^X) < 0, \forall T \in \{H, L\}$.

In this corollary, $CE(\cdot)$ indicates the competition effect on each probability, and it follows the functional form as illustrated in Definition 2. The proof of Corollary 1 is trivial and therefore not provided.

Proposition 1 and Corollary 1 together show that for certain regions of the parameter space, the DE and CE work in the same direction for some probabilities while work against each other for other probabilities. For example, when $\bar{F}_L + \bar{F}_H < 0$, CE and DE are both positive for P_H^E, but are in different directions for P_L^E. The total effect of γ on P_L^E then depends which effect dominates.

With these definitions and propositions in hand, we can sign the total effect of γ for certain regions of the parameter space. Proposition 3 and Proposition 4 establish that.

Proposition 3. When $\bar{F}_L + \bar{F}_H > 0$, the signs of the effects of γ on all equilibrium probabilities are certain except for P_H^E and P_{H1}^X. In particular, $\partial P_{Tc}^E/\partial\gamma < 0, T \in \{H, L\}$, $\partial P_{T2}^X/\partial\gamma > 0, T \in \{H, L\}$, and $\partial P_{Tc}^X/\partial\gamma > 0, T \in \{H, L\}$. As for P_H^E and P_{H1}^X, only two cases arise: (1) $\partial P_H^E/\partial\gamma > 0$ and $\partial P_{H1}^X/\partial\gamma < 0$. (2) $\partial P_H^E/\partial\gamma < 0$ and $\partial P_{H1}^X/\partial\gamma < 0$.

Proposition 3 says that when competition increases, the entry probabilities of chain restaurants decrease with γ, and the exit probabilities of established independent and chain restaurants increase with γ. In terms of the signs of P_H^E and P_{H1}^X, only two scenarios can arise: one is that the entry probability of high-quality independent restaurants increases in γ, and the exit probability of high-quality young restaurants decreases in γ. The other is that the entry probability of high-quality independent restaurants decreases in γ, and the exit probability of high-quality young restaurants also decreases in γ.

Proof of Proposition 3 is provided in the Appendix. The intuition behind the proof is that when $\bar{F}_L+\bar{F}_H > 0$, competition faced by restaurants increases with quality disclosure, i.e. $\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')/\partial\gamma > 0$. In this case, the DEs of all other probabilities work in the same direction as CEs except for P_H^E and P_{H1}^X. For these two probabilities, only two possible cases of the signs are possible because other cases would violate either the condition $\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')/\partial\gamma > 0$ or the fact that if DE overpowers CE for P_H^E, then DE will overpower CE for P_{H1}^X.[7] In particular, the first case, $\partial P_H^E/\partial\gamma > 0$ and $\partial P_{H1}^X/\partial\gamma < 0$, requires that DE overpower CE for both both probabilities. The second case, $\partial P_H^E/\partial\gamma < 0$ and $\partial P_{H1}^X/\partial\gamma < 0$, requires that DE dominate CE for P_{H1}^X at the young stage of an independent restaurant, but be dominated by CE for P_H^E upon entry. In addition, it is simple to see that this can occur when $\bar{F}_L + \bar{F}_H = 0$. The corollary below states this formally:

Corollary 2. *When $\bar{F}_L + \bar{F}_H = 0$, the effects of γ on all equilibrium probabilities come from DEs, and the signs of these effects are as outlined in Proposition 1.*

Proposition 4. When $\bar{F}_L + \bar{F}_H < 0$, the signs of the effects of γ on all equilibrium probabilities are certain except for P_L^E and P_{L1}^X. In particular, $\partial P_{Tc}^E/\partial\gamma > 0, T \in \{H, L\}$, $\partial P_{T2}^X/\partial\gamma < 0, T \in \{H, L\}$, and $\partial P_{Tc}^X/\partial\gamma < 0, T \in \{H, L\}$. As for P_L^E and P_{L1}^X, only two cases arise: (1) $\partial P_L^E/\partial\gamma > 0$ and $\partial P_{L1}^X/\partial\gamma > 0$. (2) $\partial P_L^E/\partial\gamma < 0$ and $\partial P_{L1}^X/\partial\gamma > 0$.

Proposition 4 says that when competition declines, the entry probabilities of chain restaurants increase with γ, and the exit probabilities of established independent and chain restaurants decrease with γ. In terms of the signs of P_L^E and P_{L1}^X, only two cases can happen: one is that the entry

[7] The latter condition comes from the fact that at the entry stage, for DE to dominate, DE must over come the CEs from all π_0, π_1 and π_2, but at the young stage, DE only needs to overcome the CEs from π_1 and π_2. Therefore, if DE dominates at the entry stage, it must dominate at the young stage. See the Appendix for a detailed argument.

probability of low-quality independent restaurants increases in γ, and the exit probability of low-quality young restaurants also increases in γ. The other is that the entry probability of low-quality independent restaurants decreases in gamma, and the exit probability of low-quality young restaurants increases in γ. Proof of Proposition 4 is provided in the Appendix. The intuition behind the proof is very similar to that for Proposition 3, and will not be repeated here. In particular. the first case in Proposition 4 requires that DE dominate CE for P_{L1}^{X} at the young stage, but be dominated by CE for P_{L}^{E} at the entry stage. The second case requires that DE dominates CE at all stages of an independent restaurant's life.

Proposition 3, Corollary 2 and Proposition 4 summarize all the possible cases that could arise as the result of quality disclosure. First, for chain and established independent restaurants, the entry and exit probabilities are solely determined by the competition effect. Second, in terms of the entry and exit probabilities of young independent restaurants, the total effect of quality disclosure depends on which type effect dominates, DE or CE. In both Proposition 3 (1) and Proposition 4 (2), the DEs dominate the CEs for all probabilities in question. In Proposition 3 (2) and Proposition 4 (1), the DEs dominate in the exit probabilities at the young stage of an independent restaurant, but the DEs are dominated by the CEs in the entry probabilities of independent restaurants.

As shown by Proposition 3, Corollary 2 and Proposition 4, the prediction of the effect of quality disclosure is not deterministic, and a few cases can arise depending on the parameters of the model. To illustrate some of these cases and to gain insights into the solution's properties, we provide a set of numerical examples in the next section.

4.1 Numerical Examples

As mentioned previously, the model does not have a closed-form analytical solution.[8] In this section, we turn to numerical methods and conduct a comprehensive exploration of equilibrium solutions across a wide range of parameters. In Subsection 4.1.1, we explore the parameter space and compare the OE solutions when there is no disclosure at the young stage (i.e. $\gamma = 1$) to those when there is full disclosure (i.e. $\gamma = 1$). This comparison elucidates the effect of γ and illustrates some cases as shown in the propositions above. In particular, we emphasize the interplay between the direct effect and competition effect on a selected set of outcomes. In Subsection 4.1.2, we take one point from the parameter space and examine the gradual change in all of the OE outcomes as γ increases gradually from 0 to 1. By plotting the equilibrium probabilities against γ, we show intuitively how entry and exit of firms may change as γ grows.

[8]See Table C.3 in the Appendix for the model solutions.

4.1.1 Exploring the Parameter Space

We explore the parameter space mainly along the dimensions of the average entry costs and the difference between $\bar{q}$ and $\underline{q}$. In particular, we normalize $\underline{q}$ to 0, and vary only $\bar{q}$. For the average entry costs, we vary the entry cost of high-quality independent restaurants (κ_H) and assume that the entry costs of low-quality independent and chain restaurants are of fixed proportions to κ_H. This assumption is to reflect that in reality both low-quality independent and chain restaurants usually incur lower entry costs. For example, low-quality independent restaurants do not need to buy high-end kitchen equipment as high-quality restaurants do. In addition, chain restaurants can benefit from economies of scale in entry because the chain headquarters usually select the sites and negotiate rent or property acquisition on behalf of each individual outlet. We focus on the two main parameters ($\bar{q}$ and κ_H) because they are the most economically meaningful compared to other parameters. The parameter $\bar{q}$ is directly related to the effect of γ — if $\bar{q}$ is not much higher than 0, then quality disclosure is meaningless. The entry cost κ_H directly influences the entry decisions of firms, and thereby could exacerbate the effect of γ. The detailed setup of the values of other parameters of the model is outlined in Table E.1 of the Appendix. We provide additional explanation of the parameter values in the Appendix. For the ranges of $\bar{q}$ and κ_H, they are set to be $[0.2, 3]$ and $[1, 24]$ respectively. We hope through this wide range of parameter space, we are able to capture the different cases described in Section 4.

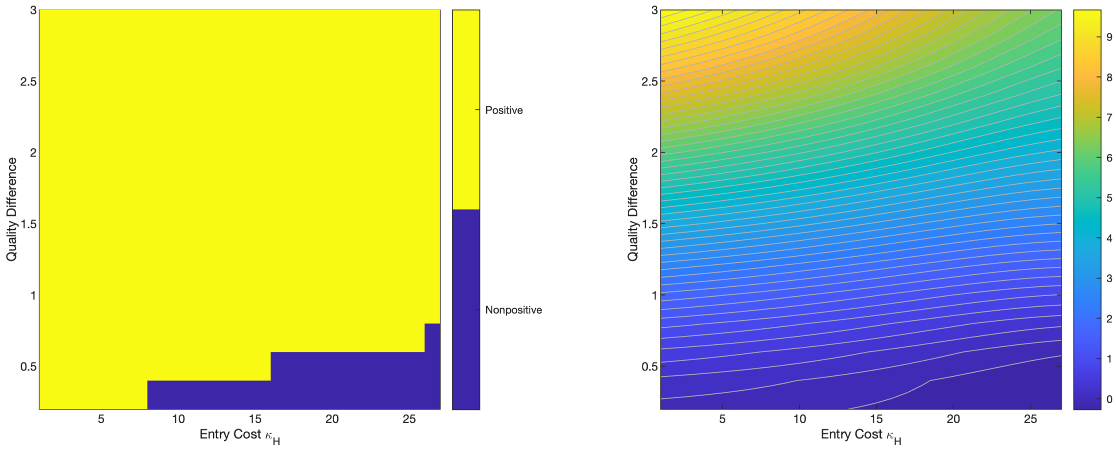
For this numerical exercise, we focus on comparing the OE outcomes under the scenario with no disclosure ($\gamma = 0$) to those with full disclosure ($\gamma = 1$). In particular, we present two types of comparison results: one is the direction of the change, i.e positive or negative, and the other is the change in magnitude, i.e. percentage change in the values of the outcome variables, such as exit probabilities. All changes are calculated as the OE outcomes when $\gamma = 1$ minus those when $\gamma = 0$. Below we present the comparison results for three sets of equilibrium outcomes: (1) change in competition (i.e. $\sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')$), (2) change in entry probabilities (i.e. P_H^E and P_L^E), and (3) change in exit probabilities of young independent restaurants (i.e. P_{H1}^X and P_{L1}^X). By focusing on these three sets of equilibrium outcomes, we hope to unravel the interplay between the various forces that influence the effect of quality disclosure.

Effect on Competition Figure 1 illustrates the change in competition. The left panel, Figure 1a, displays the direction of the change, and the right panel, Figure 1b, shows the percentage change. The x axis in both panels is the entry cost, and the y-axis is the quality difference. In panel 1a, the yellow region represents a positive change, whereas the dark blue region indicates a non-positive change. The positive change implies that competition intensities as the result of quality disclosure; in contrast, the non-positive change suggests that competition either does not change or weakens when there is quality disclosure. These results are consistent with Proposition 2, i.e. under some conditions, competition can increase, and under some other conditions, it could weaken.

Figure 1a also shows two distinct features: (1) the yellow region is much larger than the dark blue region, suggesting that competition effect is much more likely to intensify as the result of quality disclosure.[9] (2) The dark blue region occurs mostly in the lower right corner of the graph; that is, when the quality difference is small and when the entry cost is high. It is easy to understand that when the quality difference is large, the direct effect of quality disclosure will be large. High-quality independent restaurants will be encouraged to enter the market, whereas low-quality independent restaurants will exit. Given that high-quality restaurants contribute more to competition — because in competition $(\sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}'))$, the numbers of high-quality restaurants are weighted by $\exp(\bar{q})$ — competition is likely to intensify when the quality difference is large. When the quality difference is small, on the other hand, competition could weaken, as shown by the dark blue region in figure 1a. In particular, bigger entry costs would discourage the entry of all restaurants and thereby dampen competition in the market in general. When combined with a small quality difference, bigger entry costs can decrease competition. This is because the marginal benefit of quality disclosure is small for high-quality independent restaurants at this point, and due to the high entry barrier, high-quality independent restaurants' entry probability would not increase much. Low-quality independent restaurants, on the other hand, will exit due to quality disclosure. Therefore, there is likely a net loss in the number of restaurants in the market, leading to weaker competition.

The right panel, Figure 1b, displays the magnitude of the change in competition. It offers a compelling insight: the competition effect is strongest when entry costs are small and quality difference is high. When entry cost is small, restaurants of all types are incentivized to enter the market, regardless of quality disclosure. The impact of quality disclosure on competition can be amplified by small entry costs. This is because high-quality independent restaurants are more likely to enter the market as the result of quality disclosure at this point, leading to a more competitive market environment. Along the quality-difference dimension, the greater the quality difference, the higher the direct effect of quality disclosure, and the greater incentives high-quality restaurants have to enter the market. More high-quality restaurants in the market therefore intensify competition. It should be noted that too much increase in competition can reduce the entry of high-quality independent restaurants. This case will be discussed in detail when we examine the effect of quality disclosure on entry.

[9] In the main paper, we set equal number of potential entrants for high- and low- quality restaurants. In Appendix Section E.2, we also provide numerical simulations with the same specification as Table E.1 except that we set the number of potential entrants for low-quality restaurants to be significant higher than that for high-quality restaurants. In this case, we only observe decreased competition. We explore and discuss the corresponding equilibrium under this set of parameter specification as well.



(a) Direction (b) Percentage Change

Figure 1: Change in Competition When $N_L = N_H$

Effect on Entry Figure 2 displays the change in the entry probabilities for both high- and low-quality independent restaurants (i.e., P_H^E and P_L^E). The top two panels, figures 2a and 2b, are for high-quality restaurants, and the lower two, figures 2a and 2b, are for low-quality. As shown in figure 2a , high-quality independent restaurants enter more as the result of quality disclosure most of the time, except for the top left corner where the entry cost is very low but the quality difference is very high. As mentioned previously, the top left corner of the parameter space is where competition increases the most, and at this point, the effect of competition (CE) can overpower the direct effect (DE) for P_H^E, leading to a decrease in the entry of high-quality independent restaurants.

One may question why competition can increase when there are fewer high-quality independent restaurants entering the market. The reason is that if there are fewer exits of young high-quality independent restaurants, then the market can still experience an increase in the number of high-quality independent restaurants, resulting in greater competition. This is indeed the case. As will be shown later (in figure 3a), the exit probability of young high-quality independent restaurants decreases in the entire parameter space. Therefore, in the top left region of the parameter space, even though high-quality restaurants enter less, they also exit less at the young stage. The fewer exits can overcome the effect of less entry on competition, leading to more fierce competition. This phenomenon is consistent with Proposition 3 (2).

Another notable feature of the top left corner of figure 2a is that the dark blue region is relatively small. The reason for this lies in the fact that in this region, the CE dominates the DE at the entry stage (i.e. for P_H^E), but it is dominated by DE at the young stage of a high-quality restaurant (i.e. for P_{H1}^X). This is a tighter condition than DE dominating CE at all stages. (See the proof for Proposition 3 in the Appendix for detail.) Therefore, the tighter condition leads to a relatively small area in the parameter space.

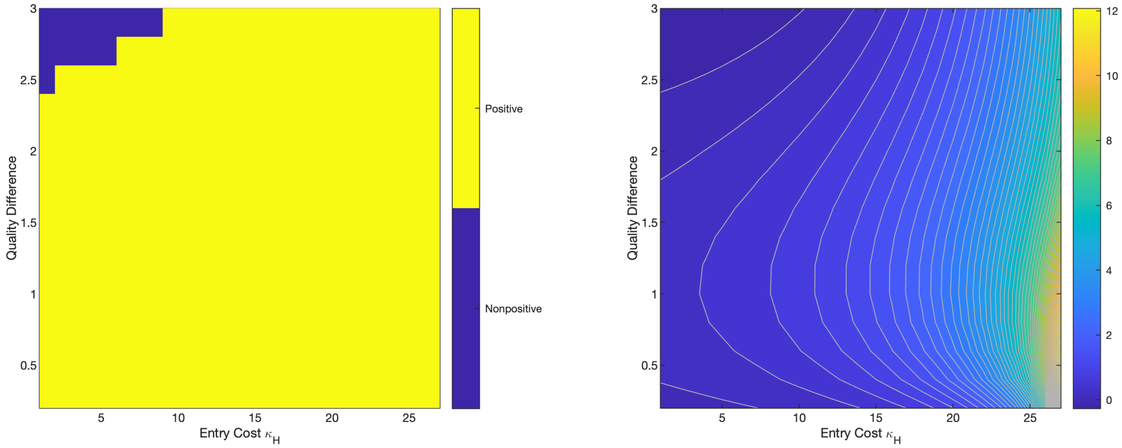
In terms of the magnitude change in P_H^E, figure 2b shows two interesting features: (1) the percentage change is higher when the entry cost is larger, and (2) the change is non-monotonic along the quality-difference dimension. Several forces are at work here. First, when entry costs are large, the entry probability is small to begin with, and is thereby more prone to a higher percentage change. Second, as shown in figure 1b, the change in competition decreases as entry costs increase, and therefore, the change in the entry probability is likely bigger. Third, the direct effect of quality disclosure increases with higher quality difference, which in turn also augments competition. Since competition and the direct effect work in different directions, the change in P_H^E ultimately presents a non-monotonic pattern with respect to quality difference. All of these forces produce the pattern of change in figure 2b .

For low-quality independent restaurants, figure 2c shows that in the entire parameter space, the change is negative. Figure 2d indicates that the percentage change in the entry probability P_L^E is the largest when the entry cost is the highest and when the quality difference is the highest. Similar to the change for high-quality restaurants, when the entry cost is high, the entry probability is small, and thereby is prone to a larger percentage change. In addition, when the quality difference is high, the direct effect of quality disclosure is high, preventing more low-quality independent restaurants from entering. Note that competition and the direct effect of quality disclosure work in the same direction for P_L^E. Therefore, greater competition when the quality difference is high further helps keep out more low-quality independent restaurants.

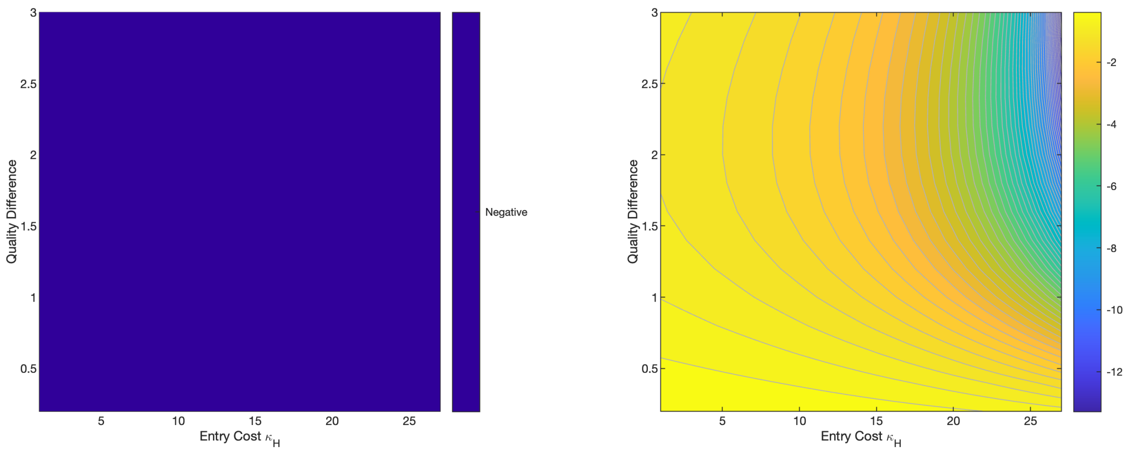
Effect on Exit Figure 3 illustrates the exit probabilities for both high- and low-quality independent restaurants at the young stage. The top two panels, figures 3a and 3b, are for high-quality restaurants, and the lower two, figures 3c and 3d, are for low-quality restaurants. The left two panels show the directional change in the exit probabilities of high- and low-quality restaurants. As shown, young high-quality independent restaurants exit less as the result of quality disclosure for the entire region of the parameter space. At the same time, as indicated by the lower left panel, young low-quality independent restaurants exit more for the entire parameter space.

In terms of magnitude, as shown in figure 3b, the percentage change in the exit probability of young high-quality restaurants (P_{H1}^X) increases with both the entry cost and the quality difference. Two factors lead to this pattern: (1) the higher the quality difference, the smaller the incentives of high-quality restaurants to exit the market, and therefore, the change in the exit probability P_{H1}^X increases with quality disclosure. In addition, (2) even though the entry cost does not affect exit probabilities directly, it affects exit through competition. As shown in figure 1a, greater entry costs lead to lower competition, which in turn reduces firms' motives to exit the market. Therefore, when the entry cost is high, the exit probability P_{H1}^X is low to begin with, and is more prone to greater changes in relative terms.

For young low-quality independent restaurants, as shown in figure 3d, the percentage change in the exit probability (P_{L1}^X) increases with the entry cost, but varies non-monotonically with respect



(a) Direction (High-quality) (b) Percentage Change (High-quality)

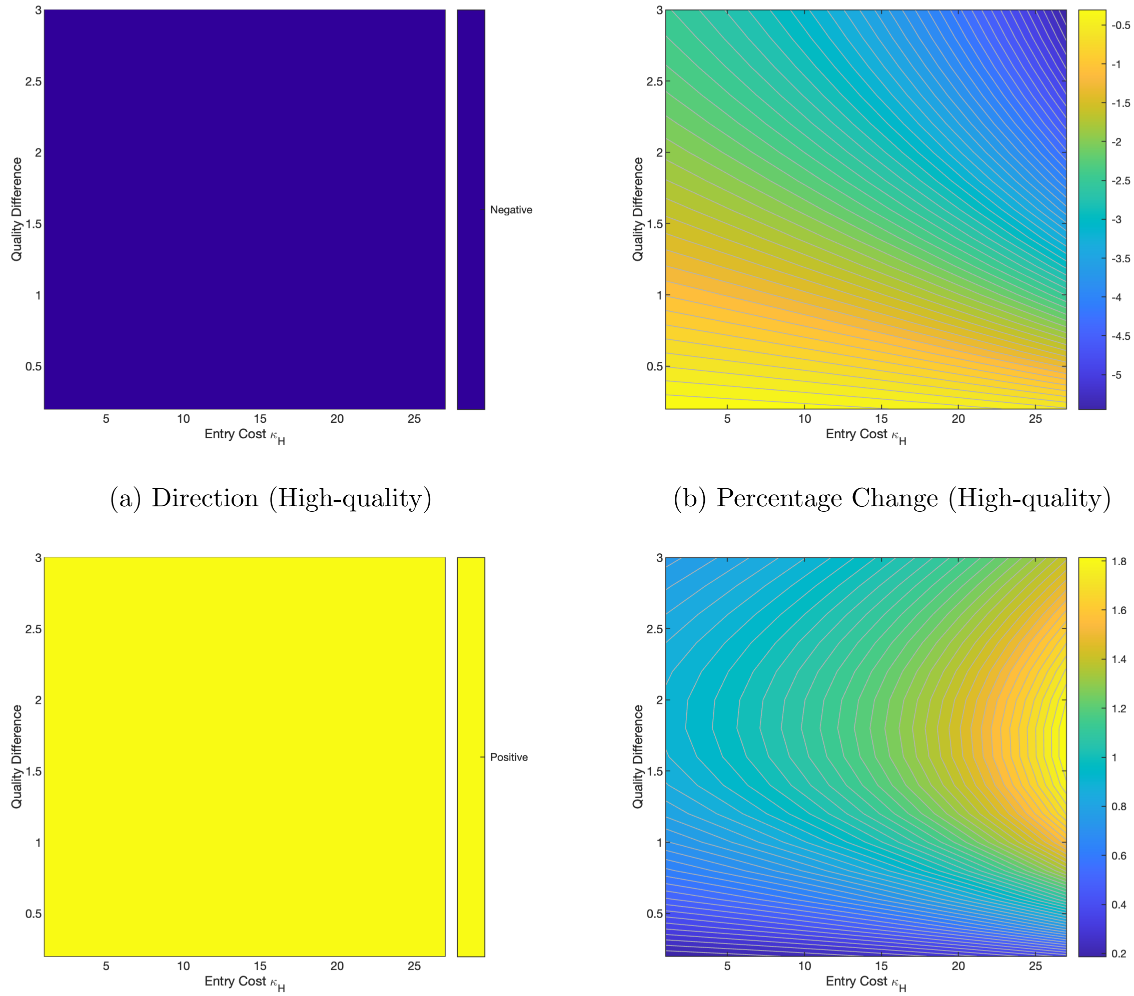


(c) Direction (Low-quality) (d) Percentage Change (Low-quality)

Figure 2: Change in Entry Probabilities of Independent Restaurants (Increased Competition)

to quality difference. Similar to the reasons discussed previously, when the entry cost is high, the exit probabilities are small to begin with, and thereby are more likely to receive a bigger change in relative percentage terms as the result of quality disclosure. Along the quality difference dimension, the change is non-monotonic because when the quality difference is very high, young low-quality restaurants' exit probabilities are high even without quality disclosure. Recall that young low-quality restaurants' true quality will be fully revealed in the next period regardless of quality disclosure; this gives a greater incentive for young low-quality restaurants to exit. Even though higher quality difference makes the direct effect of quality disclosure stronger, when it is too high, the base exit probability would be large to begin with, dampening the change in percentage terms.[10] That is why the change in P^X_{L1} varies non-monotonically in quality difference.

[10]Note that this is not the case for young high-quality restaurants, whose exit probabilities are low when quality



(a) Direction (High-quality) (b) Percentage Change (High-quality)

(c) Direction (Low-quality) (d) Percentage Change (Low-quality)

Figure 3: Changes in Exit Probabilities of Young Restaurants

To summarize, the exploration of the solutions in a large parameter space shows that competition can increase or decrease as the result of quality disclosure. In particular, the cases in Proposition 3 (1) and (2) as well as Proposition 4 (2) show up in this exercise. The parameter region for Proposition 3 (2) (i.e. the dark blue region in figure 2a) is relatively small, and the most common case with the largest region in the parameter space is Proposition 3 (1). The case in Proposition 4 (1) does not appear here. It is likely because of the stringent conditions it requires. See the proof of Proposition 4 in the Appendix for detail. Specifically, for this case to appear, there need to be much more low-quality independent restaurants than high-quality in the market, a condition that can be achieved either through having a lot more potential entrants of low-quality than those of high-quality, i.e. $N_L >> N_H$, or through a very low entry cost for low-quality inde-

difference is high when there is no quality disclosure.

pendent restaurants. In our numerical exercise shown here, we set $N_L = N_H$, and the entry cost of low-quality independent restaurants is fixed at a ratio of 0.7 to the entry cost of high-quality independent restaurants. Therefore, Proposition 4 (1) is unlike to show up in our numerical setting.

To show the possibility of Proposition 4 (1), in Appendix Section E.2, we re-did the numerical simulation with the same parameter specification in Table E.1 except that we set the number of potential entrants for low-quality restaurants to be significantly higher than that for high-quality restaurants (i.e., $N_L = 3000, N_H = 500$). With our parameter space specification, the numerical simulation suggests decreased competition, and the possibility of an increased entry probability for low-quality restaurants. We also provide detailed discussion about the equilibrium entry and exit probabilities in Appendix Section E.2.

4.1.2 Gradual Information Disclosure

Having examined the difference between the scenarios with no disclosure and with full disclosure for a wide range of parameters, we now zoom in onto one point in the parameter space, and investigate how equilibrium outcomes change when γ increases gradually. Unlike the previous section, which focuses on a selected set of outcomes, this section provides a detailed and complete picture of all equilibrium probabilities. In our analysis, we also explore a counterfactual scenario where only the direct effect is present and juxtapose these counterfactual probabilities with the equilibrium outcomes. The difference between them reflects the competition effect.

We choose the point in the parameter space where $\kappa_H = 22$ and $\bar{q} = 3$. As shown in the figures from the previous section, this point is aligned with the most common case, Proposition 3 (1). We compute equilibrium solutions for 100 evenly spaced values of γ between 0 and 1, and plot the equilibrium probabilities against γ in figures 4 to 6. Figures 4 and 5 are for independent restaurants, and figure 6 is for chain restaurants. As both the direct effect and competition effect are at work for independent restaurants, we plot the counterfactual outcomes as well as the equilibrium outcomes in figures 4 and 5. In these graphs, we use solid lines for the equilibrium outcomes and dashed lines for the counterfactuals. For chain restaurants, because they are affected only by the competition effect, we omit the counterfactual outcomes in figure 6, and use solid and dashed lines to differentiate entry probabilities from exit probabilities.

Figure 4 plots the entry probabilities for both high- and low-quality independent restaurants. The blue lines represent those for high-quality and the red lines for low-quality. The dashed lines are the counterfactual entry probabilities. As can be seen, as γ increases, the dashed lines diverge from the solid lines, suggesting that competition effect grows as γ increases. Furthermore, for both high- and low-quality restaurants, the counterfactual entry probabilities are higher than the equilibrium probabilities, implying that competition has intensified as γ grows. The increase in competition attenuates the direct effect and reduces the equilibrium entry probabilities.

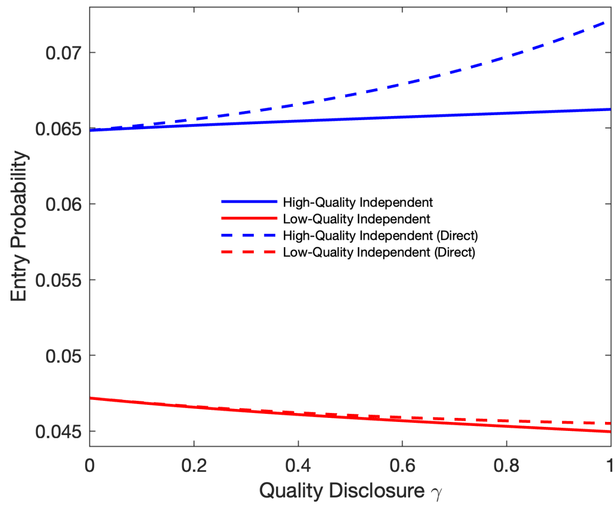


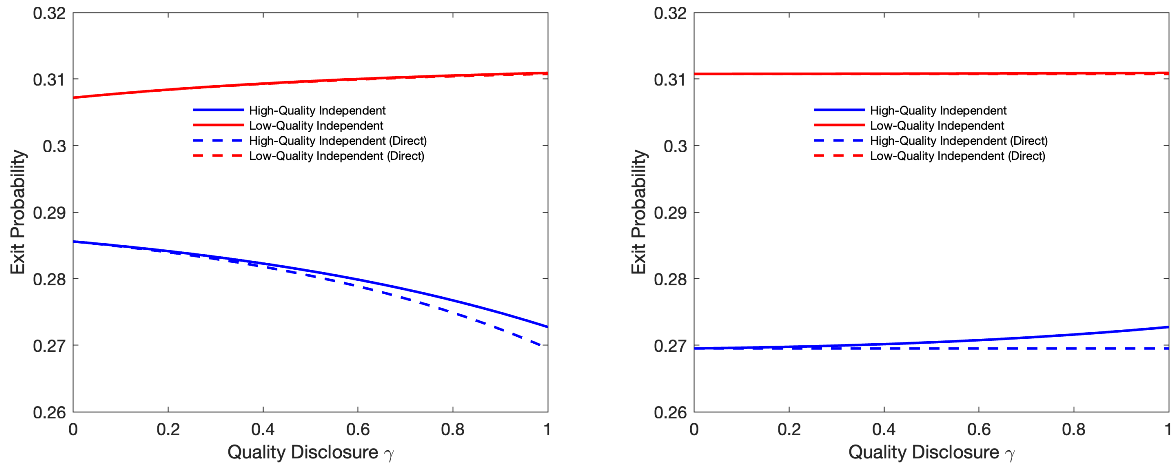
Figure 4: Effect on Entry Probabilities of Independent Restaurants

Figure 5 displays the exit probabilities for independent restaurants. The left panel, figure 5a, is for young restaurants, and the right panel, figure 5b , for established restaurants. As shown in figure 5a, the exit probabilities of young high-quality restaurants decrease with γ, and those probabilities of young low-quality restaurants increase with γ. The difference between the dashed lines and the solid lines is much more pronounced for high-quality restaurants, suggesting that competition affects high-quality restaurants much more than low-quality restaurants. This feature seems to be consistent across all figures of the independent restaurants.

Figure 5b plots the exit probabilities of established independent restaurants. Restaurants' exit probabilities are affected only by competition at this stage. Therefore, the counterfactual probability lines (dashed lines) are flat, showing a constant value. The equilibrium exit probabilities of both high- and low-quality restaurants increase with γ, consistent with the notion of increased competition. Again, competition seems to influence high-quality restaurants much more than low-quality restaurants.

For chain restaurants, figure 6 illustrates the entry and exit probabilities for both high- and low-quality chain restaurants. The green lines are for high-quality and purple lines for low-quality. As show in the graph, both the entry probabilities (solid lines) and the exit probabilities (dashed lines) are relatively flat, suggesting that γ does not have a large effect on chain restaurants. Of all probabilities, the change in the exit probability of high-quality chain restaurants is the most pronounced. Again, this pattern is consistent with the feature shown in the previous two figures that competition appears to affect high-quality restaurants more than low-quality restaurants.

Overall, the results in this section suggest that quality disclosure has heterogeneous effects on restaurants across quality types and chain affiliation. The effect is most pronounced for high-quality independent restaurants and relatively small for chain restaurants.



(a) Young Restaurants

(b) Established Restaurants

Figure 5: Effect on Exit Probabilities of Independent Restaurants

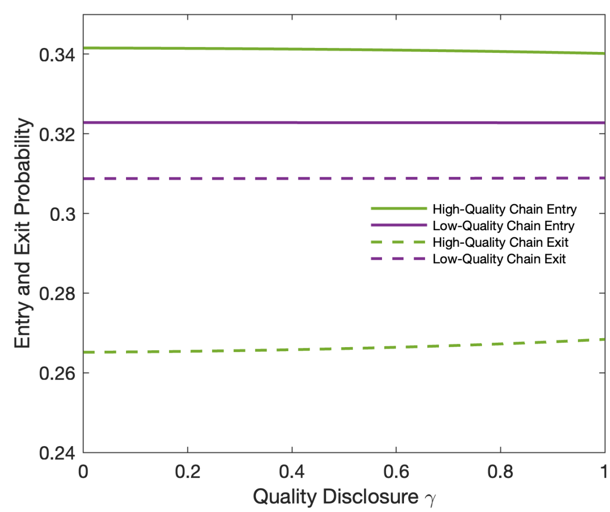


Figure 6: Effect on Entry and Exit Probabilities of Chain Restaurants

Both the comparative statics and the numerical examples show that the effect of quality disclosure on the entry and exit dynamics firms is not deterministic. It really depends on the economic fundamentals, such as the entry cost. Nonetheless, the most common case is the most intuitive one, i.e. quality disclosure increases competition, encourages the entry of high-quality independent restaurants and reduces the exit of high-quality young independent restaurants. Therefore, the overall effect of quality disclosure is an empirical question. In the next section, we test the model predictions in an empirical setting.

5 Empirical Application

Our empirical context is the effect of online reviews platforms' penetration on firm entry and exit dynamics in the restaurant industry in Texas. Online reviews disclose the quality of restaurants and allow consumers to learn from each other's experiences. In areas where consumers frequently use online reviews to share experiences, the quality disclosure of restaurants is likely fast, and the reverse would be true in areas where consumers do not share reviews often. Online review platforms, such as Yelp and Google, penetrated different regions in Texas during various periods of time. This variation in the timing of penetration allows us to tease out the effect of quality disclosure on industry dynamics.

We test the model predictions from the following aspects: (1) the effect of online review platforms on the number of new entries of restaurants across quality and chain affiliation; (2) the effect of online review platforms on the exit probabilities of restaurants across quality, chain affiliation, and stage (young v.s. established). Although the model in Section 3 has entry probabilities as part of the main equilibrium outcomes, we cannot measure entry probabilities directly in the real world because the numbers of potential entrants are unobservable. Therefore, we opt to test the number of new entries in lieu of entry probabilities. For exits, we test the exit probabilities directly because incumbent firms are observed.

In addition, we leverage the heterogeneity in consumers' learning speed across locations to demonstrate the heterogeneous effects of online review platforms. Fang (2022) show that consumers' learning about quality is much faster in local areas than touristy areas because local consumers can learn from their repeated trials at a restaurant in addition to word-of-mouth; tourists or transient consumers, on the other hand, learn only from word of mouth. Based on the results from the model extension with slow learning, shown in Appendix F, the effect of quality disclosure in areas with slow learning should be stronger than that with fast learning. To investigate this difference in impact, we follow the practice in Fang (2022) to use areas within 500 meter radius of interstate highway exits to represent locations with transient consumers, and the rest as local areas. We estimate the effects of online review platforms for highway areas and non-highway areas separately to compare the difference.

We begin with a description of our data and the construction of various measures in Section 5.1. Then we discuss our identification strategy and potential endogeneity in Section 5.2. Finally in Section 5.3, we illustrate the empirical results.

5.1 Data and Measures

The data are the same as those used in Fang (2022), which studies the effect of online review platforms on restaurant revenue. We use this data to investigate the effect on firm entry and exit dynamics. The data are drawn from a variety of sources: (1) Texas restaurant mixed beverage gross receipts data from the Texas Comptroller Office of Public Accounts. It contains monthly revenue from alcoholic drinks at the establishment level in Texas from January, 1995 to December, 2015, and it tracks the entry and exit dates of each restaurant. (2) Restaurant characteristics and review data collected from Yelp, TripAdvisor and Google, including snapshots of overall average ratings on each platform, prices in $ ranges and restaurant cuisine types. For restaurants listed on Yelp and TripAdvisor, we have the rating history data that show the time stamp and star rating for each review of each restaurant. (3) Consumer demographics data gathered from sources including the decennial census and the American Community Survey. Although the Texas mixed beverage gross receipts dataset contains all establishments that hold a liquor license, we restricted the sample to only full-service restaurants. In total, there are 15,417 restaurants in the dataset.

We use these data to construct four measures that are particularly important for the empirical analysis. They are measures for (1) online review platforms' penetration, (2) the quality of a restaurant, (3) the number of new entries, and (4) the action of exit. For market definition, we choose county-month. County is a natural choice for market definition because it is an administrative entity and a basic unit for infrastructure provision. In total, there are about 110 counties in our dataset.

To construct the first measure, online review platforms' penetration, we follow the practice in Fang (2022) and use the average number of new reviews received by each restaurant per month on Yelp at the county level. This measure is constructed from the rating history data on Yelp. It represents consumers' review activity in each county each month.[11] Although only the review history data from Yelp is used in the construction of the measure, it can be seen as capturing the penetration of all online review platforms as consumers' review activity on each platform is highly correlated. This measure varies widely across different counties in Texas. As shown in Fang (2022), this variation reflects the availability of broadband internet in each county (Connected Texas, 2011). It is this variation that we leverage to tease out the effect of online review platforms on restaurant entry and exit dynamics. The rating history on Yelp shows that the first review on Yelp was written in March 2005. Because Yelp is the pioneer of online review platforms, we use March 2005 as the start time of all online review platforms' penetration in our analysis.

For the second measure, the quality of a restaurant, we use mainly the overall average rating on Google as of November 2016, the time of data collection. As demonstrated by Fang (2022), Google rating covers the highest number of restaurants in the sample (9,0240 or 59%) and is a good measure of quality. Among all restaurants operated after March 2005, the start of the online review platforms' penetration, over 68% of restaurants have ratings on Google.

For the third measure, the number of new entries, we count the number of newly entered restaurants by their chain affiliation and quality level at each county in each month. In particular, by

[11] As described in Fang (2022), averaging the number of new reviews across restaurants makes the measure less sensitive to the size of a county, so that larger counties do not necessarily have larger penetration measures. Furthermore, Berry and Waldfogel (2010) show that the number of restaurants in a region is generally proportional to the region's population size. The average number of new reviews per restaurant therefore reflects the average review activity from each person.

using the revenue information, we define an entry as the first month that a restaurant makes positive revenue. In total, during our sample period, there were about 10,310 new entries of independent restaurants and 2,500 of chain restaurants. While it is easy to separate chain restaurants from independent restaurants, counting the number of new entries by quality level is harder. This is because the quality measure, Google rating, is continuous. We need to discretize the ratings into bins first before doing the tally. For the number of bins, we choose 3, 5 and 7 to show robustness of the results. The discretization is based on the quantiles of the rating distribution of all restaurants in the sample. For example, to discretize the ratings into 3 bins, we rank the ratings of all restaurants, and classify the highest 33.3% of the ratings into the high-quality bin. Ratings between 33.3% and 66.6% are in the medium-quality bin, and the remainder is in the low-quality bin. Breaking the ratings into 3 bins creates cutoff ratings for each bin as 4.1+ for high quality, between 3.7 and 4.1 for medium quality, and below 3.7 for low quality. The new entrants with ratings that fall into these cutoffs are classified into their appropriate bins. The quality of the new entrants in each bin in each market is then the average quality of the new entrants' ratings in that market.[12] This type of discretization thus retains the scale in Google rating regardless of the number of the bins chosen, and the coefficients from regressions using different bins are thereby comparable. The discretization with 5 and 7 bins are done in a similar way.

For the last measure, the measure of exit, we use a restaurant's action of exit. The month of exit is informed by the out-of-business (OOB) date in the Texas mixed beverage dataset. The OOB date is the official date of business closure, at which point, the business no longer needs to report taxable earnings. However, for some restaurants, their revenues had already turned 0 before the OOB date. In those cases, we define the timing of exit as the month after which a restaurant's revenue is 0. In our sample, 8,594 restaurants ever exited, of which about 3,000 have ratings on Google.[13]

Table 1 provides the key summary statistics of our data. In terms of entry, the number of entries in each market varies from 0 to 19 with a mean of 0.44 for independent restaurants, and ranges from 0 to 10 with a mean of 0.11 for chain restaurants. Figure 7 illustrates the distribution of the total number of new entries in a market. As shown, the distribution is highly skewed to the right, with the majority of the observations falling between 0 and 5. In terms of exit, Table 1 shows that the

[12] We choose discretization based on quantile instead of equal distance in rating scale because the latter can generate disproportionally large bins. For example, most restaurants have a rating greater than 3.5 on Google. If we use equal distance in rating scale to create bins, then the cutoff ratings would be 1.67, 1.67 to 3.33, and above 3.33. In this case, almost all restaurants will be classified into high-quality bins, leaving very few in the other two bins.

[13] For both entry and exit definitions, we adjust for regular or major renovation. If some restaurants temporarily withdrew from the market and then reappeared after less than two months, then we treat this as regular renovation and do not count the withdrawal as exit nor the reappearance as a new entry. However, if a restaurant disappeared from the market for longer than two months, then we treat this as a major renovation that likely changes the restaurant substantially. We count this incidence in both exit and new entry. We do not, however, change the Google rating before and after the major renovation due to lack of data. Given that there are very few major renovation incidents (less than 10), this treatment of the rating should not cause significant bias in empirical testing.

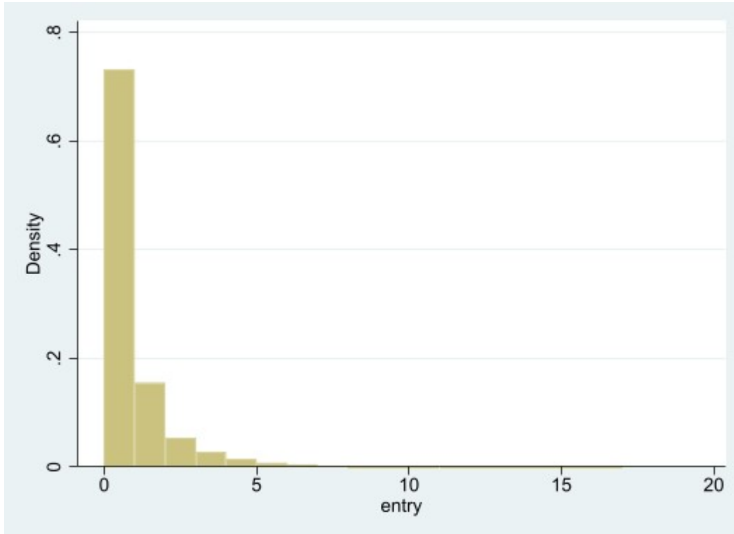


Figure 7: Distributions of New Entries

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	Number of Observations
Average # of entries for independent per county per month	0.44	1.35	0	19	23,288
Average # of entries for chain per county per month	0.11	0.43	0	10	23,288
Average # of exits for independent per county per month	0.32	1.05	0	15	23,288
Average # of exits for chain per county per month	0.048	0.32	0	19	23,288
Number of months in operation	74.6	71.3	1	265	15,417
Average rating for independent	3.93	0.43	1.5	5.0	6,356
Average rating for chain	3.63	0.46	1.9	4.8	2,668
Average rating for local areas	3.85	0.46	1.5	5.0	7,810
Average rating for highway areas	3.73	0.47	2.0	4.9	1,214
Average # of new reviews per restaurant on Yelp per county per month	0.109	0.33	0	5	23,288

number of exits in each market goes from 0 to 15 with a mean of 0.32 for independent restaurants, and extends from 0 to 19 with a mean of 0.048 for chain restaurants. There were a lot more exits among independent restaurants than chain restaurants during the sample period. In fact, of the 8,594 restaurants that ever exited, only 1,125 were chains. The average life span of a restaurant is about 75 months or 6 years. With regard to ratings, the average rating for independent restaurants is 3.93, much higher than the average of 3.63 for chain restaurants. Restaurants' ratings also differ across local areas and highway areas, with the average rating being higher in local markets, 3.85, than that in highway markets, 3.73. This pattern is consistent with the literature, which finds that the quality of restaurants or hotels in locations with transient consumers tends to be lower than that in locations with repeat consumers (Mazzeo, 2004; Blair and Lafontaine, 2005).

5.2 Regression Design and Identification Strategy

The identification strategy we employ to test the model predictions is a triple difference-in-difference (DiD) approach. Following Fang (2022), we exploit the variation in the penetration of online review platforms across geographic regions and time to tease out their effects on restaurant entries and exits. Because online reviews disclose quality of restaurants, for a given quality, the change (increase or decrease) in new entries or exits should be larger in regions with greater amount of consumer review activity than in those with a lower amount, and the change should vary with chain affiliation, age and location. See Figures 4 to 6 in Section 4.1.2 for a demonstration. Here we also make the implicit assumption that across all markets in our sample, the changes in equilibrium outcomes with respect to quality disclosure have the same direction; that is, it should not be the case that new entries (or exit probabilities) increase with quality disclosure in some markets but decrease in other markets. With this assumption, we use the following econometric specifications to examine new entries and exit.

Entry To test the effect on new entries, we use a Poisson regression. Poisson DiD regressions yield consistent estimates as long as the conditional mean of the dependent variable is correctly specified (Wooldridge, 2023). The main econometric specification is as follows:

$$\begin{aligned}\log(E(N_{qfct}|\mathbf{X},\boldsymbol{\theta},\ldots)) = &(\theta_y + \theta_{yr} Rating_{qfct})\log(Yelp_{ct})(1-D_f^{ch}) + (\theta_y^{ch} + \theta_{yr}^{ch} Rating_{qfct})\log(Yelp_{ct})D_f^{ch} \\ &+ \mathbf{X_{ct}}\boldsymbol{\theta_x} + \theta_\alpha \log(\alpha_{fct}) + \theta_{lt} + \theta_{qfc} + \theta_{Mt} + \theta_{Mt}^{ch}, \end{aligned} \tag{16}$$

where N_{qfct} is the number of new entries by quality level q and chain affiliation f per county c each month t. D_f is a dummy variable for chain affiliation. If f indicates chain, then $D_f^{ch} = 1$; otherwise, 0. $Rating_{qfct}$ is the numerical average of the Google ratings of all new entries with the quality level q and affiliation f in market ct. As mentioned before, we group restaurants based on their ratings into 3, 5, and 7 levels, high, medium and low. q simply indicates which level a new restaurant falls into, but $Rating_{qfct}$ is the group average of the Google ratings for all new entries in level q. The variable $\log(Yelp_{ct})$ is the natural logarithm of the penetration measure in county c at time t. $\log(\alpha_{fct})$ is the natural logarithm of the share of new entries by chain affiliation f in each county c and each month t. The variable θ_{lt} is the fixed effect of new entries with low quality l at each month t.[14] $\mathbf{X_{ct}}$ is county-level market characteristics such as demographics, income, and the number of incumbent independent and chain restaurants in the market at time $t-1$.[15] The variable θ_{qfc} is the fixed effect of new entries with quality level q, chain affiliation f, and county c. This fixed effect is to capture that restaurants with certain quality levels and chain affiliation are more likely to enter in some counties than in other counties. θ_{Mt} is a metro-region-time fixed effects, and

[14]The definition for low-quality is the lowest 2 levels in regressions with 5 and 7 quality levels, and the lowest level in the regression with 3 quality levels.

[15]As will be discussed later, we also include in $\mathbf{X_{ct}}$ the natural logarithm of the ratio of new entries that are listed on Google.

θ^{ch}_{Mt} is metro-region-time fixed effects for chains. A metro region is a core-based statistical area as defined by the US Census Bureau. The fixed effects θ_{Mt} and θ^{ch}_{Mt} are to control for the varying time trend across different regions in Texas in the entry of either independent or chain restaurants.

In this regression, the key parameters of interest are $\theta_y, \theta_{yr}, \theta^{ch}_y$, and θ^{ch}_{yr}. In particular, the composite coefficient $\theta_y + \theta_{yr} Rating_q$ represents the impact of online review platforms on the entries of independent restaurants with quality rating q, and $\theta^{ch}_y + \theta_{yr} Rating^{ch}_q$ represents that for chain restaurants. They can be interpreted as the percentage change in the expected number of entries when the activity on online review platforms increases by 100%.

The sample for this regression includes all entries after March 2005, the start time of online review platforms' penetration. New entries before this date should not be affected by online reviews. In addition to the specification in equation 16, we also estimate a regression where the effect of online review platforms is interacted with a location indicator for being within 500 meters of an interstate highway. Through this regression, we aim to see differential effects of online review platforms across locations with fast learning and with slow learning.

The identifying assumptions for this DiD regression include (1) the treatment – online review platform's penetration – is exogenous to the change in outcome, and (2) the new entries in the treated markets should follow the same trend as those in the non-treated markets in the absence of the treatment. With these two assumptions, the effect of online review platforms estimated from the regression can be interpreted as causal. Like Fang (2022), we deal with the potential endogeneity of our measure of penetration by controlling for observable market characteristics as well as a rich set of fixed effects. For market characteristics, we control for the demographic information at the county level, such as population, income, age, and race. We also take into account the numbers of incumbent chain and independent restaurants in the same county from the last period, which likely describe the competitive environment in the market. In addition, we include a number of fixed effects to address the endogeneity concern that our measure of penetration might be correlated with county-time specific demand shocks, such as popular festivals. These demand shocks can increase both consumers' review activity and new entries of restaurants, leading to a spurious positive correlation between them. To account for county-time specific demand shocks, we use metro-region×time fixed effects because one county's demand shocks are likely to spill over to the entire metro region.[16] To capture idiosyncratic shocks in each county for a specific type of chain affiliation and quality level, we include quality-level×chain-affiliation×county fixed effect. All of our errors are clustered two-way at the county level and time level in order to account for correlations across time for the same county and geographic correlation between counties at a given time.

An important challenge to identification in the entry analysis is that we do not observe the quality of all new entrants during our sample period. Although we observe all new entries and their chain affiliation in each market, we cannot tell the quality of a new restaurant if it did not have a rating on Google. To approximate N_{qfct} in equation 16, we use the number of new entries

[16]We cannot use a county-time fixed effect because it would absorb the penetration measure.

that have ratings on Google instead; however, they represent only a portion of N_{qfct}. Figure 8 displays the portion of those new entrants that have ratings on Google out of the total entries over time. As shown, about 60% of the new entrants in around March, 2005 had presence on Google. This share increased over time. By the end of the sample period, about 85% of the new entrants have ratings on Google. This increasing trend is likely due to two processes: (1) one is that a smaller proportion of restaurants were listed online when online review platforms first started; (2) the other is that many restaurants exited long before the data on ratings were collected.[17] These two processes could cause bias in our estimates if they are correlated with online review platforms' penetration.

For the first process, if the portion is uncorrelated with online review platforms' penetration, then the metro-region×time fixed effect will absorb the effect of the changing ratio because the logarithm of the ratio comes into equation 16 linearly. However, if the ratio is correlated with online review platform's penetration, then not accounting for it will cause omitted variable bias. Therefore, on the right-hand side of equation 16, we also add the natural logarithm of the share of the new entries listed on Google by chain affiliation in each county and each month, denoted by $\log(\alpha_{fct})$, where α indicates the ratio.[18] For the second process related to exit, it is likely that more lower-quality restaurants had exited than higher-quality restaurants by the end of the sample period. Therefore, in terms of the quality-makeup, the new entries with Google ratings from the earlier years are likely to have a lower share of low-quality restaurants than those from the later years. If exits are uncorrelated with online review platforms' penetration, then by controlling for a common trend in the entries of low-quality restaurants across high- and low penetration areas, we can account for this systematic under-representation of low-quality entries observed in the older years. For this reason, we also add low-quality×time fixed effects to the right-hand side of equation 16. However, based on our theory from Section 3, we know that exits should be affected by online review platforms' penetration. In particular, there is a greater under-counting of low-quality entries in high-penetration areas in the older years than in low-penetration areas because online reviews speed up the exit of low-quality restaurants (especially young independent restaurants). In this case, the change in low-quality entries in high-penetration area will be dampened, leading to a downward bias on the magnitude of the estimated effect of online review platforms' penetration. In this regard, our estimates from equation 16 can be seen as a lower bound.

[17]Note that Google keeps a record of restaurants that are closed, but if they have been closed for a very long, they may not show up in the query from Google Places API.

[18]Note that it is not possible to have this ratio by quality level because we simply do not observe the quality of all restaurants.

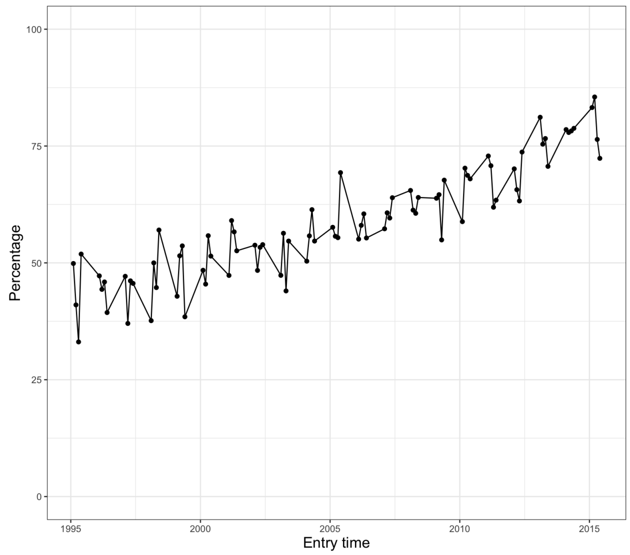


Figure 8: Percentage of New Entrants Listed on Google (Quarterly), 1995-2015

Exit To examine the effect of online review platforms on exit, we use a linear probability regression:

$$\begin{aligned} a_{jt} =& (\theta_y + \theta_{yr} Rating_j) \log(Yelp_{ct})(1 - D_j^{ch}) + (\theta_y^{ch} + \theta_{yr}^{ch} Rating_j) \log(Yelp_{ct}) D_j^{ch} \\ &+ \mathbf{X_{jt}} \boldsymbol{\theta_x} + \theta_{jmnth} + \theta_{Mt} + \theta_{Mt}^{ch} + \varepsilon_{jt}, \end{aligned} \tag{17}$$

where a_{jt} is a dummy variable for the exit action. It is 1 if the restaurant decides to exit at time t, and 0 if the restaurant decides to stay in the market. $D_j^{ch} \equiv \mathbb{1}\{\text{restaurant} j \text{is affiliated with a chain.}\}$ is a dummy variable for chain affiliation. $\mathbf{X_{jt}}$ includes restaurant characteristics as well as county-level demand and cost conditions. θ_{jmnth} is the restaurant×month fixed effect, where $mnth$ indicates calendar months as in January to December. θ_{jmnth} controls for restaurant-specific seasonality because different types of restaurants may be affected by seasonality to various degrees, and they may decide to exit in different months of the year. The rest of the variables are defined the same way as in equation 16.

The identifying assumption in this test is the same as those for the entry. In particular, because the exit regression is done at the restaurant level, where we observe both the quality and the exit decision, we do not have the issue of having to approximate the dependent variable as in the entry regression. Here the restaurants that were not listed on Google are simply not included in the regression. The identification comes from comparing those restaurants listed on Google in high-penetration areas to those in low-penetration areas in terms of the change in their exit decisions.

The sample for this regression is limited to the periods when a restaurant was treated by online reviews, i.e. those periods after a restaurant had received at least one review online from either Yelp, TripAdvisor or Google. For those restaurants also listed on Yelp, we use the date of their first Yelp review because Yelp was usually the go-to platform for reviews for new restaurants during our sample period. For those restaurants listed not on Yelp but on Google, because we could not observe the date of their first review on Google, we follow the practice in Fang (2022) and use the penetration date of Google in Texas as a proxy, which is around January 2011.[19].

Similar to the analysis of entry, we also examine the differential effects of online review platforms across areas with fast and slow learning by interacting the penetration measure with a high-way area dummy in equation 17. In addition, we investigate the heterogeneous effects of online reviews on young v.s. established restaurants' exits by interacting the penetration measure with an age dummy of older than 12 years. One of the important predictions from the model in Section 3 is that young and established restaurants' exit rates react differently to quality disclosure. In particular, how established restaurants' exit probability changes with respect to online review platforms' penetration can tell us about the effect of online reviews on competition. We choose 12 years as the cutoff for young and established restaurants based on the findings from Fang (2022), who shows that the effect of online review platforms peters out after a restaurant becomes 12 years old.

Pre-trend Analysis For both the entry and exit regressions, we conduct a pre-trend analysis to check if entries and exits in high-penetration areas and low-penetration areas shared the same trend before the penetration of online review platforms. As mentioned previously, treated and non-treated areas sharing the same trend absent of the treatment is an important assumption for identification. To implement the pre-trend analysis, we move the penetration measure backward in time by 10 years. Instead of starting in March 2005, the penetration now starts in March 1995. We then run the regressions in equation 16 and equation 17 respectively by using the sample from March 1995 to March 2005. If our penetration measure picks up inherent differences across high- and low-penetration regions unrelated to online review platforms' penetration, then the regression results from the pre-trend analysis will show significant effects of online review platforms' penetration in both entry and exit. The results from the pre-trend analysis are displayed in Tables G.3 and G.4 of Appendix G. As shown, none of the coefficients associated with $\log(Yelp_{ct})$ are significant in these tables. These results imply that the high- and low-penetration areas share the same trend in entry and exit without online reviews.

5.3 Results

The results of the entry and exit analyses are shown below in in Sections 5.3.1 and 5.3.2 respectively.

5.3.1 Entry

Table 2 displays the results from the main entry regression with 7, 5 and 3 levels of quality respectively in each column. As mentioned previously, the way we constructed the quality bins preserves

[19]Fang (2022) provides justification for this date.

the scale of Google rating; therefore, the coefficient estimates from all columns in the table are comparable. As shown, across the different numbers of quality levels, the estimates are very similar. The coefficients for chain are all insignificant, indicating that online review platforms' penetration had very little effect on the entry of chain restaurants. The coefficients for independent are all significant at the 1% level. The coefficient for log(Yelp) is θ_y in equation 16. It represents the percentage change in the expected number of entries in a market when consumers' review activity increases by 100%. It being negative implies that for the very low quality levels, the number of new entries declines with the penetration of online review platforms. The coefficient for log(Yelp)×rating is θ_{yr} in equation 16. It being positive means that the effect of online review platforms increases with quality levels. In particular, for very high quality levels, the overall effect from online reviews on entry would be positive.

For ease of interpretation, we calculate the composite coefficient $\theta_y + \theta_{yr} Rating_q$ in order to gauge the total effect of online review platforms at each star rating level on Google. Table 3 illustrates the effects based on the coefficients from using 7 quality levels (1st column in Table 2). As can be seen, for restaurants with a quality of only 2 stars, the number of new entries declines by 18.4% as consumers' review activity doubles. For restaurants with a quality of 5 stars, however, the effect is the opposite, with new entries increasing by 14% as consumers' review activity doubles. For restaurants with a quality of 3 or 4 stars, the effects are close to 0, which is consistent with the observation from the summary statistics (in Table 1) that the average Google rating for independent restaurants is about 3.93. That is, the entry of a restaurant with a quality at the population average is affected very little by quality disclosure because consumers' initial perception of the restaurant quality is the same as the true quality. These results indicate that high-quality restaurants' entry is encourage by quality disclosure from online reviews, whereas low-quality restaurants' entry is discouraged. These results are consistent with the model predictions shown by Proposition 3 (1), Proposition 4 (2), and Corollary 2 in Section 4. That is, the direct effect of quality disclosure through online reviews dominates the competition effect.

To investigate the heterogeneous effect of online review platforms across fast and slow learning areas, we run the regression in equation 16 by interacting log(Yelp) with a location indicator for being within 500 meters of an interstate highway. The results from using 7 quality levels are shown in Table 4. As illustrated, the effects of online review penetration are again significant only for independent restaurants, not chains. Furthermore, when comparing the effects across locations, we can see that the coefficients from the highway areas are slightly bigger in magnitude than those from the non-highway areas (i.e. local areas). This is consistent with our model prediction that quality disclosure has a bigger effect in areas with slow learning than areas with fast learning. Nonetheless, these results are not robust when we use 5 or 3 quality levels; the results from regressions with 5 and 3 quality levels show that the effects are somewhat similar across highway and local areas. See Tables G.1 and Table G.2 in Appendix G.

Table 2: Effects of Online Review Platforms on Entry

	(1) entry	(2) entry	(3) entry
log(Yelp) (independent)	-0.400***	-0.419***	-0.447***
	(0.0940)	(0.106)	(0.118)
log(Yelp)×rating (independent)	0.108***	0.103***	0.109***
	(0.0197)	(0.0278)	(0.0287)
log(Yelp) (chain)	-0.178	-0.0599	0.0791
	(0.146)	(0.147)	(0.124)
log(Yelp)×rating (chain)	0.0494	0.0464	-0.00540
	(0.0349)	(0.0341)	(0.0276)
Controls	✓	✓	✓
Group FE	✓	✓	✓
Year× Month× Metro× Chain FE	✓	✓	✓
Year× Month× Low-Quality× Chain FE	✓	✓	✓
N	3,301	3,126	2,734
N of Clusters	34	35	41
Number of Quality Levels	7	5	3

Controls include demographics (population, income, age, race), ratio of new entries that are listed on Google, and the numbers of incumbent chain and independent restaurants in the same county from the last period. Group FE is quality-levels × chain-affiliation × county × highway. Low-Quality includes the lowest 2 levels when 5 and 7 quality levels are used, and only the lowest level when 3 levels are used. All standard errors are two-way clustered at the county level and time level. They are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 3: Effect of Online Review Platforms on Entry by Google Star Rating (Independent)

Star Rating	2	3	4	5
Effect	-0.1841***	-0.0760*	0.0320	0.1401***
	(0.0584)	(0.0432)	(0.0330)	(0.0331)

All standard errors are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 4: Effects of Online Review Platforms on Entry by Chain Affiliation and Location (7 Levels)

Dependent variable	Number of New Entries			
	Independent		Chain	
	Non-Highway	Highway	Non-Highway	Highway
log(Yelp)	-0.295***	-0.333**	-0.0304	-0.0641
	(0.0937)	(0.134)	(0.152)	(0.205)
log(Yelp)×rating	0.0856***	0.0891***	0.00627	0.0100
	(0.0208)	(0.0291)	(0.0326)	(0.0458)
Controls	✓			
Group FE	✓			
Year×Month×Metro×Chain FE	✓			
Year×Month×Low-Quality×Chain FE	✓			
N	3344			
N of Clusters	33			
Quality Measure	Google Rating			

Controls include demographics (population, income, age, race), ratio of new entries that are listed on Google, and the numbers of incumbent chain and independent restaurants in the same county from the last period. Group FE is quality-levels × chain-affiliation × county × highway. Low-Quality includes the lowest 2 levels when 5 and 7 quality levels are used, and only the lowest level when 3 levels are used. All standard errors are two-way clustered at the county level and time level. They are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01

5.3.2 Exit

To examine the effect of online review platforms on exit, we run the regression in equation 17. The results are shown in Table 5. As can be seen, similar to the results from the entry regressions, the coefficients for chains are all insignificant, whereas the coefficients for independent restaurants are all significant at the 1% level. In particular, the coefficient for log(Yelp) being positive indicates that when a restaurant is very low-quality, the penetration of online review platforms will speed out its probability of exit. The coefficient for log(Yelp)×rating being negative implies that the effect of online review platforms on exit decreases with quality. In particular, for a very high-quality restaurant, the overall effect of online review platforms' penetration can be negative. That is, online reviews can reduce the exit of high-quality restaurants.

Again for ease of interpretation, we calculate the composite coefficients in order to show the overall effect of online review platforms on a restaurant with a given star rating on Google. Table 6 displays these coefficients. As can be seen, when consumers' review activity doubles, the exit rate of a restaurant with a 2-star rating on Google will increase by 0.19 percentage points, and this effect is significant. For a 5-star restaurant, the exit rate will decrease by 0.17 percentage points. For medium quality restaurants with 3 and 4 star ratings, the effects are very muted. These results are again consistent with the model predictions shown by Proposition 3 (1), Proposition 4 (2), and Corollary 2.

To see how the effect of online review platforms vary across highway and non-highway local

Table 5: Effects of Online Review Platforms on Exit

	(1)
	exit
log(Yelp) (independent)	0.00795***
	(0.00284)
log(Yelp)×rating (independent)	-0.00205***
	(0.000703)
log(Yelp) (chain)	0.000570
	(0.000745)
log(Yelp)×rating (chain)	-0.000246
	(0.000206)
Controls	✓
Restaurant× Month FE	✓
Year× Month× Metro× Chain FE	✓
N	371,085
N of Clusters	97

Controls include demographics (population, income, age, race) and the number of chain and independent rivals in the same zip code tabulation area at the same period. All standard errors are two-way clustered at the county level and time level. They are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 6: Effect of Online Review Platforms on Exit by Google Star Rating (Independent)

Star Rating	2	3	4	5
Effect	0.0019***	0.0007*	-0.0005	-0.0017***
	(0.0006)	(0.0004)	(0.0004)	(0.0005)

All standard errors are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01

areas, we run the regression in equation 17 again by interacting the penetration measure with a highway dummy. The results are shown in Table 7. As can be gleaned, the coefficients for independent restaurants in highway areas are almost twice as large as those in the non-highway areas, suggesting that the effect of online review platforms on exit is much stronger in slow-learning areas than in fast-learning areas. This is consistent with the model predictions in Section 3. It is nonetheless puzzling that the difference in the effect on exit across highway and non-highway areas is much stronger than the difference in the effect on entry across these two types of locations. Both entry and exit decisions are affected by firms' profits, which are directly influenced by the degree of quality disclosure in the market, but revenue has a more direct impact on exits as it directly affects the curent period review. This phenomenon may be explained by a large entry cost and a small exit cost (or scrap value). That is, when the exit cost is very small, firms would exit as soon as their expectations of sales decline, but with a large entry cost, firms may still hesitate to enter even if their expected revenues or profits increase substantially. Furthermore, when it comes to independent restaurants' entry around highway exits, the opportunities can be very limited because those areas are dominated by strip malls and plazas, which often prefer leasing to chain restaurants due to financial security. As a result, even though online review platforms' penetration affects the revenues of those independent restaurants in highway areas much more than those in non-highway areas, the difference in the effect on entry across the two types of areas is much more muted because the highway area has a higher entry barrier for independent restaurants.

Table 7: Effects of Online Review Platforms on Exit by Chain Affiliation and Location

Dependent variable	Exit			
	Independent		Chain	
	Non-Highway	Highway	Non-Highway	Highway
log(Yelp)	0.00702**	0.0137***	0.000422	0.000915
	(0.00284)	(0.00447)	(0.000625)	(0.00184)
log(Yelp)×rating	-0.00183**	-0.00352***	-0.000189	-0.000376
	(0.000696)	(0.00114)	(0.000195)	(0.000434)
Controls	✓			
Restaurant× Month FE	✓			
Year×Month×Metro×Chain FE	✓			
N	371085			
N of Clusters	97			

Controls include demographics (population, income, age, race) and the number of chain and independent rivals in the same zip code tabulation area at the same period. All standard errors are two-way clustered at the county level and time level. They are shown in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

To test the model predictions regarding the differential effect of quality disclosure on exit across a restaurant's stage, young and established, we run the regression in equation 17 by interacting the penetration measure with an age dummy of over 12 years old. The results are displayed in Table 8. As can be seen, only the coefficients for young independent restaurants are significant. All the other coefficients are not statistically significant, indicating that the effect on exit is solely driven by the effect on young independent restaurants. This result implies that the effect of online review platforms did not lead to a significant increase or decrease in the overall competitive environment in the market. It is mostly consistent with the model predictions shown in Corollary 2. Nonetheless, it is possible that if the effect on competition (either increase or decrease) is small, the regression may not be able to pick up significant effects. Therefore, we cannot exclude scenarios from Proposition 3 (1) and Proposition 4 (2) completely.

Table 8: Effects of Online Review Platforms on Exit by Chain Affiliation and Age

Dependent variable	Exit			
	Independent		Chain	
	Established	Young	Established	Young
log(Yelp)	-0.000103	0.0103***	-0.00139	0.000838
	(0.00328)	(0.00363)	(0.00114)	(0.000980)
log(Yelp)×rating	-0.000299	-0.00260***	0.000202	-0.000321
	(0.000828)	(0.000895)	(0.000351)	(0.000262)
Controls	✓			
Restaurant×Month FE	✓			
Year×Month×Metro×Chain FE	✓			
N	363630			
N of Clusters	97			

Established restaurants are those which are older than 12 years. Young restaurants are those which are 12 years old or younger. The regressions account for all controls including demographics, traffic counts, visitor's spending, the number of chain and independent rivals in the same zip code tabulation area to control for endogenous exits. All standard errors are clustered at the county level and are shown in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

To summarize, the results from the analyses on both entry and exit show that the direct effect of quality disclosure through online reviews dominate the competition effect. Specifically, online review platforms' penetration increases the entry of high-quality young independent restaurants and reduces the entry of low-quality young independent restaurants. It also reduces the exit of high-quality independent restaurants, but speeds up the exit of low-quality independent restaurants. It has very little effect on chain and established independent restaurants' entry or exit, and it did not lead to a significant change in competition during our sample period. These results are most consistent with our model prediction in Corollary 2; however, we cannot fully rule out predictions from Proposition 3 (1) and Proposition 4 (2) either.

6 Conclusion

Online resources like reviews and social media have made quality information critical in purchase choices. Policymakers also recognize the importance of quality disclosure. Previous literature focuses more on consumer demand, or firm's voluntary quality disclosure decisions. Our paper investigate the impact from an unexplored perspective— how quality disclosure shapes firms' entry and exit in markets with many firms.

Building on the dynamics of oligopoly games, our model introduces two key driving forces for market dynamics: the direct effect, magnifying perceived quality gaps, and the competition effect, reshaping market competition and entry-exit behavior. These forces create several possible scenarios where quality disclosure's impact can encourage or discourage the entry of high-quality firms depending on the relative magnitude of the two effects. Using data from restaurants industry in Texas, our empirical findings confirm the theoretical insights. In particular, we demonstrate the penetration of online review encourages the entry of high-quality independent restaurants, and speeds up the exit of low-quality independent restaurants. We do not find significant changes for chain restaurants.

Our results shed light on quality disclosure's broader implications, beyond matching consumers with products. The insights guide businesses to navigate information availability and competition. In terms of policy implication, our paper suggests that policymakers should be cautious about the complex interplay of forces that can lead to unintended outcomes, such as reduced competition and more concentrated industries.

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A Table of Notations

In the main text, we write profits, value functions and costs as functions of quality, chain affiliation, age type and so on. For the simplicity of notation, we use subscript to represent those parameters. For instance, we let $T \in \{H, L\}$ denote the quality type subscript for high- and low-quality, respectively, then $\pi(\bar{q}, g, D)$ in the main text is denoted by π_{Hg} for high-quality independent restaurants with age type g and by π_{Hc} for high-quality chain restaurants.

Table A.1: Table of Notations

Variable	Meaning
$q \in \{\underline{q}, \bar{q}\}$	true quality of restaurants, $\bar{q}$: quality of high-quality (H) restaurants; $\underline{q}$: quality of low-quality (L) restaurants
$g \in \{0, 1, 2\}$	age type of the restaurants, 0: new entrant; 1: young; 2: established
$\hat{q} \in \{\hat{q}_0, \hat{q}_1, q\}$	perceived quality of the restaurants, $\hat{q}_0$: perceived quality for new entrants; $\hat{q}_1$: perceived quality for young restaurants; q: perceived (true) quality for established restaurants
$D \in \{I, c\}$	chain affiliation c: chain; I: independent restaurants [1]
γ	level of quality disclosure
β	discount factor
M	market size
ϕ	scrape value, $\phi \sim U[-b_1, b_1]$
ε	random shock associated with entry $\varepsilon \sim U[-b_0, b_0]$
$T \in \{H, L\}$	type of the restaurant, H: high quality with $q = \bar{q}$, L: low quality with $q = \underline{q}$
N_T	number of potential independent entrants with quality type $T \in \{H, L\}$
N_{Tc}	number of potential chain entrants with quality type $T \in \{H, L\}$
κ_T	average entry cost for independent restaurants with quality type $T \in \{H, L\}$
κ_{Tc}	average entry cost for chain restaurants with quality type $T \in \{H, L\}$
π_{Tg}	flow profit for independent restaurants quality type $T \in \{H, L\}$ with age type $g \in \{0, 1, 2\}$
π_{Tc}	flow profit for chain restaurants quality type $T \in \{H, L\}$[2]
V_{Tg}	integrated value function for independent restaurants with quality type $T \in \{H, L\}$ with age type $g \in \{0, 1, 2\}$
V_{Tcg}	integrated value function for chain restaurants quality type $T \in \{H, L\}$ with age type $g \in \{0, 1, 2\}$. Here $V_{Tc1} = V_{Tc2}$

[1] For notation simplicity, we dropped the subscription I for independent restaurants

[2] For a chain restaurant, the flow profit does not change across different age type

B Proof of Compliance with the OE Assumptions

In this section, we provide proofs to show that our model is in compliance with the OE concept proposed by Weintraub et al. (2008).

Assumption 2.
(1) $For\ all\ n(\hat{q}, D, \gamma) \in \mathbf{n}, \pi(\hat{q}, D)$ is increasing in $\hat{q}$.
(2) $For\ all\ n, n' \in \mathbf{n}, if\ n \geq n', then\ \pi(\hat{q}, D, n) < \pi(\hat{q}, D, n')$
(3) $For\ all\ n \in \mathbf{n}, \pi(\hat{q}, D, n) > 0\ and\ \sup_n \pi(\hat{q}, D, n) < \infty$
(4) $For\ all\ n \in \mathbf{n}$, the function $\ln \pi(.) : \mathbf{n}$ is continuously Frechet differentiable. Hence, for all $y \in \mathbb{N}$, and $n \in \mathbf{n}$, $\ln \pi(n)$ is continuously differentiable with respect to $n(y)$. Further, for any $n \in \mathbf{n}$ *and* $h \in \mathbf{n}$ such that $n + \alpha h \in \mathbf{n}$ for $\alpha > 0$ sufficiently small, if

$$\sum_{y \in \mathbb{N}} h(y) | \frac{\partial \ln \pi(n)}{\partial n(y)} | < \infty$$

, then

$$\frac{d \ln \pi(n + \alpha h)}{d\alpha}|_{\alpha=0} = \sum_{y \in \mathbf{n} h(y)} \frac{\partial \ln \pi(n)}{\partial n(y)}$$

Proof. Assumption 2 (1) states that the flow profit increases wit perceived quality. From Table A.1 and C.1, we know that $\hat{q}$ is a function of q and g. As a result, $\pi(q, g, D)$ can be written as $\pi(\hat{q}, D)$. Given the expression of profit function (2), we can easily show that $\frac{\partial \hat{q}}{\partial \pi(\hat{q}, D)} > 0$.

Here, following Weintraub et al. (2008), let's denote $n \geq n'$ as n dominates $n' \in \mathbf{n}$ if for all q, $\sum_{q \geq \hat{q}} n(q) \geq \sum_{q \geq \hat{q}} n'(q)$. Assumption 2 (2) means strengthened competition cannot result in increased profit.

if $\pi(\hat{q}, D, n) < \pi(\hat{q}, D, n')$ holds, based on our model setup, we will have

$$\begin{aligned} &\sum_{q > \hat{q}} n(q) exp(q) + n(\hat{q}) exp(\hat{q}) + \sum_{q < \hat{q}} n(q) exp(q) \\ &> \sum_{q > \hat{q}} n'(q) exp(q) + n'(\hat{q}) exp(\hat{q}) + \sum_{q < \hat{q}} n'(q') exp(q) \end{aligned} \tag{B.1}$$

Hence,

$$\sum_{q \geq \hat{q}} (n(q) - n'(q)) exp(q - \hat{q}) - \sum_{q < \hat{q}} (n'(q) - n(q)) exp(q - \hat{q}) \tag{B.2}$$

is the key expression we need to examine.

We know that $\sum_{q \geq \hat{q}} n(q) \geq \sum_{q \geq \hat{q}} n'(q)$ holds for all q. To make our proof understandable, let's assume the quality level q are indexed by $i \in \{0, 1, 2 ... I\}$. That is to say, the lowest quality will be indexed by 0, and the next higher quality is q_1, and so on.

The definition of dominance implies the following inequalities will hold:

$$
\begin{aligned}
&n(q_I) \geq n'(q_I) \\
&\sum_{q \geq q_0} n(q) \geq \sum_{q \geq q_0} n'(q) \\
&\sum_{q \geq \hat{q}} n(q) \geq \sum_{q \geq \hat{q}} n'(q)
\end{aligned} \tag{B.3}
$$

Here, we define

$$
\begin{aligned}
B_{\hat{q}} = &\sum_{q > \hat{q}} (n'(q) - n(q)) exp(q - \hat{q}) + n'(\hat{q}) - n(\hat{q}) \\
&+ \sum_{q < \hat{q}} (n'(q) - n(q)) exp(q - \hat{q})
\end{aligned} \tag{B.4}
$$

To begin with, we assume $\hat{q} = q_0$, which represents the lowest quality, we can re-write equation B.2 and define $B_0 = (n'(q_0) - n(q_0)) + \sum_{q > q_0} (n'(q) - n(q)) exp(q - q_0)$.

After re-arrange the equation, $B_0 = (\sum_{q \geq q_0} (n'(q) - n(q))) + \sum_{q > q_0} (n'(q) - n(q))(exp(q - q_0) - 1)$ According to equation B.3, we can easily show the first term from B_0, $\sum_{q' \geq q_0} (n'(q') - n(q')) < 0$. The second term in B_0 can be re-written as follows.

$$
\begin{aligned}
&\sum_{q > q_0} (n'(q) - n(q))(exp(q - q_0) - 1) \\
&= \frac{1}{exp(q_1 - q_0)} (\sum_{q > q_1} (n'(q) - n(q))(exp(q - q_1) - 1))
\end{aligned} \tag{B.5}
$$

Basically, B_0 can be written as a function of higher quality levels. Moreover, $\sum_{q > q_0} (n'(q) - n(q))(exp(q - q_0) - 1) < \sum_{q > q_0} (n'(q) - n(q)) < 0$ since $exp(q - q_0) - 1 > 0$ holds for all $q > q_0$. Therefore, we show that $B_0 < 0$

If $\hat{q} = q_I$, the highest quality, the dominance condition essentially becomes $n(q_I) \geq n'(q_I)$. Based on equation B.2, we define $B_{q_I} = n'(q_I) - n(q_I) + \sum_{q < q_I} (n'(q) - n(q)) exp(q - q_I)$ According to equation B.3, we know that $n'(q_I) - n(q_I) < 0$ holds. B_{q_I} can be written as follows: $B_{q_I} = \frac{1}{exp(q_0 - q_I)} B_0 < 0$

It means if $B_0 < 0$, we can easily show $B_{q_I} < 0$. Hence, $B_{\hat{q}}$ can be written as follows

$$
\begin{aligned}
B_{\hat{q}} = &\sum_{q > \hat{q}} (n'(q) - n(q)) exp(q - \hat{q}) + n'(\hat{q}) - n(\hat{q}) \\
&+ \sum_{q < \hat{q}} (n'(q) - n(q)) exp(q - \hat{q}) \\
&= \frac{1}{exp(q_0 - \hat{q})} B_{\hat{q}_-} + n'(\hat{q}) - n(\hat{q}) + \frac{1}{exp(\hat{q} - q_0)} B_{\hat{q}_+}
\end{aligned} \tag{B.6}
$$

As shown before, any B_q can be written as a function of B_0, and we can easily show $B_0 < 0$. Hence, $B_{\hat{q}} < 0$, and $\pi(\hat{q}, D, n) < \pi(\hat{q}, D, n')$ holds.

Assumption 2 (3) ensures profit is positive and bounded. In our model, the profit function essentially comes from logit demand system and we assume $\pi(q, g, D) > 0$ and it is bounded: $\sup_n \pi(\hat{q}, D, n) < M$

Assumption 2 (4) requires the log profits to be Frechet differentiable. As discussed by Weintraub et al. (2008), profit function that are smooth such as logit model will satisfy this assumption. This is our case where our profit comes from logit demand system. So it automatically satisfies this assumption.

□

Assumption 3. The random variable $\{\phi_{it} | t \geq 0, i \geq 1\}$ are independent and identically distributed (i.i.d.) and have finite expectations and well-defined density functions with support $\mathbb{R}_+$

Proof. This assumption implies that the exit is idiosyncratic conditional on the state. In our model, we assume ϕ_{it} is i.i.d and follows a $U[-b_1, b_1]$, which has mean 0, and a well defined density function $\frac{1}{2b_1}$. As a result, our model complies the OE assumption. □

Assumption 4.
1. The number of firms entering during period t is a Poisson random variable that is conditionally independent of $\phi_{it} | t \geq 0, i \geq 1$, conditional on n_t.
2. $\kappa > 0$

Proof. In our model, given quality level $T \in \{H, L\}$ and chain affiliation, we have N_T and N_{Tc} potential entrants for independent and chain restaurants, respectively, deciding whether to enter the market or not. The proof and argument is identical to Weintraub et al. (2008). In particular, each potential entrant enters if the entry cost κ is less than integrated value function upon entry. One can then pose the problem faced by potential entrants as a game in which each entrant employs a mixed strategy and enters with some probability P^E.

As discussed in Weintraub et al. (2008), this equation is solved by a unique $p_N^E \in [0, 1]$ when $\kappa \in [V(N), V(1)]$. Here, $V(N)$ is the integrated value function for the firm for the lowest value and $V(1)$ is the integrated value function for the firm with the highest value. If $k < V(N)$, the equilibrium is given by $p^E = 0$, and if $k > V(1)$, the equilibrium is given by $p_N^E = 1$.

The equilibrium entry and exit probability is a fixed point. the Poisson entry model can be viewed as a limiting case as the number of potential entrants N_T and N_{Tc} grows large. As stated in Weintraub et al. (2008), if the number of potential entrants grows to infinity, then the entry process converges to a Poisson random variable. As a result, the Poisson entry can be understood as the result of a large population of potential entrants, each playing a mixed strategy and entering the industry with a very small probability. In our model, we require a large number of potential entrants, and the entry probability is small. Hence, our model satisfy this assumption.

Assumption (2) $\kappa > 0$ is assumed in our model. □

Assumption 5.
(1) $\sup_{n \in \mathbf{n}} \pi_m(n) = O(m)$
(2) For all increasing sequences $m_k \in \mathbb{N} | k \in \mathbb{N}$, $n : \mathbb{N} \to \mathbb{N}$ with $n(m) = o(m_k)$, $x, z \in \mathbb{N}$ with $x > z$, and $f \in \mathbf{n}_{\mathbf{1},\mathbf{z}}$, $\lim_{k \to \infty} \pi_{m_k}(f, n(m_k)) = \infty$.
(3) The following holds

$$\sup_{m \in \mathbb{R}, f \in \mathbf{n_1}, n > 0} |\frac{d \ln \pi_m(f, n)}{d \ln N}| < \infty$$

.

Proof. Assumption 5 (1) states that the profit increases with at most linearly with market size. In our model, the profit function (2) derived from logit demand increases with M. In particular, $0 < \frac{\partial \pi}{\partial M} < \infty$, here for simplicity, we omit the subscript T and Tc for the profit. So it satisfies this assumption

Assumption 5 (2) means that if the number of firms grows slower than the market size, then the largest firm's profit becomes arbitrarily large as the market grows.

In our model (see profit function 2, firm's profit increases with M, but grow slower than M as the market share a any firm is smaller than 1. Moreover, as M increases, the profit from the firm with highest perceived quality will grown arbitrarily large. Hence, our model satisfy this assumption.

Assumption 5 (3) states that the profit to be smooth with respect to the number of firms, and the relative rate of change of profit with respect to the relative change in the number of firms is uniformly bounded.

In our model, the profit function is a smooth function of n_T and n_{Tc}. Moreover, we can show that

$$\frac{d \ln \pi_m(f, n)}{d \ln N} = \frac{d \ln \pi_m(f, n)}{d \ln (n/f)}$$

. Since f is time invariant, we can write the above equation as follows:

$$\frac{d \ln \pi_m(f, n)}{d \ln N} = \frac{d \ln \pi_m(f, n)}{d \ln (n/f)} = \frac{d \ln \pi_m(f, n)}{\partial n}$$

Because of assumption 2 (4), we have $|\frac{d \ln \pi_m(f,n)}{dn}| < \infty$. Hence, our model satisfies this assumption. $\square$

Assumption 6. For all quality levels $x, g(x) < \infty$. For all $\epsilon > 0$, there exists a quality level z such that

$$E\left(g(\tilde{x}^{(m)}) \mathbb{1}_{\tilde{x}^{(m)} > z}\right) \le \epsilon$$

for all market sizes m.

Proof. Here, $g(x)$ is defined as follows:

$$g(x) = \sup_{m \in \mathbb{R}+, y \in \mathbb{N}, f \in \mathbf{S}, n > 0} |\frac{d \ln \pi_m(y, f, n)}{df(x)}|$$

This assumption is the light-tail condition, and it states that the probability that a small change in the fraction of firms has a large impact on the profits of other firms must be small under the invariant distribution.

In our model,

$$\frac{d\ln\pi_m(y,f,n)}{df(x)} = \frac{d\ln\pi_m(y,f,n)}{d(n/N)} = N\frac{d\ln\pi_m(y,f,n)}{dn(x)}|$$

□

We have shown that $\frac{d\ln\pi_m(y,f,n)}{dn(x)} < \infty$ from 5 (3), hence, $E(g(x)) = |\frac{d\ln\pi_m(y,f,n)}{df(x)}| = |\frac{d\ln\pi_m(y,f,n)}{d(n/N)}| < \infty$. Hence, our model satisfies this assumption.

C Model Solution

In this section, we provide the OE solution to the model described in Section 3 and the long-run invariant distribution of restaurants in equilibrium. For notation simplicity, we will convert (q, g, D) into subscripts. We also omit the subscript I for independent restaurants but use the "c" subscript to indicate chain. For example, $P^X(\bar{q}, 1, I)$ will be denoted as P^X_{H1}, and $P^X(\bar{q}, g, c)$ denoted by P^X_{Hc}. The detailed definition of each of these notations can be found in Table A.1. As described in the main text, a restaurant experience 3 stages: new entrant, young, and established. The perceived quality of a restaurant at the young stage is heavily influenced by the level of quality disclosure. Given different perceptions of quality, restaurants at different stages will have different flow profits. We summarize the perceived quality of a restaurant, as well as their corresponding flow profits, in Table C.1 below.

Table C.1: Perceived Qualities and Profits at Different Stages

Type	Perceived Quality	Flow Profit
New entrant ($g = 0$)	$\hat{q}_0 = \frac{1}{2}(\bar{q} + \underline{q})$	$\pi_0 = \frac{M\exp(\hat{q}_0)}{\sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')+1} - C_T$ for $T \in \{H, L\}$
Young high-quality ($g = 1$)	$\hat{q}_{H1} = \frac{1}{2}(\bar{q} + \underline{q}) + \frac{1}{2}(\bar{q} - \underline{q})\gamma$	$\pi_{H1} = \frac{M\exp(\hat{q}_{H1})}{\sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')+1} - C_H$
Young low-quality ($g = 1$)	$\hat{q}_{L1} = \frac{1}{2}(\bar{q} + \underline{q}) - \frac{1}{2}(\bar{q} - \underline{q})\gamma$	$\pi_{L1} = \frac{M\exp(\hat{q}_{L1})}{\sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')+1} - C_L$
Established high-quality ($g = 2$)	$\bar{q}$	$\pi_{H2} = \frac{M\exp(\bar{q})}{\sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')+1} - C_H$
Established low-quality ($g = 2$)	$\underline{q}$	$\pi_{L2} = \frac{M\exp(\underline{q})}{\sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')+1} - C_L$
High-quality chain	$\bar{q}$	$\pi_{Hc} = \frac{M\exp(\underline{q})}{\sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')+1} - C_{Hc}$
Low-quality chain	$\underline{q}$	$\pi_{Hc} = \frac{M\exp(\underline{q})}{\sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')+1} - C_{Lc}$

Following Weintraub et al. (2008), we can compute the integrated value functions for restaurants at different stages. To establish the existence of OE solution, we require the extreme value of error term, b_0 and b_1 to be high enough. In particular, the following conditions should hold:

$$-2\beta b_1 < -A_T + 2\sqrt{b_1}B_T < 0 \tag{C.1}$$

$$b_1 > \frac{1}{(1-\beta)^2}\max\{B_T, B_{Tc}\} \tag{C.2}$$

$$b_0 > (1-\beta)\max\{E_T, E_{Tc}\}, \tag{C.3}$$

where $A_T = 2b_1 + \beta(\pi_{T1} - \pi_{T2})$, $B_T = \sqrt{(b_1 - \beta b_1 - \beta\pi_{T2})}$, $B_{Tc} = \sqrt{(b_1 - \beta b_1 - \beta\pi_{Tc})}$, $E_T = -\kappa_T + \beta V_{T1} + \pi_{T0}$, and $E_{Tc} = -\kappa_{Tc} + \beta V_{Tc1} + \pi_{Tc}$ for $T \in \{H, L\}$.

Table C.2: Value Functions

Symbol	Expression
V_{T0}	$(-b_0(-2+\beta) + \beta E_T - 2\sqrt{b_0(1-\beta)(b_0+\beta E_T})/\beta^2$
V_{T1}	$(A_T - 6\sqrt{b_1}B_T)(A_T + 2\sqrt{b_1}B_T)/(4b_1\beta^2)$
V_{T2}	$(\sqrt{b_1} - \sqrt{b_1}B_T)^2/\beta^2$
V_{Tc0}	$(-b_0(-2+\beta) + \beta E_{Tc} - 2\sqrt{b_0(1-\beta)(b_0+\beta E_{Tc}})/\beta^2$
V_{Tc1}	$(\sqrt{b_1} - \sqrt{b_1}B_{Tc})^2/\beta^2$

Note: $A_T = 2b_1 + \beta(\pi_{T1} - \pi_{T2})$, $B_T = \sqrt{(b_1 - \beta b_1 - \beta\pi_{T2})}$, $B_{Tc} = \sqrt{(b_1 - \beta b_1 - \beta\pi_{Tc})}$, $E_T = -\kappa_T + \beta V_{T1} + \pi_{T0}$, and $E_{Tc} = -\kappa_{Tc} + \beta V_{Tc1} + \pi_{Tc}$ for $T \in \{H, L\}$

Based on the definition of OE (Weintraub et al., 2008), along with integrated value functions computed in Table C.2, we are able to write down the OE solution, which includes the equilibrium entry and exit probabilities for high- (H) and low- (L) quality restaurants, respectively, across different age types ($g \in \{0, 1, 2\}$). Table C.3 shows the symbol, meaning and expressions of each element in the solution.

Table C.3: Model Solution

Variable	Meaning	Expression
P_T^E	entry probabilities for independent new entrants ($g=0$) of quality type $T \in \{H,L\}$	$1+\frac{-\sqrt{b_0}+\sqrt{(1-\beta)(b_0+\beta E_T)}}{\beta\sqrt{b_0}}$
P_{T1}^X	exit probabilities for young independent restaurants ($g=1$) of quality type $T \in \{H,L\}$	$1+\frac{-A_T+2\sqrt{b_1}B_T}{2\beta b_1}$
P_{T2}^X	exit probabilities for established independent restaurants ($g=2$) of quality type $T \in \{H,L\}$	$1+\frac{-\sqrt{b_1}+B_T}{\beta\sqrt{b_1}}$
P_{Tc}^E	entry probabilities for chain new entrants ($g=0$) of quality type $T \in \{H,L\}$	$1+\frac{-\sqrt{b_0}+\sqrt{(1-\beta)(b_0+\beta E_{Tc})}}{\beta\sqrt{b_0}}$
P_{Tc}^X	exit probabilities for chain restaurants ($g=1,2$) of quality type $T \in \{H,L\}$	$1+\frac{-\sqrt{b_1}+B_{Tc}}{\beta\sqrt{b_1}}$

Note: $A_T = 2b_1+\beta(\pi_{T1}-\pi_{T2})$, $B_T=\sqrt{(b_1-\beta b_1-\beta\pi_{T2})}$, $B_{Tc}=\sqrt{(b_1-\beta b_1-\beta\pi_{Tc})}$, $E_T=-\kappa_T+\beta V_{T1}+\pi_{T0}$, and $E_{Tc}=-\kappa_{Tc}+\beta V_{Tc1}+\pi_{Tc}$ for $T\in\{H,L\}$

In addition to the entry and exit probabilities, we provide the long run invariant distributions of restaurants in Table C.4 .

Table C.4: The Long-run Invariant Distribution

Variable	Meaning	Expression
n_{T0}	the number of independent new entrants of quality type $T \in \{H,L\}$	$N_T P_T^E$
n_{T1}	the number of young independent restaurants of quality type $T \in \{H,L\}$	$N_T P_T^E(1-P_{T1}^X)$
n_{T2}	the number of established independent restaurants of quality type $T \in \{H,L\}$	$\frac{N_T P_T^E(1-P_{T1}^X)(1-P_{T2}^X)}{P_{T2}^X}$
n_{Tc}	the number of chain restaurants of quality type $T \in \{H,L\}$	$\frac{N_{Tc} P_{Tc}^E(1-P_{Tc}^X)}{P_{Tc}^X}$

D Proof of Propositions

D.1 Proposition 1 Proof

Proof. For chain restaurants, the perceived quality does not change with respect to γ, and therefore, the DEs on chain restaurants are 0. For independent restaurants, we need to show the following:

$$\frac{\partial P_H^E}{\partial \pi_{H1}} \frac{\partial \pi_{H1}}{\partial M \exp(\hat{q}_{H1})} \frac{\partial M \exp(\hat{q}_{H1})}{\partial \hat{q}_{H1}} \frac{\partial \hat{q}_{H1}}{\partial \gamma} > 0, \tag{D.1}$$
$$\frac{\partial P_{H1}^X}{\partial \pi_{H1}} \frac{\partial \pi_{H1}}{\partial M \exp(\hat{q}_{H1})} \frac{\partial M \exp(\hat{q}_{H1})}{\partial \hat{q}_{H1}} \frac{\partial \hat{q}_{H1}}{\partial \gamma} < 0, \tag{D.2}$$
$$\frac{\partial P_{H2}^X}{\partial \pi_{H1}} \frac{\partial \pi_{H1}}{\partial M \exp(\hat{q}_{H1})} \frac{\partial M \exp(\hat{q}_{H1})}{\partial \hat{q}_{H1}} \frac{\partial \hat{q}_{H1}}{\partial \gamma} = 0, \tag{D.3}$$
$$\frac{\partial P_L^E}{\partial \pi_{L1}} \frac{\partial \pi_{L1}}{\partial M \exp(\hat{q}_{L1})} \frac{\partial M \exp(\hat{q}_{L1})}{\partial \hat{q}_{L1}} \frac{\partial \hat{q}_{L1}}{\partial \gamma} < 0, \tag{D.4}$$
$$\frac{\partial P_{L1}^X}{\partial \pi_{L1}} \frac{\partial \pi_{L1}}{\partial M \exp(\hat{q}_{L1})} \frac{\partial M \exp(\hat{q}_{L1})}{\partial \hat{q}_{L1}} \frac{\partial \hat{q}_{L1}}{\partial \gamma} > 0, \tag{D.5}$$
$$\frac{\partial P_{L2}^X}{\partial \pi_{L1}} \frac{\partial \pi_{L1}}{\partial M \exp(\hat{q}_{L1})} \frac{\partial M \exp(\hat{q}_{L1})}{\partial \hat{q}_{L1}} \frac{\partial \hat{q}_{L1}}{\partial \gamma} = 0. \tag{D.6}$$

Equations D.3 and D.6 are obvious because $\pi_{T1}, T \in \{H, L\}$ does not enter the exit probabilities at the "established" stage of the firm. It is also evident that $(\partial \pi_{T1}/\partial M \exp(\hat{q}_{T1}))(\partial M \exp(\hat{q}_{T1})/\partial \hat{q}_{T1}) = \pi_{T1} > 0, \forall T \in \{H, L\}$. Furthermore, $\partial \hat{q}_{H1}/\partial \gamma = (\bar{q} - \underline{q})/2 > 0$ and $\hat{q}_{L1}/\partial \gamma = (\underline{q} - \bar{q})/2 < 0$. The only work left to show is the signs of the derivatives of the probabilities with respect to the "young" stage flow profit. Below we derive these derivatives.

$$\frac{\partial P_T^E}{\partial \pi_{T1}} = \frac{\partial P_T^E}{\partial V_{T1}} \frac{\partial V_{T1}}{\partial \pi_{T1}} > 0, \tag{D.7}$$
$$\frac{\partial P_{T1}^X}{\partial \pi_{T1}} = -\frac{1}{2b_1} < 0, \forall T \in \{H, L\} \tag{D.8}$$

For the entry probabilities, as shown in the expression for entry probabilities in Table C.3, $\partial P_T^E/\partial V_{T1} > 0$, and as shown in the expression for V_{T1} in Table C.2, $\partial V_{T1}/\partial \pi_{T1} > 0$. Therefore, $\partial P_T^E/\partial \pi_{T1} > 0$. With the signs of $\partial P_T^E/\partial \pi_{T1}$ and $\partial P_{T1}^X/\partial \pi_{T1}$ in hand, the signs of the expressions D.1 to D.6 follow naturally. Q.E.D. □

D.2 Proposition 2 Proof

Proof. As shown in Definition 2, the key determining factor of the directions of CEs is $\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')/\partial \gamma$. In particular, when $\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')/\partial \gamma = 0$, the CEs are 0. Below we expand $\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')/\partial \gamma$, and derive the expressions of $\bar{F}_H$ and $\bar{F}_L$.

$$\frac{\partial \sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')}{\partial\gamma} = \sum_{\hat{q}'}\left[\frac{\partial n(\hat{q}')}{\partial\gamma}\exp(\hat{q}') + n(\hat{q}')\frac{\partial\exp(\hat{q}')}{\partial\gamma}\right]$$

$$= \sum_{\hat{q}'}\frac{\partial n(\hat{q}')}{\partial\gamma}\exp(\hat{q}') - \left(n_{L1}\exp(\hat{q}_{L1}) - n_{H1}\exp(\hat{q}_{H1})\right)\frac{(\bar{q}-\underline{q})}{2}, \text{ where} \tag{D.9}$$

$$\sum_{\hat{q}'}\frac{\partial n(\hat{q}')}{\partial\gamma}\exp(\hat{q}') = \left(\frac{\partial n_{L0}}{\partial\gamma} + \frac{\partial n_{H0}}{\partial\gamma}\right)\exp(\hat{q}_0) + \frac{\partial n_{L1}}{\partial\gamma}\exp(\hat{q}_{L1}) + \frac{\partial n_{H1}}{\partial\gamma}\exp(\hat{q}_{H1})$$

$$+\left(\frac{\partial n_{L2}}{\partial\gamma} + \frac{\partial n_{Lc}}{\partial\gamma}\right)\exp(\underline{q}) + \left(\frac{\partial n_{H2}}{\partial\gamma} + \frac{\partial n_{Hc}}{\partial\gamma}\right)\exp(\bar{q}) \tag{D.10}$$

Based on the expressions of equilibrium $n(\hat{q})$ shown in Table C.4, we can write

$$\frac{\partial n_{L0}}{\partial\gamma} = N_L\frac{\partial P_L^E}{\partial\gamma} \tag{D.11}$$

$$\frac{\partial n_{H0}}{\partial\gamma} = N_H\frac{\partial P_H^E}{\partial\gamma} \tag{D.12}$$

$$\frac{\partial n_{L1}}{\partial\gamma} = N_L\frac{\partial P_L^E(1-P_{L1}^X)}{\partial\gamma} \tag{D.13}$$

$$\frac{\partial n_{H1}}{\partial\gamma} = N_H\frac{\partial P_H^E(1-P_{H1}^X)}{\partial\gamma} \tag{D.14}$$

$$\frac{\partial n_{L2}}{\partial\gamma} = N_L\frac{\partial P_L^E(1-P_{L1}^X)(1/P_{L2}^X-1)}{\partial\gamma} \tag{D.15}$$

$$\frac{\partial n_{H2}}{\partial\gamma} = N_H\frac{\partial P_H^E(1-P_{H1}^X)(1/P_{H2}^X-1)}{\partial\gamma} \tag{D.16}$$

$$\frac{\partial n_{Lc}}{\partial\gamma} = N_L\frac{N_{Lc}}{N_L}\frac{\partial P_{Lc}^E(1/P_{Lc}^X-1)}{\partial\gamma} \tag{D.17}$$

$$\frac{\partial n_{Hc}}{\partial\gamma} = N_H\frac{N_{Hc}}{N_H}\frac{\partial P_{Hc}^E(1/P_{Hc}^X-1)}{\partial\gamma} \tag{D.18}$$

$$\tag{D.19}$$

Substituting equations D.11 to D.18 into equation D.10 and then D.9, we have the effect of γ on competition as follows:

$$\frac{\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')}{\partial \gamma} = \bar{F}_L + \bar{F}_H, \text{ where} \tag{D.20}$$

$$\bar{F}_L = N_L \left[\exp(\hat{q}_0) \frac{\partial P_L^E}{\partial \gamma} + \exp(\hat{q}_{L1}) \left(\frac{\partial P_L^E (1 - P_{L1}^X)}{\partial \gamma} + P_L^E (1 - P_{L1}^X) \frac{(\underline{q} - \bar{q})}{2} \right) \right.$$
$$\left. + \exp(\underline{q}) \left(\frac{\partial P_L^E (1 - P_{L1}^X)(1/P_{L2}^X - 1)}{\partial \gamma} + \frac{N_{Lc}}{N_L} \frac{\partial P_{Lc}^E (1/P_{Lc}^X - 1)}{\partial \gamma} \right) \right] \tag{D.21}$$

$$\bar{F}_H = N_H \left[\exp(\hat{q}_0) \frac{\partial P_H^E}{\partial \gamma} + \exp(\hat{q}_{H1}) \left(\frac{\partial P_H^E (1 - P_{H1}^X)}{\partial \gamma} + P_H^E (1 - P_{H1}^X)) \frac{(\bar{q} - \underline{q})}{2} \right) \right.$$
$$\left. + \exp(\bar{q}) \left(\frac{\partial P_H^E (1 - P_{H1}^X)(1/P_{H2}^X - 1)}{\partial \gamma} + \frac{N_{Hc}}{N_H} \frac{\partial P_{Hc}^E (1/P_{Hc}^X - 1)}{\partial \gamma} \right) \right] \tag{D.22}$$

Q.E.D. □

D.3 Proposition 3 Proof

Proof. It is easy to show the statement in the first sentence. As shown in Proposition 1 and Corollary 1, when $\bar{F}_L + \bar{F}_H > 0$, DE and CE work in the same direction for all equilibrium probabilities, except for P_H^E and P_{H1}^X. In particular, $\partial P_L^E/\partial\gamma < 0$, $\partial P_{L1}^X/\partial\gamma > 0$, $\partial P_{L2}^X/\partial\gamma > 0$, $\partial P_{H2}^X/\partial\gamma < 0$, $\partial P_{Hc}^E/\partial\gamma < 0$, $\partial P_{Lc}^E/\partial\gamma < 0$, $\partial P_{Hc}^X/\partial\gamma > 0$, and $\partial P_{Lc}^X/\partial\gamma > 0$. Four cases are possible in terms of the signs of $\partial P_H^E/\partial\gamma$ and $\partial P_{H1}^X/\partial\gamma$. We examine each case one by one and eliminate those cases that lead to contradictions with $\bar{F}_L + \bar{F}_H > 0$ or other conditions of the model. For ease of labeling and interpretation, in the following text, we refer to $\sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')$ as "competition."

Case 1 $\partial P_H^E/\partial\gamma > 0$ and $\partial P_{H1}^X/\partial\gamma < 0$. This case requires the DE dominates the CE for both probabilities. This condition is possible as long as DEs are large enough for both probabilities. In particular, $\partial P_H^E/\partial\gamma$ and $\partial P_{H1}^X/\partial\gamma$ can be written as follows:

$$\frac{\partial P_H^E}{\partial \gamma} = \frac{\partial P_H^E}{\partial \pi_{H1}} \frac{\partial \pi_{H1}}{\partial M \exp(\hat{q}_{H1})} \frac{\partial M \exp(\hat{q}_{H1})}{\partial \hat{q}_{H1}} \frac{\partial \hat{q}_{H1}}{\partial \gamma}$$
$$+ \left(\frac{\partial P_H^E}{\partial \pi_{H0}} \frac{\partial \pi_{H0}}{\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')} + \frac{\partial P_H^E}{\partial \pi_{H1}} \frac{\partial \pi_{H1}}{\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')} + \frac{\partial P_H^E}{\partial \pi_{H2}} \frac{\partial \pi_{H2}}{\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')} \right) \frac{\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')}{\partial \gamma} \tag{D.23}$$

$$\frac{\partial P_{H1}^X}{\partial \gamma} = \frac{\partial P_{H1}^X}{\partial \pi_{H1}} \frac{\partial \pi_{H1}}{\partial M \exp(\hat{q}_{H1})} \frac{\partial M \exp(\hat{q}_{H1})}{\partial \hat{q}_{H1}} \frac{\partial \hat{q}_{H1}}{\partial \gamma}$$
$$+ \left(\frac{\partial P_{H1}^X}{\partial \pi_{H1}} \frac{\partial \pi_{H1}}{\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')} + \frac{\partial P_{H1}^X}{\partial \pi_{H2}} \frac{\partial \pi_{H2}}{\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')} \right) \frac{\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')}{\partial \gamma} \tag{D.24}$$

Using equations D.23 and D.24, we can derive that $\partial P_H^E/\partial\gamma > 0$ and $\partial P_{H1}^X/\partial\gamma < 0$ imply the following conditions:

$$\tilde{\pi}_{H1}\left(\frac{1}{2}(\bar{q}-\underline{q})-\Lambda\right) > \frac{2b_1}{(A_H-2\sqrt{b_1}B_H)}\tilde{\pi}_{H0}\Lambda + \left(-1+\frac{b_1(A_H+6\sqrt{b_1}B_H)}{(A_H-2\sqrt{b_1}B_H)\sqrt{b_1}B_H}\right)\tilde{\pi}_{H2}\Lambda \tag{D.25}$$

$$\tilde{\pi}_{H1}\left(\frac{1}{2}(\bar{q}-\underline{q})-\Lambda\right) > \frac{(\sqrt{b_1}-B_H)}{B_H}\tilde{\pi}_{H2}\Lambda, \tag{D.26}$$

where $\tilde{\pi}_{Hg} = \pi_{Hg} + C_H, \forall g \in \{0,1,2\}$, and

$$\Lambda = \frac{\partial \sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')}{\partial\gamma}\frac{1}{\sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')+1}$$

Inequality D.25 comes from $\partial P_H^E/\partial\gamma > 0$, and uses the condition C.1. Inequality D.26 comes from $\partial P_{H1}^X/\partial\gamma < 0$.

It is easy to show that the right-hand-side (RHS) of inequality D.25 is larger than the RHS of inequality D.26. The rationale is that when $\bar{F}_L + \bar{F}_H > 0$, $\partial \sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')/\partial\gamma > 0$. Therefore, $\Lambda > 0$, and based on condition C.1, $\frac{2b_1}{(A_H-2\sqrt{b_1}B_H)}\pi_{H0}\Lambda > 0$. In addition,

$$\left(-1+\frac{b_1(A_H+6\sqrt{b_1}B_H)}{(A_H-2\sqrt{b_1}B_H)\sqrt{b_1}B_H}\right)\pi_{H2}\Lambda > \frac{(\sqrt{b_1}-B_H)}{B_H}\pi_{H2}\Lambda, \tag{D.27}$$

This is because inequality D.27 implies $b_1(A_H+6\sqrt{b_1}B_H) > b_1(A-2\sqrt{b_1}B_H)$, which always holds as long as $B_H > 0$. Therefore, the RHS of inequality D.25 is always larger than the RHS of inequality D.26. These two conditions imply that as long as inequality D.25 holds, Case 1 is possible.

Now we can check whether this case can support the assumption $\bar{F}_L + \bar{F}_H > 0$. We know that low-quality restaurants enter less and exit more as γ increases, therefore, there should be fewer low-quality restaurants. Furthermore, because both high-quality chain and established independent restaurants exit more often, there should also be fewer high-quality chain or established independent restaurants. The decrease in the number of competitors can reduce competition. However, because high-quality independent restaurants enter more and because high-quality young independent restaurants exit less, there are more new and young high-quality independent restaurants. The increase in the number of new and young high-quality independent restaurants can compensate the loss in the number of restaurants from other types. In particular, it should be noted that the number of low-quality restaurants affects competition, which can be summarized by $\sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')$, much less than the number of high-quality restaurants because the number of restaurants from each type $n(\hat{q}')$ is weighted by $\exp(\hat{q}')$, i.e. the exponential of the perceived quality. Therefore, the increase in the number of young high-quality independent restaurants can more than offset the effect of a decreasing number of low-quality restaurants on competition.

Case 2 $\partial P_H^E/\partial\gamma > 0$ and $\partial P_{H1}^X/\partial\gamma > 0$. This case requires the $DE(P_H^E)$ dominates $CE(P_H^E)$, but $DE(P_{H1}^X)$ is dominated by $CE(P_{H1}^X)$. This case is impossible. It requires inequality D.25 and the reverse of inequality D.26 to hold at the same time. It is impossible because the RHS of inequality D.25 is larger than the RHS of inequality D.26. $\tilde{\pi}_{H1}\left(\frac{1}{2}(\bar{q}-\underline{q})-\Lambda\right)$ cannot be simultaneously bigger than a large number and smaller than a small number.

Case 3 $\partial P_H^E/\partial\gamma < 0$ and $\partial P_{H1}^X/\partial\gamma < 0$. This case requires the $DE(P_H^E)$ is dominated by $CE(P_H^E)$, but $DE(P_{H1}^X)$ dominates $CE(P_{H1}^X)$. More specifically, it requires the reverse of inequality D.25, but retains inequality D.26. These conditions can be satisfied. Now we only need to check whether this case complies with $\bar{F}_L + \bar{F}_H > 0$, i.e. $\partial \sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')/\partial\gamma > 0$. The directions of the change in probabilities with respect to γ imply that the number of restaurants of all types is declining as γ increases, except for the numbers of high-quality young and established restaurants (i.e. n_{H1} and n_{H2}). The changes in n_{H1} and n_{H2} are uncertain because although high-quality independent restaurants are entering less, they are also exiting less at the young stage. This means that potentially more young high-quality independent restaurants are in the market, and more of them will become established, and n_{H1} and n_{H2} can increase. The increase in n_{H1} and n_{H2} can make up for the loss in the number of restaurants from other types. Therefore, this case is possible.

Case 4 $\partial P_H^E/\partial\gamma < 0$ and $\partial P_{H1}^X/\partial\gamma > 0$. This case requires the DE is dominated by the CE for both probabilities. This case implies that the numbers of restaurants from all types are declining as γ increases. That is, $U \equiv \sum\limits_{\hat{q}'} \frac{\partial n(\hat{q}')}{\partial\gamma}\exp(\hat{q}') < 0$. This will not contradict with $\partial \sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')/\partial\gamma > 0$ if $\Delta \equiv -\left(n_{L1}\exp(\hat{q}_{L1}) - n_{H1}\exp(\hat{q}_{H1})\right)\frac{(\bar{q}-\underline{q})}{2}$ is large enough.

In addition, this case also requires the signs of both inequality D.25 and inequality D.26 be reversed. Given that the RHS of inequality D.25 is larger than that of inequality D.26, we only need the reverse of inequality D.26 to be true. That requires the following:

$$\frac{\bar{q}-\underline{q}}{2} < \left(1 + \frac{(\sqrt{b_1} - B_H)}{B_H}\exp(\bar{q} - \hat{q}_{H1})\right)\frac{U + \Delta}{\sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}') + 1}; \tag{D.28}$$

Based on Assumption 1, $\left(1 + \frac{(\sqrt{b_1}-B_H)}{B_H}\exp(\bar{q} - \hat{q}_{H1})\right)\frac{\Delta}{\sum_{\hat{q}'} n(\hat{q}')\exp(\hat{q}')+1} < \frac{\bar{q}-\underline{q}}{2}$. In addition, given $U < 0$, the above inequality cannot hold. Therefore, Case 4 is impossible.

Q.E.D □

D.4 Proposition 4 Proof

Proof. The proof for this proposition is very similar to that for Proposition 3. First, it is easy to show the statement in the first sentence of the proposition. Based on Proposition 1 and Corollary 1, when $\bar{F}_L + \bar{F}_H < 0$, DE and CE work in the same direction for all equilibrium probabilities, except for P_L^E and P_{L1}^X. In particular, $\partial P_H^E/\partial\gamma > 0$, $\partial P_{H1}^X/\partial\gamma < 0$, $\partial P_{H2}^X/\partial\gamma < 0$, $\partial P_{L2}^X/\partial\gamma < 0$, $\partial P_{Hc}^E/\partial\gamma > 0$, $\partial P_{Lc}^E/\partial\gamma > 0$, $\partial P_{Hc}^X/\partial\gamma < 0$, and $\partial P_{Lc}^X/\partial\gamma < 0$. Second, we can iterate over the four possible combinations of the signs of $\partial P_L^E/\partial\gamma$ and $\partial P_{L1}^X/\partial\gamma$.

Case 1 $\partial P_L^E/\partial\gamma < 0$ and $\partial P_{L1}^X/\partial\gamma > 0$. This case requires the DE dominates the CE for both probabilities. This condition is possible as long as the DEs are large enough for both probabilities.

As with the proof for Proposition 3, we can write $\partial P_L^E/\partial\gamma < 0$ and $\partial P_{L1}^X/\partial\gamma > 0$ as

$$\begin{aligned}\frac{\partial P_L^E}{\partial\gamma} =& \frac{\partial P_L^E}{\partial\pi_{L1}}\frac{\partial\pi_{L1}}{\partial M\exp(\hat{q}_{L1})}\frac{\partial M\exp(\hat{q}_{L1})}{\partial\hat{q}_{L1}}\frac{\partial\hat{q}_{L1}}{\partial\gamma} \\ &+\left(\frac{\partial P_L^E}{\partial\pi_{L0}}\frac{\partial\pi_{L0}}{\partial\sum_{\hat{q}'}n(\hat{q}')\exp(\hat{q}')}+\frac{\partial P_L^E}{\partial\pi_{L1}}\frac{\partial\pi_{L1}}{\partial\sum_{\hat{q}'}n(\hat{q}')\exp(\hat{q}')}+\frac{\partial P_L^E}{\partial\pi_{L2}}\frac{\partial\pi_{L2}}{\partial\sum_{\hat{q}'}n(\hat{q}')\exp(\hat{q}')}\right)\frac{\partial\sum_{\hat{q}'}n(\hat{q}')\exp(\hat{q}')}{\partial\gamma} \qquad (D.29)\\ \frac{\partial P_{L1}^X}{\partial\gamma} =& \frac{\partial P_{L1}^X}{\partial\pi_{L1}}\frac{\partial\pi_{L1}}{\partial M\exp(\hat{q}_{L1})}\frac{\partial M\exp(\hat{q}_{L1})}{\partial\hat{q}_{L1}}\frac{\partial\hat{q}_{L1}}{\partial\gamma} \\ &+\left(\frac{\partial P_{L1}^X}{\partial\pi_{L1}}\frac{\partial\pi_{L1}}{\partial\sum_{\hat{q}'}n(\hat{q}')\exp(\hat{q}')}+\frac{\partial P_{L1}^X}{\partial\pi_{L2}}\frac{\partial\pi_{L2}}{\partial\sum_{\hat{q}'}n(\hat{q}')\exp(\hat{q}')}\right)\frac{\partial\sum_{\hat{q}'}n(\hat{q}')\exp(\hat{q}')}{\partial\gamma} \qquad (D.30)\end{aligned}$$

Using D.29 and D.30, we can derive the following conditions that satisfy $\partial P_L^E/\partial\gamma < 0$ and $\partial P_{L1}^X/\partial\gamma > 0$:

$$\pi_{L1}\left(\frac{1}{2}(\underline{q}-\bar{q})-\Lambda\right) < \frac{2b_1}{(A_L-2\sqrt{b_1}B_L)}\pi_{L0}\Lambda+\left(-1+\frac{b_1(A_L+6\sqrt{b_1}B_L)}{(A_L-2\sqrt{b_1}B_L)\sqrt{b_1}B_L}\right)\pi_{L2}\Lambda \qquad (D.31)$$

$$\pi_{L1}\left(\frac{1}{2}(\underline{q}-\bar{q})-\Lambda\right) < \frac{(\sqrt{b_1}-B_L)}{B_L}\pi_{L2}\Lambda, \qquad (D.32)$$

where

$$\Lambda = \frac{\partial\sum_{\hat{q}'}n(\hat{q}')\exp(\hat{q}')}{\partial\gamma}\frac{1}{\sum_{\hat{q}'}n(\hat{q}')\exp(\hat{q}')+1}$$

Inequality D.31 comes from $\partial P_L^E/\partial\gamma < 0$, and uses the condition C.1. Inequality D.32 comes from $\partial P_{L1}^X/\partial\gamma > 0$.

These two inequalities have a very similar form compared with inequalities D.25 and D.26. In particular, it is easy to show that the RHS of inequality D.31 is smaller than that of inequality D.32. When $\bar{F}_L+\bar{F}_H > 0$, $\Lambda < 0$. Therefore, $\frac{2b_1}{(A_L-2\sqrt{b_1}B_L)}\pi_{L0}\Lambda < 0$, and

$$\left(-1+\frac{b_1(A_L+6\sqrt{b_1}B_L)}{(A_L-2\sqrt{b_1}B_L)\sqrt{b_1}B_L}\right)\pi_{L2}\Lambda < \frac{(\sqrt{b_1}-B_L)}{B_L}\pi_{L2}\Lambda, \qquad (D.33)$$

Then we have

$$\frac{2b_1}{(A_L-2\sqrt{b_1}B_L)}\pi_{L0}\Lambda+\left(-1+\frac{b_1(A_L+6\sqrt{b_1}B_L)}{(A_L-2\sqrt{b_1}B_L)\sqrt{b_1}B_L}\right)\pi_{L2}\Lambda < \frac{(\sqrt{b_1}-B_L)}{B_L}\pi_{L2}\Lambda, \qquad (D.34)$$

For Case 1 to be possible, we only need inequality D.31 to hold.

Now we can check if this case complies with the condition $\partial\sum_{\hat{q}'}n(\hat{q}')\exp(\hat{q}')/\partial\gamma < 0$. Although both the number of high-quality independent restaurants and the number of chain restaurants from all quality types will increase as γ increases, the number of low-quality independent restaurants decreases. As long as this decrease is large enough, it could compensate the increase in the number of high-quality restaurants, leading to a decrease in competition.

Case 2 $\partial P_L^E/\partial\gamma < 0$ and $\partial P_{L1}^X/\partial\gamma < 0$. This case requires the $DE(P_L^E)$ dominates $CE(P_L^E)$, but $DE(P_{L1}^X)$ is dominated by $CE(P_{L1}^X)$. More specifically, it requires inequality D.31 and the reverse of inequality D.32. This is impossible because the RHS of inequality D.31 is smaller than that of inequality D.32.

Case 3 $\partial P_L^E/\partial\gamma > 0$ **and** $\partial P_{L1}^X/\partial\gamma > 0$**.** This case requires the $DE(P_L^E)$ be dominated by $CE(P_L^E)$, but $DE(P_{L1}^X)$ dominates $CE(P_{L1}^X)$. This condition is possible. This case requires the reverse of inequality D.31, but retains inequality D.32. These conditions are consistent with each other.

We can now check if it contradicts with $\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')/\partial\gamma < 0$. The directions of the probabilities in this case imply that the number of restaurants from all types is increasing, except for the numbers of young and established low-quality restaurants (i.e., n_{L1} and n_{L2}). The change in n_{L1} and n_{L2} is unclear because although low-quality independent restaurants are entering more, they are also exiting more at the young stage. This means that potentially fewer young low-quality independent restaurants are in the market, and fewer of them will become established. The decrease in n_{L1} and n_{L2} could overpower the increase in the number of restaurants from other types if n_{L1} and n_{L2} are large enough. Therefore, this case is possible.

Case 4 $\partial P_L^E/\partial\gamma > 0$ **and** $\partial P_{L1}^X/\partial\gamma < 0$**.** This case requires the DE is dominated by the CE for both probabilities. This case leads to an increase in the number of restaurants from all types; that is, $U > 0$. However, if Δ is negative and large in magnitude, the condition $\partial \sum_{\hat{q}'} n(\hat{q}') \exp(\hat{q}')/\partial\gamma < 0$ can still hold.

This case also requires the reverse of inequality D.32 to hold, which implies

$$\frac{\bar{q} - \underline{q}}{2} < \left(1 + \frac{(\sqrt{b_1} - B_L)}{B_L} \exp(\bar{q} - \hat{q}_{L1})\right)(-\Lambda) \tag{D.35}$$

Based on Assumption 1, this condition D.35 cannot hold. Therefore, this case is impossible. Q.E.D

□

E Parameter Space Setup for Numerical Examples

This section serves two goals: one is to provide parameter space specification in the main paper. The other is to show additional simulation results to demonstrate the existence of Proposition 4 (1) where with decreased competition, the equilibrium entry probability for low-quality restaurants increases.

E.1 $N_L = N_H$

The specifications of all parameters of the model are shown in Table E.1. For the market size parameter M and the numbers of potential entrants (e.g. N_H), we set them to a very large number because the OE solution concept requires a very high market size and large numbers of entrants. We set the number of potential entrants for chain restaurants at a relatively smaller level than those for independent restaurants to reflect the fact that in reality, chain restaurants are harder to come by. Altering the market size and potential entrants parameters would not make a difference in our solutions or the properties of these solutions. Therefore, we set them constant.

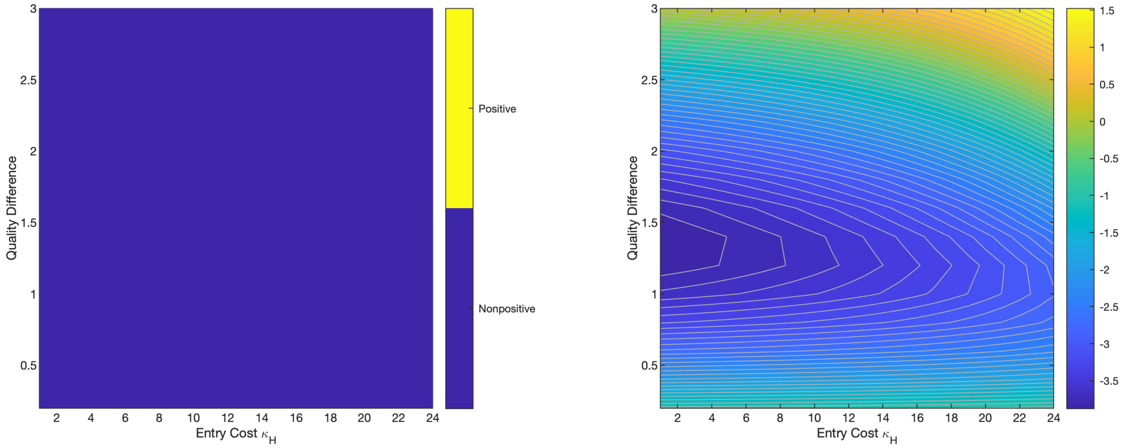
For the per-period fixed cost parameters (e.g. C_H), we set them relatively small in order to ensure that the flow-profits in each period for all firms are positive. Again this is a requirement in the OE solution concept. See Assumption 2 (3). Regarding the discount factor β, we set it to a relatively small number 0.8 to capture the fact that consumer learning make take a long time. A smaller β makes the profits from established stage of independent restaurants less important and therefore allows a greater effect of γ. For b_0 and b_1, we set them equal for simplicity, and we set them large enough such that the model has a real solution. Smaller bs also amplifies the effect of γ on equilibrium entry and exit probabilities.

Table E.1: Parameter Specifications in the Numerical Example

Variable	Value	Variable	Value	Variable	Value
M	1000	β	0.8	$\underline{q}$	0
N_H	1000	C_H	0.4	$\bar{q}$	$[0.2, 3]$
N_L	1000	C_L	0.2	κ_H	$[1, 24]$
N_{Hc}	200	C_{Hc}	0.2	κ_L	$0.7\kappa_H$ $[0.7, 18.9]$
N_{Lc}	200	C_{Lc}	0.1	$\kappa_{Hc} = \kappa_{Lc}$	$0.8\kappa_H$, $[0.8, 21.6]$
				$b_0 = b_1$	55

E.2 $N_L >> N_H$

As discussed in the proof for Proposition 4 in the subsection D.4, the condition for Proposition 4 (1) to occur is stringent. To show this scenario is possible, we require the number of potential entrants for low-quality restaurants to be significantly greater than that for high-quality restaurants. In particular, we use the same parameter space specification shown in Table E.1 except that $N_L = 3000$ and $N_H = 500$. As shown in figure **??**, with a new set of parameters, we observe decreased competition. The rationale is quite intuitive: with a large number of potential entrants for low-quality restaurants, the number of low-quality restaurants will be much larger than the number of high-quality restaurants in the market. With quality disclosure, it is likely that a large number of low-quality firms exit the market, possibly leading to a decreased competition.

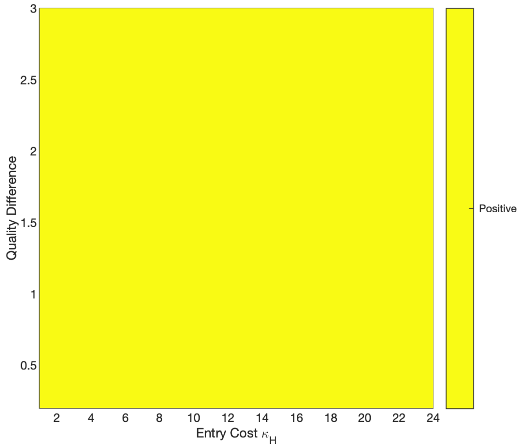


(a) Direction (b) Percentage Change

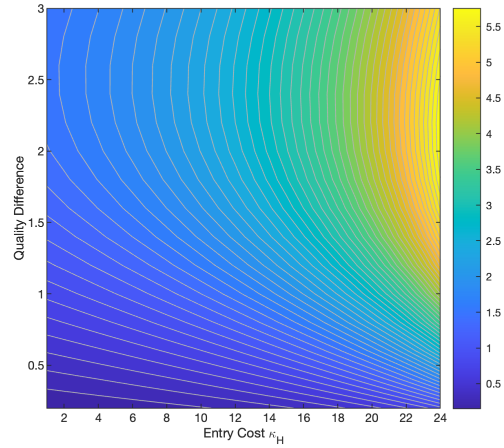
Figure E.1: Change in Competition When $N_L \gg N_H$

Figure E.2 shows the corresponding entry probabilities of independent restaurants. Figure E.2a and E.2b in the top panel show the entry probabilities for the high-quality independent restaurants in terms of directional and percentage changes respectively. The rationale behind the figures is similar to the discussion in the main paper. In this case, high-quality firms do not only enjoy the direct benefit from quality disclosure, but also get indirect benefit from decreased competition. As a result, they are encouraged to enter the market. As for the percentage change in entry probabilities as shown in figure E.2b, we see the biggest change occur when both entry cost and quality difference are high. The reason is quite similar to the discussion for figure **??** in the main paper.

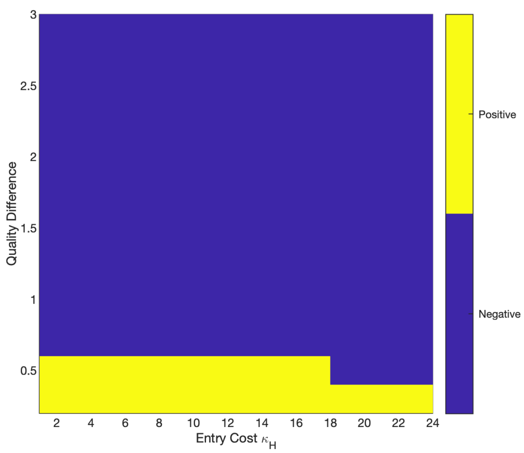
For low-quality restaurants, the changes in entry probabilities in terms of direction and percentage are shown in figure E.2c and E.2d. We observe some interesting features: (1) the entry probability may increase or decrease. It confirms the existence of Proposition 4. (2) the increase in entry probability occurs when quality difference is low. With a low quality difference, the direct effect from quality disclosure is limited, and the benefit from a decreased competition may dominate. In this case, despite the fact that quality disclosure makes low-quality restaurants less desirable, those restaurants are still motivated to enter the market. In terms of percentage change, the increase in entry probability is higher when the entry cost is lower. With low entry costs, restaurants from all types are encouraged to enter. When the quality difference is low, even with quality disclosure, high-quality restaurants are not as much encouraged to enter the market, implying low-quality restaurants do not lose much market due to the quality disclosure. When combining the low entry costs with low quality difference, we expect to see a much bigger increase in the entry probabilities for low-quality firms. Here, we do not show the figure for exit probabilities for young independent restaurants as they are the same as the figures 3 and the rationale is the same.



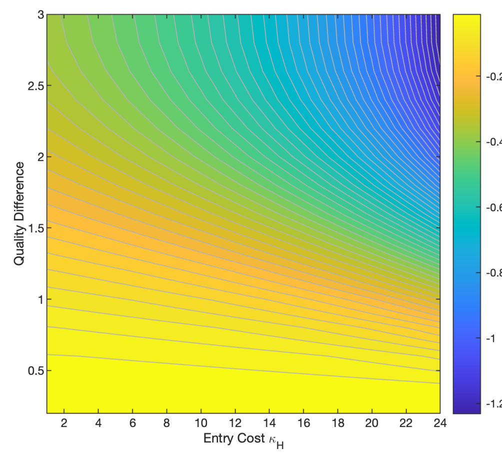
(a) Direction (High-quality)



(b) Percentage Change (High-quality)



(c) Direction (Low-quality)



(d) Percentage Change (Low-quality)

Figure E.2: Change in Entry Probabilities of Independent Restaurants (Decreased Competition)

F Model Extension to Extreme Case of Slow Learning

Our main model assumes that it takes consumers one period to learn the true quality of a restaurant fully. However, it is possible that learning is slow, hence it takes consumers many periods to completely learn the true quality of restaurants. For example, in transient locations, such as tourist areas or areas around highway exits, consumers are travelers and they visit the stores only once. They are not repeat consumers. Learning is likely very slow in the transient locations.

To consider this scenario, we take the learning period to the extreme and assume that without yelp, quality is never fully revealed to consumers. That is, restaurants stay young forever in terms of their perceived quality. The analysis for slow learning is analogous to that of the baseline model in the main text. Any learning process in reality can be understood as a scenario in between these two cases.

Below we discuss the model solutions. Because, in this extension, firms stay young forever after entry, we have only two distinct stages for independent restaurants: potential/new entrants ($g = 0$) and young ($g = 1$). This means that the flow profits with slow learning stay constant after the period of entry. That is, the original established-period profit π_{T2} is equal to $\pi_{T1}, \forall T \in \{H, L\}$) in this extension. This is the key difference between the solutions for the two models. The rest of the solutions is the same.

With sleight of hand, we derive the algebraic expressions of the integrated value functions and the entry and exit probabilities. Table F.1 displays the integrated value functions, and Table F.2 shows the OE entry and exit probabilities. Again, to establish the existence of OE solutions, we need b_0 and b_1 to be large enough. The conditions are identical to Equations C.1 to C.3, except that A_T is now defined as $A_T = 2b_1$ instead of $A_T = 2b_1 + \beta(\pi_{T1} - \pi_{T2})$.[20]

Table F.1: Value Functions

Symbol	Expression
V_{T0}	$(-b_0(-2+\beta) + \beta E_T - 2\sqrt{b_0(1-\beta)(b_0+\beta E_T})/\beta^2$
V_{T1}	$(\sqrt{b_1} - \sqrt{b_1} B_T)^2/\beta^2$
V_{Tc0}	$(-b_0(-2+\beta) + \beta E_{Tc} - 2\sqrt{b_0(1-\beta)(b_0+\beta E_{Tc}})/\beta^2$
V_{Tc1}	$(\sqrt{b_1} - \sqrt{b_1} B_{Tc})^2/\beta^2$

Note: $B_T = \sqrt{(b_1 - \beta b_1 - \beta\pi_{T1})}$, $B_{Tc} = \sqrt{(b_1 - \beta b_1 - \beta\pi_{Tc})}$, $E_T = -\kappa_T + \beta V_{T1} + \pi_{T0}$, and $E_{Tc} = -\kappa_{Tc} + \beta V_{Tc1} + \pi_{Tc}$ for $T \in \{H, L\}$

[20] This is because $\pi_{T1} = \pi_{T2}$ in this extension.

Table F.2: Model Solution

Variable	Meaning	Expression
P_T^E	entry probabilities for independent new entrants ($g=0$) of quality type $T \in \{H, L\}$	$1+\frac{-\sqrt{b_0}+\sqrt{(1-\beta)(b_0+\beta E_T)}}{\beta\sqrt{b_0}}$
P_{T1}^X	exit probabilities for independent restaurants ($g=1$) of quality type $T \in \{H, L\}$	$1+\frac{-\sqrt{b_1}+B_T}{\beta\sqrt{b_1}}$
P_{Tc}^E	entry probabilities for chain new entrants ($g=0$) of quality type $T \in \{H, L\}$	$1+\frac{-\sqrt{b_0}+\sqrt{(1-\beta)(b_0+\beta E_{Tc})}}{\beta\sqrt{b_0}}$
P_{Tc}^X	exit probabilities for chain restaurants ($g=1,2$) of quality type $T \in \{H, L\}$	$1+\frac{-\sqrt{b_1}+B_{Tc}}{\beta\sqrt{b_1}}$

Note:$B_T = \sqrt{(b_1 - \beta b_1 - \beta\pi_{T2})}$, $B_{Tc} = \sqrt{(b_1 - \beta b_1 - \beta\pi_{Tc2})}$, $E_T = -\kappa_T + \beta V_{T1} + \pi_{T0}$, and $E_{Tc} = -\kappa_{Tc} + \beta V_{Tc1} + \pi_{Tc}$ for $T \in \{H, L\}$

Comparative Statics As for the comparative statics, Propositions 1 to 4 all apply to this extension. The proof is trivial and will not be repeated here. Similar to the analysis in the main text, we also provide the same numerical examples of the OE outcomes in this extension. The parameters are set to be exactly the same as those examples in the main text. To be concise, we here present only the effect of quality disclosure on the entry probabilities of high-quality restaurants. The effects on exits and low-quality restaurants are very similar to those shown in figures 7 and 3, and will not be repeated here.

Figure F.1 shows the percentage change in the entry probabilities of high-quality independent restaurants in the case of extremely slow learning. This graph shows several interesting patterns. First, bigger increases in the entries of high-quality independent restaurants occurs when the entry cost is high and when quality difference between the two types of restaurants is large. Second, when the entry cost is low or when the quality difference between the two types of restaurants is small, the effect on entries is limited. The rationale behind these results are similar to that for our main model: when the quality difference between high- and low-quality restaurants is small, the benefit of quality disclosure is small, leaving less incentive or motivation for the high-quality firm to enter the market. When the entry cost is low, high-quality independent restaurants are motivated to enter the market regardless, the incremental benefit from quality disclosure is then small.

Third, the effects tend to be monotonically increasing in the quality difference. This is different from the non-monotonic pattern shown in Figure 2b for the main model. Last but not the least, compared to those effects from the main model, as shown in Figure 2b, the effects from the extremely-slow-learning case are much bigger. The effect of quality disclosure in the slow-learning case is in the order of hundreds of percentage points, whereas that from the main model is in mostly single digits. The bigger effect of quality disclosure in the slow-learning case is very reasonable because quality disclosure now affects flow profits forever instead of just one period.

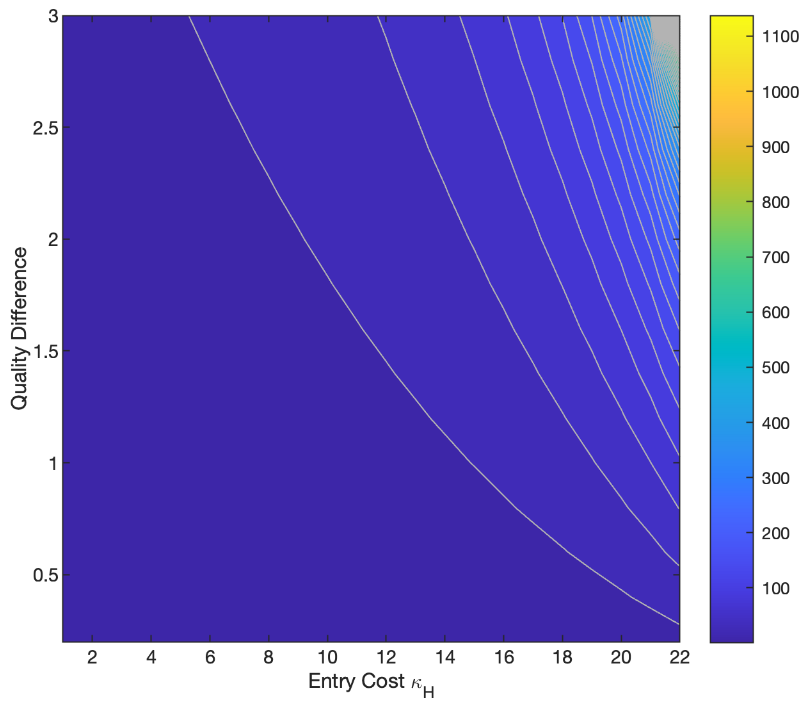
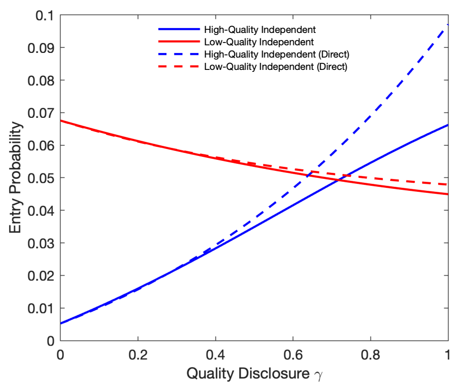


Figure F.1: Percentage Change in the Entry Probability of High-quality Independent Restaurants (Slow Learning)

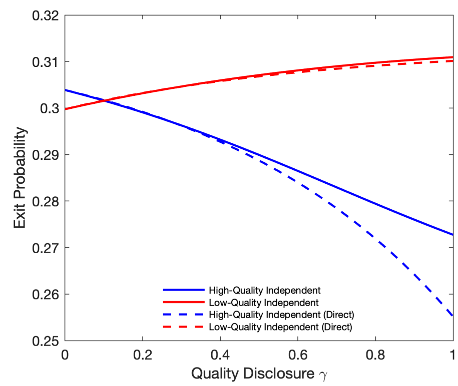
Figure F.1 is based on the comparison between the cases when $\gamma = 0$ and when $\gamma = 1$. To illustrate the effect of graduate change in quality disclosure, we plot the OE outcomes against γ in figure F.2. The top two panels, figures F.2a and F.2b, are for independent restaurants, and the bottom panel, figure F.2c, is for chain restaurants. In figures F.2a and F.2b , the solid lines represent the OE entry and exit probabilities, and the dashed lines capture the counterfactual probabilities when we have only direct effects of quality disclosure, i.e. by holding the competition effect constant. The difference between the dashed lines and the solid lines then reveals the competition effect. The figures F.2a and F.2b show that without considering the competition effect, we would observe higher entry probabilities and lower exit probabilities for both high- and low- quality restaurants as γ increases. Moreover, the competition effect is stronger for high-quality restaurants; in other words, the high-quality restaurants are more sensitive to competition than the low-quality restaurants. These patterns are consistent with those shown in figures 4 and 5a for the main model.

Compared to the main model, the most notable feature of figures F.2a and F.2b is that the slopes of the entry and exit probabilities are much steeper, implying that the effect of quality disclosure is much stronger in the setting with slow learning.

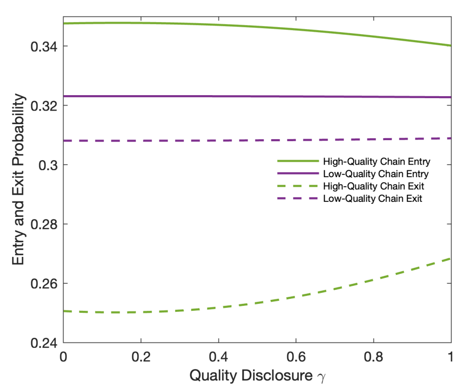
When it comes to chain restaurants, the effect of quality disclosure comes from solely the change in competition. Figure F.2c shows how chain restaurants' entry and exit probabilities change as γ increases. The solid lines represent entry probabilities, whereas the dashed are for the exit probabilities. As shown, changes in these probabilities are smaller for low-quality than high-quality, consistent with the patterns shown in the two previous graphs: competition effect influences high-quality restaurants more than low-quality restaurants. Again when compared with the main model, figure F.2c shows steeper slopes than those in figure 6, implying that the effect of quality disclosure is stronger in the setting with slow learning, even for chains.



(a) Entry Probability for Independent Restaurants



(b) Exit Probability for Independent Restaurants



(c) Entry and Exit Probability for Chain Restaurants

Figure F.2: Effect of Quality Disclosure with Slow Learning

G Figures and Robustness Check

Table G.1: Effects of Online Review Platforms on Entry by Chain Affiliation and Location (5 Levels)

Dependent variable	Number of New Entries			
	Independent		Chain	
	Non-Highway	Highway	Non-Highway	Highway
log(Yelp)	-0.338***	-0.280**	-0.0383	-0.0618
	(0.106)	(0.135)	(0.165)	(0.180)
log(Yelp)×rating	0.0925***	0.0733**	0.0291	0.0440
	(0.0292)	(0.0368)	(0.0384)	(0.0415)
Controls	✓			
Group FE	✓			
Year× Month× Metro× Chain FE	✓			
Year×Month×Low-Quality×Chain FE	✓			
N	3199			
N of Clusters	35			
Quality Measure	Google Rating			

Controls include demographics (population, income, age, race), ratio of new entries that are listed on Google, and the numbers of incumbent chain and independent restaurants in the same county from the last period. Group FE is quality-levels × chain-affiliation × county × highway. Low-Quality includes the lowest 2 levels when 5 and 7 quality levels are used, and only the lowest level when 3 levels are used. All standard errors are two-way clustered at the county level and time level. They are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table G.2: Effects of Online Review Platforms on Entry by Chain Affiliation and Location (3 Levels)

Dependent variable	Number of New Entries			
	Independent		Chain	
	Non-Highway	Highway	Non-Highway	Highway
log(Yelp)	-0.304***	-0.329**	-0.0496	0.113
	(0.117)	(0.159)	(0.124)	(0.217)
log(Yelp)×rating	0.0853***	0.0838*	0.0275	-0.00224
	(0.0292)	(0.0439)	(0.0280)	(0.0509)
Controls	✓			
Group FE	✓			
Year× Month× Metro× Chain FE	✓			
Year×Month×Low-Quality×Chain FE	✓			
N	2923			
N of Clusters	39			
Quality Measure	Google Rating			

Controls include demographics (population, income, age, race), ratio of new entries that are listed on Google, and the numbers of incumbent chain and independent restaurants in the same county from the last period. Group FE is quality-levels × chain-affiliation × county × highway. Low-Quality includes the lowest 2 levels when 5 and 7 quality levels are used, and only the lowest level when 3 levels are used. All standard errors are two-way clustered at the county level and time level. They are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table G.3: Placebo Test for Exit

	(1) exit
log(Yelp) (independent)	0.000825
	(0.00257)
log(Yelp)×rating (independent)	-0.000390
	(0.000623)
log(Yelp) (chain)	0.000551
	(0.00139)
log(Yelp)×rating (chain)	0.000328
	(0.000260)
Controls	✓
Restaurant× Month FE	✓
Year× Month× Metro× Chain FE	✓
N	224,026
N of Clusters	69

Controls include demographics (population, income, age, race) and the number of chain and independent rivals in the same zip code tabulation area at the same period. All standard errors are two-way clustered at the county level and time level. They are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table G.4: Placebo Test for Entry

	(1)
	entry
log(Yelp) (independent)	0.187
	(0.218)
log(Yelp)×rating (independent)	-0.0338
	(0.0480)
log(Yelp) (chain)	0.298
	(0.244)
log(Yelp)×rating (chain)	-0.104
	(0.0814)
Controls	✓
Year× Month× Metro × Chain FE	✓
Year× Month× Low Quality × Chain FE	✓
Group FE	✓
N	1,300
N of Clusters	22

Controls include demographics (population, income, age, race), ratio of new entries that are listed on Google, and the numbers of incumbent chain and independent restaurants in the same county from the last period. Group FE is quality-levels × chain-affiliation × county × highway. Low-Quality includes the lowest 2 levels when 5 and 7 quality levels are used, and only the lowest level when 3 levels are used. All standard errors are two-way clustered at the county level and time level. They are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01