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# WHEN DO CONSUMERS TALK?

By

Ishita Chakraborty, Joyee Deb, and Aniko Öry

August 2020

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# When do consumers talk?

Ishita Chakraborty, Joyee Deb and Aniko Öry\*

August 2020

## Abstract

The propensity of consumers to engage in word-of-mouth (WOM) differs after good versus bad experiences, which can result in positive or negative selection of user-generated reviews. We show how the dispersion of consumer beliefs about quality (brand strength), informativeness of good and bad experiences, and price can affect selection of WOM in equilibrium. WOM is costly: Early adopters talk only if they can affect the receiver's purchase. Under homogeneous beliefs, only negative WOM can arise. Under heterogeneous beliefs, the type of WOM depends on the informativeness of the experiences. We use data from Yelp.com to validate our predictions.

Keywords: costly communication, recommendation engines, review platforms, word of mouth

## 1 Introduction

Many consumption decisions are influenced by what we learn from social connections, driving the explosion of user-generated information online. Empirical research shows that user-generated reviews can significantly impact firm revenues.<sup>1</sup> This paper investigates a strategic motive behind providing reviews and explains how strategic communication affects the selection of user-generated content, and in turn a firm's pricing decision.

We find a striking pattern for restaurant reviews on Yelp.com: On a 5-star scale, the modal rating is 1 star (46.9% in our data) for national established chain restaurants, but 5 stars for comparable independent restaurants (41.2%). Unless there are large quality differences between chain and independent restaurants, this suggests positive or negative selection of content due to

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<sup>1</sup>See Chevalier and Mayzlin (2006); Luca (2016); Liu, Lee and Srinivasan (2019)

differences in the propensity to review after a positive versus a negative experience. A selection effect has implications on how review data should be interpreted.<sup>2</sup>

We develop a model of word-of-mouth (WOM) communication that explains how positive or negative selection of WOM information arises in equilibrium. We identify three determining factors: dispersion of consumer beliefs about quality, which in practice can be measured by brand strength, informativeness of good and bad experiences, and the split of surplus between consumers and the firm captured by the price.<sup>3</sup>

Formally, we consider early adopters of a monopolist’s product who each receive a private noisy binary quality signal. The monopolist sets its price and an early adopter can choose to share her signal with another potential consumer, and influence his purchase decision. We characterize positive and negative WOM behavior in pure-strategy perfect Bayesian equilibria.

Our key premise is that writing reviews is costly and early adopters share their experience only if they can instrumentally affect the purchase decision of the receiver of the message (“follower”). This assumption is motivated by research in psychology and marketing that highlights two complementary functions of WOM: First, WOM helps consumers acquire information when they are uncertain about a purchase decision. Second, people engage in WOM to enhance their self-image, causing them to share information with instrumental value because this improves the image of the sharer as being smart or helpful.<sup>4,5</sup>

The type of WOM that arises depends on the follower’s purchase decision in the absence of WOM. If the follower was likely to buy (not buy) in the absence of information, then there is no reason for an early adopter to engage in positive (negative) WOM after a good (bad) experience, but she may affect the follower’s action through negative (positive) WOM after a bad (good) experience.

The firm can use pricing to directly affect the follower’s ex ante purchase decision, which indirectly affects WOM. For instance, by setting a high (low) price, the firm can make followers less (more) likely to buy ex ante, causing early adopters to engage in positive (negative) WOM. Dispersion of consumer beliefs about quality also plays a critical role: If all followers have ex ante identical beliefs, then the firm and early adopters can anticipate the followers’ decision after receiv-

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<sup>2</sup>Reviews are well-known to be skewed (see Schoenmüller, Netzer and Stahl (forthcoming)). Chevalier and Mayzlin (2006) and Fradkin, Grewal, Holtz and Pearson (2015) document positive skews in user ratings for books and home rentals, respectively.

<sup>3</sup>Ke, Shin and Yu (2020) model brand strength as dispersion of beliefs focusing on positioning rather than vertical quality.

<sup>4</sup>See Berger (2014) for a survey. Grice, Cole, Morgan et al. (1975) also purport that conversations should provide relevant information, but not more than required.

<sup>5</sup>Gilchrist and Sands (2016) instead consider WOM that brings pleasure in itself.

ing a message. But, if beliefs of followers are heterogeneous for idiosyncratic reasons, then early adopters cannot predict the followers' decisions; some followers might buy after hearing positive WOM, while others might not buy despite positive news. This uncertainty crucially impacts both the equilibrium decision to engage in WOM and the optimal pricing decision.

First, we find that if all followers have the same point belief about quality, then positive WOM cannot arise. If the fraction of new adopters is small, it is optimal for the firm to induce negative WOM. Intuitively, this is driven by the way “no WOM” is interpreted. If followers expect only negative experiences to be shared, then no WOM becomes a positive signal. With few early adopters, no WOM is observed with high probability and this increases the belief about quality, and can be optimal. If the fraction of early adopters is above a threshold, then the number of early adopters with a negative signal increases, which decreases the benefit of a negative WOM equilibrium. In this case, the unique equilibrium involves no WOM.

Second, we consider followers with heterogeneous beliefs. The type of WOM in equilibrium now depends on the distribution of an early adopter's signal conditional on quality. We focus on equilibria when the fraction of new adopters is small. For the intuition, consider two extreme signal structures. If the signal structure is a “good news” process in that a positive experience is a strong signal for good quality, but a negative experience occurs with both good and bad quality, then the firm optimally sets a price that induces positive WOM. Conversely, for a “bad news” process, where a negative experience is very informative, the firm optimally induces only negative WOM.

Finally, using restaurant review data from Yelp.com and data on restaurant chains, we verify that our theory is consistent with empirical observation. We posit that consumers are likely to have homogeneous beliefs about restaurants that belong to a chain like Dunkin' with a strong brand image, but heterogeneous beliefs about independent restaurants like a new local coffee shop in New Haven. Controlling for restaurant and user characteristics, our regression shows that being a chain restaurant results in approximately a 1-star reduction in rating relative to a similar independent restaurant. We also show that the propensity of a review being negative increases with the age of brand and the number of stores which can thought of proxies for brand strength.

## 2 Literature Review

Early papers treat WOM as a costless diffusion process (Bass (1969)).<sup>6</sup> We contribute to the more recent literature about strategic WOM communication. Campbell, Mayzlin and Shin (2017) assume that senders talk to be perceived as knowledgeable, so that advertising crowds out the incentives to engage in WOM. Bialogorsky, Gerstner and Libai (2001) and Kornish and Li (2010) compare referral rewards and pricing as tools to encourage WOM. Kamada and Öry (2017) examine the role of contracts.<sup>7</sup> In contrast to these papers, we consider WOM not about the existence of a product, but about the experience, and we characterize the connection between optimal pricing and WOM.<sup>8</sup>

There is a growing literature that measures valence (i.e., positive versus negative), variance, and content of user-generated reviews. Chintagunta, Gopinath and Venkataraman (2010) show that an improvement in reviews leads to an increase in movie sales. Seiler, Yao and Wang (2017) document the impact of microblogging on TV viewership.<sup>9</sup> Chevalier and Mayzlin (2006) find that negative reviews have a larger effect on sales than positive reviews. Luca (2016) finds that a 1-star increase in Yelp ratings can decrease revenue by 5-9 percent for independent restaurants, but not for chain restaurants. Godes (2016) studies how the type of WOM affects investment in quality.<sup>10</sup>

This paper is the first to provide an information-theoretic foundation for what determines valence of WOM. The only other paper that studies different propensities to review after positive versus negative experiences is by Angelis, Bonezzi, Peluso, Rucker and Costabile (2012), who provide experimental evidence that consumers with a self-enhancement motive generate positive WOM, but transmit negative WOM about other peoples' experiences. Chakraborty, Kim and Sudhir (2019) study attribute selection in review texts.

Finally, we complement Hollenbeck (2018) who argues that the rise of review platforms has diminished the importance of branding.

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<sup>6</sup>The role of network structures is investigated by Galeotti (2010), Galeotti and Goyal (2009) and Leduc, Jackson and Johari (2017), who consider pricing and referral incentives. Campbell (2013) analyzes the interaction of advertising and pricing. See also Godes, Mayzlin, Chen, Das, Dellarocas, Pfeiffer, Libai, Sen, Shi and Verlegh (2005) for a survey.

<sup>7</sup>Relatedly, social learning models, e.g., Banerjee and Fudenberg (2004) and McAdams and Song (2018), allow for strategic actions.

<sup>8</sup>The WOM mechanism is similar to the incentive to search in Mayzlin and Shin (2011).

<sup>9</sup>See also Onishi and Manchanda (2012)

<sup>10</sup>Nosko and Tadelis (2015), Dhar and Chang (2009) and Duan, Gu and Whinston (2008) show that the volume of reviews matter. Sun (2012) shows that niche products have high variance in reviews.

### 3 Model

A firm produces a new product at a normalized marginal cost of zero. The quality  $\theta \in \{H, L\}$  of the technology is high ( $H$ ) with probability  $\phi_0 \in [0, 1]$ , and is unknown to the firm.<sup>11</sup> The firm faces a continuum of consumers of measure 1. A fraction  $\beta \in [0, 1]$  of consumers are *early adopters* (he) who try the product first and observe a realized quality signal  $q \in \{h, \ell\}$ . Given  $\theta$ ,  $q$  is drawn independently such that  $Pr(q = h|\theta = H) = \pi_H$  and  $Pr(q = h|\theta = L) = \pi_L$  where  $1 \geq \pi_H > \pi_L \geq 0$ . The remaining fraction  $1 - \beta$  of consumers are called *followers* (she). If the firm does not have a strong brand value, then a consumer's prior about  $\theta$  depends on idiosyncratic reasons. To capture this idea, we assume consumers' priors  $\phi$  are distributed according to cdf  $F$  on  $[0, 1]$  with  $\mathbb{E}^F[\phi] = \phi_0$ . We consider two cases:

*Homogeneous priors:* All followers have the same prior belief ( $F(\phi) = \mathbb{1}(\phi \geq \phi_0)$ ). This is a good assumption, for instance, for a product with a strong existing brand name.

*Heterogeneous priors:* We assume that  $F$  is twice continuously differentiable with  $F'' \geq 0$ .<sup>12</sup>

Consumers are randomly matched in pairs, and do not know if they are matched to an early adopter or a follower: A consumer is matched to an early adopter with probability  $\beta$ .<sup>13</sup>

**Timing and payoffs.** The game proceeds as follows:

1. The firm chooses price  $p$ .
2. Each early adopter decides whether to engage in WOM by sharing his signal ( $m = q$ ) or to remain silent ( $m = \emptyset$ ). Given realized quality  $q \in \{h, \ell\}$ , the message space is  $M_q := \{q, \emptyset\}$ , so communication is verifiable.<sup>14</sup> Engaging in WOM ( $m = q$ ) entails a cost  $c > 0$ . An early adopter gets utility  $r > 0$  if  $q = h$  and the matched consumer buys, or if  $q = \ell$  and the matched consumer does not buy.
3. Each follower updates her belief about  $\theta$ , and decides whether to buy. If she buys a high (low) quality product, she receives payoff  $1 - p$  ( $-p$ ). If she does not buy she gets 0.

<sup>11</sup>The Online Appendix considers a privately informed firm.

<sup>12</sup>We impose this assumption only to have a unique profit-maximizing price.

<sup>13</sup>One can think of this as two representative consumers being randomly picked who are most recently active on the review platform or individuals meeting off-line.

<sup>14</sup>We do not consider review manipulation as in Mayzlin, Dover and Chevalier (2014) and Luca and Zervas (2016).

Our modeling is motivated by the information acquisition motive of the follower and self-enhancement motive of the early adopter discussed in Berger (2014).  $r$  represents the utility of an enhanced self-image from providing information of instrumental value.<sup>15</sup>

**Histories, strategies, and equilibrium.** A firm’s strategy comprises a price  $p \in [0, 1]$ . An early adopter’s set of histories is  $\mathcal{H}^a = [0, 1] \times \{h, \ell\}$  and his WOM strategy  $\mu : \mathcal{H}^a \rightarrow M := M_h \cup M_\ell$  maps the price and signal  $q \in \{h, \ell\}$  to a message, where  $\text{supp}(\mu(p, q)) = \{q, \emptyset\}$ . A follower’s history is in  $\mathcal{H}^f = [0, 1] \times M \times [0, 1]$  and her purchasing strategy  $\alpha : \mathcal{H}^f \rightarrow \{\text{buy, not buy}\}$  maps  $p$ , the message received  $m \in M$  and her prior  $\phi$  to a purchasing decision. We consider *perfect Bayesian equilibria (PBE) in pure strategies*. A PBE comprises a tuple  $\{p, \mu, \alpha, \hat{\phi}\}$  such that all players play mutual best-responses given their beliefs about  $\theta$ , where  $\hat{\phi}(\phi, m)$  describe a follower’s posterior belief given prior  $\phi$  and message  $m$ . Let  $\mu_q(p) \in \{0, 1\}$  denote the probability with which an early adopter, who sees signal  $q$  and price  $p$ , engages in WOM in equilibrium. We omit  $p$  and write  $\mu_q$  if there is no ambiguity.

Let  $\xi := \frac{c}{r}$ . We assume  $1 - \beta > \xi$ , to rule out the trivial case of early adopters never engaging in WOM because they are unlikely to face a follower.

## 4 Equilibrium Characterization

We proceed by backwards induction and start with the sub-game after the price is set. We call this the “WOM subgame” and its equilibria “WOM equilibria.” Proofs are in the Appendix.

### 4.1 Word-of-Mouth subgame

**Purchase decision of a follower:** It is optimal for a follower with prior  $\phi$  and message  $m$  to purchase if and only if her expected utility from purchasing exceeds the outside option:

$$\hat{\phi}(\phi, m)\pi_H + (1 - \hat{\phi}(\phi, m))\pi_L - p \geq 0.$$

Let  $\Phi(p)$  denote the posterior belief that makes a follower indifferent:

$$\Phi(p) := \frac{p - \pi_L}{\pi_H - \pi_L}.$$

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<sup>15</sup>Restaurant reviewers on Yelp.com cite simplified decision-making for first-time visitors as one of the reasons for writing a review. See Carman (2018).



Then, a follower's best response is

$$\alpha(p, \phi, m) = \begin{cases} \text{buy} & \text{if } \hat{\phi}(p, \phi, m) > \Phi(p) \\ \text{buy or not buy} & \text{if } \hat{\phi}(p, \phi, m) = \Phi(p) \\ \text{not buy} & \text{otherwise} \end{cases} . \quad (\alpha)$$

A follower's posterior belief after message  $m \in \{h, \ell\}$  is  $\hat{\phi}(\phi, h) = \frac{\phi\pi_H}{\phi\pi_H+(1-\phi)\pi_L}$  and  $\hat{\phi}(\phi, \ell) = \frac{\phi\pi_H}{\phi\pi_H+(1-\phi)\pi_L}$ , respectively. If the early adopter sends no WOM message ( $m = \emptyset$ ), then the posterior depends on the equilibrium strategy of the early adopter captured by  $\mu_h$  and  $\mu_\ell$ :

$$\hat{\phi}(\phi, \emptyset) = \frac{\phi [1 - \beta + \beta (\pi_H(1 - \mu_h) + (1 - \pi_H)(1 - \mu_\ell))]}{1 - \beta + \phi\beta (\pi_H(1 - \mu_h) + (1 - \pi_H)(1 - \mu_\ell)) + (1 - \phi)\beta (\pi_L(1 - \mu_h) + (1 - \pi_L)(1 - \mu_\ell))}.$$

Note that  $\hat{\phi}(\phi, h) \geq \hat{\phi}(\phi, \emptyset) \geq \hat{\phi}(\phi, \ell)$ , but  $\hat{\phi}(\phi, \emptyset)$  can be higher or lower than the prior  $\phi$ . The follower gets “good news” about the product if  $\hat{\phi}(\phi, m) > \phi$  and “bad news” if  $\hat{\phi}(\phi, m) < \phi$ .<sup>16</sup>

Followers' posterior beliefs  $\hat{\phi}(\phi, m)$  and strategy  $\alpha$  define thresholds, such that after a message  $m$ , a follower purchases only if his prior is above this threshold. Let  $\bar{\phi}(p)$  be such that after  $m = \ell$ , it is optimal to buy if and only if  $\phi \geq \bar{\phi}(p)$ , i.e.,

$$\bar{\phi}(p) = \frac{1}{\frac{1-\pi_H}{1-\pi_L} \frac{1-\Phi(p)}{\Phi(p)} + 1}.$$

Similarly, let  $\underline{\phi}(p)$  be such that after  $m = h$ , it is optimal to buy if and only if  $\phi \geq \underline{\phi}(p)$ , i.e.,

$$\underline{\phi}(p) = \frac{1}{\frac{\pi_H}{\pi_L} \frac{1-\Phi(p)}{\Phi(p)} + 1}.$$

Finally, let  $\tilde{\phi}(p; (\mu_h, \mu_\ell))$  be such that after  $m = \emptyset$ , it is optimal to buy if and only if  $\phi \geq \tilde{\phi}(p; (\mu_h, \mu_\ell))$ , i.e.,

$$\tilde{\phi}(p; (\mu_h(p), \mu_\ell(p))) = \frac{1}{1 + \frac{1-\beta+\beta(\mu_h(p)(1-\pi_H)+\mu_\ell(p)\pi_H)}{1-\beta+\beta(\mu_h(p)(1-\pi_L)+\mu_\ell(p)\pi_L)} \frac{1-\Phi(p)}{\Phi(p)}},$$

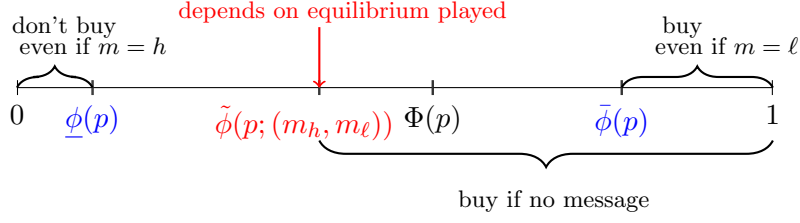
given message strategy  $(\mu_h(p), \mu_\ell(p))$ . Figure 1 summarizes these thresholds which characterize the follower's best response  $\alpha$ . We call a WOM equilibrium

1. *full WOM equilibrium* if  $\mu_h = \mu_\ell = 1$ . Then,  $\tilde{\phi}(p; (1, 1)) = \Phi(p)$ ;

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<sup>16</sup> $m \in \{h, \ell\}$  is verifiable and  $m = \emptyset$  is on-path since a follower is matched to another follower with positive probability.

Figure 1: Followers' decisions for given prior beliefs



2. *no WOM equilibrium* if  $\mu_h = \mu_\ell = 0$ . Then,  $\tilde{\phi}(p; (0, 0)) = \Phi(p)$ ;

3. *negative WOM* if  $\mu_h = 0, \mu_\ell = 1$ . Then,

$$\Phi(p) \geq \tilde{\phi}(p; (0, 1)) = \frac{1}{1 + \frac{1-\beta+\beta\pi_H}{1-\beta+\beta\pi_L} \frac{1-\Phi(p)}{\Phi(p)}};$$

4. *positive WOM* if  $\mu_h = 1, \mu_\ell = 0$ . Then

$$\Phi(p) \leq \tilde{\phi}(p; (1, 0)) = \frac{1}{1 + \frac{1-\beta+\beta(1-\pi_H)}{1-\beta+\beta(1-\pi_L)} \frac{1-\Phi(p)}{\Phi(p)}}.$$

The absence of WOM ( $m = \emptyset$ ) means “good news” in a negative WOM equilibrium, but “bad news” in a positive WOM equilibrium. The number of early adopters  $\beta$  determines the informativeness of  $m = \emptyset$ . It is a weaker signal, the less likely a follower is matched to an early adopter ( $\beta$  small).

**Early adopter's WOM decision:** Assume  $F$  has no mass point at  $\underline{\phi}(p), \bar{\phi}(p), \tilde{\phi}(p; (\mu_h, \mu_\ell))$  for  $\mu_h, \mu_\ell \in \{0, 1\}$ . Then, an early adopter who observes  $q = h$  weakly prefers to engage in WOM whenever

$$\underbrace{(1 - \beta)r(F(\tilde{\phi}(p; (\mu_h, \mu_\ell))) - F(\underline{\phi}(p)))}_{\text{benefit of talking if } q=h} \geq \underbrace{c}_{\text{cost of talking}}.$$

Similarly, if  $q = \ell$ , an early adopter weakly prefers to engage in WOM whenever

$$\underbrace{(1 - \beta)r(F(\bar{\phi}(p)) - F(\tilde{\phi}(p; (\mu_h, \mu_\ell))))}_{\text{benefit of talking if } q=\ell} \geq \underbrace{c}_{\text{cost of talking}}.$$

To characterize the WOM equilibrium, we call followers

*pessimistic*, whenever  $F(\Phi(p)) - F(\underline{\phi}(p)) \geq \frac{\xi}{1-\beta} \geq F(\bar{\phi}(p)) - F(\Phi(p))$ ;

*optimistic*, whenever  $F(\bar{\phi}(p)) - F(\Phi(p)) \geq \frac{\xi}{1-\beta} \geq F(\Phi(p)) - F(\underline{\phi}(p))$ ;

*uninformed* whenever  $F(\Phi(p)) - F(\underline{\phi}(p)), F(\bar{\phi}(p)) - F(\Phi(p)) \geq \frac{\xi}{1-\beta}$ ;

*well-informed* whenever  $F(\Phi(p)) - F(\underline{\phi}(p)), F(\bar{\phi}(p)) - F(\Phi(p)) \leq \frac{\xi}{1-\beta}$ .

Importantly, this definition is independent of the WOM equilibrium played.

**Lemma 1 (WOM sub-game)** *Let price  $p$  be such that  $F$  has no mass point at  $\underline{\phi}(p), \bar{\phi}(p), \tilde{\phi}(p; (\mu_h, \mu_\ell))$  for  $\mu_h, \mu_\ell \in \{0, 1\}$ . There exist thresholds  $\hat{\beta}^{neg}(p), \hat{\beta}^{pos}(p) > 0$  such that*

1. **A full WOM equilibrium** exists if and only if followers are uninformed.
2. **A no WOM equilibrium** exists if and only if followers are well-informed.
3. **A negative WOM equilibrium** exists for all  $\beta \in [0, 1]$  if followers are optimistic. For  $\beta < \hat{\beta}^{neg}(p)$ , a negative WOM equilibrium does not exist if buyers are not optimistic.
4. **A positive WOM equilibrium** exists for all  $\beta \in [0, 1]$  if followers are pessimistic. For  $\beta < \hat{\beta}^{pos}(p)$ , a positive WOM equilibrium does not exist if buyers are not pessimistic.

An early adopter incurs the WOM cost only if the followers' decision is affected with a sufficiently high probability. Thus, with pessimistic followers, early adopters with a positive experience have a strong incentive to talk, while those with a negative experience have a weaker incentive. Indeed, in that case, a positive WOM equilibrium exists and  $m = \emptyset$  is bad news. Similarly, with optimistic priors a negative WOM equilibrium exists. With well-informed followers, a large proportion of followers cannot be influenced, implying that there is no WOM. Analogously, with uninformed followers, the unique WOM equilibrium entails full WOM.

Multiplicity arises for large  $\beta$ . For example, with pessimistic followers, in a positive WOM equilibrium,  $m = \emptyset$  is bad news and is almost equivalent to  $m = \ell$ . Thus, a negative WOM equilibrium also exists. The case when  $F$  has mass-points at the thresholds, is considered in the proof of Proposition 1.

## 4.2 The firm's pricing decision

Finally, we consider the firm's pricing decision. Define  $\pi(\phi_0) := \phi_0\pi_H + (1 - \phi_0)\pi_L$  to be the firm's belief that an early adopter has a good experience.

### 4.2.1 Homogeneous priors

**Proposition 1 (No positive WOM under homogenous priors)** *In any pure-strategy equilibrium, negative WOM can be sustained in equilibrium if and only if*

$$\beta \leq \bar{\beta}^{hom} := \frac{(1 - \phi_0)\phi_0(\pi_H - \pi_L)^2}{(1 - \pi(\phi_0))(\pi(\phi_0) - (\phi_0\pi_H^2 + (1 - \phi_0)\pi_L^2))}.$$

*No WOM can be sustained if and only if  $\beta \geq \bar{\beta}^{hom}$ . No other WOM equilibria can be sustained.*

Intuitively, if all followers have the same belief, the firm can set a price low enough such that all followers buy in the absence of WOM. Can the firm improve upon this? For small  $\beta$ , the firm can increase the price if  $m = \emptyset$  is a weak good signal, which is the case in a negative WOM equilibrium. Followers who receive a negative signal will not buy, but for small  $\beta$ , there are only few such followers. If  $\beta$  is large, negative WOM is not worthwhile because too many followers receive the negative signal. Positive WOM is worthwhile only if the firm can charge a higher price to followers with a positive message. However, this is dominated by no WOM, where all consumers buy.

### 4.2.2 Heterogeneous priors

Next, consider heterogeneous priors, with  $F$  twice differentiable and  $F'' > 0$ . First, we define the profit-maximizing price absent any WOM by

$$p^* := \arg \max_p p(1 - F(\Phi(p))),$$

which is unique since  $1 - F(\Phi(p))$  is concave. Then, for sufficiently small  $\beta$ , there is a generically unique equilibrium.

**Proposition 2 (Heterogeneous Priors)** *Given  $\beta$ , the profit maximizing price  $\hat{p}(\beta)$  is continuous in  $\beta$  and  $\lim_{\beta \rightarrow 0} \hat{p}(\beta) = p^*$ . For thresholds  $\bar{\xi} := F(\bar{\phi}(p^*) - F(\Phi(p^*)))$ ,  $\underline{\xi} := F(\Phi(p^*)) - F(\underline{\phi}(p^*)) > 0$  and sufficiently small  $\beta$ , there is a generically unique pure strategy equilibrium.*

*If  $\xi < \min\{\underline{\xi}, \bar{\xi}\}$ , it entails full WOM. If  $\xi > \max\{\underline{\xi}, \bar{\xi}\}$ , no WOM arises. If  $\bar{\xi} > \underline{\xi}$  and for  $\xi \in (\underline{\xi}, \bar{\xi})$ , it entails negative WOM. If  $\bar{\xi} < \underline{\xi}$  and  $\xi \in (\bar{\xi}, \underline{\xi})$ , it entails positive WOM.*

Intuitively, as  $\beta \rightarrow 0$ , under any WOM regime, the demand converges uniformly to  $1 - F(\Phi(p))$ . Hence, the profit maximizing price in any equilibrium converges to  $p^*$ . The type of WOM is determined by where  $\xi$  lies relative to  $F(\Phi(p^*)) - F(\underline{\phi}(p^*))$  and  $F(\bar{\phi}(p^*) - F(\Phi(p^*)))$ . With heterogeneous

priors, we focus on small  $\beta$  due to the richness of equilibria, and because WOM is most relevant for new products where the number of adopters is still small.

To understand the role of the signal structure, consider the example of  $F = U[0, 1]$ . Then,  $\bar{\xi} = \frac{\pi_H(\pi_H - 2\pi_L)}{2(\pi_H - \pi_L)(2 - \pi_H - 2\pi_L)}$  and  $\underline{\xi} = \frac{\pi_H(\pi_H - 2\pi_L)}{2(\pi_H - \pi_L)(\pi_H + 2\pi_L)}$ . Note that  $\bar{\xi} > \underline{\xi} \Leftrightarrow 2\pi_L > 1 - \pi_H$ . Think about two limiting cases. Suppose  $\pi_L \approx 0$ , i.e., it is unlikely for a bad firm to be able to generate a good experience. Hence,  $q = h$  is particularly informative since it fully reveals that  $\theta = H$ : Examples are categories like independent restaurants where the consumer is discerning and is looking for specialized qualities. In such situations, negative WOM is never optimally induced by the firm, but positive WOM is induced for an intermediate range of WOM costs. For  $\pi_L = 0$  we have  $\bar{\xi} = \frac{\pi_H}{2(2 - \pi_H)} < \underline{\xi} = \frac{1}{2}$  and  $\bar{\xi}$  is increasing in  $\pi_H$ . Thus, positive WOM is optimal for a wider range of costs if  $\pi_H$  is also small.

Next, suppose  $\pi_H \approx 1$ . Then, a good firm can generate a positive experience with high likelihood. Here,  $q = l$  is particularly informative. Standard hotels or car rentals might fall into this category: Customers are happy as long as no major quality flaws such as cleanliness or terrible service occur. In this case,  $\bar{\xi} = \frac{1}{2(1 - \pi_L)} > \underline{\xi} = \frac{1 - 2\pi_L}{2(1 + \pi_L - 2\pi_L^2)}$  and  $\bar{\xi} - \underline{\xi}$  is increasing in  $\pi_L$ . Now, negative WOM is optimal for a wider range of costs if  $\pi_L$  is large. Finally, if  $\pi_H < 2\pi_L$ , then the firm induces no WOM because no signal is sufficiently informative about quality.

## 5 Empirical evidence

We now examine our theoretical prediction that with homogeneous priors no positive WOM can arise, while under heterogeneous priors and good news processes, positive WOM arises.

### 5.1 Data description

Restaurant review platforms are well-suited to validate our predictions. Restaurants are experience goods (Nelson, 1970; Luca, 2016), making recommendations from social contacts important.<sup>17</sup> Moreover, we can distinguish between homogeneous and heterogeneous priors. National chains have invested heavily to create a consistent brand resulting in homogeneous beliefs about quality. Alternately, independent one-outlet restaurants start out with more variance in consumer beliefs. Moreover, since restaurants lack strong loyalty programs, reviewers are unlikely to be motivated by referral rewards.

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<sup>17</sup>94 -97 % of US diners are influenced by online reviews as per Tripadvisor (2018)

We construct our dataset from Yelp Data Challenge 2017 and chain restaurant data. It contains reviews for restaurants in several North American cities (Pittsburgh, Charlotte, Las Vegas, Cleveland, Phoenix and Montreal) between 2004-2017. Every review involves unique business and reviewer identifiers, overall ratings, review text and timestamp. Business information includes name, location, price range. Reviewer characteristics incorporate experience, Elite membership and number of friends, fans and compliments. We identify 72 chains and cluster them into two categories, based on age of the chain and number of stores in the US: *national established chains* and *less-established chains*. Restaurant cuisines are derived from corporate reports and name-matching. We compare chains with independent restaurants of the same cuisine. Details about the data construction and additional results are in the Online Appendix.

## 5.2 Rating distributions

Table 1 shows that review-level average ratings are higher for independent restaurants (3.8) than for national chains (2.3) or less-established chains (3.1). The histogram of ratings in Figure 2 shows that national established chains receive a large number of 1-star reviews whereas independent restaurants receive mostly 4 and 5 star reviews. Consistent with our theory, the distribution for less-established chains is somewhere in between.

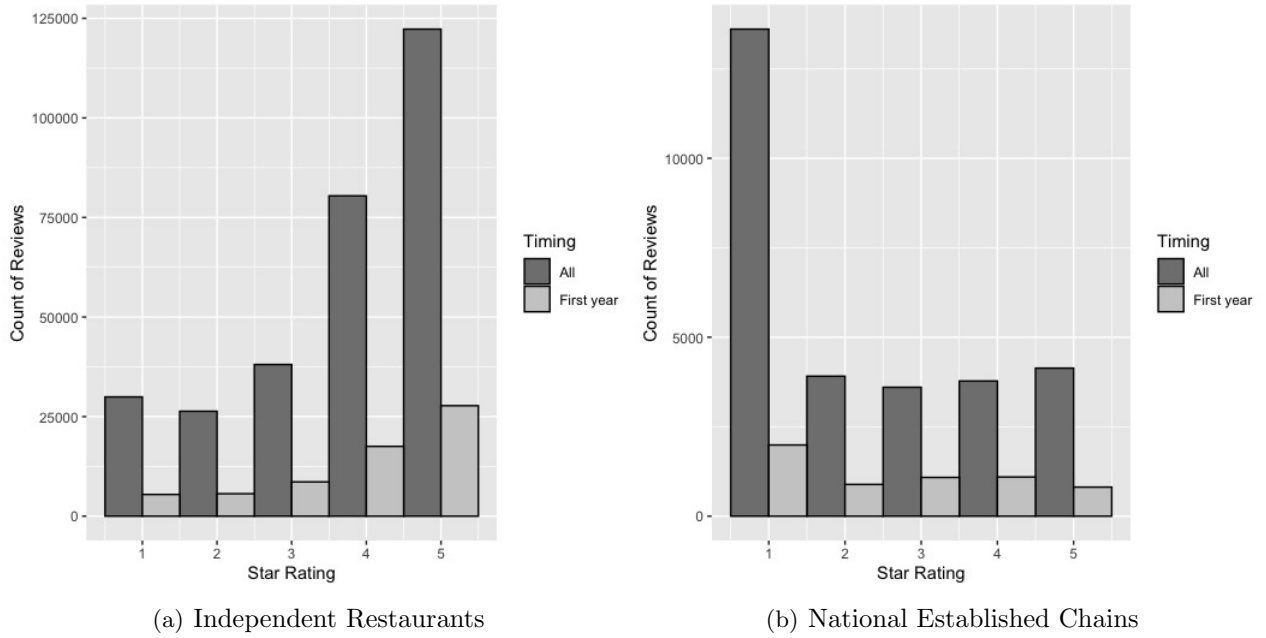
Table 1: Summary Statistics of Independent and Chain Restaurants

	Independent			National Chains			Less Estd Chains		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Age of Brand (Yrs)		NA		63	62	13	50	48	18
Stores in US ('000)		NA		15.8	15	5.9	1.9	1.0	2.5
Age of Store (Yrs)	3.4	3	2.9	2.9	3	2.3	3.9	4	2.8
Store Rating	3.54	3.91	0.55	2.46	2.27	0.7	2.9	3.1	0.6
Review Rating	3.8	4	1.3	2.3	2	1.5	3.1	3	1.5
No of Stores in Data		6228			2834			2913	
No of Reviews in Data		307,622			30,419			86,359	

Note: Store Rating is the average of the aggregate ratings at the individual store-level. Review rating is simply the average of all reviews. Thus, store rating gives equal weight to stores irrespective of review count. Differences in means are statistically significant ( $p < 0.00001$ ).

It is unlikely that these differences arise due to quality differences: Chain and independent restaurants have similar survival durations on the platform (Age of store in Table 1). Moreover, we find that for national established chains, the average rating at the individual store-level (2.46) is higher than the review-level average rating (2.34). The opposite holds for independent restaurants:

Figure 2: Histograms of Star Ratings: Independent versus Established National Chains



Note: The national established chains have a median brand age of 62 years and 15K stores in US (e.g., Burger King, Domino’s Pizza, Dunkin’ Donuts, KFC, McDonald’s, Pizza Hut and Subway). The dark grey bars show the distribution over the lifetime of the restaurant whereas the light grey bars show it only for the first year, which corresponds to small  $\beta$  in the model. The patterns are qualitatively similar.

The average store-level rating (3.54) is lower than average review-level rating (3.8). This indicates that the propensity to write a review for national established chain restaurants (independent restaurants) is higher (lower) after a bad (good) experience.

### 5.3 Chain effect on ratings

Next, we estimate the model specification

$$R_{ijt} = \beta_0 + \beta_1 \text{Chain}_j + \beta_2 X_j + \beta_3 U_i + \epsilon_{ijt}$$

where  $R_{ijt}$  denotes the rating of restaurant  $j$  by reviewer  $i$  at time  $t$ ,  $\text{Chain}_j$  captures whether restaurant  $j$  is a chain or not,  $X_j$  includes restaurant controls and  $U_i$  captures reviewer controls. We also estimate the impact of brand age and number of stores (coverage) since these can be proxies for the brand strength:

$$R_{ijt} = \beta_0 + \beta_1 \text{Brand age}_{jt} + \beta_2 \text{No of stores}_{jt} + \beta_3 X_j + \beta_4 U_i + \epsilon_{ijt}$$

where  $\text{brand age}_{jt}$  measures the age of chain  $j$  (0 for non-chains) at time  $t$ , and  $\text{no of stores}_{jt}$  is the number of stores of chain  $j$  in the year 2017.<sup>18</sup>

Table 2 shows that being a chain restaurant results in getting almost 1 star less than a similar independent restaurant. Further, the propensity to write a negative review increases with age of brand and number of stores: A 50 year older brand with thousands of additional stores will receive 0.5 lesser stars as compared to a new chain with very few stores. The chain and brand age effects are quite resilient controlling for different user characteristics though the magnitude of the chain effect is slightly reduced when we account for reviewer fixed effect. In the Online Appendix, we also show that a chain restaurant receives 8 fewer positive reviews in its first year than a comparable independent restaurant and 26 fewer positive reviews over its lifetime.

## 6 Conclusion

We propose a theoretical model of strategic WOM that explains how positive and negative WOM arises. We highlight three factors that determine equilibrium selection of positive versus negative WOM — dispersion of beliefs about quality, informativeness of good and bad experiences, and price.

On platforms like Yelp.com, users rely mostly on average ratings to sort. A practical implication of our results is that since the propensity to review varies after good or bad experiences based on the variance of beliefs, average reviews are not a reliable measure of quality. We leave for future work, the question of optimal design of review aggregation mechanisms.

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<sup>18</sup>We control for competition by including no of stores in the same zipcode but the effect was insignificant.



Table 2: Impact of Business and User Characteristics on Overall Rating

	<i>Dependent variable: Overall Rating</i>				
	rev_stars				
	(1)	(2)	(3)	(4)	(5)
Chain Dummy	-1.061*** (0.0641)	-1.062*** (0.0633)	-1.021*** (0.00958)		
Brand Age(Yrs)				-0.0104*** (0.000166)	-0.0106*** (0.000159)
No of Stores (US)				-0.0000435*** (0.000000871)	-0.0000380*** (0.000000831)
Age of Store(Yrs)	-0.0103** (0.00329)	-0.00834* (0.00365)	-0.0113*** (0.000813)	-0.0119*** (0.000865)	-0.0142*** (0.000807)
<b>Price Range</b>					
\$\$	-0.144*** (0.0338)	-0.143*** (0.0334)	-0.130*** (0.00585)	-0.148*** (0.00563)	-0.133*** (0.00543)
\$\$\$	0.0477 (0.0627)	0.0434 (0.0628)	0.0725*** (0.0128)	0.170*** (0.0131)	0.186*** (0.0126)
\$\$\$	0.161* (0.0755)	0.153* (0.0751)	0.196*** (0.0149)	0.267*** (0.0151)	0.293*** (0.0146)
<b>Price Range × Chain</b>					
\$\$ × Chain	0.255*** (0.0595)	0.258*** (0.0588)	0.255*** (0.0122)		
\$\$\$ × Chain	0.704** (0.245)	0.700** (0.242)	0.654*** (0.0556)		
\$\$\$ × Chain	0.724*** (0.162)	0.732*** (0.156)	0.614*** (0.0679)		
<b>Select Cuisines</b>					
burger	-0.0531 (0.0905)	-0.0548 (0.0895)	-0.0694** (0.0242)	0.184*** (0.0259)	0.136*** (0.0247)
chicken	-0.0563 (0.0837)	-0.0549 (0.0831)	-0.0232 (0.0282)	0.0328 (0.0296)	0.0459 (0.0283)
chinese	-0.165* (0.0741)	-0.162* (0.0736)	-0.167*** (0.0354)	-0.470*** (0.0378)	-0.482*** (0.0357)
coffee	0.296*** (0.0732)	0.293*** (0.0724)	0.275*** (0.0245)	0.534*** (0.0261)	0.482*** (0.0249)
dessert	0.407*** (0.0659)	0.401*** (0.0654)	0.376*** (0.0277)	0.314*** (0.0288)	0.291*** (0.0275)
pizza	-0.116 (0.0750)	-0.114 (0.0744)	-0.0855*** (0.0244)	0.157*** (0.0261)	0.143*** (0.0249)
sandwich	0.107 (0.0668)	0.103 (0.0655)	0.111*** (0.0245)	0.243*** (0.0262)	0.218*** (0.0251)
<b>Reviewer characteristics</b>					
Yelp Experience		0.0000620 (0.000229)		-0.000126 (0.000110)	
Elite Years		0.0263*** (0.00194)		0.0245*** (0.00209)	
N	418653	415423	418653	415423	418653
adj. R-sq	0.096	0.097		0.106	
User Fixed Effect	N	N	Y	N	Y

Note: Standard errors clustered by business

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Note: Restaurant controls include restaurant price range, cuisine and city, where the price range is calculated from user perceptions of a restaurant's price range. User controls include user experience in years, an Elite dummy and reviewer average rating from other reviews. To account for competition we further control for the city location of the restaurant. Specification (1) measures the chain effect without reviewer controls, (2) with reviewer controls, (3) with reviewer fixed effect, (4) and (5) measures the differential impact of brand age and no of stores for a chain brand. (4) and (5) establish that the chain effect is mainly driven by brand strength.

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## A Appendix: Proofs

### A.1 Proof of Lemma 1

Assume  $F$  has no mass point at any threshold.

In a *full WOM equilibrium*, a follower purchases after an  $\emptyset$ -message iff  $\phi \geq \Phi(p)$ . It exists iff an early adopter wants to talk after both  $q = \ell, h$ , i.e., exactly iff followers are uninformed.

Analogously, a *no WOM equilibrium* exists iff an early adopter does not want to talk regardless of his signal, i.e., exactly iff followers are well-informed.

In a *negative WOM equilibrium*,  $\tilde{\phi}(p; (0, 1)) \leq \Phi(p)$  is decreasing in  $\beta$ . It exists iff an early adopter does not want to talk with  $q = h$ , and wants to talk otherwise, i.e.,

$$\beta \in B^{\text{neg}}(p) := \left\{ \beta \in [0, 1] \mid F(\tilde{\phi}(p; (0, 1))) - F(\underline{\phi}(p)) \leq \frac{\xi}{1 - \beta} \leq F(\bar{\phi}(p)) - F(\tilde{\phi}(p; (0, 1))) \right\}.$$

For optimistic followers,  $B^{\text{neg}}(p) = [0, 1]$ , so negative WOM equilibria always exists.

If followers are not optimistic, since  $\lim_{\beta \rightarrow 0} \tilde{\phi}(p, (0, 1)) = \Phi(p)$  and  $\lim_{\beta \rightarrow 0} \frac{\xi}{1 - \beta} = \xi$ , there exists a threshold  $\hat{\beta}^{\text{neg}}(p) > 0$  such that  $\beta \leq \hat{\beta}^{\text{neg}}(p) \implies \beta \notin B^{\text{neg}}(p)$ . So, for  $\beta \leq \hat{\beta}^{\text{neg}}(p)$ , negative WOM equilibria cannot exist.

Analogously, in a *positive WOM equilibrium*,  $\tilde{\phi}(p; (1, 0)) \geq \Phi(p)$  is increasing in  $\beta$  and it exists iff

$$\beta \in B^{\text{pos}}(p) := \left\{ \beta \in [0, 1] \mid F(\bar{\phi}(p)) - F(\tilde{\phi}(p; (1, 0))) \leq \frac{\xi}{1 - \beta} \leq F(\tilde{\phi}(p; (1, 0))) - F(\underline{\phi}(p)) \right\}.$$

Hence, a positive WOM equilibrium always exists if followers are pessimistic and does not exists if  $\beta \leq \hat{\beta}^{\text{pos}}(p)$  for  $\hat{\beta}^{\text{pos}}(p) > 0$ .

## A.2 Proof of Proposition 1 and Proposition 2

The demand function depends on the WOM equilibrium played. In a full WOM equilibrium, the demand, defined as the probability of a follower buying, is given by

$$D^{\text{full}}(p) = (1 - \beta)(1 - F(\Phi(p))) + \beta (\pi(\phi_0)(1 - F(\underline{\phi}(p))) + (1 - \pi(\phi_0)) (1 - F(\bar{\phi}(p)))).$$

With no WOM,

$$D^{\text{no}}(p) = 1 - F(\Phi(p)).$$

With negative WOM,

$$D^{\text{neg}}(p) = (1 - \beta + \beta\pi(\phi_0)) (1 - F(\tilde{\phi}(p; (0, 1)))) + \beta(1 - \pi(\phi_0))(1 - F(\bar{\phi}(p))).$$

With positive WOM,

$$D^{\text{pos}}(p) = (1 - \beta + \beta (1 - \pi(\phi_0)))(1 - F(\tilde{\phi}(p; (1, 0)))) + \beta\pi(\phi_0)(1 - F(\underline{\phi}(p))).$$

### A.2.1 Proof of Proposition 1

$p$  determines whether followers are optimistic, pessimistic, well-informed, or uninformed, and Lemma 1 then pins down the type of WOM when no threshold is  $\phi_0$ , which we analyse separately.

We compute cutoffs  $p^{\text{neg}}, p^{\text{pos}}$  such that  $p < p^{\text{neg}} \Leftrightarrow \beta \in B^{\text{neg}}(p)$  and  $p < p^{\text{pos}} \Leftrightarrow \beta \in B^{\text{pos}}(p)$ .

1. If  $\phi_0 < \underline{\phi}(p)$ , then  $F(\underline{\phi}(p)) = F(\bar{\phi}(p)) = F(\Phi(p)) = 1$ . Followers are well-informed. No WOM is the unique equilibrium. Since profits are zero, the firm never induces this case.
2. If  $\underline{\phi}(p) < \phi_0 < \Phi(p)$ , then  $F(\underline{\phi}(p)) = 0 < F(\Phi(p)) = F(\bar{\phi}(p)) = 1$ . Followers are pessimistic. A positive WOM equilibrium exists for all  $\beta \in [0, 1]$ . Negative WOM arises iff  $F(\tilde{\phi}(p; (0, 1))) = 0$  or  $\tilde{\phi}(p; (0, 1)) = \phi_0$  which is satisfied iff

$$\tilde{\phi}(p; (0, 1)) \leq \phi_0 \Leftrightarrow \beta \geq \frac{\Phi(p) - \phi_0}{\Phi(p) - \phi_0 + (1 - \Phi(p))\phi_0\pi_H - \Phi(p)(1 - \phi_0)\pi_L} =: \hat{\beta}^{\text{neg}}(p).$$

Otherwise,  $F(\tilde{\phi}(p; (0, 1))) = 1$ . Hence,  $B^{\text{neg}}(p) = (\hat{\beta}^{\text{neg}}(p), 1 - \xi]$  and  $\hat{\beta}^{\text{neg}}(p) > 0$  if  $\Phi(p) > \phi_0$  because the denominator is strictly positive.

Finally, let  $p^{\text{pess}}$  be such that  $p < p^{\text{pess}} \Leftrightarrow \underline{\phi}(p) < \phi_0$ . It is defined implicitly by  $\phi_0 = \underline{\phi}(p^{\text{pess}})$

or  $p^{\text{pess}} = \frac{\phi_0 \pi_H^2 + (1 - \phi_0) \pi_L^2}{\phi_0 \pi_H + (1 - \phi_0) \pi_L}$ .  $\hat{\beta}^{\text{neg}}(p)$  is increasing in  $p$  and hence,  $\beta \geq \hat{\beta}^{\text{neg}}(p)$  iff

$$p \leq p^{\text{neg}} := \frac{\phi_0(\pi_H - \pi_L)(1 - \beta(1 - (\pi_H + \pi_L))) - \beta(1 - \pi_L)\pi_L + \pi_L}{1 - \beta(1 - (\phi_0 \pi_H + (1 - \phi_0) \pi_L))}.$$

One can show that for all  $\beta > 0$ ,  $p^{\text{pess}} > p^{\text{neg}}$ , so at any  $p < p^{\text{neg}}$  priors are pessimistic, but a negative WOM equilibrium can exist.

3. If  $\phi_0 = \underline{\phi}(p)$ , either a no or positive WOM equilibrium is played as 2.
4. If  $\Phi(p) < \phi_0 < \bar{\phi}(p)$ , then  $F(\underline{\phi}(p)) = F(\Phi(p)) = 0 < F(\bar{\phi}(p)) = 1$ , i.e., followers are optimistic. Full or no WOM equilibrium cannot exist. A negative WOM equilibrium exists for all  $\beta \in [0, 1]$ . Positive WOM exists iff  $F(\tilde{\phi}(p; (1, 0))) = 1$  or  $\tilde{\phi}(p; (1, 0)) = \phi_0$  which is satisfied iff

$$\tilde{\phi}(p; (1, 0)) \geq \phi_0 \Leftrightarrow \beta \geq \frac{\phi_0 - \Phi(p)}{\phi_0 - \Phi(p) + \Phi(p)(1 - \phi_0)(1 - \pi_L) - (1 - \Phi(p))\phi_0(1 - \pi_H)} =: \hat{\beta}^{\text{pos}}(p)$$

Otherwise,  $F(\tilde{\phi}(p; (1, 0))) = 0$ .  $\hat{\beta}^{\text{pos}}(p) > 0$  for  $\phi_0 > \Phi(p)$  for the same reason as  $\hat{\beta}^{\text{neg}}(p) > 0$  when followers are pessimistic. Hence,  $B^{\text{pos}}(p) = [\hat{\beta}^{\text{pos}}(p), 1 - \xi]$ .

Finally, let  $p^{\text{opt}}$  be such that  $p < p^{\text{opt}} \Leftrightarrow \Phi(p) < \phi_0$ . It is defined implicitly by  $\phi_0 = \Phi(p^{\text{opt}})$  or  $p^{\text{opt}} = \phi_0 \pi_H + (1 - \phi_0) \pi_L$ .  $\hat{\beta}^{\text{pos}}(p)$  is decreasing in  $p$  and hence,  $\beta \geq \hat{\beta}^{\text{pos}}(p)$  iff

$$p \geq p^{\text{pos}} := \frac{\phi_0(\pi_H - \pi_L)(\beta(\pi_H + \pi_L) - 1) + \pi_L(\beta\pi_L - 1)}{\beta(\phi_0(\pi_H - \pi_L) + \pi_L) - 1}$$

One can show that for all  $\beta \in (0, 1]$ ,  $p^{\text{pos}} < p^{\text{opt}}$ , i.e., if  $p < p^{\text{opt}}$ , both positive and negative WOM equilibria exist. Further,  $p^{\text{pess}} > p^{\text{opt}}$  because  $x \mapsto x^2$  is convex and  $p^{\text{neg}} > p^{\text{opt}}$ , i.e., the firm always sets the price as close as possible to  $p^{\text{neg}}$  ( $p^{\text{pess}}$ ) to induce negative (positive) WOM where followers are pessimistic.

5. If  $\phi_0 = \Phi(p)$ , both positive and negative WOM equilibria exist for all  $\beta > 0$ , since  $\tilde{\phi}(p; (0, 1)) < \phi_0 < \tilde{\phi}(p; (1, 0))$  for  $\beta > 0$ .
6. If  $\phi_0 > \bar{\phi}(p)$ , then  $F(\underline{\phi}(p)) = F(\Phi(p)) = F(\bar{\phi}(p)) = 0$ . Followers are well-informed. No WOM is the unique equilibrium. Such beliefs are induced iff

$$p < p^{\text{well}} := \frac{\pi(\phi_0) - (\phi_0 \pi_H^2 + (1 - \phi_0) \pi_L^2)}{1 - \pi(\phi_0)}$$

7. If  $\phi_0 = \bar{\phi}(p)$ , then either no one talks as in 6, or negative WOM arises as in 4.

Lastly, we compare profits. In a positive WOM equilibrium given  $p$ , profits are

$$\Pi^{\text{pos}}(p) := p D^{\text{pos}}(p) = p \beta \pi(\phi_0).$$

It is then straightforward to compute the maximal profit when positive WOM is induced is

$$\Pi^{\text{pos}}(p^{\text{pess}}) = \beta(\phi_0 \pi_H^2 + (1 - \phi_0) \pi_L^2).$$

Analogously, with negative WOM the maximum profit is

$$\begin{aligned} \Pi^{\text{neg}}(p^{\text{neg}}) &= (1 - \beta) \pi(\phi_0) + \beta(\phi_0 \pi_H^2 + (1 - \phi_0) \pi_L^2) \\ &> \Pi^{\text{pos}}(p^{\text{pess}}) \quad \text{for } \beta < 1. \end{aligned}$$

The maximal profit with no WOM is  $\Pi^{\text{no}}(p^{\text{well}}) = p^{\text{well}}$ . Negative WOM is an equilibrium iff  $\Pi^{\text{neg}}(p^{\text{neg}}) \geq \Pi^{\text{no}}(p^{\text{well}}) \Leftrightarrow \beta \leq \bar{\beta}^{\text{hom}}$ , and no WOM iff  $\beta \geq \bar{\beta}^{\text{hom}}$ . No other WOM equilibria can exist.

### A.2.2 Proof of Proposition 2

Given a WOM regime  $w \in \{\text{full, no, neg, pos}\}$ , the firm maximises  $\max_p p D^w(p)$ .  $D^w(p)$  uniformly converges to  $1 - F(\Phi(p))$ . Thus, for sufficiently small  $\beta$ , any profit-maximizing price is arbitrarily close to  $p^*$ . Denote an arbitrary sequence of solutions by  $p^w(\beta)$ . Let  $\bar{\xi} := F(\bar{\phi}(p^*)) - F(\Phi(p^*))$  and  $\underline{\xi} := F(\Phi(p^*)) - F(\bar{\phi}(p^*))$ . If  $\xi < \min\{\bar{\xi}, \underline{\xi}\}$ , then for sufficiently small  $\beta$

$$\xi < \min\{(1 - \beta)(F(\bar{\phi}(p^w(\beta))) - F(\Phi(p^w(\beta)))) , (1 - \beta)(F(\Phi(p^w(\beta))) - F(\phi(p^w(\beta))))\},$$

so that followers are well-informed, and Lemma 1 implies the unique equilibrium features no WOM.

The other three cases  $\xi > \max\{\bar{\xi}, \underline{\xi}\}$ ,  $\bar{\xi} > \xi > \underline{\xi}$ ,  $\bar{\xi} > \xi > \underline{\xi}$ , follow analogously.



# Online Appendix

(not for publication)

## When do consumers talk?

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### Privately informed firm

In the baseline model, we assumed that the firm was unaware of its quality when it set its price. This captures situations where the firm might be launching an entirely new product and does not know about product efficacy prior to a large-scale launch. However, in other settings, the firm may be aware of its quality at the time that it makes its pricing decision. The reader may wonder whether our insights extend to such settings. In this section, we consider a straightforward extension of the baseline model, now with private information. For simplicity, we focus on situations with few early adopters (small  $\beta$ ). Also, we consider the uniform distribution in the case of heterogeneous priors.

If firms set prices with private information about quality, then it can signal its quality through its price choices, and followers may update their beliefs about the firm's type. However, such signaling via prices cannot arise in a pure-strategy equilibrium, i.e., there is no fully separating equilibrium.<sup>20</sup> To see this, note that in a fully separating equilibrium, all buyers are willing to buy at any price  $p \leq \pi_H$ . Thus, if  $p_H > p_L$ , then the  $L$ -firm wishes to deviate to offering  $p_H$ . If  $p_L > p_H \geq \pi_L$ , then no one buys at the price  $p_L$  and the  $L$ -firm can increase profits by deviating to  $p_H$ . Consequently, any pure-strategy equilibrium must be pooling, that is both firm types choose the same price. In such an equilibrium, the posterior belief is independent of the observed price. We characterize the unique pooling equilibrium in which the  $H$ -type firm maximizes its profits. This equilibrium has similar features to the equilibrium constructed in Section 4. In particular, the WOM subgame is identical and Lemma 1 applies. However, the profit function differs, as a  $\theta$ -type firm can now calibrate demand using its private information about its quality. The following proposition is the analogous to the results in the baseline model.

**Proposition 3** *1. Consider a setting with homogeneous priors. For sufficiently small  $\beta$ , firms*

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<sup>20</sup>We conjecture that a semi-separating may exist if we allowed for mixed strategies.

induce a negative WOM equilibrium in any pooling equilibrium.

2. Consider a setting with heterogeneous priors and  $F = U[0, 1]$ . For sufficiently small  $\beta$ , in the  $H$ -optimal pooling equilibrium, given the same cutoff costs  $\bar{\xi}$  and  $\underline{\xi}$  as Proposition 2, the equilibrium entails full WOM if  $\xi \leq \min\{\underline{\xi}, \bar{\xi}\}$  and no WOM if  $\xi \geq \max\{\underline{\xi}, \bar{\xi}\}$ . Furthermore,

- if  $2\pi_L \geq 1 - \pi_H$ , then  $\bar{\xi} \geq \underline{\xi}$  and for  $\xi \in [\underline{\xi}, \bar{\xi}]$  the equilibrium entails negative WOM,
- if  $2\pi_L \leq 1 - \pi_H$ , then  $\bar{\xi} \leq \underline{\xi}$  and for  $\xi \in [\bar{\xi}, \underline{\xi}]$  the equilibrium entails positive WOM.

All in all, only the profit-maximizing price differs from the setting with symmetric information, but all WOM equilibria are unchanged.

**Proof.** We characterize the pooling equilibrium in which the  $H$ -type firm maximizes its profits. Because the price is not informative on equilibrium path, beliefs of the followers and early adopters are the same on equilibrium path whether or not the firm has private information. Hence, Lemma 1 applies unchanged. However, the induced demand functions faced by an  $\theta$ -type firm is now different, as the firm knows that it is a  $\theta$  type. Thus, for an equilibrium price  $p^*$ , the demand faced by a  $\theta$ -type firm in a no, full, negative, and positive WOM equilibrium, respectively is:

$$\begin{aligned}
D^{\text{no}}(p; \theta) &= 1 - F(\Phi(p)) \\
D^{\text{full}}(p; \theta) &= \beta (\pi_\theta(1 - F(\underline{\phi}(p))) + (1 - \pi_\theta) (1 - F(\bar{\phi}(p)))) \\
&\quad + (1 - \beta) (1 - F(\Phi(p))), \\
D^{\text{neg}}(p; \theta) &= (1 - \beta + \beta\pi_\theta) (1 - F(\tilde{\phi}(p; (0, 1)))) + \beta(1 - \pi_\theta)(1 - F(\bar{\phi}(p))) \\
D^{\text{pos}}(p; \theta) &= (1 - \beta + \beta(1 - \pi_\theta))(1 - F(\tilde{\phi}(p; (1, 0)))) + \beta\pi_\theta(1 - F(\underline{\phi}(p))).
\end{aligned}$$

1. We start with the case of homogeneous priors  $F = \mathbb{1}(\phi \geq \phi_0)$ . Since the WOM stage is identical the baseline case, points 1-7 of the proof of Proposition 1 apply here too. However, the profits differ and are given by the following. The maximal profit of and H-type firm when positive WOM is induced is given by

$$\Pi^{\text{pos}}(p^{\text{pess}}; H) := p^{\text{pess}} \beta \pi_H = \frac{\phi_0 \pi_H^2 + (1 - \phi_0) \pi_L^2}{\pi(\phi_0)} \beta \pi_H.$$

The maximal profit of an H-type firm when negative WOM is induced is given by

$$\begin{aligned}\Pi^{\text{neg}}(p^{\text{neg}}; H) &:= p^{\text{neg}} (1 - \beta + \beta\pi_H) \\ &= \frac{\phi_0(\pi_H - \pi_L)(1 - \beta(1 - (\pi_H + \pi_L))) - \beta(1 - \pi_L)\pi_L + \pi_L}{(1 - \beta + \beta\pi(\phi_0))} (1 - \beta + \beta\pi_H) \\ &> \Pi^{\text{pos}}(p^{\text{pess}})\end{aligned}$$

for sufficiently small  $\beta$ . The maximal profit with no WOM is given by

$$\Pi^{\text{no}}(p^{\text{well}}; H) := \frac{\pi(\phi_0) - (\phi_0\pi_H^2 + (1 - \phi_0)\pi_L^2)}{1 - \pi(\phi_0)} < \Pi^{\text{neg}}(p^{\text{neg}}; H)$$

for sufficiently small  $\beta$ . Hence, for sufficiently small  $\beta > 0$ , there can only be negative WOM. No other WOM equilibria can be sustained.

2. For the uniform distribution,  $F$  is the identity function. Again an analogous argument to the proof of Proposition 2 can be applied with the adjusted demand and profit functions. Note, that the profit-maximizing price as  $\beta$  tends to zero is, however, identical and equal to  $\frac{\pi_H}{2}$ . Hence, the exact same proof can be applied. ■

## Dataset creation

Our main dataset is from Yelp Data Challenge (Yelp.com, 2017). Yelp.com was started in 2004 and is now present in 31 countries, with 214 million customer reviews and over 5.2 million unique businesses listed (Yelp Investor Relations Q2 2020) which are local businesses like restaurants, spas, grocery shops etc. The dataset shared in the challenge is a subset of the full Yelp Dataset and has around 1.2 million restaurant reviews mainly from North America and Canada.

We augmented this dataset with some additional variables to test our main hypothesis — how priors impact reviews. We identified 72 chain restaurants, firstly by creating a list of restaurants names that had presence in multiple locations. We then verified this list using surveys like ACSI (American Customer Satisfaction Index) and US restaurant and food service industry dossier (statista.com). We used these data sources to further identify the establishment date of each restaurant and number of US locations. We also validated this information from corporate websites of major chains like Subway, Pizza Hut etc. While we could get the exact number of locations year-wise for major chains like Subway and McDonald's, this data was not available for lesser-known chains. So we decided to use the number of stores in US in a particular year (2017) for which

we could get data for most chains. We dropped few of the lesser-known chains for which reliable information on date of establishment and no of stores was not available.

We also added a cuisine variable as the baseline rating could vary based on a certain cuisine’s popularity in a city. It is fairly easy to get the cuisine of corporate chain restaurants. For independent restaurants, we used name-matching with cuisine keywords like “burger”, “sandwich” etc. Most restaurants have cuisine included in their names e.g., Johnny’s Pizzeria or Tom’s Sandwich. The restaurants in the dataset cover a huge variety of cuisines; we restrict attention to cuisines for which there exist both independent restaurants and chains.

We ran a K-means clustering algorithm for the chain restaurants using two dimensions — age of chain and no of stores in United States (2017). The clustering originally gave 3 categories— national established chains, old chains with few stores and new chains. We however, combined the last two categories as both these categories have less-established priors than national chains (also empirically, they have similar star rating distributions). We named this group *less established chains*.

## Additional data analysis

We estimate the chain effect on the number of positive, negative and neutral reviews at a business level. In particular, we run three specifications

$$\text{Count(Rev)}_{gjt} = \beta_0 + \beta_1 \text{Chain}_j + \beta_2 X_j + \beta_3 U_j + \epsilon_{jt},$$

where  $\text{Count(Rev)}_{gjt}$  denotes the number of reviews of type  $g =$  positive, negative or neutral, that a restaurant  $j$  receives in the first year and over its lifetime on the platform. The reviewer characteristics  $U_j$  are averaged across all reviewers of restaurant  $j$ . See Table 3 below. A chain restaurant receives 8 fewer positive reviews in its first year and 26 fewer over its lifetime, than a comparable independent restaurant. Coupled with the fact that chains are less likely to receive all types of reviews, this is a large number of reviews and can sufficiently alter the search outcomes in a platform like Yelp.com where users rely mostly on average ratings and more recent reviews for sorting.

Table 3: Positive, Negative and Neutral reviews by Restaurant Type

<i>Dependent variable: No of Reviews by Business</i>						
	<b>First Year</b>			<b>Lifetime</b>		
	Positive (1)	Negative (2)	Neutral (3)	Positive (4)	Negative (5)	Neutral (6)
Chain Dummy	-7.739*** (0.383)	-1.033*** (0.133)	-1.203*** (0.0878)	-26.46*** (3.145)	-0.973 (0.501)	-3.769*** (0.508)
<b>Price Range</b>						
\$\$	1.957*** (0.397)	1.149*** (0.145)	0.717*** (0.0832)	5.003** (1.772)	4.366*** (0.397)	2.480*** (0.339)
\$\$\$	0.142 (0.998)	-0.0353 (0.336)	0.0932 (0.196)	23.43** (8.330)	2.085 (1.509)	3.767** (1.170)
\$\$\$\$	2.674 (3.081)	0.871 (0.802)	0.723 (0.678)	85.65*** (24.01)	13.14** (4.896)	13.97*** (3.996)
<b>Select Cuisines</b>						
burger	2.960*** (0.526)	1.082*** (0.277)	0.814*** (0.141)	5.128* (2.470)	-3.987*** (1.129)	-0.619 (0.584)
chinese	-1.965** (0.603)	-0.292 (0.379)	-0.221 (0.155)	-15.63*** (2.092)	-10.26*** (1.282)	-3.980*** (0.575)
coffee	2.125*** (0.619)	-0.274 (0.248)	-0.207 (0.132)	-1.150 (2.550)	-7.356*** (1.121)	-3.332*** (0.550)
mexican	-0.991* (0.457)	-0.320 (0.251)	-0.252* (0.108)	-11.16*** (1.661)	-10.49*** (1.105)	-3.974*** (0.472)
pizza	-2.081*** (0.549)	-0.403 (0.254)	-0.627*** (0.129)	-9.794*** (2.842)	-6.051*** (1.168)	-4.226*** (0.615)
sandwich	0.684 (0.469)	0.240 (0.278)	0.0956 (0.116)	-3.208 (2.998)	-8.481*** (1.102)	-2.749*** (0.588)
<b>Select States</b>						
Phoenix (AZ)	-0.980* (0.387)	-0.703*** (0.169)	0.377*** (0.0981)	18.58*** (2.205)	8.518*** (0.425)	3.498*** (0.354)
Charlotte (NC)	-3.534*** (0.399)	-1.690*** (0.162)	0.0714 (0.0987)	-3.536 (1.920)	-0.412 (0.377)	-0.408 (0.324)
Las Vegas (NV)	2.938*** (0.747)	0.390 (0.332)	1.285*** (0.199)	-7.280*** (1.951)	-1.191*** (0.355)	-0.141 (0.320)
New York (NY)	-8.184*** (0.908)	-3.328*** (0.369)	-0.536* (0.269)	-2.604 (2.201)	1.021* (0.435)	0.398 (0.373)
Pittsburgh (PA)	-5.667*** (0.395)	-2.016*** (0.169)	-0.241* (0.0987)	1.040 (2.713)	2.216*** (0.581)	1.374** (0.489)
<b>Reviewer characteristics</b>						
No of Reviews (Avg)	-0.00203*** (0.000192)	-0.000782*** (0.0000697)	-0.000135*** (0.0000295)	0.00379 (0.00231)	-0.0000842 (0.000473)	0.00213*** (0.000601)
Star Rating (Avg)	2.331*** (0.156)	-1.053*** (0.0571)	0.0584* (0.0285)	15.01*** (1.050)	-1.142*** (0.251)	1.749*** (0.169)
N	12024	12024	12024	9719	9719	9719
R2	0.1095	0.076	0.08	0.1	0.21	0.12
adj. R-sq	0.106	0.071	0.076	0.099	0.212	0.117

Note: Standard errors clustered by business

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01