Price Signaling and Reputation Building: Evidence from a Consulting Platform*

YANGGUANG HUANG[†] CHENYANG LI[‡] SI ZUO[§]

April 8, 2022

Abstract

Earning a good reputation is crucial for the survival of new firms on online retailing and service platforms. With a dynamic price signaling model, we show that a high-quality firm can signal its unobserved quality by setting a lower introductory price than its low-quality counterpart. After accumulating sufficient favorable reviews, the high-quality firm will raise its price and enjoy a quality premium. Using data from Zaihang, a consulting service platform, we find empirical evidence that experts with high unobserved ability indeed adopt low introductory prices and exhibit a rising price dynamic over time. We use the performance of the expert on another platform as an instrument for the expert's ability on Zaihang to provide evidence that the relationship is causal. Our empirical findings reject alternative models in which firms do not know their own types, or consumers can observe firm types.

Keywords: asymmetric information, price signaling, reputation system, online platform

JEL codes: D4, L15, L86

*We greatly appreciate the valuable comments and suggestions by Michael Waldman, Justin Johnson, Panle Jia Barwick, Benjamin Leyden, Yi Chen, Thomas Jungbauer, John Asker, Xiaogang Che, Chongwoo Choe, Ginger Jin, Yao Luo, Mo Xiao, Steve Tadelis, and Juuso Välimäki. We thank participants at Cornell IO, LWIPS and TWIPS Workshops, Shanghai University of Finance and Economics, HKUST Industrial Organization Workshop, China Meeting and North American Summer Meeting of Econometric Society, Asian-Pacific Industrial Organization Conference, China Virtual IO Seminar, and Monash University. We sincerely thank Wei Fan, Jingyu Li, and Haijing Zong for their excellent research assistance.

[†]Hong Kong University of Science and Technology, Hong Kong. Email: huangyg@ust.hk.

[‡]Cornell University, New York, U.S.A. Email: cl2453@cornell.edu.

[§]Cornell University, New York, U.S.A. Email: sz549@cornell.edu.

1 Introduction

Earning a good reputation is crucial for the survival of new firms on online retailing and service platforms. Obtaining high ratings and accumulating positive reviews are difficult for small firms without an existing reputation or outside channels to build up their reputation. In this paper, we construct a dynamic model of asymmetric quality information with both a signaling mechanism and a review-based reputation system. The model predicts that high-quality firms can signal quality and build a reputation by setting low introductory prices. We then use empirical data from an online consulting service platform to test the model predictions and adopt a novel instrumental variable (IV) to show the causal relationship that the high unobserved ability leads to the low introductory price.

In the model, firms set prices and sell products to consumers who newly arrive in each period. Consumers cannot directly observe firms' private types that determine whether the product quality is high or low. Consumers who purchase the product can leave reviews that affect the firm's reputation in later periods. A high-quality firm is more likely to obtain positive reviews from sales, whereas a low-quality firm is more likely to receive negative reviews. There are two types of consumers. Sophisticated consumers can perfectly infer the product quality given a separating equilibrium in which the high- and low-quality firms set different prices. On the other hand, naive consumers do not derive quality information from the prices because they face uncertainty about some market fundamentals such as the production costs of the firms and the true value of the products. Thus, they can only infer product quality from the reviews left by consumers in earlier periods.

We show that as long as the cost difference between high- and low-quality firms is sufficiently small, there is a unique perfect Bayesian equilibrium (PBE) that survives the D1 criterion (Banks and Sobel, 1987) in which the high-quality firm can strategically choose to set a low introductory price to signal its unobserved high quality. The low period-1 price promotes sales, generates more reviews, and results in a better reputation in period 2. The low-quality firm does not want to mimic because more period-1 sales may result in more negative reviews, which leads to a worse reputation and lower profit in period 2. Our model fits the environment of most online e-commerce platforms with a review-based reputation system. Different from many existing models of price signaling quality (Bagwell and Riordan, 1991; Daughety and Reinganum, 2008; Nelson, 1974; Schmalensee, 1978; Farrell, 1981; Shapiro, 1983; Milgrom and Roberts, 1986), our model is dynamic and considers the arrival of different groups of new consumers in each period. Moreover, we consider that the market may consist of both sophisticated and naive consumers. Sophisticated consumers are able to interpret price signals, but naive consumers cannot.

Next, we test the model predictions using 2015-2021 data from Zaihang (`www.zaih.com`), a leading online consulting platform in China. On Zaihang, individuals can register as experts in certain areas and provide consulting services to clients. Experts have their web pages on Zaihang that display photos, self-introductions, consulting products, and product prices. Clients search for experts and purchase consulting services through Zaihang. Experts providing services on the platform do not have established brands or other channels to build their reputation other than the platform. Hence, the information listed on Zaihang covers nearly all the information that consumers know when making decisions, which makes Zaihang a desirable platform to study the reputation-building process.

We assume that an expert's overall ability consists of the observed and unobserved parts. When clients make purchase decisions, they observe some ability measures in the expert's self-introduction, such as working years and positions in the firm. However, clients, especially those in early periods, observe few ratings and review information as reviews are still being accumulated at the time of the transaction. Therefore, a part of the expert's unobserved ability is known to the expert but not to clients. Thus, we test whether an expert with high unobserved ability will strategically use a low introductory price to signal her type.

We use the review ratio (the proportion of consumers leaving reviews) as the main overall ability measure. There are two reasons for this choice: first, consumers on Zaihang are more likely to be silent than leaving negative reviews because they have met the expert personally and do not want to embarrass themselves publicly. Hence, a lower review ratio indicates more disapproval (Nosko and Tadelis, 2015). Second, we find that the review ratio has the strongest positive correlation with working years and holding a high position in the company, which implies that the review ratio is a good measure of the expert's ability. Then, we regress each expert's overall ability measures on the observed characteristics and treat the residual as unobserved ability. Note that we use the data at the end of the sample period to construct the ability measures based on the rationale that the expert's true ability will be gradually revealed by the reputation system over time (Ko, 2021).

After constructing the unobserved ability of experts, we test the existence of the low-intro price equilibrium and find that a one standard deviation higher unobserved ability implies a 20.46 RMB (4%) lower introductory price. To tackle the potential endogeneity problem that the low introductory price drives up the overall ability, we construct an IV for the unobserved ability: the number of likes per answer provided by the expert on a question-and-answer (Q&A) platform Zhihu (`www.zhihu.com`). The likes on Zhihu are correlated with the unobserved ability on Zaihang because providing high-quality consulting services on Zaihang and good answers on Zhihu require similar skills of the experts. However, the number of likes on Zhihu is not directly related to the introductory price on Zaihang because Zhihu is a free Q&A platform. This novel IV helps us establish causality for our empirical findings.

The remainder of the paper is organized as follows. Section 2 summarizes the related literature. Section 3 presents the model and testable predictions. Section 4 introduces the Zaihang platform and data. The empirical tests and results are in Section 5. Section 6 concludes.

2 Literature Review

Early works by Nelson (1974), Kihlstrom and Riordan (1984), Schmalensee (1978), Farrell (1981), and Milgrom and Roberts (1986) have demonstrated how a high-quality firm can use wasteful expenditures such as advertisement spending and low prices to signal quality. These papers focus mainly on repeat purchases by the same group of consumers. Instead, we consider the setting in which different groups of consumers arrive sequentially, and later consumers rely on reviews left by earlier consumers and price history to infer quality. The new consumer assumption applies to platforms where most consumers only purchase the products once. Many service and consulting platforms have this feature. We also consider that some consumers may lack the ability to collect price information and interpret the quality signals in prices.

Some scholars find that a high-quality firm can set a high price to signal high quality. For example, Bagwell and Riordan (1991), Judd and Riordan (1994), and Daughety and Reinganum (2008) consider a setting in which a high-quality firm sets a very high price and sells a small quantity, but a low-quality firm cannot profitably mimic such a high price. Cooper and Ross (1984) model the price as a signal in a static competitive market and show that in a rational expectation equilibrium, both high- and low-quality firms set the same price. Our model predicts a unique separating equilibrium for almost all parameterization except some knife-edge cases. When the marginal cost of the high- and low-quality firms are sufficiently close, the low-intro-price equilibrium is unique. Rob and Fishman (2005) point to the effect of "word-of-mouth reputation" on firms' consumer bases and profits. A high-quality firm invests more to maintain its quality and raises price and sales over time. Differently, we focus on the introductory price gap between the high- and low-quality firms and the signaling mechanism.

There are a few empirical papers studying the signaling role of prices. Existing papers can be divided into two strands. Fan et al. (2016) find that new firms on Taobao tend to set lower prices than old firms. However, our paper finds that only high-quality firms would set a low price and that there is a signaling mechanism behind it. Dawar and Sarvary (1997) provide experimental evidence that although consumers tend to buy lower priced products, the signaling mechanism may not be effective. In comparison, we use real data from an online platform to show that a low introductory price can signal high quality. Firms can also signal their qualities by joining reward-for-feedback (RFF) programs that allow firms to offer rebates to consumers who provide feedback or reviews Li and Xiao (2014); Li et al. (2020).[1] Rebates and low introductory prices play a similar role because they can both boost sales in earlier period and speed up review accumulation. perform a lab experiment and show that the RFF programs induce the low quality firms to mimic the high quality services. Li and Xiao (2014); Li et al. (2020) study how the decision to join the program can signal quality. In comparison, we demonstrate the dynamic aspects of firms' pricing strategies and show that high-quality firms use low introductory prices when they first enter the market and

[1] Many popular e-commerce platforms RFF programs. See Table 11 in Appendix C4 for examples.

characterize how prices and reputation change over time.

Our paper is also related to the broad empirical literature on how review-based reputation systems help high-quality firms increase sales. For example, Anderson and Magruder (2012) and Luca (2016) find that a high rating on Yelp can significantly increase a restaurant's revenue. Resnick et al. (2006) find that eBay consumers are willing to pay an average of 8.1% more to reputable sellers. Fang (2022) finds that online review platforms improve the welfare of restaurant consumers by USD2.5 per person per meal. We not only confirm that rating and textual reviews help firms to raise prices but also explore how the reputation system interacts with the pricing strategy.

3 Model

3.1 Setting

Consider a market of differentiated products. A generic firm (she) sells a product and has monopolistic power in her small market. The firm maximizes the total profit from all periods without discounting. In each period, different groups of consumers (he) arrive. Consumers in earlier periods leave reviews that transmit information to consumers in later periods. For simplicity, we present a two-period model in the main text and a general model with multiple periods in the Appendix B1. Initially, nature determines the quality type, θ, of the firm. The firm is either high-quality ($\theta = H$) with probability λ_0 or low-quality ($\theta = L$) with probability $1 - \lambda_0$. λ_0 is a common prior to all the players. The firm knows her type, but consumers cannot observe θ. A high-quality product yields a value v_H to the consumer. A low-quality product yields a value v_L. We refer to a firm with type θ as firm θ. Firm θ incurs a constant marginal cost, c_θ. Assume that $v_H > v_L$, $v_H > c_H$, $v_L > c_L$, $c_H > c_L$. Without loss of generality, we normalize $v_H = 1$ and $c_L = 0$.

There is an introductory period (period 1) followed by a long-run period (period 2) (Bagwell and Riordan, 1991). In each period, the firm moves first by choosing her price p_t. Then, consumers observe the price, form beliefs about the quality, and decide whether to purchase the product. Lastly, consumers who purchase the product leave reviews, which are noisy information about the product quality.

We assume that the consumer can be one of two types. With probability $(1 - m) \in (0, 1)$, the consumer is sophisticated and infers product quality from both prices and reviews. If firm H and firm L set systematically different prices, sophisticated consumers can correctly infer the firm's true type. With probability m, the consumer is naive and only infers product quality from reviews but not from prices. Having a fraction of naive consumers in the market is also a widely adopted assumption in the literature (Gabaix and Laibson, 2006; Eyster and Rabin, 2010; Bohren, 2016) and supported by empirical evidence (Chetty et al., 2009; Brown et al., 2010). This setting captures the fact that inferring quality from reviews is much easier than understanding the quality signal in prices.[2]

[2] We provide a micro-foundation for the behavior of naive consumers in Appendix A4. Naive consumers are rational

Let $r_t \in \{good, bad, \emptyset\}$ denote the realized reputation that summarizes the information in the reviews. After period-1 consumers write the reviews, we assume a firm can either obtain a good reputation (if reviews are mostly positive), a bad reputation (if reviews are mostly negative), or an inconclusive reputation ($\emptyset$). The inconclusive reputation occurs if the firm has no reviews because of no sales. In period 1, the introductory period, all firms have $r_1 = \emptyset$. In period 2, all players observe the realized reputation, r_2.

A sophisticated consumer i in period t has expected utility:

$$u_{i,t} = \max\{E\{V|r_t, \{p_\tau\}_{\tau\leq t} - p_t + \epsilon_{it}, \overline{u}\ \}. \tag{1}$$

Here, $E\{V|r_t, \{p_\tau\}_{\tau\leq t}\}$ is the expected value of the product given the reputation r_t and the price sequence from period 1 to period t. ϵ_{it} is an idiosyncratic preference shock drawn independently from the uniform distribution with support $[-v_H, 0]$. A consumer purchases the product if he expects a higher utility from buying the product than the outside option with $\overline{u}$.[3] The demand of the sophisticated consumer (the probability of purchasing the product) is

$$q_t = \Pr\left(E\{V|r_t, \{p_\tau\}_{\tau\leq t} - p_t + \epsilon_{it} \geq \overline{u}\right) = E\{V|r_t, \{p_\tau\}_{\tau\leq t} - p_t - \overline{u}, \quad t = 1, 2. \tag{2}$$

This downward-sloping demand function is consistent with our empirical study of the consulting service market where products are highly differentiated, and every expert has a certain level of market power.

A naive consumer i in period t has expected utility:

$$u_{i,t} = \max\{E\{V|r_t\} - p_t + \epsilon_{it}, \overline{u}\ \}. \tag{3}$$

The only difference to (1) is that such a naive consumer cannot infer the value of the product using price information. The demand function of the naive consumer is

$$q_t = \Pr\left(E(V|r_t) - p_t + \epsilon_{it} \geq \overline{u}\right) = E(V|r_t) - p_t - \overline{u}, \quad t = 1, 2. \tag{4}$$

If firm H and firm L set different period-1 prices in equilibrium, sophisticated consumers in both periods can perfectly infer the product quality of the firm.[4] However, if prices do not provide sufficient information, both sophisticated and naive consumers will rely on reviews to form beliefs about the product quality in period 2 using the Bayes rule. For example, if firm H sells her product in period 1, then she will be perceived as a high-quality firm with probability $\frac{a\lambda_0}{a\lambda_0+b(1-\lambda_0)}$, and as

but they face uncertainty about the market fundamentals such as the true value of the high and low-quality product. When such uncertainty is high, naive consumers will rely on reviews but not prices to infer the product quality.

[3]The demand function here is a special case of Daughety and Reinganum (2008). They consider a one-period model with multiple firms. We consider a two-period setting with the reputation system.

[4]In principle, if firm H and firm L set different period-2 prices in equilibrium, period-2 sophisticated consumers can inter the true quality. However, because the firm does not have the dynamic incentive in period 2, a period-2 separating equilibrium would not arise if there is no period-1 separating equilibrium.

a low-quality firm with probability $\frac{(1-a)\lambda_0}{(1-a)\lambda_0+(1-b)(1-\lambda_0)}$.

The timing of the model is as below: In period 0, nature chooses the quality of the firm: high (with prob λ_0) or low (with prob $1-\lambda_0$). In period 1, the firm observes its quality and chooses a price p_1. A consumer observes the period-1 price and his own preference, infers the unobserved quality, and makes a purchase decision. If the consumer buys the product, he observes its actual quality and leaves a review. In period 2, the firm observes the review and chooses a new price p_2. A new consumer arrives. Nature chooses his preference shock. The consumer observes the preference shock, period-1 price, period-2 price, and the review, and chooses whether to buy the product. The profit is realized and the game ends.

3.2 Equilibrium Analysis

We use perfect Bayesian Equilibrium (PBE) as the solution concept. Note that sophisticated consumers and naive consumers may have different beliefs of the firm's type in equilibrium. Let $\pi_2^*(H,H,\lambda_0)$ ($\pi_2^*(L,L,\lambda_0)$) denote the profit of firm H (L) when the period-2 sophisticated consumers believe the firm being high (low) quality, and period-2 naive consumers believe the firm being high quality with probability λ_0. Then, we express a firm's expected period-2 profit as $\Phi^*(q_1,\theta)$, which is a function of the firm period-1 sales (q_1) and the true type $\theta\in\{H,L\}$.

Lemma 1. *The period-2 expected profit, $\Phi^*(q_1,\theta)$, is linear in period-1 quantity sold.*

$$\begin{aligned}\Phi^*(q_1,H) &= q_1k_H+\pi_2^*(H,H,\lambda_0)\\ \Phi^*(q_1,L) &= -q_1k_L+\pi_2^*(L,L,\lambda_0).\end{aligned} \tag{5}$$

Here, the slopes $k_H>0$ and $k_L>0$. k_H means when firm H sells one more unit in period 1, her period-2 profit increases by k_H. k_L means when firm L sells one more unit in period 1, her period-2 profit decreases by k_L. Both k_L and k_H increase in a, and decrease in b and m. Intuitively, the period-2 profit is more responsive to period-1 sales if reviews become more accurate or if the fraction of naive consumers increases.

We define a *low-intro-price equilibrium* as a PBE of the game characterized by period-1 prices $p_{1,H}$ and $p_{1,L}$ satisfying $p_{1,H}<p_{1,L}$. We have the following result:

Proposition 1. *When difference between the marginal costs of firm H and firm L is sufficiently small ($c_H<k_L+k_H$), the game has a unique PBE that survives the D1 criterion (Banks and Sobel, 1987).*[5] *This PBE is a low-intro-price equilibrium.*

The critical condition that determines the existence of the low-intro-price equilibrium is the relative magnitude between c_H-k_H and k_L. For firm H, lowering the period-1 price leads to higher sales with marginal cost c_H and yields a marginal benefit of k_H. Thus, c_H-k_H can be

[5]The D1 criterion is used to rule out the pooling equilibria in each period. It is a stronger refinement than the Intuitive Criterion Cho and Kreps (1987). The Intuitive Criterion does not rule out all the pooling equilibria in our model.

interpreted as the cost of firm H selling one more unit of product. For firm L, lowering p_1 causes a marginal period-2 profit reduction with the size k_L (firm L's marginal cost is normalized to zero). The existence of a low-intro price equilibrium requires that firm H faces a lower cost than firm L when reducing the introductory price.

The intuition of the low-intro-price equilibrium is that firm H sets a low period-1 price that firm L does not want to mimic because firm L wants to avoid making too many sales that lead to a low reputation in period 2. This intuition is similar to that of Shapiro (1983) except that we introduce a signaling mechanism. Notably, in the low-intro-price equilibrium, firm H earns a higher total profit than firm L as long as the reputation system is sufficiently accurate. In some previous models (e.g., Daughety and Reinganum 2008), firm H earns a lower profit than firm L because firm H faces higher marginal costs and must charge a very high price to deter mimicry.

Note that if $c_H - k_H > k_L$, it is more costly for firm H than for firm L to reduce p_1. In this case, there exists a PBE in which firm H sets a higher introductory price than firm L (*high-intro-price equilibrium*).[6] This result echoes the mixed prediction in the literature. For example, Milgrom and Roberts (1986) shows that firm H can signal quality by either a high price or a low price depending on the parameters. Based on Proposition 1, we have the following corollary:

Corollary 1. *For any fraction of naive consumer $m > 0$ and holding other parameters fixed, there exists a positive cutoff $\bar{c}_H$ such that if the marginal cost of firm H is lower than this cutoff ($c_H < \bar{c}_H$), there is a unique low-intro price-equilibrium.*

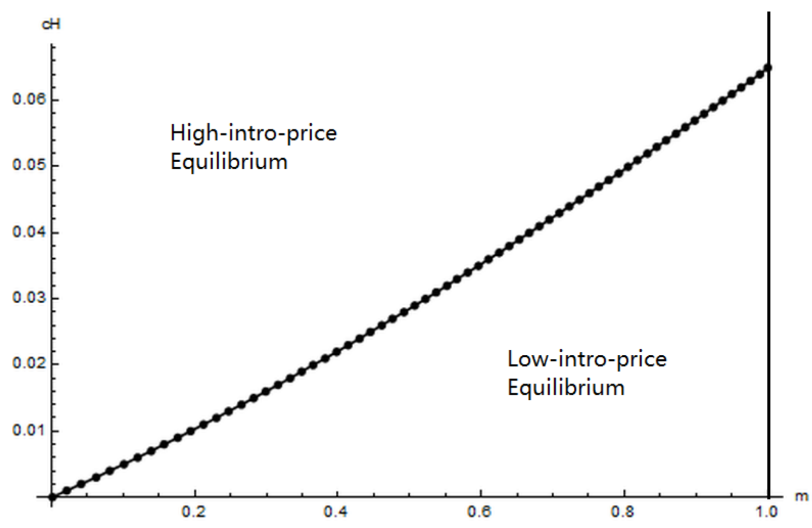

Figure 1: Parameter Values and Low-intro-price Equilibrium

Note: $v_H = 1$, $v_L = 0.4, c_L = 0$, $a = \Pr(r_2 = good|H) = 0.9$, $b = \Pr(r_2 = good|L) = 0.1$.

Figure 1 illustrates Corollary 1. The region below the black curve is the range of the parameters c_H and m that supports the low-intro price equilibrium. Intuitively, as the fraction of naive consumers decreases, the effect of current sales on future profit would also gradually vanish. When the

[6]When $c_H - k_H = k_L$, both the low- and high- intro-price equilibria exist and survive the D1 criterion.

market only has sophisticated consumers ($m = 0$) who can perfectly infer product quality based on prices, the reputation system becomes useless and the dynamic incentive disappears. In this case, the only PBE that survives the D1 criterion is the one in which firm H sets a higher price than firm L, which is similar to the conclusion of Daughety and Reinganum (2008).

The results of the low-intro-price equilibrium are robust under more general model with multiple periods, multiple consumers providing independent reviews, and RFF programs (Li et al., 2020). The details are in Appendix B. In a multiple-period model, we find that firm H can signal her type by setting a low introductory price and then, after accumulating enough reviews, switch to high long-term prices in all later periods. Under RFF programs, firms offer rebates for consumers writing reviews. Rebates boost period-1 sales, signal high quality, and speed up reputation building. Therefore, RFF programs and low introductory prices play similar roles.

3.3 Testable Predictions

We argue that the many service-based platforms, including Zaihang (a consulting platform), satisfy the conditions for the low-intro-price equilibrium to exist uniquely: First, firms have hidden qualities; second, the platform has a review-based reputation system; third, new consumers arrive in each period (tested in Section 4); fourth, firms face downward-sloping demand curves (tested in Section 4); finally, the marginal cost difference between the high- and low-quality firms is small (justification in Section 4). Therefore, we have the following three testable predictions if the above conditions are satisfied:

Prediction 1. *Firms with high unobserved quality set lower introductory prices than firms with high unobserved quality ($p_{1,L} > p_{1,H}$).*

Under the same conditions, we also derive predictions regarding the dynamics of prices and sales over time. In the introductory period, a high-quality firm sets a low price to achieve higher sales. After successfully signaling her high quality, the high-quality firm will set a high price to harvest the reputation. For firm L, the prediction is the opposite.

Prediction 2. *Firms with high unobserved quality tend to increase their prices over time ($p_{1,H} < p_{2,H}$). The price difference between firms with high and low unobserved quality reverse in later periods ($E(p_{2,H}) > E(p_{2,L})$).*

Prediction 3. *In the early periods, firms with high unobserved quality sell more than firms with low unobserved quality ($q_{1,H} > q_{1,L}$).*[7]

3.4 Alternative Models

To better understand the conditions of the low-intro-price equilibrium, we consider two alternative model settings in which the low-intro-price equilibrium no longer exists.

[7] The prediction of sales in period 2 depends on the fraction of naive consumers.

Firm does not know her own type.

Suppose that the firm does not know her own type. This is an important scenario in the labor market in which a labor supplier (worker) does not know her unobserved ability compared with others in the market.[8] Then, we have the following result.

Proposition 2. *When firms cannot observe their own quality, then both firm H and L will set the same introductory price.*

A firm cannot signal what she does not know, both the low and high-quality firms have to set the same introductory price before getting additional information on their own quality.

Firm type is commonly known

Consider the case that both the firms and the consumers perfectly know product quality. In this case, the reputation system becomes irrelevant, because a firm's period-1 price does not affect period-2 sales. Firms will choose the monopolist prices in both periods, $p_H = \frac{1}{2}(v_H - \overline{u} + c_H)$ and $p_L = \frac{1}{2}(v_L - \overline{u})$.

Proposition 3. *When firm types are commonly known to firms and consumers, firm H sets a higher introductory price than firm L, and the prices do not change over time.*

Propositions 2 and 3 indicates that the low-intro-price equilibrium does not exist if period-2 consumers can observe historical prices, firms do not observe their own types, and firm type is commonly observed. Of course, if firms are myopic or there is just only one period, the low-intro-price equilibrium based on dynamic incentives will also disappear. Empirical evidence of the low-intro-price equilibrium will lead to rejecting the above alternative model settings.

4 Industry Background and Data

Zaihang is a leading online personal consultancy service platform in China.[9] Our data contains all transactions on Zaihang from 2015 Q1 to 2021 Q4.[10] The platform matches clients (he) who seek advice from experts (she) in the corresponding category. The main categories of services on Zaihang are listed in Table 1.

On Zaihang, experts post information about their qualifications, experience, prices, and description of their consultancy service products. Zaihang will verify all the information provided by the experts. An expert can offer multiple products at different prices. Figure 2 shows an example of the page of an expert who offers psychology consulting. Clients seeking consulting service observe

[8] Rob and Fishman (2005) also adopts a similar assumption.

[9] The term "Zaihang" means "expertise" in Chinese. There are similar consultancy service platforms in other countries, for example, `www.popexpert.com`, `www.evisors.com`, and `www.mentornow.com`. There are more and more platforms where a firm is an individual and a product is service, i.e. Amazon Mechanical Turk.

[10] Q1, Q2, Q3, and Q4 refer to the first, second, third, and fourth quarter of the year, respectively.

expert's web pages that list relevant information, including a textual introduction, historical sales, products (services), ratings, and reviews written by previous clients. Once a client finds a desirable product, he pays the price and schedules an appointment with the expert. The consulting appointment typically lasts 1 to 2 hours. After the consulting service, the client can rate the expert and leave a review on the platform. These reviews and historical sales records are displayed to future clients.

Table 1: Categories and Tags on Zaihang

Category	Tag
Career development	finding a job, getting a promotion, career planning, ...
Industry experience	marketing, human resources, public relations, ...
Internet+	data analysis, product development, operations, ...
Entrepreneurship	business model, forming a team, obtaining investments, opening a restaurant, ...
Living	travel planning, home decoration, ...
Psychology	family relations, stress control, character, ...
Investment	stock, real estate, insurance, ...
Education	early education, middle school, study abroad, ...
Others	design, new media, travel ...

Figure 2: A Web Page of an Expert on Zaihang

Sources: `www.zaih.com/falcon/mentors/2bkofn0ibsl`

There is an important reason that makes the Zaihang data desirable for studying the reputation-building process. Experts providing services on the platform do not have established brands or other channels to build their reputation other than the platform. This scenario is different from Amazon or other e-commerce platforms where sellers have other channels to build up their reputation.[11] For example, Fang (2022) find that reviews on Yelp and TripAdvisor do not have a significant impact on the revenues of restaurant chains because these restaurants formed their reputation by other means. In contrast, on Zaihang, we as researchers can observe nearly all the information available to clients when they make purchas decisions. Moreover, experts on Zaihang are divided into many markets because they are segregated by cities and expertise (category). This property allows us to examine the behaviors of experts with different ability levels across different markets.

Table 2: Summary Statistics

Variable name	Obs	Mean	St. Dev.	Min	Median	Max
	Observed Characteristics of Experts					
rating	6459	9.35	0.390	3.2	9.4	10
review.ratio	7467	66.42	21.059	1.36	66.67	100
response.rate	7467	2.69	0.470	1	3	3
entry.year (2015 is year 0)	7467	1.41	1.35	0	1	5
entry.quarter (2015 Q1 is quarter 0)	7467	7.17	5.25	0	5	23
num.product	7467	1.74	0.939	1	1	7
working.years	7467	9.90	6.800	2	10	40
high.position	7467	0.31	0.464	0	0	1
age	7467	37.51	9.613	4	36	82
gender (male=1)	7467	0.69	0.462	0	1	1
appearance	7467	57.97	10.567	24.23	58.05	91.04
	Prices (RMB) and Sales					
p^{intro}	7467	513.75	256.221	100	499	1690
$p^{intro'}$	7467	521.51	278.529	100	499	1999
p^{second}	3152	694.70	420.795	150	623	2998
total.sales	7467	43.89	107.82	1	17	3349
$review.num^{intro}$	3152	2.16	2.892	.05	1.33	45.5
$review.num^{second}$	3152	1.02	1.19	.095	1	31
	Constructed Ability Measures					
ability.index	7467	0.00	0.64	-5.81	.05	1.44
$Std.Abil^U$ (review ratio)	7467	0.01	0.99	-3.13	.017	2.04
$Std.Abil^U$ (ability index)	7467	-0.01	1.00	-8.91	.045	2.30

Note: *review.ratio* is the proportion of clients who leave reviews, which is calculated by the number of reviews divided by total sales. *response.rate* =3, 2, and 1 represent the expert's frequency of accepting consulting requests in high, medium, and low, respectively. *entry.year* is the year the expert enters the platform. Year 2015 is normalized as the year 0. $high.position = 1$ if the expert is a CEO, founder, or chairman of the board in a company; otherwise, $high.position = 0$. $gender = 1$ if the expert is male; otherwise, $gender = 0$. The introductory price is the price of the introductory product. For experts with multiple introductory products, p^{intro} is calculated as the average price weighted by sales; $p^{intro'}$ is the price of the introductory product with the most sales. p^{second} is the price of the second product released by the expert. $review.num^{intro}$ and $review.num^{second}$ are the quarterly average review number of the introductory product and the second product, respectively. See Section 5.1 for definitions of the constructed ability measures. There are fewer observations for the rating because some experts have too few sales and thus have no rating.

[11] On some e-commerce platforms, most sellers list branded products such as Apple iPhones and Canon cameras. Consumers can partly infer the product quality based on brand and thus rely less on reviews. On other platforms, sellers may also have other sales channels or means of reputation building.

Our main data set is panel data covering the period from the platform's opening in 2015 Q1 to 2021 Q4.[12] We focus on the 7467 experts who entered before 2020Q4 (including 2020Q4). Table 2 show the summary statistics of the main variables. We observe experts' photos, self-introduction, product introduction, prices, sales, rating, all reviews, and review date. Figure 12 (Appendix D1) shows a sample web page of expert reviews. To enrich expert characteristics, we use Face++ (`www.faceplusplus.com.cn`) to obtain experts' gender, age, and appearance scores from their photos [13].

Empirical evidence for model assumptions

Figure 16 (in Appendix D4) shows that 66.59% of clients leave reviews only once in the data and 77.99% of clients only leave a review once for one product, which indicates that most consumers only purchased once in the sample period. This finding supports our assumption in the theoretical model that new consumers arrive in each period instead of making repeat purchases.

Figures 13 and 14 (Appendix D2) show that as more experts enter the platform, the average sales per expert decrease over time. In addition, there is a significant dispersion of prices (Table 8, Appendix C1) and a large variety of consulting products (Figure 15, Appendix D3). This data pattern supports our assumption of a monopolistic competition market structure.

We have an additional assumption in the theory part that the marginal cost difference between high- and low-quality firms is small. On Zaihang, the experts' marginal costs are their opportunity costs (or wages). Wages are mainly determined by the observed qualities (i.e., working years and working position). Thus, after controlling the observed qualities, we would argue that the high-unobserved-ability experts' marginal costs are not much higher than the low-unobserved-ability counterparts.

5 Empirical Analysis

5.1 Ability Measures

Observed and unobserved ability

We first need to construct measures of the ability (or quality) of experts. The experience-goods nature of consulting service makes it difficult for clients to fully observe experts' ability before the service (Nelson, 1970). When a client browses the experts' pages and decides whether to make an appointment, he observes the price and the expert's self-introduction with information of working years and positions in the firm. However, he cannot observe certain aspects of the expert's ability

[12] We scraped the platform data for three times: 2018 Q3, 2020 Q4, and 2021 Q4. All reputation measures are from the 2021 Q4 Data. For experts who entered the Zaihang market before 2018 Q3, the prices of their products are from the 2018 Q3 data; for those who entered Zaihang between 2018 Q3 and 2020Q4, their prices are from the 2020 Q4 data.

[13] The Face++ AI algorithm is used in Edelman et al. (2017) to construct borrower characteristics on a peer-to-peer lending platform.

such as communication skills, and service attitude. These unobserved abilities will be gradually revealed by the reputation system over time and be reflected in the final rating and review ratio at the end of the sample period.

Consider an expert i in category c. The expert's ability ($Abil_{ic}^{all}$) can be decomposed into an observable part and an unobservable part:

$$Abil_{ic}^{all} = \alpha_m Abil_{ic}^{O} + Abil_{ic}^{U}. \tag{6}$$

$Abil_{ic}^{O}$ is a vector of observable characteristics including working years and *high.position*. The unobserved ability is captured by the OLS regression error term $Abil_{ic}^{U}$, which is observed by the expert but not by the clients. We assume $Abil_{ic}^{U}$ has mean zero.

Measuring overall ability

Following equation (6), there is a one-to-one mapping from the overall ability ($Abil_{ic}^{all}$) to the unobserved ability ($Abil_{ic}^{U}$). Therefore, the key is to find a measure for the expert's overall ability. We use the review data at the end of the sample period (2021 Q4) as ability measures for experts who entered Zaihang before 2020 Q4. A similar method is used by Ko (2021) to measure the true quality of workers on a freelance platform. We consider several potential measures including the rating, the review ratio, and the expert's response rate.

Ratings are widely used as measures of product quality in studies of online platforms (e.g., Hui et al., 2016; Fang, 2022; Li et al., 2020). However, the rating is not a good measure for ability on Zaihang. Table 3 shows how the potential ability measures correlated with each other and the observed characteristics. Note that rating has no significant correlation with observed working years, the main exogenous ability measure. In the data, the rating has a very high mean (9.35 out of 10) and little variations (sd is 0.39). One possible reason is that the rating tends to be positively biased on online service platforms. In the case of Zaihang, at the time of rating, because the client has already met the expert in person, he is more likely to give a high rating out of politeness. This "inflated rating" problem is also found in other occasions of human services. For example, Harrington and Emanuel (2020) show that ratings for the call-center workers has a very high mean (4.9/5); Filippas et al. (2018) show that the rating is usually very high in the online labor market because consumers feel pressured to leave a high rating.

Nosko and Tadelis (2015) also find this "inflated reputation" problem, and their approach is to use the ratio of the number of positive reviews to total sales as the quality measure. Following their method, we use the review ratio as the main measure of overall ability because nearly all reviews are positive on Zaihang. Table 3 shows that the review ratio has the strongest positive correlation with working years and having a high position in a firm. This finding suggests that the review ratio is a good measure of the expert's ability.[14] We also construct a one-dimensional ability index as the

[14] DeVaro and Waldman (2012) use the positive correlation between working years and the rating to argue that the

average of standardized review.ratio, response rate and rating. In the following empirical study, we mainly use the review ratio as the ability measure and the ability index for the robustness check. The summary statistics of the ability index are reported in Table 2.

Table 3: Correlation Table of Ability Measures

	review.ratio	*response.rate*	*rating*	*ability index*	*working.years*
rating	0.132***	0.103***			
ability index	0.623***	0.585***	0.682***		
working.years	0.023**	0.034***	0.0110	0.033***	
high.position	0.042***	0.040***	0.052***	0.057***	0.119***

Note: *** indicates the correlation coefficient between the two variables is significantly different from zero with a p-value less than 1%. ** indicates the p-value is less than 5%.

5.2 Testing Low-intro-price Equilibrium

Prediction 1 states that high-unobserved-ability experts set lower initial prices than the low-unobserved-ability experts in the same market. In this section, we construct a measure of unobserved ability for each expert and show the evidence consistent with the prediction.

Using the review ratio and the one-dimensional ability index as the overall ability measures, we obtain the unobserved ability as the residual of regression (6). In Table 2, we report the summary statistics of the standardized unobserved ability ($Std.Abil^U$) constructed from the review ratio and the ability index.

Note that an expert only has the incentive to use price to signal the unobserved part of her ability ($Abil^U$) but not the observed part ($Abil_i^O$). Therefore, to test the model prediction of the low-intro-price equilibrium, we need to compare the introductory prices set by experts with different levels of unobserved ability after controlling the observed part of the overall ability. We test Prediction 1 by investigating whether experts with high unobserved ability set lower introductory prices than those with low unobserved ability after controlling for observed characteristics.

The constructed unobserved ability is a continuous variable. We first test whether, on average, experts with higher unobserved ability set lower introductory prices. Then, to match the setting of binary types in our theoretical model, we divide the experts into two groups based on different cutoffs of the continuous unobserved ability.

Continuous Unobserved Ability

The regression specification is

$$p_{imt}^{intro} = \delta_1 + \beta Std.Abil_{ic}^U + \delta_2 Abil_i^O + \delta_3 X_i + \xi_{subcate} + \xi_{mt} + \epsilon_{imt}, \tag{7}$$

rating is a good measure of the worker's ability.

where p^{intro}_{imt} is the introductory price set by expert i in market m during entry quarter t. $Std.Abil^U_{ic}$ is the standardized unobserved ability constructed from the residual of OLS regression (6) in the category c. Our model predicts that β should be negative (Prediction 1). X_i includes expert characteristics including gender, age, and appearance. $\xi_{subcate}$ is the subcategory fixed effect. For example, within the category "psychology", there are subcategories such as "family relation" and "depression". ξ_{mt} is the market-quarter fixed effect for each market and entry quarter of experts, where market is defined as the category-city level. ϵ_{imt} is the error term.

Table 4 reports the estimates of β as the test results. The estimated β is -20.456 (se 4.398) in column (1) of Panel A. This result indicates that a one standard deviation higher unobserved ability implies a 20.46 RMB (4%) lower introductory price. The estimated β is -12.994 (se 4.136) in column (1) of Panel B. This result indicates that a one standard deviation higher unobserved ability implies a 12.99 RMB (2.5%) lower introductory price when the unobserved ability is based on the ability index.

Table 4: Introductory Price Regression on Continuous Ability Measures

	(1)	(2)
Dependent variable:	p^{intro}	$p^{intro'}$
	Panel A	
$Std.Abil^U$ (review ratio)	-20.465***	-20.465***
	(4.398)	(4.398)
Observations	7464	7464
R-Squared	0.124	0.124
	Panel B	
$Std.Abil^U$ (ability index)	-12.994***	-12.994***
	(4.136)	(4.136)
Observations	7464	7464
R-Squared	0.120	0.120

Note: Columns (1) and (2) are based on regression specification (7) with observed ability measures, expert characteristics, subcategory fixed effects, and market-quarter fixed effects. The observed ability measures ($Abil^O$) include *working.years* and *high.position*. Expert characteristics (X_i) include gender, age, and appearance. Unobserved ability is calculated using regression (6). The overall ability in Panel A is measured by the review ratio. The overall ability in Panel B is measured by the ability index. In column (1), the introductory price is the weighted average price when the expert has multiple introductory products (p^{intro}). In column (2), the introductory price is the price of the introductory product with the most sales ($p^{intro'}$). Standard errors are in parenthesis. $***p < 0.01, **p < 0.5, *p < 0.1$.

Discrete unobserved ability

We divide the experts into two groups based on their continuous unobserved ability. Let $H.Abil^U_{ic} = 1$ indicate experts with high unobserved ability and $H.Abil^U_{ic} = 0$ for all other experts. We estimate the regression specification:

$$p^{intro}_{imt} = \delta_1 + \gamma H.Abil^U_{ic} + \delta_2 Abil^O_i + \delta_3 X_i + \xi_{subcate} + \xi_{mt} + \epsilon_{imt}. \quad (8)$$

Here, γ is the difference of the log introductory price between the high- and low-unobserved-ability groups, and our model predicts γ should be significantly negative. Figure 3 shows the estimates of γ using different levels of cutoffs based on the unobserved ability. For example, when we choose the high-versus-low cutoff value at the 75% percentile, it means that the expert is regarded as having high unobserved ability if and only if her ability is higher than the 75% of all experts in her category. In the left panel, $\gamma = -24.68$ when the cutoff is set at the 50% percentile, meaning that the introductory prices of experts with high unobserved ability are 24.68 RMB (4.8%) lower than those with low unobserved ability when the unobserved ability is constructed from review ratio. The estimates of γ are all significantly negative (5% significance level) when we choose different cutoff values, different price representations, and different ability measures.

We further investigate the different pricing adopted by experts with different unobserved ability by dividing experts into five groups. Let $D.Abil^{0-25} = 1$ indicate experts with the bottom 25% unobserved ability. Similarly, $D.Abil^{25-50} = 1$, $D.Abil^{50-75} = 1$, and $D.Abil^{75-100} = 1$ indicate experts with unobserved ability in the range of $25-50\%$, $50-75\%$, and $75-100\%$ respectively. We use the experts with bottom 25% unobserved ability $(0-25\%)$ as the base group and perform the following regression:

$$\begin{aligned} p_{imt}^{intro} =& \delta_1 + \gamma_1 D.Abil_{ic}^{25-50} + \gamma_2 D.Abil_{ic}^{50-75} + \gamma_3 D.Abil_{ic}^{75-100} \\ &+ \delta_2 Abil_i^O + \delta_3 X_i + \xi_{subcate} + \xi_{mt} + \epsilon_{imt}. \end{aligned} \tag{9}$$

Figure 4 depicts the estimates of γ_1, γ_2 and γ_3, which are the log introductory price differences compared with the medium group. We observe a clear pattern that experts with higher unobserved ability set lower introductory prices.

All the above results support the prediction that the high quality firms set low initial prices to signal their qualities. In addition, the results reject the alternative models that assume firms are myopic, firms don't know their types, or firms' types are perfectly known.

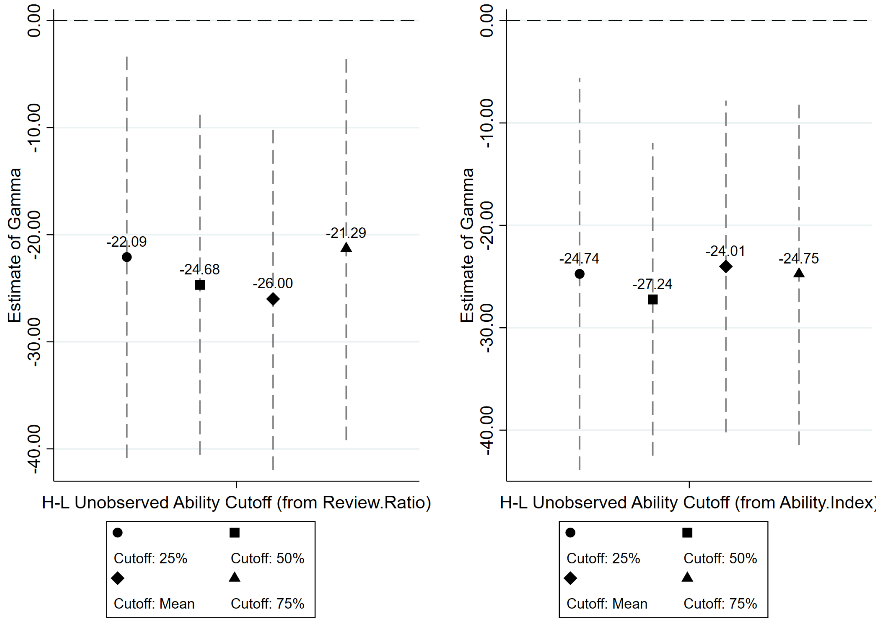

Figure 3: Introductory Price Difference between Experts with High and Low Unobserved Ability

Note: The left panel shows the result when the unobserved ability is derived from the review ratio. The right panel shows the results when the unobserved ability is derived from the ability index. "Cutoff: x%" means high-unobserved-ability experts and low-unobserved-ability experts are divided by the x percentage point of $Std.Abil^U$. The dotted line represents the 95% CI.

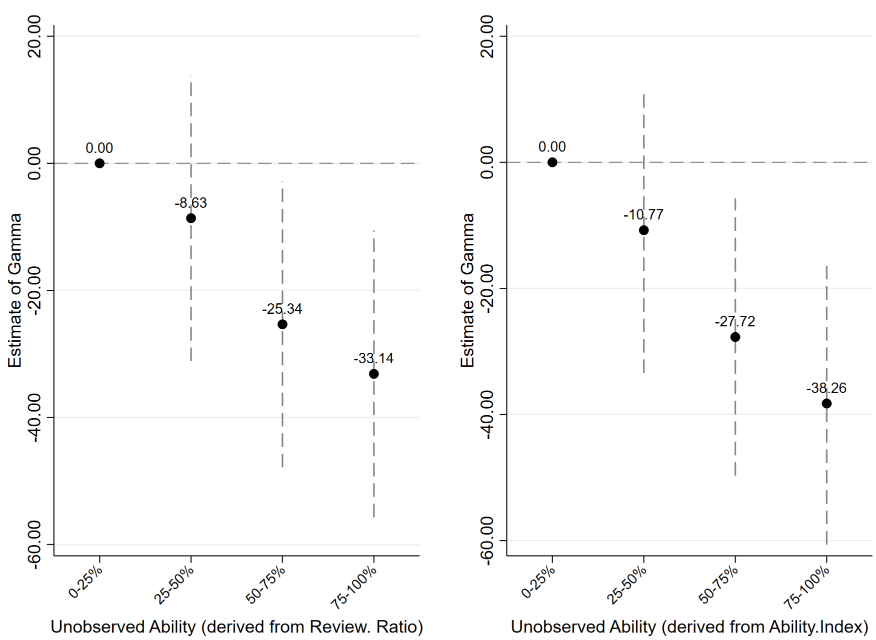

Figure 4: Introductory Price Difference Among Five Ability Groups

Note: The left panel shows the result when the unobserved ability is derived from the review ratio. The right panel shows the results when the unobserved ability is derived from the ability index. The dotted line represents the 95% CI.

5.3 IV for Unobserved Ability

There is a concern that the low introductory price may directly influence reviews and thus making our estimates biased. For example, consumers may be more tolerant to low-ability experts who charges low price. Thus the consumers may give low-price experts higher ratings than those who have the same ability but charge higher prices. Given this possibility, we cannot conclude from the above results that the high unobserved ability causes the low introductory price.

To deal with this potential endogeneity problem, we propose a novel IV for the unobserved ability: the number of likes per answer by the same expert on another platform, Zhihu (`www.zhihu.com`). Zhihu is similar to Quora (`www.quora.com`) where people can ask and answer questions free of charge. Figure 5 shows the webpage of a user on Zhihu. The quality of answers on Zhihu serves as a good IV for the unobserved ability of experts on Zaihang. Experts on Zaihang need the consulting skills to provide services. Similar skills are also needed for experts on Zhihu. Therefore, the quality of answers by the expert on Zhihu is correlated with her unobserved ability on Zaihang. Furthermore, the quality of answers on Zhihu will not directly affect the product price on Zaihang, since they are separate platforms running different business models. Zhihu is essentially a social media platform, and users do not charge money for their answers. Hence, the IV constructed from the Zhihu data should be valid.

Figure 5: A Web Page of a User on Zhihu

Sources: `www.zhihu.com/people/zhang-yi-18-26`

We measure the quality of answers of a Zhihu user by the total number of likes divided by the number of answers provided by the user. On most social media platforms, the number of likes is an important measure of the performance of content providers. Users do not have ratings on Zhihu. The number of comments depends on the content of the answer as more controversial answers tend to receive more comments, so it is not a good measure of quality. Clicking like is an easy way for viewers to show their support for the user who provides the answer.

We use the name, photo, and self-introduction to match Zhihu users to Zaihang experts. For example, the user displayed in Figure 5 is identified as the same person in Figure 2. We successfully matched 835 Zaihang experts to Zhihu users. Figure 6 shows the density distribution of unobserved ability in the full sample and the matched sample (835 experts), the average unobserved ability in the matched sample is lower than the full sample by 0.14 standardized deviations. (Table 12, Appendix C5) Because Zhihu is a free platform, experts with very high ability may choose not to join Zhihu because joining incurs high opportunity costs of time. Moreover, the entry barrier of Zhihu is lower than that of Zaihang, so there are more low-ability experts on Zhihu than on Zaihang. To make the matched sample similar to the full sample, we balance the observations in the matched sample to match the first, second, and third moments of the unobserved ability of the full sample. After balancing the matched sample, the density distribution of unobserved ability on the matched sample is very close to that of the full sample (Appendix D5 Figure 17).

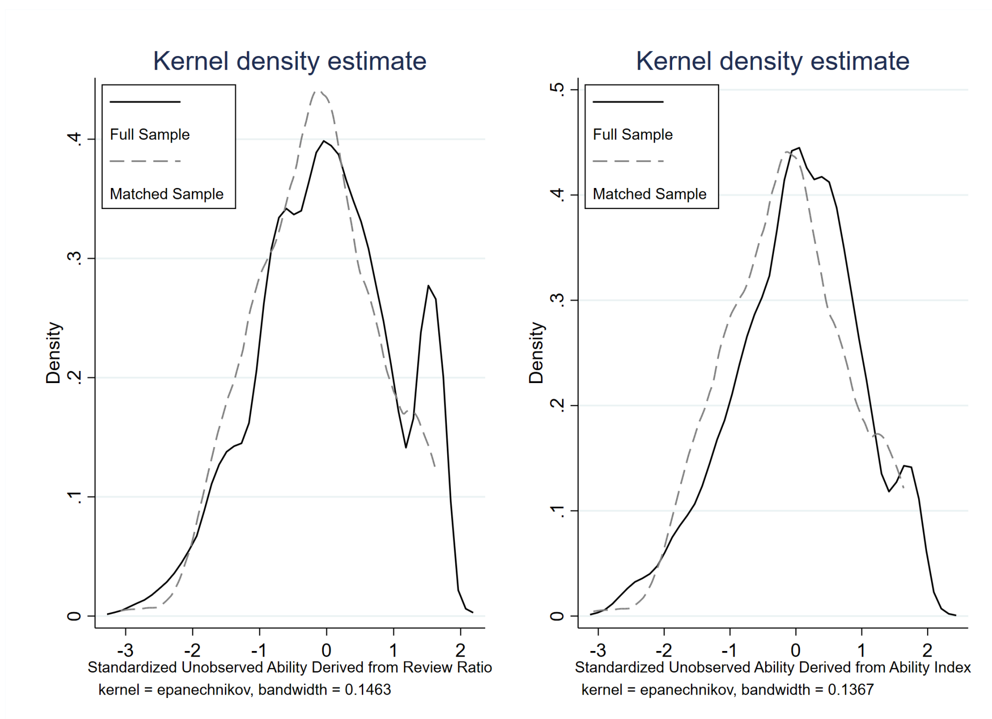

Figure 6: Density of Unobserved Ability, Matched Sample versus Full Sample

Table 5: Introductory Price IV Regression

Dependent variable:	p^{intro}		$p^{intro'}$	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
	Panel A			
$Std.Abil^U$ (review ratio)	-36.338**	-77.586*	-35.643*	-86.380*
	(17.042)	(46.254)	(19.051)	(50.461)
Observations	831	835	831	835
R-Squared	0.138	0.063	0.129	0.049
	Panel B			
Zhihu.like.per.answer		0.046***		0.046***
		(0.012)		(0.012)
Observations		835		835
R-Squared		0.124		0.124
Excluded Instrument F-Statistics		23.883		23.883
F-Statistics pvalue		0.000		0.000

Note: All regressions include expert controls, subcategory fixed effects, and market-quarter fixed effects. Expert control includes age, gender, and appearance score. Panel B shows the first-stage results of IV regressions. The minimum eigenvalue statistic (same as the F statistics in this case) is larger than the cutoff value (16.38) under a rejection rate of at most 10% in Stock and Yogo (2002). The mean initial price in the matched sample is 584 RMB. In columns (1) and (2), the introductory price is the weighted average price when the expert has multiple introductory products (p^{intro}). In columns (3) and (4), the introductory price is the price of the introductory product with the most sales ($p^{intro'}$). Standard errors are in parenthesis. $***p < 0.01, **p < 0.5, *p < 0.1$.

With the IV, we perform the same regression specification in Table 4. Table 5 compares the results from OLS and IV two-stage least squares. Both the OLS and IV regressions use the matched and weighted sample. In the first stage, the coefficient of *Zhihu.like.per.answer* is significantly positive, which confirms that the quality of answers of an expert on Zhihu is correlated with her unobserved ability on Zaihang.

According to the estimates in column (1), a one standard deviation higher unobserved ability implies a 36.34 RMB (6.2%) lower introductory price in the OLS regression. In column (2), a one standard deviation higher unobserved ability implies a 77.59 RMB (13.2%) lower introductory price in the IV regression. The IV regression results provides evidence for the causal relationship that experts with high unobserved ability choose to set low introductory prices.

Note that this cross-platform IV can be used to establish causality in other similar contexts. The limitation of our IV is the low matching rate. The main reason behind the low matching rate is that even though many experts choose to use their real names on Zaihang, they may use nicknames on Zhihu. Therefore, this type of across platform IV could perform better for celebrities and firms because they tend to use the same names across different platforms.

There is a concern that consumers can directly observe the expert's true ability from Zhihu and thus affect the validity of the IV. We argue that this is not the case for two reasons. First, there are only 5% experts who had more than ten likes on Zhihu before they entered Zaihang. Hence, for most experts, consumers could not infer their abilities from Zhihu. Second, only a small proportion of the Zhihu experts mention they also provide consulting services on Zaihang, which implies that there is no direct connection between the two platforms. In addition, the number of likes on Zhihu is a noisy signal of the expert's ability on Zaihang, so it is difficult for consumers to derive accurate quality information.

Possible Alternative Explanations and Robustness Check The data pattern is consistent with our low-intro price signaling, but there could be several alternative explanations behind this pattern. First, the observed low-intro-price may be explained by the different learning speeds among the experts. Suppose the initial low-ability experts learn faster than initial high-ability experts. When we observe a high rating expert in the final period, she may be a low-ability expert in period 1, thus setting a low initial price. In addition, if an expert's ability increases with the number of services that she provides, the fast-learning experts may have additional incentives to lower their initial prices since they could accumulate more sales and improve their future service quality. Therefore, they could raise their prices later as their abilities grow. On the other hand, the slow-learning experts may not follow such pricing strategy because their ability does not rise equally fast; they prefer to make more profit in period 1.

To investigate the learning story, we look at the experts who had Zhihu accounts before the Zaihang platform launched in 2015 Q1. So their Zhihu performance reflects their true ability before their pricing and learning behavior on Zaihang. Then we regress the experts' initial price on Zaihang on the consulting ability based on the Zhihu likes in 2014 Q4. The result is in Table 13 (Appendix C6). The experts with more likes on Zhihu 2014 Q4 set significantly lower prices than those with fewer likes on Zhihu for the same period. The result shows that the experts' pricing behavior is driven by the initial ability of the experts rather than a result of differentiated learning speed.

In addition to the regression, we plot the average review ratio of the high- and low-unobserved-ability experts from 2018 to 2020 in Figure 19 (Appendix D7). The high-versus-low unobserved ability cutoff is the 50% unobserved ability derived from the review ratio in 2021 Q4. The low ability group's review ratio decreased from 2018 to 2020, which is not consistent with the learning story but is consistent with our true type revealing story. That is the review ratio should converge to the experts' true abilities over time.

5.4 Price and Sales Dynamics

Prediction 2 states that high-unobserved-ability experts increase their prices from period 1 to period 2 because their reputation improves over time on average. In addition, the theory predicts that the price gap between the high- and low-unobserved-ability groups is negative in period 1 and positive in period 2. To test this prediction, we look at two types of price changes: 1. the price change from the first to second product. 2. the price change of the same product over time.

We first look at the price change from the introductory product (p^{intro}) to the second product

(p^{second}). To control observed heterogeneity across experts, we compare the standardized residual prices. The residual prices are the residuals from OLS regressions of prices on the observed expert characteristics and market-quarter fixed effect.

Table 6 shows the difference between the high- and low-unobserved-ability experts on the standardized residual introductory price (std.residual.p^{intro}), standardized residual period-2 price (std.residual.p^{second}), price change ($p^{second} - p^{intro}$), and the dummy for price increase (= 1 if $p^{second} > p^{intro}$). The results show that high-unobserved-ability experts' residual introductory prices are 0.12 standard deviations lower than those of their low-unobserved-ability counterparts. By contrast, the high-unobserved-ability experts' period-2 prices are 0.34 standard deviations higher than those of the low-unobserved-ability experts.

Table 6: Price Dynamics, Experts with High vs. Low Unobserved Ability

	Mean		Difference
	low unobserved ability	high unobserved ability	
std.residual.p^{intro}	0.1471	0.0220	-0.1251^{***}
std.residual.p^{second}	-0.0416	0.2987	0.3402^{***}

Note: The high-versus-low unobserved ability cutoff is set at 50% for each market and each entry quarter. Experts within each group are weighted by the total sales.

Figure 7 visualizes the price dynamics of the introductory product and the second product. The red and black lines represent experts with high and low unobserved abilities, respectively. We observe an "X" shape in the two panels with different levels of cutoffs for high-versus-low unobserved ability. The "X" shape indicates that high-unobserved-ability experts set lower introductory prices than low-unobserved-ability experts do, but their period-2 prices surpass those set by low-unobserved-ability experts. These results are all consistent with Prediction 2.

For the price change of the same product over time, we checked the same introductory product price from 2018 Q3 to 2020 Q4 for experts who entered before 2018 Q3 in Table 9 (Appendix C2). There is hardly any price change for the same product from 2018 and 2020. We do not find any heterogeneous price dynamics for the high- and low-unobserved-ability groups. This phenomenon can be explained by the theory of sticky prices (Kashyap, 1995; Bils and Klenow, 2004). As shown in Figure 18 (Appendix D6), 48.78% of high-unobserved-ability experts and 45.53% low-unobserved-ability experts do not change their prices from 2018 to 2020. Therefore, we conclude that most experts increase prices by introducing new products instead of changing the price of existing products.

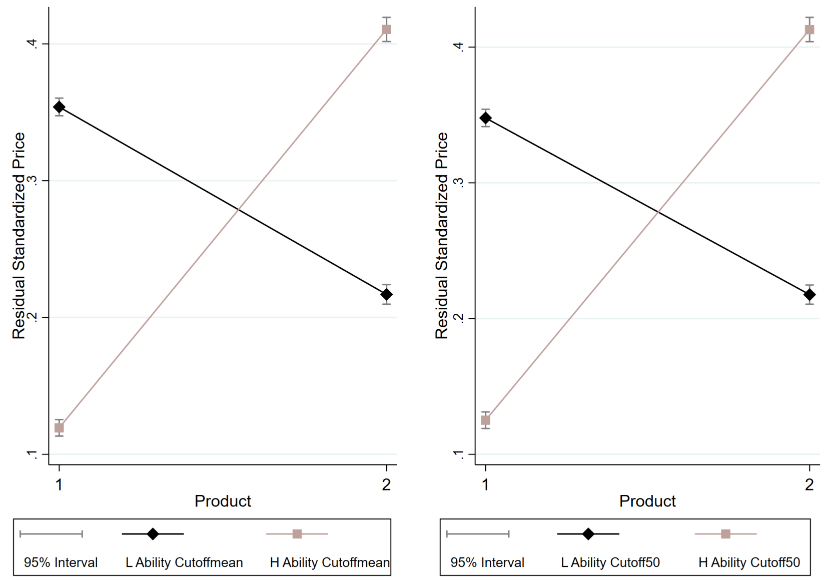

Figure 7: Average Price Comparison, Experts with High vs. Low Unobserved Ability

Note: "Cutoff$x$" means high-unobserved-ability experts and low-unobserved-ability experts are divided by the x percentage point of $Std.Abil^U$. Experts within each group are weighted by the total sales.

Prediction 3 states that high-unobserved-ability experts' sales are higher than those of the low-unobserved-ability experts in period 1. Table 7 shows the difference between the high- and low-unobserved-ability experts on the standardized residual sales of the introductory product (std.residual.q^{intro}),[15] standardized residual sales of the second product (std.residual.q^{second}), sales change ($q^{second} - q^{intro}$), and the dummy for sales increase($= 1$ if $q^{second} > q^{intro}$). [16] The results show that, for the introductory product, high-unobserved-ability experts' sales are 0.23 standard deviations higher than those of low-unobserved-ability experts; for the second product, high-unobserved-ability experts' sales are 0.05 standard deviation lower than those of low-unobserved-ability experts. The results are consistent with the model prediction that high-quality firms have higher sales than low-quality firms in period 1. In addition, high-unobserved-ability experts' sales decrease from period 1 to period 2 because they use low prices to boost sales of their introductory product. Figure 8 depicts the sales dynamics of the introductory product and second product. There is an "X" shape when the cutoff is set at the 50% ability level. High-unobserved-ability experts have higher sales in period 1 but lower sales in period 2, as they increase the prices. However, High-unobserved-ability experts have higher revenue than low-unobserved-ability experts (Figure 20, Appendix D8) in both periods. It implies that high reviews could help firms to obtain high revenue.

[15]The residual sales are the OLS regression residuals after controlling the observed expert characteristics and market-quarter fixed effect.

[16]Since we don't have the product level sales, we use the product review number to approximate the sales dynamics.

Table 7: Sales Dynamics, Experts with High vs. Low Unobserved Ability

	Mean		Difference
	low unobserved ability	high unobserved ability	
std.residual.q^{intro}	0.4237	0.6567	0.2330***
std.residual.q^{second}	-0.2381	-0.2916	-0.0535***

The high-versus-low unobserved ability cutoff is the 50% unobserved ability in each market and each entry quarter. Experts within each group are weighted by the total sales.

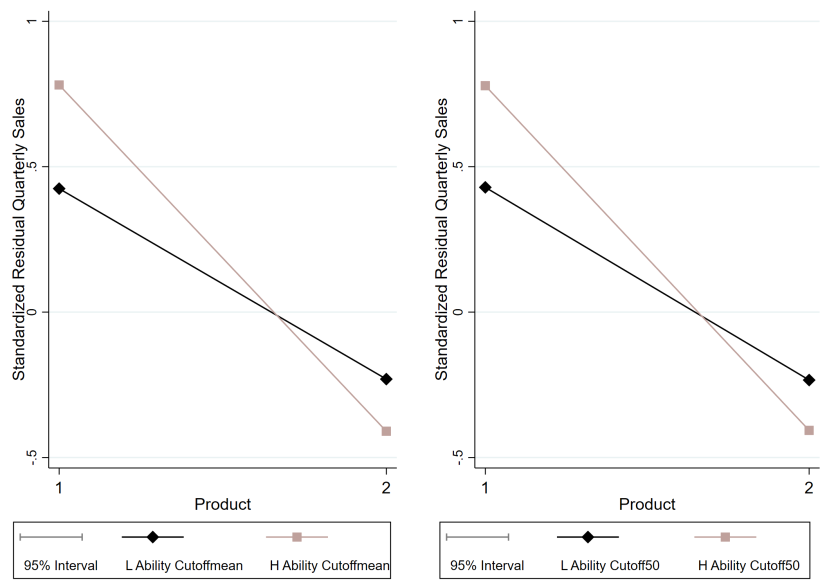

Figure 8: Average Sales Comparison, Experts with High versus Low Unobserved Ability
Note: "Cutoff$x$" means high-unobserved-ability experts and low-unobserved-ability experts are divided by the x percentage point of $Std.Abil^U$. Experts within each group are weighted by the total sales. The sales is the quarterly sales.

6 Conclusion

In this paper, we construct a dynamic model of asymmetric quality information with both price signaling and a review-based reputation system. These features make our model fit the environment of online e-commerce platforms better than many previous models in the literature. We characterize the low-intro-price equilibrium in which a high-quality firm uses a low introductory price to signal her quality. Then, we provide empirical evidence for the model predictions using data from a consulting service platform. We overcome the challenge of measuring the unobserved ability of experts on the platform and find that experts with high unobserved ability indeed set low introductory prices. We also construct an IV using data from a Q&A platform to establish the causal relationship.

One interesting direction of future research is studying how price and RFF program interact in signaling and reputation building. If consumers have heterogeneous costs of writing reviews, offering rebates for reviews would have different effects to cutting prices. In addition, the effectiveness of reputation systems may vary across different product categories due to difference in accuracy of reviews (market transparency in (Klein et al., 2016)) and competition intensity. Our model can be extended to consider these factors that affects the reputation building process, pricing, and sales. With this knowledge, platform designers can adopt different designs of reputation systems for different product categories and improve the efficiency of the markets.

References

Anderson, M. and J. Magruder (2012). Learning from the crowd: Regression discontinuity estimates of the effects of an online review database. *Economic Journal 122*(563), 957–989.

Bagwell, K. and M. H. Riordan (1991). High and declining prices signal product quality. *American Economic Review*, 224–239.

Banks, J. S. and J. Sobel (1987). Equilibrium selection in signaling games. *Econometrica 55*(3), 647–661.

Bils, M. and P. J. Klenow (2004). Some evidence on the importance of sticky prices. *Journal of Political Economy 112*(5), 947–985.

Bohren, J. A. (2016). Informational herding with model misspecification. *Journal of Economic Theory 163*, 222–247.

Brown, J., T. Hossain, and J. Morgan (2010). Shrouded attributes and information suppression: Evidence from the field. *Quarterly Journal of Economics 125*(2), 859–876.

Chetty, R., A. Looney, and K. Kroft (2009). Salience and taxation: Theory and evidence. *American economic review 99*(4), 1145–77.

Cho, I.-K. and D. M. Kreps (1987). Signaling games and stable equilibria. *Quarterly Journal of Economics 102*(2), 179–221.

Cooper, R. and T. W. Ross (1984, 04). Prices, Product Qualities and Asymmetric Information: The Competitive Case. *Review of Economic Studies 51*(2), 197–207.

Daughety, A. F. and J. F. Reinganum (2008). Imperfect competition and quality signalling. *RAND Journal of Economics 39*(1), 163–183.

Dawar, N. and M. Sarvary (1997). The signaling impact of low introductory price on perceived quality and trial. *Marketing Letters 8*(3), 251–259.

DeVaro, J. and M. Waldman (2012). The signaling role of promotions: Further theory and empirical evidence. *Journal of Labor Economics 30*(1), 91–147.

Edelman, B., M. Luca, and D. Svirsky (2017). Racial discrimination in the sharing economy: Evidence from a field experiment. *American Economic Journal: Applied Economics 9*(2), 1–22.

Eyster, E. and M. Rabin (2010). Naive herding in rich-information settings. *American economic journal: microeconomics 2*(4), 221–43.

Fan, Y., J. Ju, and M. Xiao (2016). Reputation premium and reputation management: Evidence from the largest e-commerce platform in china. *International Journal of Industrial Organization 46*, 63–76.

Fang, L. (2022). The effects of online review platforms on restaurant revenue, consumer learning, and welfare. *Management Science*.

Farrell, J. v. R. (1981). Prices as signals of quality. *University of Oxford*.

Filippas, A., J. J. Horton, and J. Golden (2018). Reputation inflation. In *Proceedings of the 2018 ACM Conference on Economics and Computation*, pp. 483–484.

Gabaix, X. and D. Laibson (2006). Shrouded attributes, consumer myopia, and information suppression in competitive markets. *Quarterly Journal of Economics 121*(2), 505–540.

Harrington, E. and N. Emanuel (2020). Working remotely? selection, treatment, and market provision of remote work. *Working Paper 10*.

Hui, X., M. Saeedi, Z. Shen, and N. Sundaresan (2016). Reputation and regulations: evidence from ebay. *Management Science 62*(12), 3604–3616.

Judd, K. L. and M. H. Riordan (1994). Price and quality in a new product monopoly. *Review of Economic Studies 61*(4), 773–789.

Kashyap, A. K. (1995). Sticky prices: New evidence from retail catalogs. *Quarterly Journal of Economics 110*(1), 245–274.

Kihlstrom, R. E. and M. H. Riordan (1984). Advertising as a signal. *Journal of Political Economy 92*(3), 427–450.

Klein, T. J., C. Lambertz, and K. Stahl (2016). Market transparency, adverse selection, and moral hazard. *Journal of Political Economy 124*(6), 1677–1713.

Ko, G. Y. (2021). Gender discrimination in the gig economy: Evidence from online auctions for freelancing. *Working Paper*.

Li, L. (2010). Reputation, trust, and rebates: How online auction markets can improve their feedback mechanisms. *Journal of Economics & Management Strategy 19*(2), 303–331.

Li, L., S. Tadelis, and X. Zhou (2020). Buying reputation as a signal of quality: Evidence from an online marketplace. *RAND Journal of Economics 51*(4), 965–988.

Li, L. and E. Xiao (2014). Money talks: Rebate mechanisms in reputation system design. *Management Science 60*(8), 2054–2072.

Luca, M. (2016). Reviews, reputation, and revenue: The case of yelp.com. *Working Paper* (12-016).

Milgrom, P. and J. Roberts (1986). Price and advertising signals of product quality. *Journal of Political Economy 94*(4), 796–821.

Nelson, P. (1970). Information and consumer behavior. *Journal of Political Economy 78*(2), 311–329.

Nelson, P. (1974). Advertising as information. *Journal of Political Economy 82*(4), 729–754.

Nosko, C. and S. Tadelis (2015). The limits of reputation in platform markets: An empirical analysis and field experiment. *NBER Working paper*.

Resnick, P., R. Zeckhauser, J. Swanson, and K. Lockwood (2006). The value of reputation on ebay: A controlled experiment. *Experimental Economics 9*(2), 79–101.

Rob, R. and A. Fishman (2005). Is bigger better? customer base expansion through word-of-mouth reputation. *Journal of Political Economy 113*(5), 1146–1162.

Schmalensee, R. (1978). A model of advertising and product quality. *Journal of Political Economy 86*(3), 485–503.

Shapiro, C. (1983). Optimal pricing of experience goods. *Bell Journal of Economics*, 497–507.

Sorensen, A. T. (2000). Equilibrium price dispersion in retail markets for prescription drugs. *Journal of Political Economy 108*(4), 833–850.

Stock, J. H. and M. Yogo (2002). Testing for weak instruments in linear IV regression. *Working Paper*.

Appendix

A. Proofs

A1. Proof of Proposition 1

Period-2 equilibrium We first solve the equilibrium price and profit for firm H and firm L in period 2. We need to consider two cases: (i) period-1 is a pooling equilibrium and (ii) a separating equilibrium.

We focus on the following belief of period-2 sophisticated consumers: A firm is high-quality if and only if she sets the period-2 separating price $p_{2,H}$ regardless of period-1 prices and reviews. This is a natural result of D1 criterion, because if a low-quality firm cannot benefit from setting $p_{2,H}$ in period 2. Thus, if a firm sets $p_{2,H}$, she must be high quality. Firm H would lose profits under all consumer beliefs by deviating to a price higher than it. If firm H deviate to a lower price, firm L would mimic her, and the updated consumer beliefs would harm her.

Next, consider the period-2 separating equilibrium. Let γ denote the belief hold by consumers about the probability of the firm being high-quality. Let $\pi_2(p_2|\theta, \gamma_{sophisticate}, \gamma_{naive})$ denote the expected period-2 profit of firm θ. $\gamma_{sophisticate}$ is the belief of sophisticated consumers, and γ_{naive} is the belief of naive consumers. For simplicity, when $\gamma = 1$, we denote $\gamma = H$; when $\gamma = 0$, we denote $\gamma = L$.

$$
\begin{aligned}
\pi_2(p_{2,H,H,\gamma}|H, H, \gamma) &= ((1-m)v_H + m\overline{v}(\gamma) - \overline{u} - p_{2,H,H,\gamma})(p_{2,H,H,\gamma} - c_H) \\
\pi_2(p_{2,H,L,\gamma}|H, L, \gamma) &= ((1-m)v_L + m\overline{v}(\gamma) - \overline{u} - p_{2,H,L,\gamma})(p_{2,H,L,\gamma} - c_H) \\
\pi_2(p_{2,L,H,\gamma}|L, H, \gamma) &= ((1-m)v_H + m\overline{v}(\gamma) - \overline{u} - p_{2,L,H,\gamma})p_{2,L,H,\gamma} \\
\pi_2(p_{2,L,L,\gamma}|L, L, \gamma) &= ((1-m)v_L + m\overline{v}(\gamma) - \overline{u} - p_{2,L,L,\gamma})p_{2,L,L,\gamma},
\end{aligned} \tag{10}
$$

where $\overline{v}(\gamma) = \gamma v_H + (1-\gamma)v_L$ is the expected quality of a firm when naive consumers hold the belief γ.

The period-2 separating equilibrium requires the following two incentive compatibility (IC) constraints:

$$
\begin{aligned}
\pi_2(p_{2,H,H,\gamma}|H, H, \gamma) &\geq \pi_2(p_{2,H,L,\gamma}|H, L, \gamma) \\
\pi_2(p_{2,L,L,\gamma}|L, L, \gamma) &\geq \pi_2(p_{2,H,H,\gamma}|L, H, \gamma).
\end{aligned} \tag{11}
$$

The first IC constraint means firm H is better off setting $p_{2,H,H,\gamma}$ and being perceived as high quality than setting $p_{2,H,L,\gamma}$ which is the optimal price if she is mistaken perceived as low quality. The second IC constraint means firm L does not want to mimic firm H. Solving for the prices, we have the following inequalities:

$$
(12) \quad \begin{aligned}
p_{2,H,H,\gamma} &\leq \frac{(v_H - \overline{u}) - \sqrt{(v_H - \overline{u})^2 - (v_L - \overline{u})^2}}{2} \\
p_{2,H,H,\gamma} &\geq \frac{(v_H - \overline{u} + c_H) - \sqrt{(v_H - \overline{u} - c_H)^2 - (v_L - \overline{u} - c_H)^2}}{2}.
\end{aligned}
$$

Note that a high-price separating equilibrium exists when there is a $p_{2,H}$ such that the following two inequalities hold.

$$
(13) \quad \begin{aligned}
p_{2,H,H,\gamma} &\geq \frac{(1-m)v_H + z) + \sqrt{((1-m)v_H + z)^2 - (v_L - \overline{u})^2}}{2} \\
p_{2,H,H,\gamma} &\leq \frac{(1-m)v_H + z + c_H) + \sqrt{((1-m)v_H + z - c_H)^2 - (v_L - \overline{u} - c_H)^2}}{2},
\end{aligned}
$$

where $z = m\overline{v}(\gamma) - \overline{u}$. Because we assume $c_H > 0$, and $c_H < v_L - \overline{U}$, we must have the high-price separating equilibrium equilibrium in period 2. Then, applying D1 criterion (detail comes later), we find a unique separating equilibrium.

$$
(14) \quad \begin{aligned}
p^*_{2,H,H,\gamma} &= \frac{1}{2}\left((1-m)v_H + z + \sqrt{((1-m)v_H + z)^2 - ((1-m)v_L + z)^2}\right) \\
p^*_{2,H,L,\gamma} &= \frac{1}{2}\left((1-m)v_L + z + c_H\right) \\
p^*_{2,L,H,\gamma} &= \frac{1}{2}\left((1-m)v_H + z + \sqrt{((1-m)v_H + z)^2 - ((1-m)v_L + z)^2}\right) \\
p^*_{2,L,L,\gamma} &= \frac{1}{2}\left((1-m)v_L + z\right).
\end{aligned}
$$

Firm H would set a very high period-2 price to deter the mimicry of firm L. Firm L charges her optimal price being perceived as low quality. The corresponding profits are:

(15)

$$
\begin{aligned}
\pi^*_2(H,H,\gamma) &= \frac{1}{4}((1-m)v_L + z)^2 - \frac{1}{4}c_H\left((1-m)v_H + z - \sqrt{((1-m)v_H + z)^2 - ((1-m)v_L + z)^2}\right) \\
\pi^*_2(H,L,\gamma) &= \frac{1}{4}((1-m)v_L + z - c_H)^2 \\
\pi^*_2(L,H,\gamma) &= \frac{1}{4}\left((1-m)v_L + z\right)^2 \\
\pi^*_2(L,L,\gamma) &= \frac{1}{4}\left((1-m)v_L + z\right)^2.
\end{aligned}
$$

Because $\pi^*_2(H,H,\gamma) > \pi^*_2(H,L,\gamma)$, for all $c_H > 0$, firm H does not want to deviate to a different price.

For both type of firms, the expected period-2 profit increases in γ because z is increasing with γ. We later show that there is no pooling equilibrium that survives the D1 refinement in period 2 no matter the period-1 equilibrium is pooling or separating. This completes the analysis of period 2. In conclusion,

Lemma 2. *The firm always plays a separating equilibrium in period 2. The sophisticated consumers believe that if the firm chooses price $p^*_{2,H,H,\gamma}$, she is high quality, otherwise she is low quality.*

Period-1 equilibrium Lemma 2 have established that no matter what prices the firms set in period 1, their types will always be perfectly revealed to period-2 sophisticated consumers. Thus, period-1 price choice only affects the reputation accumulation and the payoff of naive consumers.

We now study period-1 separating equilibrium. Similarly, period-1 pooling equilibria would also be ruled out by the D1 Criteria. In this case, period-1 sophisticated consumers believe that a firm is high quality if and only if it charges a price $p_{1,H}$, otherwise it is a low-quality firm.

Then, we can write down the expected period-2 profit $\Phi^*(q_1, \theta)$ as a function of the firm period-1 quantity sold (q_1) and true type $\theta \in \{H, L\}$. Since the sophisticated consumers can always tell the true type of the firm, their belief does not enter this expected profit function.

(16)

$$\begin{aligned}
\Phi^*(q_1, H) &= q_1[a\pi_2^*(H, H, \frac{a\lambda_0}{a\lambda_0 + b(1-\lambda_0)}) + (1-a)\pi_2^*(H, H, \frac{(1-a)\lambda_0}{(1-a)\lambda_0 + (1-b)(1-\lambda)})] + (1-q_1)\pi_2^*(H, H, \lambda_0) \\
&= q_1 k_H^* + \pi_2^*(H, H, \lambda_0) \\
\Phi^*(q_1, L) &= q_1[a\pi_2^*(L, L, \frac{a\lambda_0}{a\lambda_0 + b(1-\lambda_0)}) + (1-a)\pi_2^*(L, L, \frac{(1-a)\lambda_0}{(1-a)\lambda_0 + (1-b)(1-\lambda)})] + (1-q_1)\pi_2^*(L, L, \lambda_0) \\
&= -q_1 k_L^* + \pi_2^*(L, H, \lambda_0).
\end{aligned}$$

As we can see, the expected period-2 profit is linear in period-1 quantity sold q_1. The slopes are k_H^* and $-k_L^*$. Both slopes are decreasing with m, and approaches zero as(1-m)goes to one.

Finally, we can write down the total profit: $\pi_{total}(p_1|\theta, \gamma_{naive,1})$ This represents the total profit of firm with true type θ, the sophisticated consumers believes the firm is high type with probability γ_{so} and the naive consumers the firm is high type with probability $\gamma_{naive,1}$. Since there is no review in period 1, $\gamma_{naive,1} = \lambda_0$.

$$\begin{aligned}
\pi_{total}^*(p_1|H, H, \lambda_0) &= [(1-m)v_H + m\overline{v}(\lambda_0) - \overline{u} - p_1)(p_1 - c_H + k_H)] + \pi_2^*(H, H, \lambda_0) \\
\pi_{total}^*(p_1|H, L, \lambda_0) &= [(1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} - p_1)(p_1 - c_H + k_H)] + \pi_2^*(H, H, \lambda_0) \\
\pi_{total}^*(p_1|L, H, \lambda_0) &= [(1-m)v_H + m\overline{v}(\lambda_0) - \overline{u} - p_1)(p_1 - k_L)] + \pi_2^*(L, L, \lambda_0) \\
\pi_{total}^*(p_1|L, L, \lambda_0) &= [(1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} - p_1)(p_1 - k_L)] + \pi_2^*(L, L, \lambda_0)
\end{aligned} \tag{17}$$

In the above equations, the slope of $\Phi^*(q_1, \theta)$ on q_1 can be represented as additional costs and benefit when the period-1 sales quantity changes ($p_1 - c_H + k_H$ and $p_1 - k_L$).

Then, for a separating equilibrium, we need to have the following IC constraint:

$$\begin{aligned}
\pi_{total}^*(p_{1,H,H}|H, H, \lambda_0) &\geq \pi_{total}^*(p_{1,H,L}|H, L, \lambda_0) \\
\pi_{total}^*(p_{1,L,L}|L, L, \lambda_0) &\leq \pi_{total}^*(p_{1,H,H}|L, H, \lambda_0)
\end{aligned} \tag{18}$$

First, we derive the optimal prices when the firms are perceived as low quality:

$$\begin{aligned}
p_{1,L} &= \frac{1}{2}((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} + k_L) \\
p_{1,H}' &= \frac{1}{2}((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} + c_H - k_H).
\end{aligned}$$

With the linear period-2 expected profit function, we can directly solve the IC constraints and obtain the range of $p_{1,H}$. The low-intro-price equilibrium exists when there is a $p_{1,H}$ satisfying the following two inequalities derived from the IC constraints:

$$
\begin{aligned}
p_{1,H} \leq &\frac{1}{2}((1-m)v_H + m\overline{v}(\lambda_0) - \overline{u} + k_L) \\
&- \frac{1}{2}\sqrt{((1-m)v_H + m\overline{v}(\lambda_0) - \overline{u} - k_L)^2 - ((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} + k_L)^2} \\
p_{1,H} \geq &\frac{1}{2}((1-m)v_H + m\overline{v}(\lambda_0) - \overline{u} + c_H - k_H) \\
&- \frac{1}{2}\sqrt{((1-m)v_H + m\overline{v}(\lambda_0) - \overline{u} - c_H + k_H)^2 - ((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} - c_H + k_H)^2}
\end{aligned} \tag{19}
$$

Note that a high-intro-price equilibrium exists when there is a $p_{1,H}$ such that the following two inequalities hold.

$$
\begin{aligned}
p_{1,H} \geq &\frac{1}{2}((1-m)v_H + m\overline{v}(\lambda_0) - \overline{u} + k_L) \\
&+ \frac{1}{2}\sqrt{((1-m)v_H + m\overline{v}(\lambda_0) - \overline{u} - k_L)^2 - ((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} + k_L)^2} \\
p_{1,H} \leq &\frac{1}{2}((1-m)v_H + m\overline{v}(\lambda_0) - \overline{u} + c_H - k_H) \\
&+ \frac{1}{2}\sqrt{((1-m)v_H + m\overline{v}(\lambda_0) - \overline{u} - c_H + k_H)^2 - ((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} - c_H + k_H)^2}
\end{aligned} \tag{20}
$$

All the parameters in the above inequalities are in $[0,1]$. Due to the limitation of the highest possible profit in period 2, the absolute value of k_L and k_H are bounded by $\frac{(v_H-\overline{u})^2}{4} - \frac{(v_L-\overline{u})^2}{4}$. Because $v_H > v_L$, the term under the square root must be non-negative. So, we do not need to worry about cases when the functions are trivially satisfied.

From the above IC constraints, we can derive that if $c_H - k_H < k_L$ then there is a set of low introductory price equilibria, while no high-intro-price exists. If $c_H - k_H > k_L$, then, only high intro-price equilibrium exists, and low intro price equilibrium does not exists. If $c_H - k_H = k_L$ then there are two singleton prices of $p_{1,H}$ and the lower one satisfies the low-intro-price equilibrium, and the higher one satisfies the high-intro-price equilibrium.

Solving the period-1 pricing strategy and then applying the D1 criterion, we have the unique period-1 equilibrium as the follow:

1. When $c_H - k_H < k_L$, we have a unique low intro-price equilibrium that survives the D1 criterion:

$$
\begin{aligned}
p_{1,L} = &\, arg\max_p \pi_{total}(p|L, L, \lambda) = \frac{1}{2}((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} + k_L) \\
p_{1,H} = &\frac{1}{2}((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} + k_L) \\
&- \frac{1}{2}\sqrt{((1-m)v_H + m\overline{v}(\lambda_0) - \overline{u} - k_L)^2 - ((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} - k_L)^2}
\end{aligned} \tag{21}
$$

2. When $c_H - k_H > k_L$, we have a unique high intro-price equilibrium that survives the D1

criterion:

$$
\begin{aligned}
p_{1,L} &= arg\max_p \pi_{total}(p|L,L,\lambda) = \frac{1}{2}(1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} + k_L) \\
p_{1,H} &= \frac{1}{2}((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} + k_L) \\
&\quad + \frac{1}{2}\sqrt{((1-m)v_H + m\overline{v}(\lambda_0) - \overline{u} - k_L)^2 - ((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} - k_L)^2}
\end{aligned} \tag{22}
$$

Then, we can also eliminate the pooling equilibria in period 1. The IC constraints are

$$
\begin{aligned}
\pi^*_{total}(p_1|H,H,\lambda_0) &\geq \pi^*_{total}(p_1|H,L,\lambda_0) \\
\pi^*_{total}(p_1|L,L,\lambda_0) &\leq \pi^*_{total}(p_1|L,H,\lambda_0)
\end{aligned} \tag{23}
$$

Let the slope of the period-2 profit with respect to period-1 sales be k^*_H and k^*_L. They are derived in similar way as before. Then, we show below, that the pooling equilibrium does not survive the D1 criterion. Thus, we have a unique separating equilibrium that survives D1. And this completes the proof.

D1 Criterion refinement

We first show that pooling equilibrium does not survive the the D1 Criterion (Banks and Sobel, 1987) when the condition of the when $c_H - k^*_H < k^*_L$. This proof also applies, but in the opposite direction when $c_H - k^*_H > k^*_L$. This proof also applies when eliminating the period-2 pooling equilibria. We can just set $k_H = k_L = 0$, so the second condition is satisfied.

Let $p_{1,H}$ ($p_{1,L}$) denotes period-1 price of firm H (L) in the low-intro-price equilibrium. Let p_{pool} be the pooling price in the pooling equilibrium. First, note that $p_{1,H} \leq p_{pool}$, because if the pooling price is any lower than $p_{1,H}$, firm L would not have an incentive to set the pooling price and would deviate to $p_{1,L}$ instead.

Then, we show for all $p_{pool} > p_{1,H}$, the pooling equilibrium does not satisfy the D1 Criterion. Consider a firm sending the off-equilibrium signal by setting period-1 price to $p_{pool} - \epsilon$, where $\epsilon > 0$ and $p_{pool} - \epsilon > p_{1,H}$. We need to first find the set of the best responses by consumers[17] such that firm H and firm L are weakly better off than sending the equilibrium signal. Here, the strategy of consumers is the probability of buying the product given the price signal, which is q_1.

If, for one type of the firms, her equilibrium dominating set of q_1 is strictly larger than that of the other type, then consumers would update their beliefs that the signal is sent by the former type of firm.[18] Finally, with the updated beliefs, we check if the firm still has an incentive to send the off-equilibrium signal. If the firm can still benefit, then we say the original equilibrium price does not survive the D1 Criterion.

[17]We consider the set of best responses under any beliefs about the probability of the firm sending this signal being high quality.

[18]Here, we ignore the details about the indifference point because for each profit level, there is only a single point where the firm would be indifferent between sending the off-equilibrium signal and the equilibrium signal.

Let $\Phi(q_1, H) = E_\gamma[\pi_2(q_1|H,\gamma)]$ denote the expected period-2 payoff of firm θ given q_1. Now, consider that firm L sends the off-equilibrium signal. We find the set of q_1, such that

$$(24)\qquad \begin{gathered}(\overline{v} - \overline{u} - p_{pool}) \times p_{pool} + \Phi^*(\overline{v} - \overline{u} - p_{pool}, L) \leq q_1 \times (p_{pool} + \epsilon) + \Phi^*(q_1, L)\\ v_H - \overline{u} - p_{pool} - \epsilon \geq q_1\end{gathered}$$

where $\overline{v} = \lambda_0 v_H + (1-\lambda_0)v_L$ is the expected value of the firm when it sets the pooling price. The first condition is to find the range of q_1 that makes firm L weakly better off than the separating equilibrium payoff. The second condition bounds q_1 by the highest probability that the consumer is willing to buy the product.

Similarly, we can find the set of q_1 that makes firm H weakly better off.

$$(25)\qquad \begin{gathered}(\overline{v} - \overline{u} - p_{pool})(p_{pool} - c_{c_H}) + \Phi^*(\overline{v} - \overline{u} - p_{pool}, H) \leq q_1(p_{pool} + \epsilon - c_H) + \Phi^*(q_1, H)\\ v_H - \overline{u} - p_{pool} - \epsilon \geq q_1\end{gathered}$$

In condition (24) and (25), the second inequalities are the same. By expanding $\Phi(\cdot)$, we obtain the following results. For firm L, the range of q_1 is

$$(26)\qquad q_1 \geq \overline{v} - \overline{u} - p_{pool} + \frac{\epsilon(\overline{v} - \overline{u} - p_{pool})}{p_{pool+\epsilon-k_L^*}}$$

For firm H, the range of q_1 is:

$$(27)\qquad q_1 \geq \overline{v} - \overline{u} - p_{pool} + \frac{\epsilon(\overline{v} - \overline{u} - p_{pool})}{p_{pool+\epsilon+k_H^*-c_H}}$$

We can see that when $k_H^* - c_H > -k_L^*$, then the range of q_1 for firm H is strictly larger than that of firm L. According to the D1 Criterion, the consumers would believe that the firm sending the off-equilibrium signal $p_{pool} - \epsilon$ must be high quality. Given this belief, it is easy to see that firm H is willing to send out the off-equilibrium signal. Thus, the pooling equilibrium equilibrium does not survive the D1 Criterion, because whenever the pooling price is strictly higher than $p_{1,H}$, firm H has the incentive to undercut firm L.

Furthermore, the condition $k_H^* - c_H > -k_L^*$ is exactly the condition that guarantees a unique low-intro-price equilibrium. The D1 Criterion gives us more reason to believe that the low-intro price equilibrium is the most stable one.

Similarly, when $k_H^* - c_H < -k_L^*$ the high quality firm would have the incentive to deviate to $p_{pool} + \epsilon$. So the pooling equilibrium still does not survive the D1 criterion. In period 2, since the quality sold in period 2 has no effect on the future, it is similar that the high quality firm always wants to increase the price since $c_H > 0$. So we rule out the pooling equilibria in period 2.

We see the direction of deviation from the pooling equilibrium coincide with the separating equilibrium. When there is a low intro-price equilibrium, the high quality firm has the incentive to decrease the price, while if there is a high intro-price equilibrium, the high quality firm would increase the price. Thus, we have eliminated the pooling equilibria in period 1, and there can only be separating equilibria.

D1 Criterion refinement to select a unique separating equilibrium

In this section, we use the D1 criterion to refine the set of low-intro-price (high-intro-price) equilibria when $c_H - k_H < k_L$ ($c_H - k_H > k_L$) and show that there is a unique $p_{1,H}$ that survives this refinement in each case. Let the set of $p_{1,H}$ that supports the low-intro-price equilibria be $[\underline{p_{1,H}}, \overline{p_{1,H}}]$, where the only point that satisfies the D1 criterion is the point $p_{1,H} = \overline{p_{1,H}}$.

We check any separating equilibrium in which $p_{1,H}$ is strictly smaller than the $\overline{p_{1,H}}$. Then firm H can deviate to a new price that is ϵ larger than $p_{1,H}$, but still $p_{1,H} + \epsilon \in [\underline{p_{1,H}}, \overline{p_{1,H}})$. If the consumers believe that such a deviation is by a high-quality firm, then the firm can increase her the profit. However, because the new price is still within the price interval that satisfy the IC constraints, firm L would not choose to deviate to such a price. Thus, if consumers observe that a firm chooses introductory price $p_{1,H} + \epsilon$, it must be a high-quality firm, so $\theta_d = H$.

Then, under this updated belief, consumers would buy the product because doing so generates more utility than the outside choice. The purchase leads to a higher profit for firm H. Hence, all PBEs with $p_{1,H} \in [\underline{p_{1,H}}, \overline{p_{1,H}})$ do not survive the D1 Criterion. The unique low-intro-price equilibrium is with $p_{1,H} = \overline{p_{1,H}}$.

Similarly, when $c_H - k_H > k_L$, the unique PBE in the last period is the lowest $p_{1,H}$ in the set of high-intro-price equilibrium.

Similar reasoning can apply to the last period. Since there is no future period, it is equivalent to have $k_H = k_L = 0$. Since $c_H > 0$, the D1 criterion selects an unique equilibrium such that the high-quality firm sets a higher price than the low-quality. □

A2. Proof of Corollary 1.

This result can be directly derived from the condition in Proposition 1. The low-intro-price equilibrium exists when $c_H < k_H + k_L = \bar{c}_H$. □

A3. Proof of Prediction 3.

We can directly write down the sales of the first and second period in the low-intro price equilibrium. Denote the $q_{1,\theta}$ as period-1 quantity of firm θ. Denote $q_{2,\theta}(\gamma)$ as period-2 quantity of firm θ when the naive consumer's belief is γ.

$$
\begin{aligned}
q_{1,L} =& \frac{1}{2}((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} - k_L) \\
q_{1,H} =& ((1-m)v_H + m\overline{v}(\lambda_0) - \overline{u}) - \frac{1}{2}((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} - k_L) \\
&+ \frac{1}{2}\sqrt{((1-m)v_H + m\overline{v}(\lambda_0) - \overline{u} - k_L)^2 - ((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} - k_L)^2} \\
q_{2,L}(\gamma) =& \frac{1}{2}((1-m)v_L + m\overline{v}(\gamma) - \overline{u}) \\
q_{2,H}(\gamma) =& \frac{1}{2}((1-m)v_H + m\overline{v}(\gamma) - \overline{u}) \\
&- \frac{1}{2}\sqrt{((1-m)v_H + m\overline{v}(\gamma) - \overline{u})^2 - ((1-m)v_L + m\overline{v}(\gamma) - \overline{u})^2}
\end{aligned} \tag{28}
$$

We can then calculate the sales gaps as the follow.

$$
\begin{aligned}
q_{1,H} - q_{1,L} =& (1-m)v_H + \frac{1}{2}(m\overline{v}(\lambda_0) - \overline{u} + k_L) \\
&+ \frac{1}{2}\sqrt{((1-m)v_H + m\overline{v}(\lambda_0) - \overline{u} - k_L)^2 - ((1-m)v_L + m\overline{v}(\lambda_0) - \overline{u} - k_L)^2} \\
q_{2,H}(\gamma) - q_{2,L}(\gamma) =& \frac{1}{2}((1-m)v_H + m\overline{v}(\gamma) - \overline{u}) - \frac{1}{2}((1-m)v_L + m\overline{v}(\gamma) - \overline{u}) \\
&- \frac{1}{2}\sqrt{((1-m)v_H + m\overline{v}(\gamma) - \overline{u})^2 - ((1-m)v_L + m\overline{v}(\gamma) - \overline{u})^2}
\end{aligned} \tag{29}
$$

Hence, we have $q_{1,H} - q_{1,L} > 0$ and for each realized reputation level γ, $q_{2,H}(\gamma) - q_{2,L}(\gamma) < 0$, firm H sells less than firm L in period 2. However, because a higher γ increases the sales of both firm H and firm L, and firm H is more likely to obtain a better reputation, it is unclear which firm has higher expected quantity sold in period 2. We consider a limit case: when the firms accumulates a large amount of reviews and the beliefs of naive consumers converge to the true type of the firm, then we can compare the quantity sold in period 2, $q_{2,H}(1)$ and $q_{2,L}(0)$:

$$
\begin{aligned}
q_{2,H}(1) &= \frac{1}{2}(v_H - \overline{u}) - \frac{1}{2}\sqrt{(v_H - \overline{u})^2 - ((1-m)v_L + mv_H - \overline{u})^2} \\
q_{2,L}(0) &= \frac{1}{2}(v_L - \overline{u})
\end{aligned} \tag{30}
$$

When there exists some cutoff value m_0, such that for all $0 \le m \le m_0$, we have $q_{2,H}(1) \le q_{2,L}(0)$; and for all $m_0 \le m \le 1$, we have $q_{2,H}(1) \ge q_{2,L}(0)$. $\square$

A4. Microfoundation for Naive Consumers

We provide a microfoundation for the behavior of naive consumers. A naive consumer faces uncertainty regarding who is the competitor of the firm, the true value of the high- and low-quality products, or other parameters. All these uncertainties can be summarized as noise in price perception. Let p_θ denotes the actual price set by the firm $\theta \in \{High, low\}$. A naive consumer perceive the price $p^* = p_H + \xi$ where ξ follows a normal distribution with mean zero and standard error σ. A larger σ means that the naive consumer face a larger uncertainty regarding the market fundamentals.

Let $q \geq 0$ denote the total number of reviews prior to the current period. Let $g \geq$ denote the number of positive reviews. Then, we can calculate the naive consumer's belief on the probability that the firm is high-quality upon observing p^*, q, and g, using the Bayes rule:

$$\Pr(\theta = H | p^*, g, q) = \frac{\lambda_0 a^g (1-a)^{q-g}}{\lambda_0 a^g (1-a)^{q-g} + (1-\lambda_0) b^g (1-b)^{q-g} \exp(\frac{(p^*-p_H)^2-(p^*-p_L)^2}{2\sigma^2})}$$

Here, $\lambda_0 \in [0,1]$ is the prior probability that the firm is high-quality and the parameter $a \in [0,1]$ is the probability that a high-quality firm obtains a good reputation, and $b \in [0,1]$ is the probability that a low-quality firm obtains a good reputation.

As the noise in the price (σ) increases, the term $\exp(\frac{(p^*-p_H)^2-(p^*-p_L)^2}{2\sigma^2})$ converges to 1. Thus, the naive consumer's belief about the firm's true quality depends only on the number of positive and negative reviews. In the model, we assume σ is sufficiently large, and thus the signaling effect of prices is negligible for naive consumers.

B. Extension of Baseline Model

B1. Multiple periods

We can extend the model to $T \geq 2$ periods. We introduce the discount factor $\beta \in (0,1)$ for each period, and the firm wants to maximize the discounted total profit for all periods. Still, we focus on the set of equilibrium that satisfies the D1 criterion and use backward induction to solve the game.

Let Q_t be the total quantity sold by the end of period. Let g_t be the number of positive reviews by the end of period and $Q_t - g_t$ be the number of negative reviews. Assume there is only one consumer in each period, the probability of the consumer buying the product is denoted as q_t which depends on the reputation of the firm, the price and whether the consumer is naive or sophisticated. Then, based on the consumer reviews, a firm's probability of being a high quality would be:

$$\lambda(Q_t, g_t) = \frac{a^{g_t}(1-a)^{(Q_1-g_t)}\lambda_0}{a^{g_t}(1-a)^{(Q_1-g_t)}\lambda_0 + b^{g_t}(1-b)^{(Q_1-g_t)}(1-\lambda_0)} \tag{31}$$

Then, we can have the following proposition:

Proposition 4. *In the multiple-period model, there is a unique PBE that survives the D1 criterion. In this PBE, if there is a period t_0, such that firm H sets a higher price than firm L, then for all*

$t' > t_0$, *firm H always sets a higher price than firm L.*[19]

The intuition is that D1 criterion guarantees a unique separating equilibrium in every subgame. Then by backward induction, the PBE in the entire game is also unique. As the firm accumulates more and more consumer reviews, the marginal change in reputation in respond to an additional positive (negative) review would decrease. So, if there is one period such that $c_H > k_{H,t} + k_{L,t}$, it also holds for all later periods. This observation represents an endogenous ending of the reputation building stage. The high quality firm would not set low price after that. The length of the reputation building stage depends on the accuracy of consumer review and the fraction of naive consumer. The more accurate the consumer reviews, the shorter the reputation building stage. The more naive consumer, the shorter the reputation building stage. Unfortunately, due to the data frequency, we are unable to directly test this prediction.

Proof: Only the separating equilibrium survives the D1 criterion, so we only need to check for each period, whether it is the high quality firm sets higher price or the high quality firm sets lower price. Again, a sophisticated consumer believe if the firm sets a separating price of the high quality firm, then regardless of its previous history and customer reviews, it must be a high-quality firm. Otherwise it is a low-quality firm. Let π_{t+1} denote the sum of discounted profit from period $t+1$ to period T.

$$
\begin{aligned}
\Phi^*_{t+1}(q_1, H) &= q_1[a\pi^*_{t+1}(H, H, \lambda(Q_t, g_t + 1)) \\
&\quad + (1-a)\pi^*_{t+1}(H, H, \lambda(Q_t + 1, g_t))] \\
&\quad + (1-q_1)\pi^*_{t+1}(H, H, \lambda(Q_t, g_t)) \\
&= q_1 k_{H,t}(Q_t, g_t) + \pi^*_{t+1}(H, H, \lambda(Q_t, g_t)) \\
\Phi^*_{t+1}(q_1, L) &= q_1[a\pi^*_{t+1}(L, L, \lambda(Q_t, g_t + 1)) \\
&\quad + (1-a)\pi^*_{t+1}(L, L, \lambda(Q_t + 1, g_t))] \\
&\quad + (1-q_1)\pi^*_2(L, L, \lambda(Q_t, g_t)) \\
&= -q_1 k_{L,t}(Q_t, g_t) + \pi^*_{t+1}(L, L, \lambda(Q_t, g_t)),
\end{aligned}
\tag{32}
$$

where $k^*_{H,t}$ and $k^*_{L,t}$ are functions of the total number of positive and negative reviews. They have the following expression.

(33)

$$
\begin{aligned}
k^*_{H,t}(Q_t, g_t) &= [a\pi^*_{t+1}(H, H, \lambda(Q_t, g_t + 1)) + (1-a)\pi^*_{t+1}(H, H, \lambda(Q_t + 1, g_t))] - \pi_{t+1}(H, H, \lambda(Q_t, g_t)) \\
-k^*_{L,t}(Q_t, g_t) &= [b\pi^*_{t+1}(L, L, \lambda(Q_t, g_t + 1)) + (1-b)\pi^*_{t+1}(L, L, \lambda(Q_t + 1, g_t))] - \pi_2(L, L, \lambda(Q_t, g_t))
\end{aligned}
$$

The profit functions $\pi^*(\cdot)$ are recursive and depends on all future period consumer reviews. Then, we can show the uniqueness of the PBE that survives the D1 criterion by using backward induction. Again, we assume away the knife edge case where $c_H = \beta(k^*_{H,t} + k^*_{L,t})$ for all $t \in \{1, 2, ...T\}$ through

[19] Assume away the possibility of $c_H = k_{H,t} + k_{L,t}$ for all t.

this section. In this game, the history is the realized customer reviews. For each realization of period T customer review, there is a corresponding unique separating equilibrium in the last period. Then, anticipating the last period game, the firms in $T-1$ period chooses the optimal price. So, $k_{H,T-1}(Q_{T-1}, g_{T-1})$ and $k_{L,T-1}(Q_{T-1}, g_{T-1})$ are also unique for each level of Q and g. Using the same way of backward induction, the equilibrium in all the subgame are unique. So the entire equilibrium is also unique. We proceed to show the second part of the proposition. We know that in a period, firm H would set a price lower than firm L in period t if and only if the following inequality holds:[20]

$$c_H < \beta(k_{H,t} + k_{L,t}).$$

If a separating equilibrium arises in period 1, then in all future periods, the sophisticated consumers can tell the firm's type with certainty. The only reason for firm H to set lower price is to accumulate positive reviews and appeal to the naive consumers.

We want to show that if there is a period t_0, such that $c_H > \beta(k_{H,t_0}(Q_{t_0}, g_{t_0}) + k_{L,t_0}(Q_{t_0}, g_{t_0}))$, then, for all $t' > t_0$, we have $c_H > \beta(k_{H,t'}(Q_{t'}, g_{t'}) + k_{L,t'}(Q_{t'}, g_{t'}))$ The reason is as follows.

Case 1. If there is no sales in period t_0, the firm enters the period t_0+1 with the same reputation, but one less period of market. Thus, the future market profit must be less responsive to the t_0+1 period's sales. So, we have the following inequality: $c_H > k_{H,t_0}(Q_{t_0}, g_{t_0}) + k_{L,t_0}(Q_{t_0}, g_{t_0}) > k_{H,t_0+1}(Q_{t_0}, g_{t_0}) + k_{L,t_0+1}(Q_{t_0}, g_{t_0})$ Thus, in period t_0+1, the high quality firm must set higher price.

Case 2. If there is one more sales in period t_0, then according to the propriety of Bayesian update, the marginal effect of one additional positive (negative) review on the reputation is weakly decreasing with the total number of positive and negative reviews. In other word, the value of $\lambda(Q, g+1) - \lambda(Q, g)$ is decreasing in g and Q. similarly, the value of $\lambda(Q+1, g) - \lambda(Q, g)$ is also decreasing in g and Q. Also, since there is one less period of market remain, we must have:

$c_H > k_{H,t_0}(Q_{t_0}, g_{t_0}) + k_{L,t_0}(Q_{t_0}, g_{t_0}) > k_{H,t_0+1}(Q_{t_0}+1, g_{t_0}) + k_{L,t_0+1}(Q_{t_0}+1, g_{t_0})$, if the consumer in t_0 writes a negative review.

$c_H > k_{H,t_0}(Q_{t_0}, g_{t_0}) + k_{L,t_0}(Q_{t_0}, g_{t_0}) > k_{H,t_0+1}(Q_{t_0}+1, g_{t_0}+1) + k_{L,t_0+1}(Q_{t_0}+1, g_{t_0}+1)$, if the consumer in t_0 writes a positive review. Thus, in period t_0+1, firm H also sets a higher price than firm L.

We can apply similar reason for all future periods and all outcomes of customer reviews. But in each period, firm H always sets a higher price than firm L. □

B2. Multiple consumers with independent reviews

In the baseline model, we consider the case of a representative consumer. Here, we have a brief discussion of the case of multiple consumers making independent purchasing decisions. Assume

[20] We assume away the knife-edge case where $c_H = \beta(k_{H,t} + k_{L,t})$.

that in each period, there are n consumers. Each consumer has an independent preference shock $\epsilon \in [-v_H, 0]$ and chooses whether to buy the product. A consumer can be one of two types: sophisticated and naive. Same as the baseline model, the naive consumer cannot infer quality firm price signaling, while the sophisticated consumers can. With probability m the consumer is naive, with probability $1-m$ the consumer is sophisticated.

In period 1, a naive consumer purchases the product with probability $\lambda_0 v_H + (1-\lambda_0)v_L - \overline{u} - p_1 = \overline{v}(\lambda_0) - \overline{u} - p_1$. A sophisticated consumer purchase with probability $E(v|p_1) - \overline{u} - p_1$ Hence, period-1 sales, q_1, is a random variable following a binomial distribution $B(n, \overline{v}(\lambda_0) - \overline{u})$ for firm L and $B(n, v_H - \overline{u})$ for firm H.

Assume that all consumers who buy the product will leave reviews. Let $g(\theta, q_1)$ be a random variable that denotes the number of positive reviews the firm receives when the firm's true type is θ and the period-1 sales is q_1. Let $q_1 - g(\theta, q_1)$ denotes the number of negative reviews in period 2. Recall that a is the probability that a consumer gives firm H a positive review, and b is the probability of a consumer gives firm L a negative review. Hence, $g(H, q_1)$ follows a Binomial distribution $B(q_1, a)$, and $g(L, q_1)$ follows binomial distribution $B(q_1, b)$. By Bayes rule, the naive consumer's belief about the probability that the firm is high quality in period 2 is

$$\gamma_{nai}(q_1, g, \theta = H) = \frac{a^g(1-a)^{(q_1-g)}\lambda_0}{a^g(1-a)^{(q_1-g)}\lambda_0 + b^g(1-b)^{(q_1-g)}(1-\lambda_0)}. \tag{34}$$

$\lambda(\cdot)$ is strictly increasing with the number of positive reviews, and is strictly decreasing with the number of negative reviews.

We can use $\lambda(\cdot)$ and the distribution of g to the calculate the expected period-2 profit, $\Phi(q_1, \theta, \gamma_{so}, \gamma_{nai})$. Here, γ_{so} is the sophisticated consumers' believes about the firms type in period 2. Because the period-2 equilibrium is separating, $\theta = \gamma_s o$. $gamma_{nai}$ is the naive consumers' belief, which is calculated by the above Bayes rule.

Then we can solve model and obtain the equilibrium price and quality by simulation. Because there is no general formula to calculate the expected γ_{nai} under binomial distribution of positive reviews, we use numerical simulations to solve the model under specific parameters.

Let $a = 0.6, b = 0.4, n = 20, v_H = 0.8, v_L = 0.7, \overline{u} = 0, c_H = 0.01, m = 0.5$. Figure 9 shows how the expected period-2 profit varies with the period-1 sales. Firm H's period-2 profit increases with $q_{1,H}$, while firm L's period-2 profit decreases with the $q_{1,L}$.

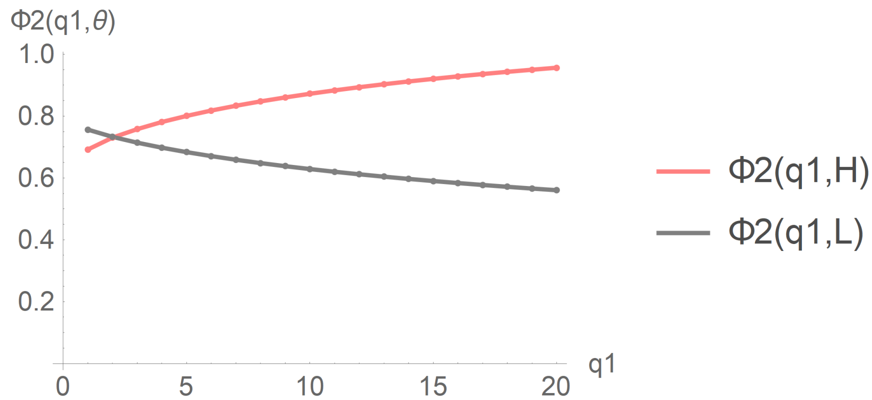

Figure 9: $\Phi(q_1, \theta)$ in the Numerical Example

We can numerically show that the low-intro-price equilibrium exists only when the marginal cost difference between firm H and firm L is small (c_H is close to zero). Fixing the other parameters as before, figure 10 shows that when c_H becomes sufficiently large, $p_{1,H}$ decreases to zero, which means the low-intro-price equilibrium stops to existing.

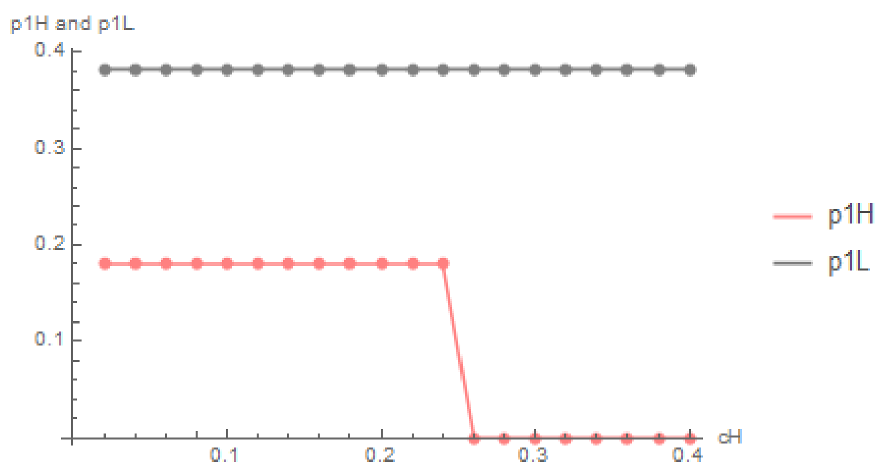

Figure 10: Equilibrium Prices versus Cost Difference

Lastly, Figure 11 shows how the introductory prices change with respect to the number of potential consumers. More consumers makes the period-2 prices more sensitive to period-1 prices, which means more accurate customer reviews. This the high quality firm does not need to set too low a price to deter mimicry. Consequently, both the firm H and firm L would set higher prices as n increases.

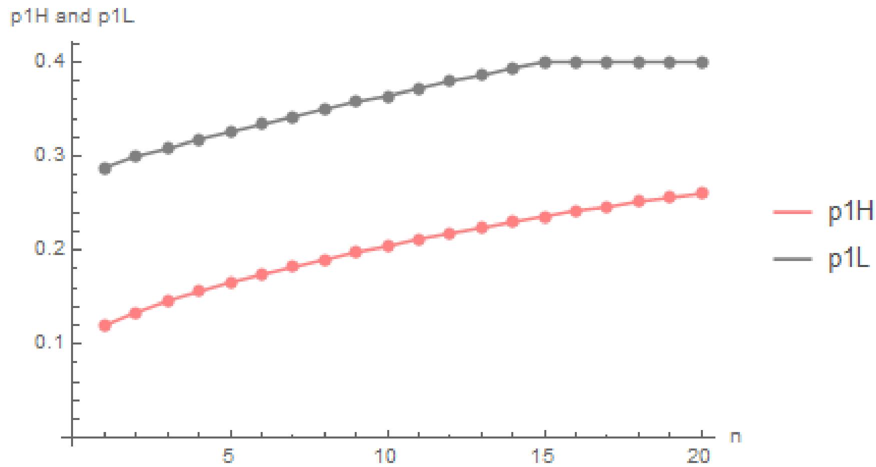

Figure 11: Equilibrium Prices versus Number of Potential Consumers

B3. RFF program

Our model can also be extended to incorporate "buying reviews" under RFF programs (Li, 2010). RFF programs allow sellers to reward consumers for leaving reviews. Most RFF programs are initiated by the platform and require the reviews to meet certain quality standards. Consumers will receive a rebate for either providing reviews. Consumers can observe whether a seller participates in the rebate program and the rebate amount, so participating in the RFF program can itself be a signal for quality.

In the baseline model, all consumer who buy the product would always provide reviews. To incorporate the incentive issue in RFF programs, we assume that the probability of a consumer leaving a review increases with the amount of the rebate. We also assume that a rebate is only provided in period 1 but not in period 2.

Let function $\xi : s \to [0, 1]$ be the probability of leaving a review given rebate amount s. After deciding to leave a review, the consumer leaves a positive review to firm H with probability a, and a negative review with probability $1 - a$; while the consumer gives a positive review to firm L with probability b and a negative review with probability review $1 - b$. We assume the reviews are informative, i.e., $a > b$.

Let s_H and s_L be the rebate that firm H and firm L pays for each review in period 1, respectively. In a separating equilibrium, the probability of the consumer buying the product and leaving a review is $q_1\xi(s_\theta) = (v_\theta - \overline{u} - p_{1,\theta} + s_\theta) \times \xi(s_\theta)$. Because q_1 and $\xi(s_\theta)$ both increase in s_θ, $q_1\xi(s_\theta)$ also increases in s_θ. This property is similar to the baseline model with q_1 decreasing in p_1. Therefore, we have the period-2 expected profit for each type of firms similar to (35):

(35)

$$E_\gamma[\pi_2(q_1|H,\gamma)] = q_1\xi(s_H)\Big[a\pi_2\big(q_1|H,H,\frac{a\lambda_0}{a\lambda_0+b(1-\lambda_0)}\big) + (1-a)\pi_2\big(q_1|H,H,\frac{(1-a)\lambda_0}{(1-a)\lambda_0+(1-b)(1-\lambda_0)}\big)\Big] + (1-q_1\xi(s_H))\pi_2(q_1|H,H,\lambda_0)$$

$$E_\gamma[\pi_2(q_1|L,\gamma)] = q_1\xi(s_L)\Big[b\pi_2\big(q_1|L,L,\frac{b(1-\lambda_0)}{a\lambda_0+b(1-\lambda_0)}\big) + (1-b)\pi_2\big(q_1|L,L,\frac{(1-b)(1-\lambda_0)\lambda_0}{(1-a)\lambda_0+(1-b)(1-\lambda_0)}\big)\Big] + (1-q_1\xi(s_L))\pi_2(\lambda_0|L,L,\lambda_0).$$

We can then use the same proof of our main proposition to obtain the values of s_H and s_L for the separating equilibrium. When the marginal costs of firm H and firm L are sufficiently close, the separating equilibrium exists and $s_H > s_L$, which means that firm H offers a higher rebate for a review than firm L does. Moreover, if all second period period-2 consumers are sophisticated, and can observe the period-1 rebate levels, then the separating equilibrium does not exists because both the firm L will have a strong incentive to participate and mimic firm H.

In our simple analysis above, we do not separately consider the signaling role of price and rebate. Price and rebate can play different role in a more complicated model with consumers having heterogeneous costs of writing reviews. The full discussion requires a separate paper.

C. Additional Tables

C1. Price Dispersion on Zaihang Platform

Table 8: Price Dispersion by Category and Year

	Coefficient of Variation					
year	2015	2016	2017	2018	2019	2020
Internet+	.7	1.08	2.79	1.04	1.11	1.08
Entrepreneurship	.71	.62	.61	1.97	.55	.55
Psychology	1.51	1.42	.86	1.13	1	.53
Investment	.43	.46	.46	1.01	1.01	.41
Education	.72	.61	.62	.6	.62	.62
Living	.82	.68	.65	.68	.81	.63
Career Development	1.23	1.12	0.83	1.68	.89	.72
Industry experience	.96	1.06	2.44	.75	.76	.62
Total	.89	.88	1.15	1.11	.84	.65

Note: We measure the price dispersion in each category and each year by the coefficient of variation (ratio of standard deviation over mean). This measure of price dispersion is also used in Sorensen (2000). The average coefficient is 0.89, which is much higher than the 0.22 in Sorensen (2000).

C2. High Low Ability Group Same Product Price from 2018 to 2020

Table 9: High Low Ability Group Same First Product Price from 2018 to 2021

	Mean		Difference
	low unobserved ability	high unobserved ability	
price.2018Q3	547.2402	494.0686	-53.1716^{*}
price.2020Q4	665.8167	588.6553	-77.1614^{**}
price.2021Q4	690.1593	611.8077	-78.3516^{**}

Note: The high-versus-low unobserved ability cutoff is the 50% unobserved ability derived from review.ratio in each category. This table shows that the relative same product price for the high and low ability groups does no change much from 2018 and 2020. There is almost no relative change from 2020 to 2021.

C3. Number of Products per Expert

Table 10: Number of Products

Product.number	Expert.num	Percentage (%)	Cum. (%)
1	4429	51.57	51.57
2	2615	30.45	82.02
3	1116	12.99	95.02
4	322	3.75	98.77
5	74	0.86	99.63
6	26	0.30	99.93
7	6	0.07	100.00
Total	8588	100	

C4. RFF Programs in Practice

Table 11: RFF Programs Among Leading Online Platforms

Company	RFF program	Region	Product Category	Market Cap	Revenue
Amazon	Yes	Global	General	1,668	386.06
Alibaba Taobao	Yes	China	General	619.84	71.99
Walmart.com	Yes	USA	General	407.84	
Meituan	Yes	China	General	219.63	17.68
Pinduoduo	Yes	China	General	167.04	4.33
Shopify	Yes	Canada	General	133.22	2.93
JD.com	Yes	China	General	115.96	114.97
Target.com	Yes	USA	General	88.4	
MercadoLibre	No	Latin America	General	73.6	
eBay	No	Global	General	41.33	10.27
Wayfair	Yes	USA	Homewares	31.92	14.15
Zalando	No	Europe	Fashion	27.37	7.98
Etsy	No	Global	Arts	25.3	1.7
Rakuten	Yes	Japan	General	19.34	13.48
Suning.com	Yes	China	General	13.47	38.06
ASOS.com	No	Global	Fashion	9.24	
Wish	Yes	Global	General	8.09	2.54
Ozon	Yes	Russia	General	7.1	1.39
Overstock	Yes	USA	General	2.89	2.55
Coolblue	No	Netherlands	General	2.89	2.55
Shopee	Yes	Southeast Asia	General		
Coupang	No	South Korea	General		6.23
Mercari	Yes	Japan, USA	General		
Otto Group	Yes	Germany	Fashion		14.1
Lazada	Yes	Southeast Asia	General		

Note: Market cap and revenue are 2020 data in billion USD. The data source is `www.markinblog.com/largest-ecommerce-companies`. Some RFF programs are initiated by the platforms. For example, the Amazon Vine program (`www.amazon.com/vine/about`) and Walmart.com Spark Reviewer program (`sparkreviewer.walmart.com`) invite trusted reviewers to provide reviews in exchange for free copies of products. Other programs are initiated by sellers. For example, JD.com and Meituan allow sellers to provide consumers with rewards or coupons in exchange for reviews.

C5. Comparison of Zhihu Matched Sample and Full Sample

Table 12: Comparison of Matched Sample and Full Sample

	Mean (full sample)	Mean (matched sample)	Difference
$Std.Abil^U$ (review ratio)	-0.0000	-0.1402	-0.1402^{***}
$Std.Abil^U$ (ability index)	0.0000	-0.1448	-0.1448^{***}
entry.year (2015 is year 0)	1.4932	1.1827	-0.3106^{***}
working.years	9.7465	9.5564	-0.1901
high.position	0.3093	0.2589	-0.0504^{***}
gender (male=1)	0.6887	0.7742	0.0855^{***}
age	37.5046	37.4492	-0.0554
appearance	58.0091	57.8179	-0.1912
Zhihu.like.per.answer		57.349	

C6. Zhihu Like Per Answer as the Ability Measure

Table 13: Introductory Price Regression on Zhihu Like Per Answer

	(1)	(2)
Dependent variable:	p^{intro}	$p^{intro'}$
	Panel A	
$Std.Abil^U$ (Zhihu Like 2022 Q1)	-35.646*	-42.112**
	(19.644)	(20.076)
Observations	263	263
R-Squared	0.020	0.018
	Panel B	
$Std.Abil^U$ (Zhihu Like 2014 Q4)	-8.083*	-10.309**
	(4.451)	(4.781)
Observations	263	263
R-Squared	0.018	0.016

Note: Columns (1) and (2) are based on regression specification (7) with observed ability measures, expert characteristics, subcategory fixed effects, and market-quarter fixed effects. The overall ability in Panel A is measured by Zhihu like per answer in 2022 Q1. The overall ability in Panel B is measured by the Zhihu like per answer in 2014 Q4. In column (1), the introductory price is the weighted average price when the expert has multiple introductory products (p^{intro}). In column (2), the introductory price is the price of the introductory product with the most sales ($p^{intro'}$). The sample includes the experts who have a Zhihu account by 2014 Q4 (before the Zaihang launches). Standard errors are in parenthesis. $***p < 0.01, **p < 0.5, *p < 0.1$.

D. Additional Figures

D1. Reviews on Zaihang

Figure 12: Reviews of an Expert on Zaihang

D2. Average Sales and Number of Experts on the Zaihang Platform

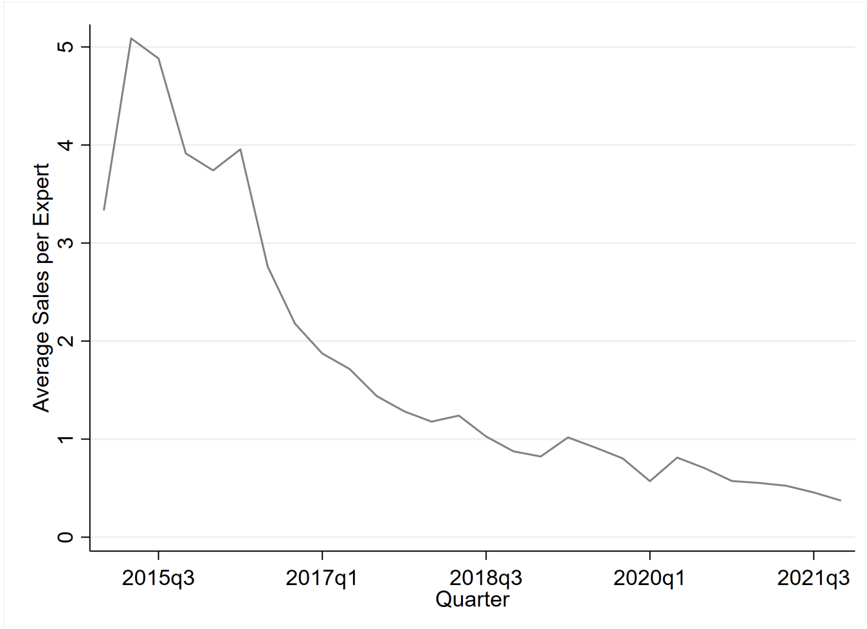

Figure 13: Average Sales by Quarter on Zaihang

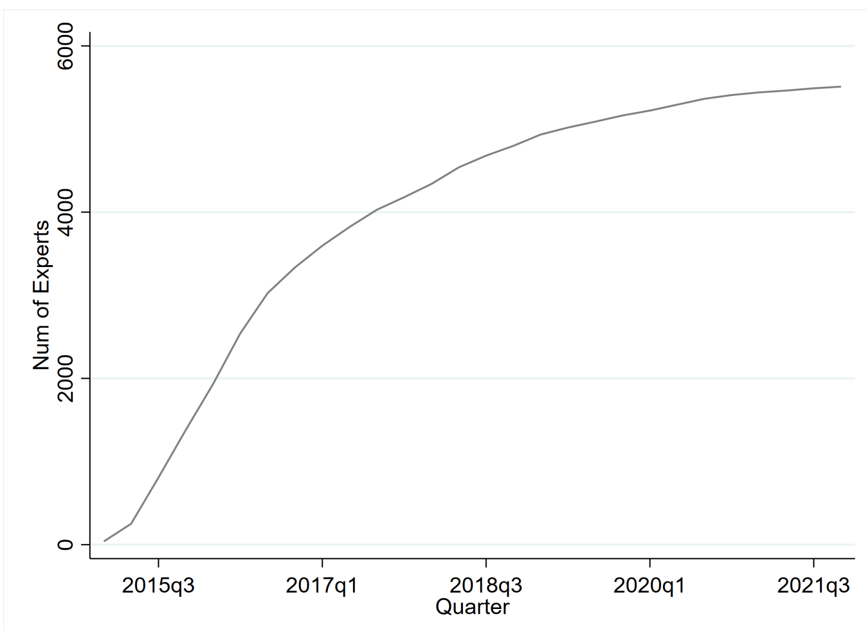

Figure 14: Active Expert Number by Quarter on Zaihang

D3. Product Differentiation on Zaihang

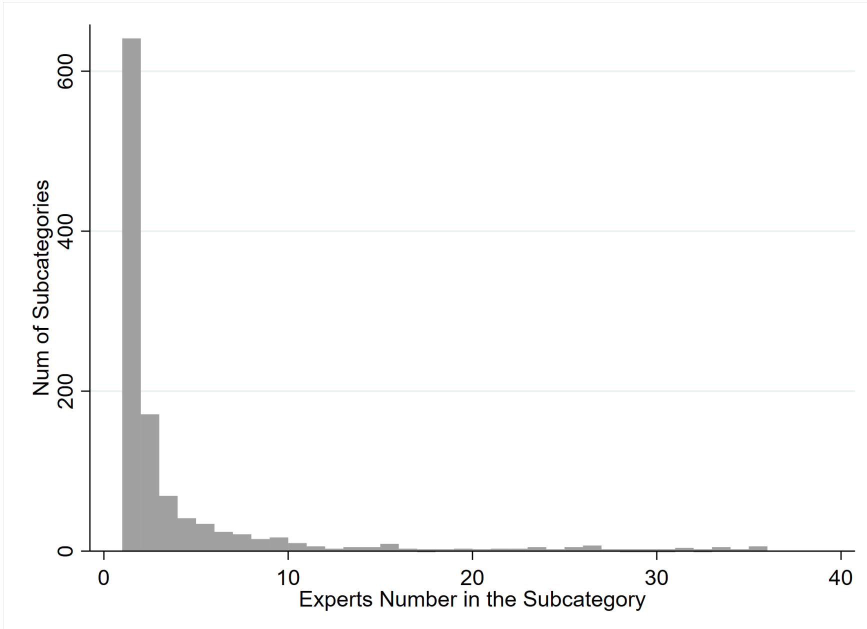

Figure 15: Number of Subcategories with a Few Experts

Note: We show the frequency of subcategories with different numbers of experts in the category. There are 882 subcategories with no more than three experts. This finding supports the assumption that the products are highly differentiated.

D4. New Clients on Zaihang

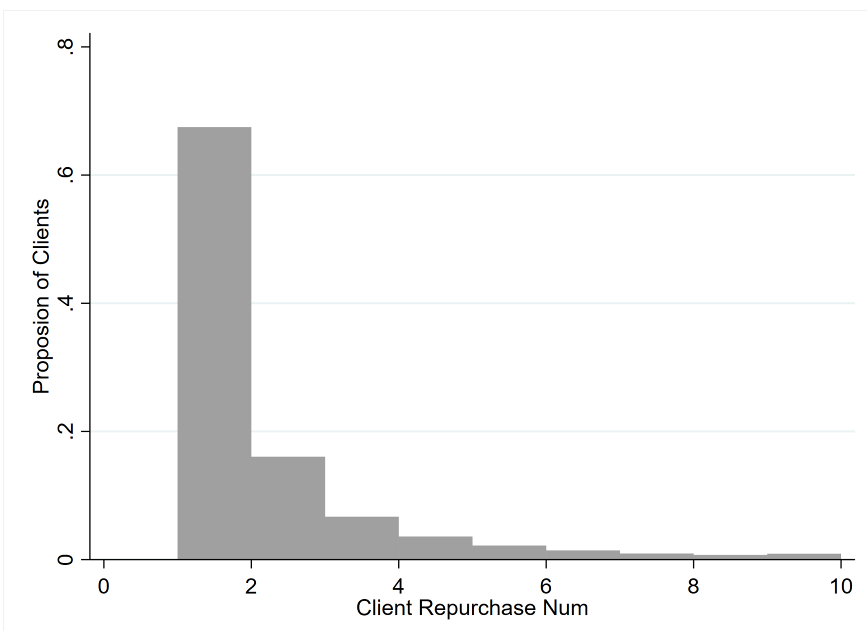

Figure 16: New Client Proportion on Zaihang

Note: 66.59% clients leave review only once in the data.

D5. Density Distribution of Unobserved Ability in Weighted Matched Sample

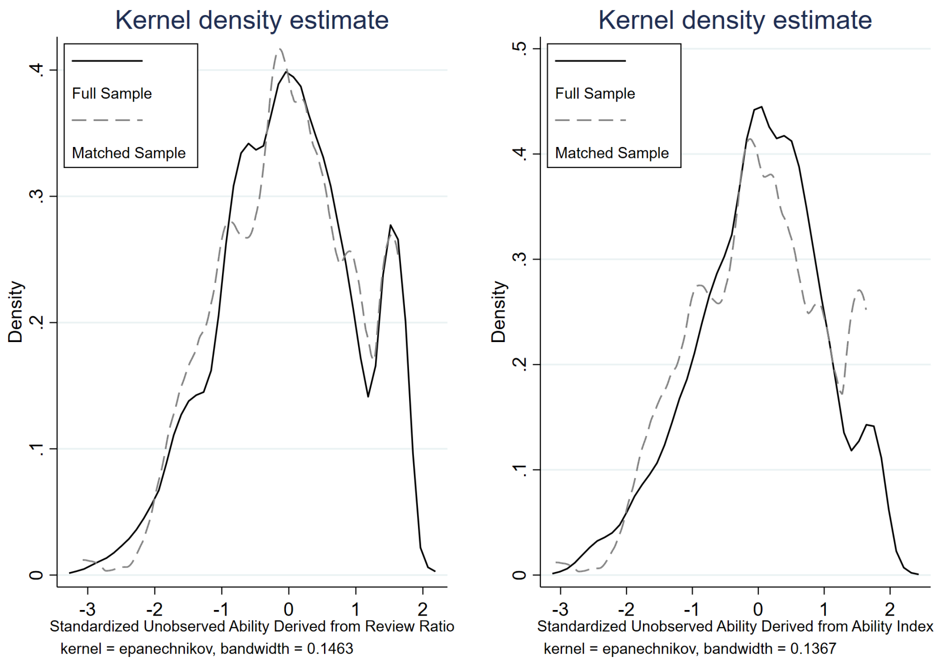

Figure 17: Density Distribution of Unobserved Ability in Weighted Matched Sample and Full Sample

D6. Density Distribution of First Product Price Change from 2018 to 2020

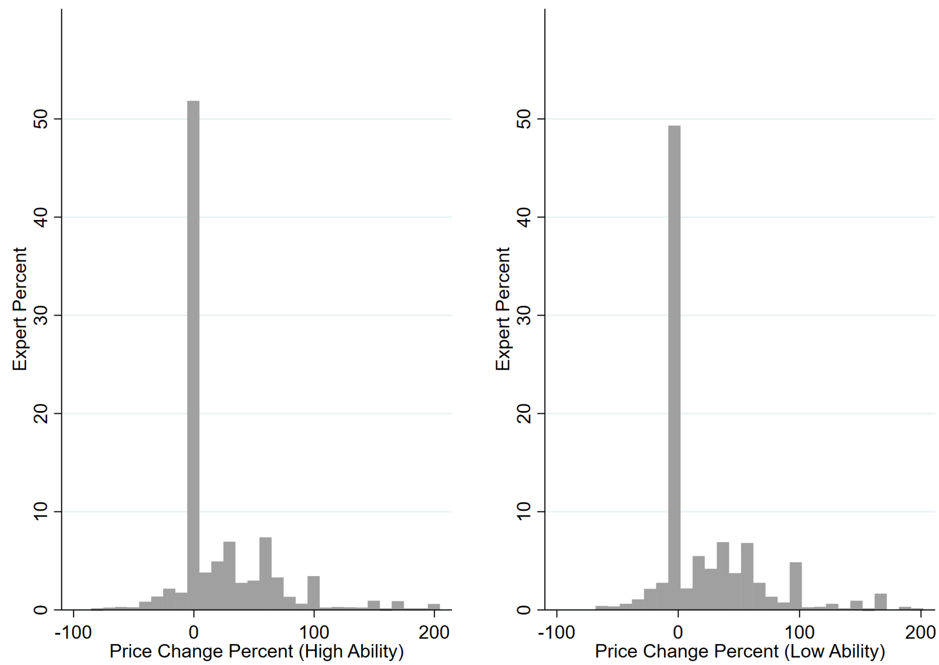

Figure 18: Density Distribution of First Product Price Change from 2018 to 2020

Note: The high-versus-low unobserved ability cutoff is the 50% unobserved ability derived from the review ratio in each category. 48.78% of high-unobserved-ability experts and 45.53% low-unobserved-ability experts do not change their prices from 2018 to 2020.

D7. Review Ratio Change from 2018 to 2020

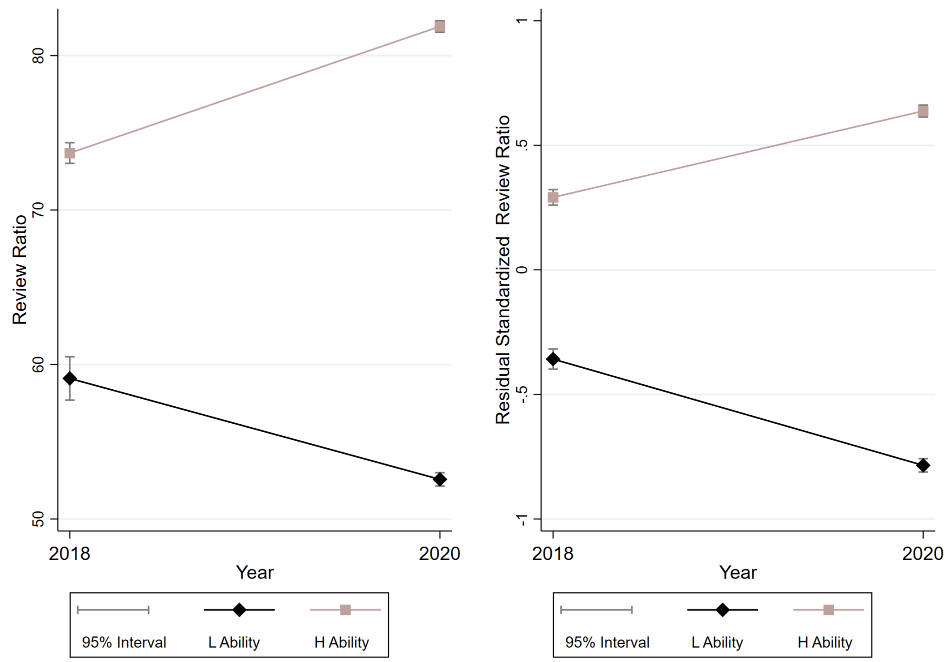

Figure 19: Review.Ratio Change from 2018 to 2020

Note: The high-versus-low unobserved ability cutoff is the 50% unobserved ability derived from the review ratio in each category in 2021. The residual standardized review ratio is the OLS regression residual after controlling the observed expert characteristics and market-quarter fixed effect.

D8. Average Revenue Comparison, Experts with High versus Low Unobserved Ability

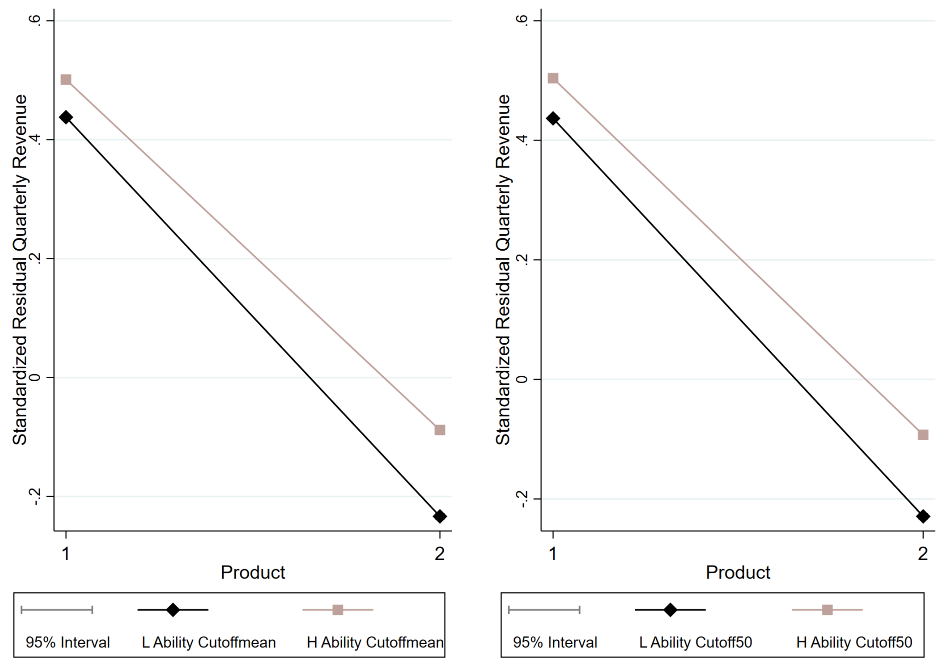

Figure 20: Review.Ratio Change from 2018 to 2020

Note: "Cutoff$x$" means high-unobserved-ability experts and low-unobserved-ability experts are divided by the x percentage point of $Std.Abil^U$. Experts within each group are weighted by the total sales. The revenue is the quarterly revenue.