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Sellers' Peer Comparison Under Uncertainty in Online Marketplace

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Abstract

How will peer pressure among sellers affect their operations in an online marketplace? Motivated by online platforms' marketplace designs that prompt sellers to compare their performances, in this paper, we develop and study a price competition model in which sellers account for both profits and peer comparison outcomes. In our model, two sellers offer substitutable products, and each of them sets a price ex ante to maximize their expected total utility, which is the sum of one's profit and the payoff from peer comparison. In particular, peer comparison takes place ex post based on sellers' realized sales. It results in a penalty for one's underperformance (i.e., sellers are behind-averse) or a reward for outperformance (i.e., sellers are ahead-seeking) relative to the other seller. Contrary to what extant research on social comparison would predict, we find that peer comparison is not always pro-competitive. Indeed, while the behind-aversion aspect of peer comparison fosters competition, the ahead-seeking aspect can be anti-competitive when the market uncertainty is sufficiently large. This is because market uncertainty causes a greater variation in sellers' performance disparity ex post (*uncertainty effect*), which can have a more salient impact on sellers than the expectation of their performance gap (*comparison effect*); While sellers' behind-aversion further aggravates the uncertainty effect and encourages them to take more aggressive actions, their ahead-seeking counterbalances the tension by absorbing part of it into the comparison effect and moderating the marginal disutility of lagging behind. Overall, we find that peer comparison can intensify sellers' price competition, which lowers the expected profits and utilities for both sellers, benefits the consumers, and reduces the hosting platform's profit. Our main insights are robust in a number of extensions, including general demand specifications, seller asymmetry, sellers' misperceptions of market uncertainties, and consumers' reference-dependent decision-making. They highlight the importance of sellers' behavioral regularities in online platforms' daily operations and shed light on marketplace designs regarding algorithmic transparency, information sharing, and so forth.

Keywords

Online Marketplaces, Small Sellers, Peer Comparison, Prospect Theory

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1 Introduction

Platforms companies such as Amazon, TikTok, and Uber offer the infrastructure for millions of individuals to run their businesses online (see, e.g., Burtch et al., 2018; Li et al., 2023), and they constantly develop and deploy marketplace algorithms to influence the operations of those small business owners ("sellers" thereafter). Notably, platforms would inform sellers of their relative performances to other sellers and reward (punish, respectively [resp.]) their outperformance (underperformance, resp.). For example, Amazon would rank and display products to consumers based on sellers' total sales,[1] ratings, likelihood of matching consumers' preferences, etc. A top-placed seller typically attracts enough eyeballs, whereas a bottom seller receives far less consumer attention (see, e.g., Ursu, 2018).[2] Top-performing sellers may also be prioritized by platforms in certain seller services (e.g., inventory management, AI-driven consulting; see, e.g., Connolly, 2022; Yang, 2024). Similarly,

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(a) (b) (c)

Figure 1. Seller comparison examples. (a) Amazon best sellers display. (b) Gig economy gamification. (c) Tik Tok "Battles".

content creators' popularity is a crucial factor when social media platforms decide what content to show viewers. Moreover, TikTok would hold live stream sessions for content creators to "battle" against each other and see who is more popular among viewers (Hallanan, 2019). In online labor markets, platforms like Uber and Lyft use performance feedback to boost "gig" workers' incentives[3] to work and compete among themselves (see, e.g., Mason, 2018); See Figure 1.[4]

It is not an easy task for any seller to consistently outperform his or her competitors. One main challenge comes from the enormous uncertainty in market dynamics. On the one hand, consumer preferences and behaviors have been evolving ever more rapidly; traditional marketing approaches to predict consumer demand are outpaced (Lellouche et al., 2020), while more effective AI-based analytics tools can be very costly for small sellers to deploy (Castellanos and Shah, 2019). On the other hand, platforms' algorithms add extra complexity to sellers' operations. Besides sellers' historical performances, platforms typically consider a swath of other factors when deciding how to allocate the consumer traffic (see, e.g., Farronato et al., 2023); they use highly sophisticated machine learning models to generate final allocation schemes (see, e.g., Smith, 2021), and update and develop new algorithms on a highly frequent basis (Ye et al., 2023). It is thus incredibly challenging for sellers to obtain precise forecasts about future consumer traffic.

Then, how would a seller navigate a marketplace with a fair amount of peer pressure and market uncertainty? The classic social comparison theory might predict that sellers take more aggressive actions than when they are solely profit-maximizing to either gain the utility of outperforming other sellers or avoid the disutility due to lagging behind their peers. However, market uncertainty garbles the payoff of any decision made by a seller and moisturizes their incentives to act aggressively. On the one hand, market downswings ex post can seriously undermine sellers' efforts to close performance gaps. On the other hand, though, a demand windfall can significantly boost sellers' sales, allowing sellers to take less aggressive actions against peers but at the same time still achieve a decent performance margin. Then, how will sellers adjust their decisions under different levels of market uncertainty? What will their reactions be to the heightened pressure of peer comparison? What are the implications of sellers' behaviors for consumers and platforms?

To answer our research questions and pursue a better understanding of modern online marketplaces, we employ the workhorse model of price competition with two additional ingredients: sellers' peer comparison and market uncertainty. We consider two sellers offering substitutable products. Each of them faces a random market size and sets prices ex ante to maximize his or her expected total utility, the sum of profit and a social utility of peer comparison. In particular, the peer comparison takes place ex post based on sellers' realized sales. It results in a linear penalty for one's underperformance (i.e., sellers are behind-averse) or a linear reward for outperformance (i.e., sellers are ahead-seeking) relative to the other seller.

Our analysis unfolds the following insights. First, unlike what the classic social comparison theory would predict, we find that peer comparison is not always pro-competitive. Indeed, while the behind-aversion aspect of peer comparison intensifies competition and reduces sellers' prices, the ahead-seeking aspect will be anti-competitive and push up the prices if the market uncertainty is sufficiently large.

To unpack the intuition behind this finding, we propose two channels through which peer comparison affects sellers' decision-making in an uncertain environment—a *comparison* effect and an *uncertainty* effect. The comparison effect captures how any seller will handle the expectation of their performance gap or, in other words, how they would behave in a completely deterministic environment. This effect is independent of market uncertainty and plays the classic pro-competitive role of social comparison. Both behind-aversion and ahead-seeking will enhance the comparison effect and intensify the price compeittion between sellers. The uncertainty effect, on the other hand, reflects how sellers will react to the variation in their performance gap, and it becomes more accentuated as the uncertainty builds up. Specifically, when setting prices ex ante, in anticipation of a negative market shock, the focal seller may wish to close the performance gap with the competitor by lowering the price, and a higher degree of market uncertainty adds extra downward pressure on the price as "harsher" shocks become more likely. In contrast, a positive market shock allows any seller to loosen the tight control of price, and market uncertainty helps further soften the price race as both sellers expect a higher chance of being hit by windfalls.

Regarding the uncertainty effect, sellers' behind-aversion reinforces its pro-competitive aspect, while their ahead-seeking enhances its anti-competitive potential. Putting the comparison and the uncertainty effects together, if market uncertainty is sufficiently large, the uncertainty effect amplifies and dominates the comparison effect, and sellers will be encouraged to raise prices as ahead-seeking strengthens; Otherwise, the uncertainty effect will be dominated by the comparison effect, and sellers will lower prices. On the other hand, behind-aversion is consistently pro-competitive through both the comparison and the uncertainty channels and therefore pushes down sellers' prices no matter what amount of uncertainty the market inherits.

Second, given the social comparison literature's premise that behind-aversion intensity-wise dominates ahead-seeking, we find that sellers' peer comparison will foster their competition, which leads to lower prices and reduces sellers' profits and utilities in equilibrium. Furthermore, a higher degree of market uncertainty will amplify such negative impacts. If ahead-seeking instead prevails over behind-aversion, then peer comparison can be anti-competitive and raise sellers' prices, profits, and utilities.

Third, following our results on sellers, we verify that sellers' peer comparison in an online marketplace enhances consumers' welfare but hurts the platform as sellers' aggressive pricing reduces the amount of revenue it can collect through sales commissions. The negative effect on the platform aggravates as sellers become increasingly behind-averse, while the positive effect on consumers tapers off as sellers grow more ahead-seeking in a sufficiently volatile market. Managerially, our result suggests that platforms should carefully design their algorithms and maintain sellers' peer comparison at an appropriate level.

In short, in this paper, we take a fresh perspective of sellers' peer comparison to study their operations in an online marketplace. We develop a parsimonious model of price competition, offer insights into the uncertainty-dependent impacts of peer comparison, and demonstrate the robustness of our key findings in several extensions. Our findings highlight the importance of considering sellers' behavioral regularities for platforms' operations and also provide managerial prescriptions to improve their marketplace designs.

2 Literature Review

Our work first relates to the literature on online marketplaces. See, e.g., Chen et al. (2020) and Belleflamme and Peitz (2021) for reviews. A particularly relevant research sub-stream in this literature studies sellers' strategic interactions under platforms' intermediations. In e-commerce settings, researchers have investigated how sellers compete over prices, quantities, etc. when platforms strategically match them with consumers (see, e.g., Dinerstein et al., 2018; Hagiu and Wright, 2020; Li et al., 2018; Long and Liu, 2024; Yu et al., 2023). Regarding the gig economy and online labor markets, ongoing research topics include how gig workers decide their working hours, service quality, and strategies for deal searching given platforms' prices, wages, worker-consumer matching policies, and service supervisions (see, e.g., Allon et al., 2023; Castillo, 2020; Knight et al., 2022). Similarly, for social media platforms (e.g., YouTube and TikTok), researchers have recently studied strategic labor inputs from independent content creators and platforms' revenue sharing, partnership management, and so forth (see, e.g., Bhargava, 2022; Cong and Li, 2023; Jain and Qian, 2021). We contribute to the ongoing discussions by incorporating sellers' peer comparison, an important yet understudied perspective, into the marketplace analysis, clarifying its implications for different stakeholders in online marketplaces, and offering several fresh insights into platform designs.

Speaking of platform designs, there has been a recent literature that studies the impacts of "gamification," a practice of using game-like features to engage individuals, on consumers' behaviors on online platforms (Liu et al., 2017). By analyzing a dataset from an online fitting platform, Bojd et al. (2022) show that leaderboards, which publicly rank users' performances for exercise and diet challenges, can help users better achieve their goals for weight loss but are not very effective in stimulating the adoption of healthy diets. Hydari et al. (2023) discover that leaderboards can surprisingly hurt active users' incentives for participation while encouraging sedentary users to do more physical exercises. Liu et al. (2024) find that virtual races on an online platform can boost users' engagement with the platform and cultivate healthy lifestyles. In an online learning setting, Leung et al. (2023) find that social (*personal*, respectively) comparison benefits users with strong "mastery" ("performance-avoidance", respectively) goal orientations. Zhou et al. (2021) find empirical evidence that leaderboards can bolster users' online learning, particularly when the difficulty of getting on a leaderboard is moderate. Chen and Roels (2024) deploy an information design approach to study the optimal level of information granularity when providing participants with feedback on their performances. Our work complements these papers by theoretically examining the implications of such comparison-stimulating designs for agents on the other side of a marketplace, i.e., sellers. We will study how the impacts are twisted by market uncertainty as well as how consumers and platforms will be affected.

Our paper also relates to the operations management literature on social comparisons. An important research topic in this literature is the strategic interactions among companies/organizations. In the supply chain setting, Loch and Wu (2008) find that social preferences, such as status seeking and reciprocation, systematically affect economic decisions, and Cui et al. (2007) show that with fairness concerns, a single wholesale price contract may coordinate the supply chain. Avcı et al. (2014) reveal how social comparisons can distort vendors' quantity decisions away from the optimal newsvendor level in a competitive environment. Ho et al. (2014) study how distributional and peer-induced fairness might influence the design of wholesale price contracts, and Pavlov et al. (2022) investigate the impacts of private preferences for fairness on the optimal contract design. Wang et al. (2023) show that a small manufacturer's distributive comparison behavior may encourage his supplier to invest in corporate social responsibility. Another research area focuses on individuals within an organization. Roels and Su (2014) investigate the optimal strategy to set reference groups and reference points from a social planner perspective. Song et al. (2018) find that the public disclosure of workers' relative performances and the best practices can improve the productivity of social-comparing workers. Tan and Netessine (2019) and Niewoehner and Staats (2022) corroborate such positive impacts of performance feedback in different service settings. Long and Nasiry (2020) show that social comparisons will not necessarily reduce collaboration among sales agents. Pierce et al. (2021) attribute women's under-compensation to their prosocial behavior and weaker bargaining power than their male counterparts. Chen et al. (2023) study the implications of pay transparency for teams with heterogeneously capable agents. They show that pay transparency will benefit (can hurt, resp.) both the principal and the agents if the agents are eyeing the disparity in their incomes (utilities, resp.) while the impact is more nuanced if the agents instead care about the difference in their income-to-effort ratios.

In particular, a few papers mentioned above similarly consider market uncertainty in their frameworks. Avcı et al. (2014) investigate the ordering decisions of two social comparing newsvendors under different demand correlation structures. Instead, we focus on how the magnitude of market uncertainty affects sellers' decisions. Roels and Su (2014) show that if the ahead-seeking aspect of social comparison prevails, the average level of agents' outputs (which consistently measures the amount of their effort) can be stable as the environment becomes increasingly noisy. We, on the other hand, find that agents' efforts (embodied by their price reduction) may decrease as market uncertainty grows; if, instead, the behind-aversion dominates ahead-seeking, then their efforts will increase in uncertainty. Long and Nasiry (2020) discover that demand uncertainty generally has a negative impact on agents' utilities (and their incentives for participation) via social comparison and thus makes it more costly for an organization to use an individual-based compensation scheme (which stimulates comparison). Our work echoes such a result but also complements it by uncovering the anti-competitive and utility-improving potentials of social comparison in sufficiently volatile markets. Fan et al. (2023) show that an overconfident player will exert more effort as the market uncertainty increases, whereas an underconfident player will retract. We, in contrast, demonstrate that even without any cognitive biases, both sellers may behave less competitively when the environment becomes sufficiently uncertain. Also note that, in these papers, agents' decisions do not directly affect each others' payoffs in a non-comparison environment; in other words, agents are only comparing but not competing. Instead, we consider both comparison and competition and reveal how these forces interact with each other.

Finally, in the revenue management literature and the service operations literature, researchers have studied firms' pricing and service designs in light of customers' behavioral regularity (see, e.g., Baron et al., 2015; Guda et al., 2023; Liu and Shum, 2013; Momot et al., 2020; Popescu and Wu, 2007; Su, 2007; Yang et al., 2018). We contribute to the scant discussions on firms' competition (see, e.g., Adida and Özer, 2019; Yang et al., 2014) and particularly focus on the implications of sellers (rather than consumers) being behavioral.

3 The Model

Consider two sellers offering substitutable products on an online platform. The demand function of seller i, $i = 1, 2$, denoted by $D_i(p_1, p_2, \epsilon_i)$, is in the following form:

$$D_i(p_1, p_2, \epsilon_i) = d_i(p_1, p_2) + \epsilon_i = m - p_i + \gamma p_{-i} + \epsilon_i, \qquad (1)$$

where $-i$ denotes the competitor of seller i, and ϵ_i is a random variable as an additive shock to the potential market size m. We assume that ϵ_1 and ϵ_2 follow independent and identically distributed (i.i.d.), continuous, and symmetric probability distributions as ϵ on $[-\bar{\alpha}, \bar{\alpha}]$, for some constant $\bar{\alpha} \in (0, m)$. In other words, there are symmetrically distributed upswings and downswings in the market size. Without loss of generality, suppose that the random shocks have zero mean, i.e., $E\epsilon_1 = E\epsilon_2 = 0$. As a result, the expected demands of the two sellers are $d_1(p_1, p_2)$ and $d_2(p_1, p_2)$, respectively. Also, we have $0 \leq \gamma < 1$ for product substitution.

For each product unit sold on the platform, seller i has to remit θp_i to the platform, where $\theta \in (0, 1)$ is the commission rate. Without loss of generality, we assume that the marginal supply cost is $c = 0$ per unit. Then, given the realization of random shock ϵ_i, seller i's profit is defined as

$$\begin{aligned}\Pi_i(p_1, p_2, \epsilon_i) &= (1-\theta)p_i D_i(p_1, p_2, \epsilon_i) \\ &= (1-\theta)p_i \left[d_i(p_1, p_2) + \epsilon_i\right].\end{aligned}$$

In addition to their profits, a gain-loss utility is incurred for both sellers when they learn from the platform about their performance disparity. Following the classic framework in the social comparison literature (Bolton and Ockenfels, 2000; Fehr and Schmidt, 1999), we define seller i's utility under peer comparisons as

$$S_i(p_1, p_2, \boldsymbol{\epsilon}) = e\left[\Pi_i(p_1, p_2, \epsilon_i) - \Pi_{-i}(p_1, p_2, \epsilon_{-i})\right]^+ \\ - \ell\left[\Pi_i(p_1, p_2, \epsilon_i) - \Pi_{-i}(p_1, p_2, \epsilon_{-i})\right]^-, \quad (2)$$

where $\boldsymbol{\epsilon} = (\epsilon_1, \epsilon_2)$, $x^+ = \max\{x, 0\}$ and $x^- = -\min\{x, 0\}$. In particular, sellers are *behind-averse* in the sense that there will be a penalty $\ell > 0$ for each revenue unit lagging behind their competitor's, and they are *ahead-seeking* given that a reward $e > 0$ will be generated for each revenue unit surpassing their competitor's. Note that, in view of the behavioral literature (e.g., the celebrated prospect theory, see Kahneman and Tversky 1979), usually there is $e \leq \ell$, which says that the loss due to an underperformance weighs more than equal-sized gain or loss due to an overperformance.

For a pair of market size shocks $\boldsymbol{\epsilon} = (\epsilon_1, \epsilon_2)$, the total utility of seller i, $i = 1, 2$, is the sum of its profit and its gain-loss utility under peer comparison, i.e., $U_i(p_1, p_2, \boldsymbol{\epsilon}) = \Pi_i(p_1, p_2, \epsilon_i) + S_i(p_1, p_2, \boldsymbol{\epsilon})$. We consider an ex ante simultaneous pricing game between two sellers, where each seller i is to maximize his or her expected total utility EU_i over the price $p_i \in [0, p^{\max}]$, where $p^{\max}$ is the upper bound for the price.

A few remarks on the model are in order. We start with the key ingredients of the model, sellers' peer comparison, and the associated utility. First, why is it important to consider the comparison among sellers and factor that into their competition in the first place? As we discussed in Section 2, a handful of research papers have demonstrated how marketplace designs deployed by online platforms significantly stimulate the rivalry among sellers and distort their decision-making (e.g., Dinerstein et al., 2018). A majority of these papers have focused on one particular type of marketplace design, product/seller ranking, and assumed that sellers know the details of platforms' ranking algorithms. In reality, however, there are many other mechanisms platforms can implement to stir sellers' rivalry (e.g., gamification), and it is typically impossible for sellers to figure out the exact rules of the games. In this regard, our work complements the previous papers by developing a more general framework based on the social comparison theory to understand the competitive landscape of modern online marketplaces. In particular, the online marketplace setting injects fresh implications into the classic formulation of social comparison utility: Since sellers who are favored by platforms' marketplace algorithms tend to receive more consumer traffic in the future, the behind penalty ℓ can be interpreted as future revenue/profit loss due to lagging behind other sellers, while the ahead reward e can be thought of as bonus transactions in the future thanks to sellers' outstanding performances. The random shocks ϵ_1 and ϵ_2 capture the uncertainty in not only consumers' tastes but also platforms' algorithms.

Second, on the formulation of sellers' peer comparison utilities. Right now the formulation presumes that sellers are comparing their sales performances directly with each other and that their perceptions of peer comparison outcomes are linear in the performance gap. Both are admittedly simplifications of reality. In particular, platforms are unlikely to share the exact information (e.g., monthly sales) about competitors with any single seller but may instead aggregate sellers' information and disclose some performance benchmarks (e.g., the median sales among all sellers[5]). That said, interestingly, our formulation (2) is equivalent to the case where the platform only informs sellers of their average sales or any convex combination of their sales,[6] and therefore all of our main findings will continue to hold. Our key insights shall also extend to other informational schemes such as when sellers are only informed of their performance percentiles.[7,8]

It is also worthwhile to expatiate on a few other aspects of the model. First, we choose to study sellers' competition over the price not only for its academic value but also because of its prevalence in online marketplaces (see, e.g., Lu, 2023). We do acknowledge, though, in reality, rivalries may also take place over other operational levers, including quality (e.g., Jain and Qian, 2021), quantity/inventory level (e.g., Yu et al., 2023) and so forth. Second, we follow the online platform literature (e.g., Dinerstein et al., 2018) and consider the simultaneous pricing game between sellers. The dynamic game can be an interesting direction for future research. Third, we have assumed that sellers are symmetric in their peer comparison behaviors and market uncertainties and are mutually aware of the symmetry. This shall be a reasonable approximation to the reality given that small merchants oftentimes face similar challenges and opportunities in an online marketplace (see, e.g., McKinsey & Co, 2023) and where sellers would share their experiences through online communities such as Reddit[9]. See Sections 6.2 for robustness checks with asymmetric sellers.

Next, we discuss several regularity assumptions and concepts that are useful for the theoretical analysis.

Assumption Assumption (R) (Regular Price Range). *The upper bound, $p^{\max}$, on the price satisfies $p^{\max} \leq m - \bar{\alpha}$.*

Assumption (R) ensures that the ex post demand $d_i(p_1, p_2) + \epsilon_i$ is always nonnegative, regardless of the realization of ϵ_i for any ex ante pair of price choices $(p_1, p_2) \in [0, p^{\max}]^2$.

In the following, we are going to introduce a few notions associated with market uncertainty.

Definition 1 (Partial Order of Randomness). *We consider a partially ordered set $(\mathcal{M}, \preceq)$, where $\mathcal{M}$ is a class of symmetrically distributed random variables on $[L, U]$ such that for any $X, Y \in \mathcal{M}$, $X \preceq Y$ (i.e., we say, Y is more variable than X) if and only if $E(X) = E(Y) = \mu$ and*

$$F_X(x) \begin{cases} \leq F_Y(x) & \text{for } x \in [L, \mu], \\ \geq F_Y(x) & \text{for } x \in [\mu, U], \end{cases} \quad (3)$$

where $F_X(x)$ and $F_Y(x)$ are the cumulative distribution functions of X and Y respectively.

Note that the partial order defined as (3) is a sufficient condition for Y to be more variable than X in the sense of the convex order. In fact, it coincides with the single-crossing condition of cumulative distribution functions confined to symmetrical distributions, which is a special case of convexly ordered distributions. Although the convex order does not necessarily imply the condition in (3), it is equivalent to Definition 2 for many common symmetric unimodal distributions, such as normal and uniform distributions. For example, a class of normal distributions with the same mean but different standard deviations satisfies Definition 2, with the partial order referring to the convex order. For ease of analysis, we focus on the partial order of Definition 2 rather than other more general stochastic orders.

DEFINITION 2 (Partial Uncertainty). *For any $X \in \mathcal{M}$ where $\mathcal{M}$ is a class of distributions, let X_1 and X_2 be i.i.d. random variables from X. We define $\sigma \equiv E[X_1 1_{\{X_1<X_2\}}]$ as the partial uncertainty of X.*

For simplicity, we may refer to σ defined above simply as the uncertainty. The following lemma confirms that this uncertainty measure is decreasing with respect to the uncertainty of ϵ, where ϵ is the generic random variable that represents the probability distribution of ϵ_1 and ϵ_2.

LEMMA 1. *Given any $X, Y \in \mathcal{M}$ where $\mathcal{M}$ is a class of distributions endowed with a partial order $\preceq$ as defined in Definition 2. Suppose that X_i, Y_i, $i = 1, 2$, are i.i.d. copies of X and Y, respectively. Then $X \preceq Y$ if and only if $E\{Y_1 1_{\{Y_1<Y_2\}}\} \leq E\{X_1 1_{\{X_1<X_2\}}\}$.*

By Lemma 1, σ indeed can be used as a measure for market uncertainty. The more variable the market size shock, the more negative the value of σ, or equivalently, the higher the absolute value of σ. The measure reaches its minimum, $-\frac{\bar{\alpha}}{4}$, when ϵ follows the two-point distribution with $\Pr(\epsilon = -\bar{\alpha}) = \Pr(\epsilon = \bar{\alpha}) = \frac{1}{2}$.

We will now move on to analyze our model.

4 Implications for Price Competitions and Seller Profitability

In this section, we will unfold the strategic interactions between sellers. We will first study the standalone effects of peer comparison and market uncertainty and then the equilibrium when both forces are at play.

4.1 Standalone Effects of Social Comparison and Market Uncertainty

4.1.1 Peer Comparison. We first consider the case when there is peer comparison but no market uncertainty. The following lemma characterizes the market outcomes, where the "$\wedge$" is defined as $x \wedge y := \min\{x, y\}$.

LEMMA 2 (Without Market Uncertainty: Pro-Competitive Effect of Sellers' Peer Comparison). *If $\epsilon_1 = 0$ and $\epsilon_2 = 0$ with probability 1, the price competition game has only symmetric equilibria. The set of equilibria is $\{(p_1, p_2) = (p, p) \mid p \in [\frac{(1+\ell)m}{2(1+\ell)-\gamma} \wedge p^{\max}, \frac{(1+e)m}{2(1+e)-\gamma} \wedge p^{\max}]\}$, which is decreasing in both the ahead-seeking parameter e and the behind-aversion parameter ℓ in the sense of the induced set ordering defined in Topkis (1998: §2.4).[10] The equilibrium profit is decreasing in e and ℓ in the same sense.*

The lemma confirms that in a deterministic world, both behind-aversion and ahead-seeking are pro-competitive, which is consistent with the classical social comparison theory.

To see the intuition here, let us start with the alternative equilibrium in which sellers are pure profit maximizers. Now, both sellers decide to "reward" ("punish", respectively [resp.]) themselves for outperforming (lagging behind, resp.) their competitor, i.e., sellers start social comparing. Because sellers are offering substitutable products, a natural reaction for any seller would be to undercut the competitor by lowering the price by at least a small amount. By doing so, although the focal seller will have a lower profit margin, he or she will be able to increase his or her own market size and reduce that of the competitor. Overall, the negative impact on one's own profit (due to margin shrinkage) is minor compared with that on his or her competitor because the base price, resulting from pure profit maximization, ensures that any small price change will only trigger some second-order variation in one's own profit,[11] which makes the focal seller prevail. Discovering this, the upset competitor will lower its price as well to close the profit gap. But then, the focal seller will again try to undercut the competitor and get on top, which in turn triggers further retaliation from the competitor. On and on, such a "race-to-the-bottom" drives the prices (and thus sellers' profits and utilities) down to a new equilibrium.

It is worthwhile to note that, unlike previous research on social comparison in the operations management literature that has considered only the comparison but not the competition among/between agents, in our model, agents are also competing with each other in the sense that one's decision directly affects his or her competitor payoff in a non-comparison setting. Specifically, as we just mentioned, any focal seller's price reduction will grab away a slice of market demand from his or her competitor and thus hurt the seller's profit (which benefits the focal seller in the peer comparison), and vice versa. As such, agents in our work will have more incentives to take aggressive measures against each other. In other words, sellers' competition complements their comparison, and comparison, in turn, further intensifies the competition.

In addition, as a technical note, Lemma 2 shows that the price equilibrium may not be unique in the deterministic model. The monotonicity of the Nash equilibria with respect to sellers' peer comparison parameters e and ℓ in the above lemma generalizes the usual notion of monotonicity. Informally, we may think of the set of price equilibria sinking (in e and ℓ) as all the equilibria falling to form a new set of equilibria. For example, by setting $\sigma = 0$ in the expression of the price equilibrium in Proposition 1, we get $p^* = \frac{[1+(\ell+e)/2]m}{2[1+(\ell+e)/2]-\gamma} \wedge p^{\max}$, which belongs to the set of equilibria[12]. This equilibrium is decreasing in both e and ℓ. Any other equilibrium in the set also decreases as e or ℓ increases.

4.1.2 Market Uncertainty. We now look at the case with market uncertainty but no peer comparison. The following lemma characterizes the equilibrium.

LEMMA 3 (Without Sellers' Peer Comparison: Uncertainty-Independent Market Equilibrium). *If $\ell = e = 0$, the price competition game has a unique equilibrium: $p_1 = p_2 = \hat{p} \equiv m/(2-\gamma)$. The symmetric equilibrium price and equilibrium profit are independent of the market uncertainty.*

From the lemma, one can see that without sellers' peer comparison, the equilibrium market outcomes are independent of the degree of market uncertainty. This naturally follows the premise that both sellers now only care about their own profits and that both are risk-neutral. When strategically setting the prices ex ante, the sellers expect that positive and negative market size shocks ex post will cancel out; as such, the sellers behave as if they were in a deterministic market.

4.2 Combined Effects of Social Comparison and Demand Uncertainty

We now allow sellers' peer comparison and market uncertainty to coexist and study how they affect sellers' decisions. We will show that market uncertainty adds an anti-competitive face to peer comparison. In the meanwhile, with peer comparison, the impact of market uncertainty becomes non-trivial.

LEMMA 4. *For any ϵ, $U_i(p_i, p_{-i}, \epsilon)$, $i = 1, 2$, is concave in p_i for a given p_{-i}.*

Lemma 4 shows that given any market shock realization ϵ, sellers' utility functions are well-behaved. As an immediate result, the ex ante expected utility function $u_i(p_i, p_{-i}) = E_\epsilon U_i(p_i, p_{-i}, \epsilon)$, $i = 1, 2$, is concave in p_i as well. By Debreu (1952), the existence of a pure Nash equilibrium ensues, and we can solve for the equilibrium from the set of first-order conditions. We characterize the equilibrium price below.

PROPOSITION 1 (Price Equilibrium Under Sellers' Peer Comparison). *The price competition game in the presence of peer comparison and market-size uncertainty has a unique pure Nash equilibrium: $p_1 = p_2 = p^* := \bar{p} \wedge p^{\max}$, where the binary operator $\wedge$ takes the smaller value of the two inputs, and*

$$\bar{p} := \frac{(2+\ell+e)m + 2(\ell-e)\sigma}{2(2+\ell+e-\gamma)}, \quad \sigma := E[\epsilon_1 1_{\{\epsilon_1<\epsilon_2\}}] \leq 0, \tag{4}$$

with $1_{\{\cdot\}}$ being the indicator function.

Recall that according to Lemma 2, without market uncertainty, there exist multiple symmetric price equilibria between two sellers. Interestingly, here, Proposition 1 implies that a nontrivial amount of market uncertainties will fine-prune the equilibrium set into a unique equilibrium price pair. The intuition is that when there is no market uncertainty, sellers' relative performances entirely hinge on their prices; so starting from any equilibrium, if a seller's price is disturbed by a small amount, his or her competitor would immediately price match so as not to lag behind (if not fare ahead), and this leads to a new (symmetric) price equilibrium. Hence, the price equilibrium cannot be unique. In contrast, market uncertainty creates a sufficient amount of performance disparity ex post regardless of whether sellers charge identical prices. Then the competitor no longer has an adequate incentive to price match when the focal seller deviates since the performance disparity is not going to be eradicated whatsoever. As such, sellers' best price responses will not follow the diagonal response trajectory (i.e., price matching as in the case without market uncertainty) anymore; Any small drift away from a symmetric equilibrium will eventually be pulled back to the same equilibrium by the (non-diagonal) best response dynamics. The uniqueness of equilibrium thus ensues.

With this fully characterized price equilibrium, we will next analyze the impacts of sellers' peer comparison on market outcomes.

PROPOSITION 2 (Comparative Statics on Sellers' Peer Comparison). *In equilibrium, we have:*

(i) (BEHIND-AVERSION) *The price p^*, the expected profit $\pi(p^*, p^*)$, and the expected utility $u(p^*, p^*)$ are decreasing in the behind-averse parameter ℓ;*
(ii) (AHEAD-SEEKING) *There exists a threshold $\bar{\sigma} = -\gamma m/(2(2+2\ell-\gamma))$ on the market uncertainty measure σ, above the scale of which the price p^*, the expected profit $\pi(p^*, p^*)$, and the expected utility $u(p^*, p^*)$ are increasing in the ahead-seeking parameter e; otherwise, the price p^* and the expected profit $\pi(p^*, p^*)$ are decreasing in e.*[13]

Proposition 2 says that ceteris paribus, the more behind-averse sellers are, the more intense price competition will be. Moreover, it is intriguing that when market uncertainty is large enough, ceteris paribus, the more ahead-seeking sellers are, the less intense price competition will be. In other words, sellers' ahead-seeking behavior alleviates price competition in a market with sufficiently high market uncertainty, while their behind-aversion behavior always intensifies price competition. See Figures 2 and 3 for illustration.

To understand the twists here, we look closely at sellers' peer comparison utility and examine how exactly behind-aversion and ahead-seeking influence competitive behavior under market uncertainty. By (2), for any seller i, we can

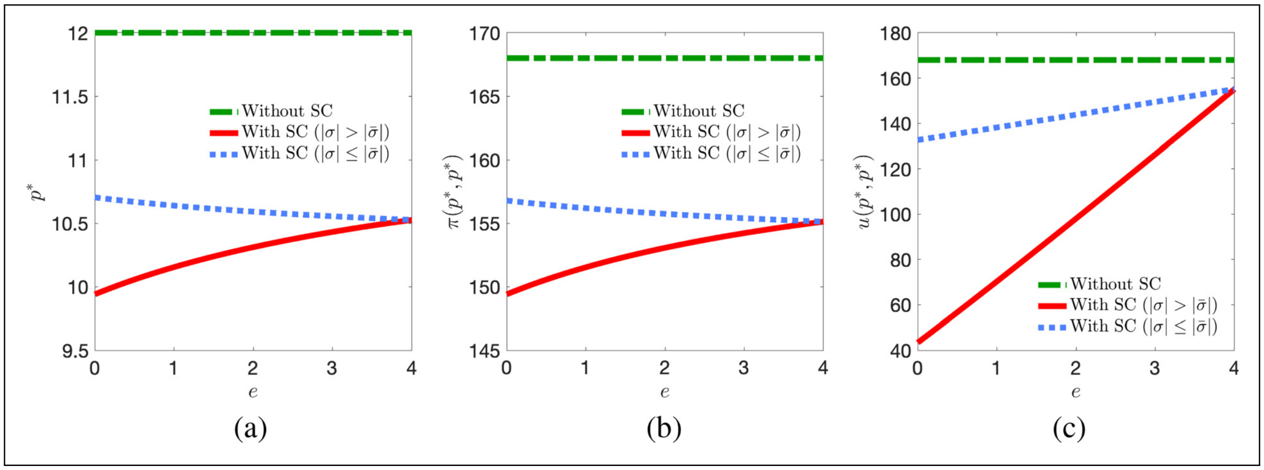

Figure 2. Implications of sellers' peer comparison (SC) - Ahead-Seeking ($m = 20$, $\gamma = 0.5$, $l = 4$, $\bar{\sigma} = -0.526$, $|\sigma| > |\bar{\sigma}| : U[-8, 8]$, $|\sigma| \leq |\bar{\sigma}|$: *Truncate* $\mathcal{N}(0, 1)$*on*$[-8, 8]$). (a) Equilibrium price. (b) Profit. (c) Utility.

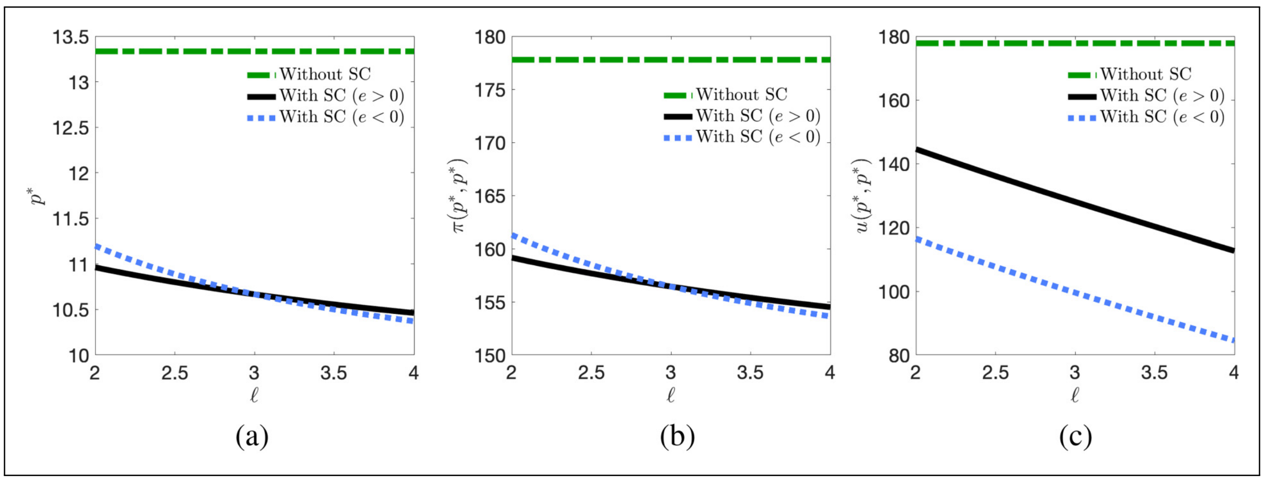

Figure 3. Implications of sellers' peer comparison (SC) - Behind-Aversion ($m = 20$, $\gamma = 0.5$, $\epsilon \sim U[-4, 4]$). (a) Equilibrium price. (b) Profit. (c) Utility.

decompose his or her peer comparison utility as follows.

$$
\begin{aligned}
E[S_i(p_1, p_2, \epsilon)] = & \underbrace{eE\left[\Pi_i(p_1, p_2, \epsilon_i) - \Pi_{-i}(p_1, p_2, \epsilon_{-i})\right]^+}_{\text{ahead-seeking}} \\
& \underbrace{-eE\left[\Pi_i(p_1, p_2, \epsilon_i) - \Pi_{-i}(p_1, p_2, \epsilon_{-i})\right]^-}_{\text{part of behind-aversion}} \\
& \underbrace{-(\ell - e)E\left[\Pi_i(p_1, p_2, \epsilon_i) - \Pi_{-i}(p_1, p_2, \epsilon_{-i})\right]^-}_{\text{remaining part of behind-aversion}}.
\end{aligned} \tag{5}
$$

The first term on the right-hand side corresponds to the ahead-seeking behavior. Given that $e \leq \ell$, the second term captures a part of the behind-aversion behavior, while the remaining part is included in the third term.

Although all three terms in (5) depend on market uncertainty, we note that the uncertainty pertaining to the first two terms (i.e., the complete ahead-seeking effect and part of the behind-aversion effect) is washed away on expectation; specifically, we have $eE[\Pi_i(p_1, p_2, \epsilon_i) - \Pi_{-i}(p_1, p_2, \epsilon_{-i})]^+ - eE[\Pi_i(p_1, p_2, \epsilon_i) - \Pi_{-i}(p_1, p_2, \epsilon_{-i})]^- = e[\pi_i(p_1, p_2) - \pi_{-i}(p_1, p_2)]$, which only hinges on the difference between sellers' expected profits and is thus independent of the market size shocks. As such, one may expect this portion in sellers' utility to create the classic *comparison effect* and escalate the competition (see, e.g., Liu et al., 2024). To intuit, analogous to solely maximizing their own profits, when involved in social comparisons, sellers will be concerned with their expected relative performance, i.e., how their expected profits compare with each other. The comparison effect essentially captures such a decision-making mindset. By applying $e = \ell$ to the pro-competitive effect of peer comparison (see Lemma 2), we can conclude that a higher level of ahead-seeking (i.e., a greater e) intensifies price competition through this comparison effect.

Now, the last term in (5) captures the part of behind-aversion not yet incorporated by the comparison effect. Because sellers operate in uncertain markets, only looking at the gap between their expected performances is not enough; they shall also account for variations in their performance gap given all possible market size realizations, particularly those "harsh" ones that lead to various degrees of underperformance vis-a-vis the competitor. We coin this as the *uncertainty effect*. As we mentioned earlier, when struck by a negative demand shock and ending up with a lower market size than the competitor, a seller would be inclined to reduce the price to stimulate the demand and close the performance gap with the competitor. Since the previous comparison effect has absorbed part of the sellers' behind-aversion, this remaining portion of behind-aversion here is weighted by a discount rate of $\tilde{\ell} \equiv \ell - e$. As such, a greater ℓ would put more downward pressure on sellers' prices, while a larger e can help reverse the down-spiraling price trend.

We now put the comparison effect and the uncertainty effect together as follows,

$$E[S_i(p_1, p_2, \epsilon)] = \underbrace{e\left[\pi_i(p_1, p_2) - \pi_{-i}(p_1, p_2)\right]}_{\text{comparison effect: } \downarrow} \underbrace{-(\ell - e)\left\{E\left[\Pi_i(p_1, p_2, \epsilon_i) - \Pi_{-i}(p_1, p_2, \epsilon_{-i})\right]^{-}\right\}}_{\text{uncertainty effect: } \downarrow \text{ or } \uparrow}. \tag{6}$$

The arrows in (6) indicate directions in which sellers' peer comparison may distort the equilibrium price. On the one hand, as behind-aversion becomes more significant (i.e., ℓ increases), the equilibrium price will decrease. This is because the comparison effect stays fixed while the uncertainty effect intensifies the competition. See Figure 3 for an illustration. The impact of ahead-seeking, on the other hand, is more nuanced: As e increases, the comparison effect makes sellers slash their prices, which is yet counterbalanced by the anti-competitive uncertainty effect. In particular, note that the scale of the uncertainty effect grows as the market becomes increasingly uncertain (see Figure OA.1(c) in the Appendix for illustration), whereas that of the comparison effect remains constant. Hence, there exists a threshold $\bar{\sigma}$ such that if (and only if) the market uncertainty σ is greater than this $\bar{\sigma}$, the anti-competitive uncertainty effect will dominate the pro-competitive comparison effect,[14] and this encourages the price to rise as sellers exhibit stronger ahead-seeking; otherwise, the comparison effect will prevail, and just as behind-aversion, ahead-seeking will similarly push down the equilibrium price. See Figure 2 for an illustration.

Note that, in the social comparison literature, e and ℓ typically measure the marginal reward and penalty at a psychological level. Here, in our setting, they are attached with yet a more concrete economic meaning. Recall that online platforms treat sellers differently based on their relative performances. For top performers, platforms may allocate more future consumer traffic, prioritize them in certain seller services, etc., and vice versa. In this regard, e and ℓ reflect sellers' expectation of marginal gain and loss of consumer traffic, added value of platforms' services, etc., generated by platforms' algorithms which factor in sellers' performance gaps. As such, the scale of ℓ and e depends on how well sellers' revenue gaps reflect their performance gaps: The more informative sellers' revenue gaps are as signals for their performance gaps, the larger ℓ and e would be, and vice versa. In markets with only a modest degree of horizontal differentiation, consumers naturally prefer offerings with higher quality; since sellers' gross merchandise sales (total revenue) is a fairly strong signal of their product quality, it can be a major factor inside platforms' marketplace algorithms, and so both e and ℓ tend to be large. In contrast, for markets with a fair amount of heterogeneity in product designs and consumers' tastes, sellers with higher GMS may not always be favored by a platform since other factors (e.g., match rates with different consumers) can also play an important role. Then, both e and ℓ can be small.

Following this line of thinking, ℓ and e are also likely to take on a larger scale in markets with matured products and services (e.g., non-foldable smartphones, human art designs) than in ones with more innovative offerings (e.g., foldable smartphones, AI-driven art designs). The rationale is that, in nascent markets, faring ahead in the short run does not guarantee a sustained advantage since consumers' perceptions are still taking shape; by the same token, falling behind temporarily does not eliminate the possibility of standing out later. Marginal intensities of peer comparison e and ℓ thus tend to be low. Indeed, it has been widely acknowledged that sellers are more likely to act (i.e., price) aggressively against each other in matured markets with less product differentiation and vice versa (see, e.g., Hoffmann et al., 2012).

We have shown how the market equilibrium changes in response to behind-aversion and ahead-seeking separately. Yet it is not clear from Proposition 2 whether price competition is more or less competitive for a market with sellers engaged in peer comparison compared to one with no such behaviors. Indeed, what would be the aggregate impacts of the pro-competitive behind-aversion and the potentially anti-competitive ahead-seeking? The following proposition answers such an inquiry.

PROPOSITION 3 (With vs. Without Sellers' Peer Comparison). *The equilibrium price, profit, and utility are lower with sellers' peer comparison than without.*

Proposition 3 says that, ultimately, sellers' peer comparison will intensify the competition between sellers and make both of them worse off than in a non-comparison environment. This implies that the potential anti-competitiveness of ahead-seeking will be dominated by the pro-competitive behind-aversion in equilibrium.

The driving force here, clearly, is that sellers put more weight on each unit of loss than on each unit of gain (i.e., $e \leq \ell$), a premise adopted by the social comparison literature. Indeed, when sellers become sufficiently ahead-seeking such that $e > \ell$, we can have that entirely opposite outcome; that is, peer comparison raises the equilibrium price and increases sellers' utilities.[15]

Our results in Proposition 3 echo the increasingly rampant competition among sellers in online marketplaces (Lui et al., 2021). Apart from technological explanations such as sellers' data-driven operations or consumers' lowered search costs, we offer an alternative perspective of sellers' peer comparison under platforms' algorithmic marketplace controls. Part of this competitive landscape, however, is twisted by sellers' sometimes less competitive behaviors (e.g., charging high prices; see Senate Banking, Housing and Urban Affairs Committee, 2024). While such "anomalies" have been rationalized by factors like sellers' dynamic pricing and platforms' anti-competitive practices, our analysis implies yet another hypothesis: that is, sellers expect a decent amount of rewards from platforms for their outstanding performances (in the sense of, e.g., extra future consumer traffic) such that they worry less about softening their decisions and potentially lagging behind in a highly uncertain market.

We now turn to the role played by market uncertainty and investigate how it intervenes in the strategic interactions between sellers. Recall that in Lemma 3, we have shown that without sellers' peer comparison, the equilibrium outcomes are uncertainty-independent. The proposition below shows that market uncertainty is no longer such a trivial matter after the peer comparison weighs in.

PROPOSITION 4 (Negative Impact of Uncertainty). *In equilibrium, the price p^* and the expected profit $\pi(p^*, p^*)$ are decreasing in the market uncertainty, and the expected utility $u(p^*, p^*)$ is decreasing in market uncertainty as long as $u(p^*, p^*)$ remains nonnegative.*

Proposition 4 says that market uncertainty is essentially amplifying the overall impacts of peer comparison, as a higher degree of uncertainty would further intensify the price competition between sellers and reduce their equilibrium profits and utilities. Note that, there is evidence showing that market uncertainty can escalate the risk of price wars among sellers (see, e.g., Langkamp et al., 2023). We numerically illustrate such negative impacts in Figure 4.

To understand these results, note that market uncertainty affects sellers' competition and their utilities in two ways. First, as we discussed earlier, a higher degree of uncertainty will aggravate the negative uncertainty effect of peer comparison, which directly reduces sellers' expected utility.

Moreover, an extra amount of market uncertainty pushes sellers to lower their prices further, which will indirectly hurt sellers' profits and utilities. The intuition is that to counteract the increasingly negative uncertainty effect, sellers have to stimulate their expected market demand by offering lower prices. As Proposition 3 would imply, the equilibrium price p^* with social comparisons is already below the profit-maximizing price $\widetilde{p} = m/(2(1-\gamma)$, i.e., what sellers will charge in a non-comparison marketplace. Therefore, as p^* falls in response to a higher degree of market uncertainty, sellers' equilibrium profits will be reduced, which, combined with the stronger uncertainty effect, also makes sellers' utility lower.

We discussed in the Introduction that there are two sources for market uncertainty: The ever-evolving consumer preferences and platforms' marketplace control algorithms. Platform-induced uncertainty will clearly grow as platforms' algorithms become more complicated and/or are updated on a more frequent basis. Consumer-induced uncertainty is more likely to be high if sellers' offerings are more innovative and/or consumers' preferences exhibit a higher degree of volatility. Note, though, under these conditions that scale up consumer-induced uncertainty, the influence of peer comparison can be modest according to our previous discussions; that is, market uncertainty and peer comparison may work in opposite directions: while the former reinforces the impacts of the latter, the latter partially counteracts itself. Interestingly, there is evidence that sellers may either price aggressively or less aggressively in markets with innovative products (e.g., electronics) and/or varying consumers' preferences (see, e.g., Hoffmann et al., 2012).

We shall note that as market uncertainty grows, sellers' expected utility decreases and may become negative and remain so thereafter. Since a negative utility no longer offers any incentive for sellers to remain in the market, we omit the analysis of market uncertainty for simplicity. Also, similarly, as we have commented earlier, if the marginal utility from faring ahead (i.e., e) dominates the marginal disutility of falling behind (i.e., ℓ), then it is possible for market uncertainty to have the opposite effect and relax the competition.

To close this section, we have seen how sellers' competition and peer comparison are shaped by market uncertainty. On the one hand, market uncertainty gives rise to this surprisingly anti-competitive potential of peer comparison (specifically, of ahead-seeking). On the other hand, though, it reinforces the

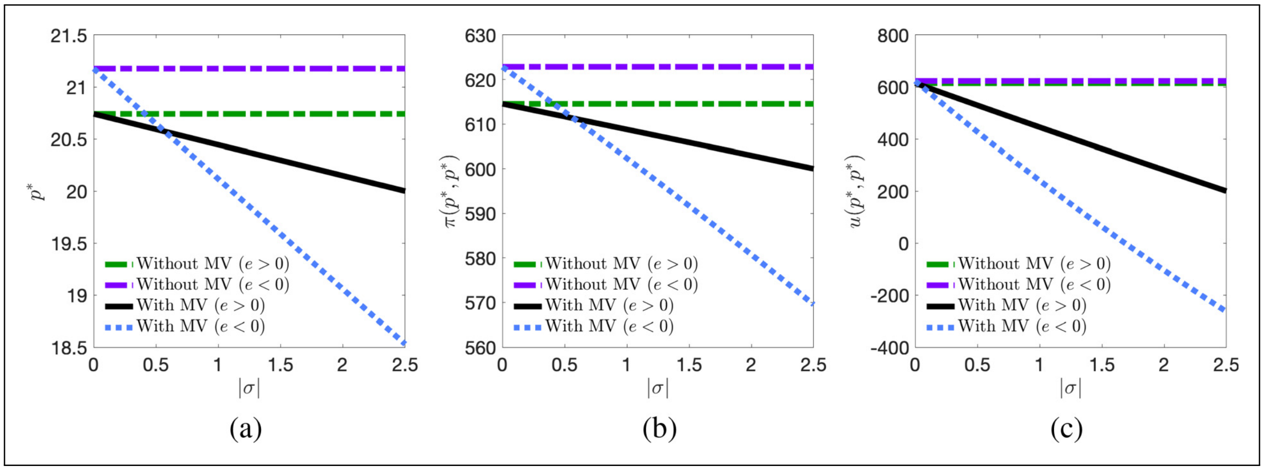

Figure 4. Implications of market uncertainty (MV) ($m = 19, \gamma = 0.8, l = 8$). (a) Equilibrium price. (b) Profit. (c) Utility.

overall pro-competitiveness of peer comparison, which lowers sellers' prices and reduces their utilities to operate in the marketplace. In the next section, we will discuss what these results mean for other marketplace stakeholders, namely consumers and the platform. We will show that sellers' lower prices benefit consumers but can hurt the platform, and we will analyze the implications for the platform's marketplace design strategies.

5 Implications for Consumer Welfare and Platform Designs

We now examine how the strategic interactions between sellers will affect consumers and the platform.

5.1 On Consumer Welfare

Notice that in our model, sellers' peer comparison influences consumers' welfare only indirectly via their prices. That is, neither does comparison parameter ℓ or e enter consumers' welfare directly, nor is any of them changing other model primitives or market outcomes relevant to the welfare. As such, Proposition 3 implies that consumers will be better off in a marketplace with peer-comparing sellers than in one with solely profit-maximizing sellers because peer comparison drives down sellers' prices overall.[16] On the other hand, if sellers already engage in peer comparison, Proposition 2(i) indicates that consumers' welfare will be further enhanced as sellers become increasingly behind-averse, whereas Proposition 2(ii) alerts that consumers can be hurt as sellers turn more ahead-seeking, especially when the market uncertainty is high.

As we mentioned, in reality, peer comparison may also influence sellers' decision-making over other operational levers such as quantity and quality, which complicate the analysis for consumers' welfare. For example, gig platforms such as Uber gamify the workplaces to entice workers to work more hours (i.e., increase supply), which helps provide more responsive services to consumers. Also, sellers' rankings on e-commerce platforms like Taobao encourage sellers to compete not only in prices but also their product page designs, consumer services, etc., which benefits consumers as well. For a negative instance, think about content creators mimicking those star creators' production. While such isomorphic behaviors might boost creators' viewership or even make their work go viral in the short run, the overall diversity and creativity of content degrade over time, which can limit consumers' choices and reduce their welfare.

The impacts of market uncertainty are more subtle. Recall that a major source of uncertainty happens to be the ever-evolving consumer preferences (Lellouche et al., 2020), which is, however, an essential determinant of consumers' welfare; in other words, it is inappropriate to treat or analyze market uncertainty as yet another cause of any variations in consumer welfare. Rather, market uncertainty is a direct manifestation of the varying consumer welfare (and similarly the other way around), as these two objects are rooted in the same microeconomic foundation, i.e., consumer preferences and their corresponding utilities.

That said, we shall remind the readers that platforms' algorithmic marketplace controls are yet another culprit for increased market uncertainty. In terms of its potential impacts, first up, they clearly go through the indirect channel of sellers' peer comparison and price competition. Our Proposition 4 implies that a higher degree of uncertainty benefits consumers by resulting in lower prices. On the other hand, because platform-induced upswings and downswings in market sizes will cancel out on average, no direct impacts of market uncertainty (on market sizes and thus on consumer welfare) shall exist.[17]

5.2 On Platform Design

To evaluate the impacts on the platform, recall that for each transaction, any seller i will pay a commission fee θp_i to the platform. For simplicity, we assume away the platform's cost to process a transaction. As such, we can define the platform's profit as $\Omega = \sum_{i=1}^{2} \theta p_i E[D_i(p_1, p_2)]$, given sellers' prices p_1 and p_2. Notice that the platform's profit is essentially the sellers' total profit times the commission rate θ.[18] Thus, based on Propositions 2, 3 and 4, we draw the following conclusions for the platform.

PROPOSITION 5 (Implications for the Platform). *Regarding the platform's profit Ω^*, we have (i) Ω^* is lower when sellers social compare than when they do not. (ii) Ω^* decreases as sellers become increasingly behind-averse; it increases as sellers become more ahead-seeking if and only if the market uncertainty is sufficiently large. (iii) Ω^* decreases in the market uncertainty.*

Somewhat ironically, Proposition 5 implies that those marketplace design tools used by platforms can backfire and reduce platforms' own profits. On the one hand, those tools throw sellers into a harsher arena of peer comparison and push them to price more aggressively, which reduces the amount of revenue the platform can collect from sellers (though lower prices also expand the expected market demand). On the other hand, as we discussed in the Introduction, due to the opacity of their underlying algorithms, marketplace design tools add an extra layer of market uncertainty for sellers' daily operations, yet this makes the negative impacts of sellers' peer comparison even more significant.

It is worthwhile to point out a few caveats for such a takeaway. First of all, if sellers are already peer comparing in the status quo, then clearly platforms may benefit from deploying their marketplace design tools and stimulating sellers' ahead-seeking behaviors in particular. Moreover, recall that platforms' marketplace algorithms create extra market uncertainty; our theories predict that platforms would indeed obscure and frequently update their algorithms so that the market remains sufficiently uncertain and sellers, driven by a stronger ahead-seeking mindset, tend to raise their prices and thus thicken platforms' revenue streams.

Second, as we mentioned earlier, in practice, marketplace design tools may also influence sellers' decisions along other dimensions. Tools that encourage sellers to scale up supply, improve quality, etc., can counterbalance the negative consequences of lower prices and even boost platforms' profits.

One may have noticed that in our current framework, the interests of sellers and the platform are more aligned but run at odds with that of consumers. Indeed, whenever sellers and the platform are hurt by intensified peer comparison between them and/or more market uncertainty, consumers are better off, and vice versa. As such, our framework does not immediately offer operational prescriptions that can Pareto improve the entire marketplace. That said, we should once again remind the readers that sellers also compare and compete over other dimensions such as quantity and quality. Marketplace designs that can encourage sellers to make more socially beneficial decisions along those dimensions should be promoted. On another matter, if the intensified competition between sellers is so significant that sellers' and platforms' losses have outweighed consumers' welfare gains, then platforms shall guard closely or frequently update their design algorithms so that the market uncertainty will be high enough to tame the downward spirals of market prices. This counters the information-sharing prescription in the extant literature (e.g., Liu et al., 2021).

6 Extensions

In this section, we will demonstrate the robustness of our main insights in a number of important extensions. See also Section OA1 in the e-companion for additional robustness checks with more general assumptions on the distributional behavior of market uncertainty.

6.1 Multiplicative Uncertainty Formulation

In the base model, the uncertainty takes the form of an additive shock to the market size. Here, we will instead study a multiplicative form of uncertainty. Compared with an additive shock, a multiplicative shock makes the market more uncertain in the sense that not only the market size but also consumers' sensitivity to price will be subject to random variations.[19]

Consider the following demand function for any seller $i = 1, 2$,

$$D_i(p_i, p_{-i}, \zeta_i) = \zeta_i d_i(p_i, p_{-i}) = \zeta_i(m - p_i + \gamma p_{-i}),$$

where ζ_1 and ζ_2 are i.i.d. and symmetrically distributed nonnegative random variables. We assume that for any i, $E\zeta_i = 1$ with support $[2 - \bar{\beta}, \bar{\beta}]$, of which the upper bound $\bar{\beta} \in (1, 2]$.

As in the base model, we can similarly define the ex post profit function $\Pi_i(p_1, p_2, \zeta_i)$, the expected profit function $\pi_i(p_1, p_2)$, the ex post utility function $U_i(p_1, p_2, \boldsymbol{\zeta})$, and the expected utility function $u_i(p_1, p_2)$ for the two sellers $i = 1, 2$. Similarly to the model with additive demand shocks, we can show that the expected utility $u_i(p_1, p_2)$ is concave in p_i and there exists a symmetric equilibrium in which

$$p_1 = p_2 = p^* = \frac{[1 + e + (\ell - e)\delta]m}{2(1 - \gamma)[1 + e + (\ell - e)\delta] + \gamma(1 + \ell + e)}, \tag{7}$$

where $\delta \equiv E[\zeta_1 1_{\{\zeta_1 < \zeta_2\}}]$. It is clear that $\delta \geq 0$ because the multiplicative shock is nonnegative. If we focus on a class of random shocks as in Definition 2 with $L = 2 - \bar{\beta}$ and $U = \bar{\beta}$, by Lemma 1, δ is a measure of the demand uncertainty within the focal class of random shocks. Again, the more variable the demand shocks, the lower the value of $\delta \geq 0$. The measure reaches its maximum value $1/2$ when $\zeta \equiv 1$, and its minimum value $(3 - \bar{\beta})/4$ when ζ follows the two-point distribution with $\Pr(\zeta = 2 - \bar{\beta}) = \Pr(\zeta = \bar{\beta}) = 1/2$.

The following proposition describes how the peer comparison parameters ℓ and e affect the price, the expected profit, and the expected utility of the sellers in equilibrium under multiplicative demand shocks.

PROPOSITION 6 (Comparative Statics on Sellers' Peer Comparison). *In equilibrium, we have, for substitutable products with multiplicative demand shocks:*

(i) (BEHIND-AVERSION) *The price p^* and the expected profit $\pi(p^*, p^*)$ are decreasing in the behind-averse parameter ℓ, and the expected utility $u(p^*, p^*)$ is decreasing in ℓ until it reaches zero, and remains nonpositive thereafter;*

(ii) (AHEAD-SEEKING) *There exists a threshold on the market size uncertainty above which the price p^* and the expected profit $\pi(p^*, p^*)$ and the expected utility $u(p^*, p^*)$ are increasing in the ahead-seeking parameter e; otherwise, the price p^* and the expected profit $\pi(p^*, p^*)$ are decreasing in e.*

Proposition 6 confirms that the results on the impact of peer comparison obtained under the additive demand shocks (see Proposition 2) are robust. In particular, behind-aversion still intensifies sellers' competition, while the impact of ahead-seeking is again uncertainty-dependent: it will be anti-competitive if and only if the market uncertainty is sufficiently high.

PROPOSITION 7 (Negative Impact of Uncertainty). *With multiplicative demand shocks, the equilibrium price p^* and the expected profit $\pi(p^*, p^*)$ are decreasing in the market size uncertainty, and the expected utility $u(p^*, p^*)$ is decreasing in the market size uncertainty before it reaches zero and remains nonpositive thereafter.*

What Proposition 7 presents is consistent with Proposition 4; that is, market uncertainty only amplifies the overall negative impacts of peer comparison and can make both sellers worse off.

The results above can be explained similarly by the comparison effect and the uncertainty effect introduced in Section 4. The key reason for our main insights to carry over is that as in (6), one can still break down sellers' comparison utility into two parts, one independent of and one hinging on the market uncertainty, and the latter of which is enhanced as the uncertainty grows. As such, the analysis of sellers' pricing decisions still anchors on how comparison parameters and market uncertainty shuffle the relative magnitude of these different utility parts.

6.2 Asymmetric Sellers

We now examine our key insights with asymmetric sellers. First up, we consider sellers who are asymmetric in their peer comparison parameters and marginal costs of production. We will then study sellers who face asymmetric market sizes and distributions of market uncertainty. Note that any form of seller asymmetry will render the equilibrium prices asymmetric; it is, therefore, no longer possible to fully characterize the equilibrium outcomes in closed form. As such, we will proceed mainly numerically.

We start with the case in which sellers are differentiated in their peer comparison parameters ℓ and e. In reality, individuals can indeed be heterogeneous in their appetites for peer comparison (see, e.g., Leung et al., 2023). Moreover, as we mentioned in the Introduction, in online marketplaces, sellers' relative performances can affect their future operations (e.g., in terms of allocated consumer traffic) in light of platforms' marketplace designs; as such, differentiation in peer comparison parameters also reflects sellers' different beliefs in how they will be awarded/punished by the platform for their over-/underperformances.

Figures 5, 6 and 7 illustrate how market outcomes vary when the behind-aversion parameter ℓ and the ahead-seeking parameter e change for one seller (e.g., seller 1) and stay constant for his or her competitor (e.g., seller 2). One can see that our key insights derived based on sellers' symmetry are still valid. First, all three figures confirm the overall pro-competitive impact of peer comparison, as sellers' equilibrium prices, profits, and utilities are all lower with peer comparison than without. Second, Figure 5 shows that the focal seller (seller 1) will drop his or her price as he or she becomes increasingly behind-averse. Finally, according to Figures 6 and 7, the impact of ahead-seeking is still determined by market uncertainty: The focal seller's equilibrium price and profit will increase in the ahead-seeking parameter e_1 if the market uncertainty exceeds a certain threshold and vice versa. It is worthwhile to note that the focal seller's equilibrium utility may now increase in e_1 even when the uncertainty is not very high; see Figure 7(c) for an illustration. The intuition is that a larger e_1 simply makes the focal seller feel more rewarded for outperforming his or her competitor (see the definition of peer comparison utility (2)); we do not observe it boosts sellers' expect utility when the uncertainty is low in the symmetric case because there the competitor's ahead-seeking also enhances, which intensifies the price competition and overshadows the focal seller's relative performance.

We shall also note that, though seller 1's peer comparison parameters ℓ_1 and e_1 do not directly affect seller 2, they impose indirect effects via the price competition between sellers. For example, in Figure 6, as e_1 increases, in equilibrium, seller 1 raises the price p_1^*, which then alleviates the price competition and thus encourages seller 2 to charge a higher price p_2^* as well.

Next, we study the asymmetry in sellers' marginal costs. Figures OA.6 and OA.7 in the Appendix and Figure 8 show that again our key insights extend. One interesting observation is under peer comparison, the seller with a higher marginal cost may actually charge a lower price than his or her competitor; see Figure 8(a) for an example. To intuit, without peer comparison, a high-cost seller naturally charges a higher price

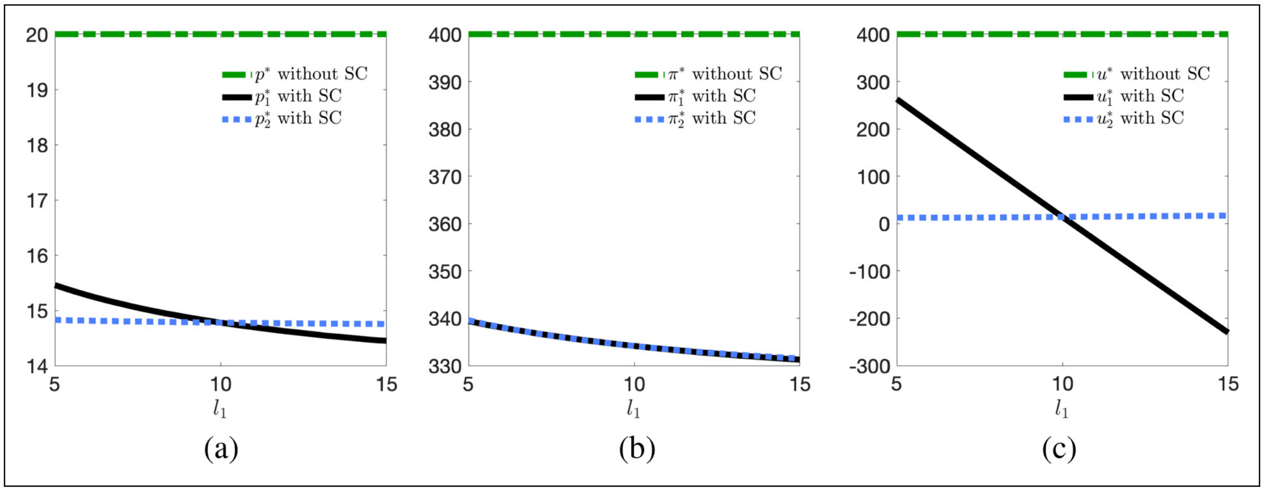

Figure 5. Implications of sellers' peer comparison (SC) under asymmetric Behind-Aversion ($m = 30$, $\gamma = 0.5$, $\ell_2 = 10$, $e = 3.5$, $\epsilon \sim U[-10, 10]$). (a) Equilibrium price. (b) Profit. (c) Utility.

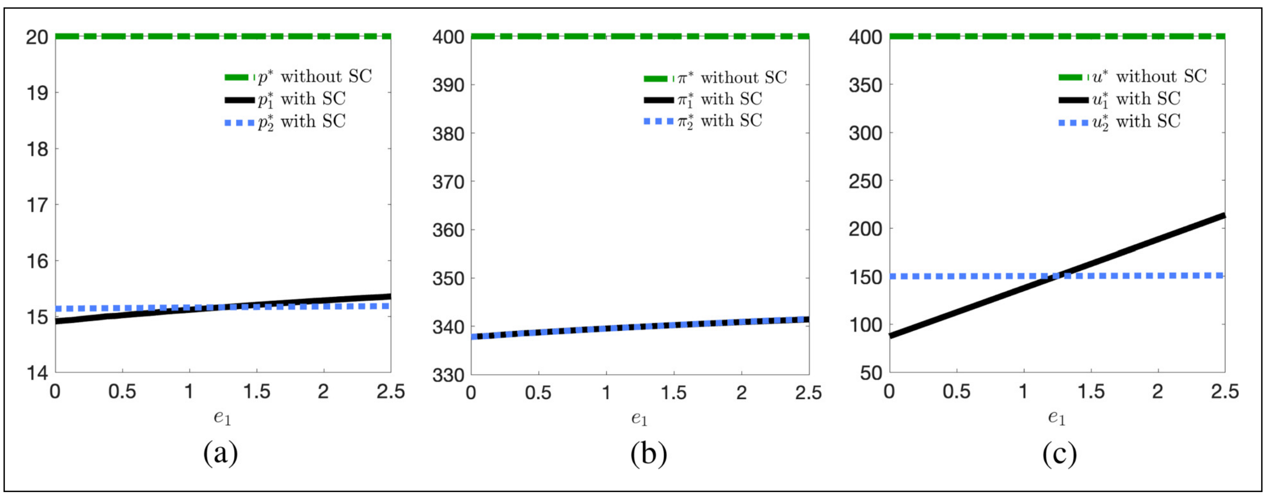

Figure 6. Implications of sellers' peer comparison (SC) under asymmetric Ahead-Seeking and high uncertainty ($m = 30$, $\gamma = 0.5$, $\ell = 5$, $e_2 = 1.25$, $\epsilon \sim U[-10, 10]$). (a) Equilibrium price. (b) Profit. (c) Utility.

than a low-cost seller. Indeed, the high-cost seller's price can be so high that his or her demand is seriously squeezed, and the profit lags far behind the competitor. As such, peer comparison may give the high-cost seller a much stronger incentive than the low-cost seller to lower the price.

Third, we consider the asymmetry in sellers' market sizes (i.e., $m_1 \neq m_2$).[20] Figures OA.8, OA.9 and 9 confirm the robustness of our main insights. One new finding is that a seller may now end up with higher expected utility with peer comparison than without, especially if he or she has a bigger consumer base. See the results for seller 1 in subfigures (c) of Figures OA.8, OA.9 and 9. To unpack such a finding, recall how we decompose sellers' expected social utility in (6). In the symmetric equilibrium, sellers end up with the same amount of expected profits, which dissipates the comparison effect and leaves both sellers only a negative uncertainty effect. By contrast, in an asymmetric equilibrium, seller 1 easily makes a higher profit than seller 2 thanks to a more sizable consumer base. Hence, the comparison effect for seller 1 will be positive. If such a positive comparison effect dominates the negative uncertainty effect (e.g., when ℓ is not too large; see Figure OA.8(c)), seller 1 can end up with a higher utility than without peer comparison.

Finally, we consider the asymmetry in market size shock distributions. Figures OA.10 and 10 illustrate an example where one seller (seller 1) is facing a smaller amount of uncertainty than his or her competitor (seller 2). One new finding is that unlike in the symmetric equilibrium (see Proposition 2(ii)), here the seller with less market uncertainty (seller 1) will also end up with higher profit and utility as the ahead-seeking

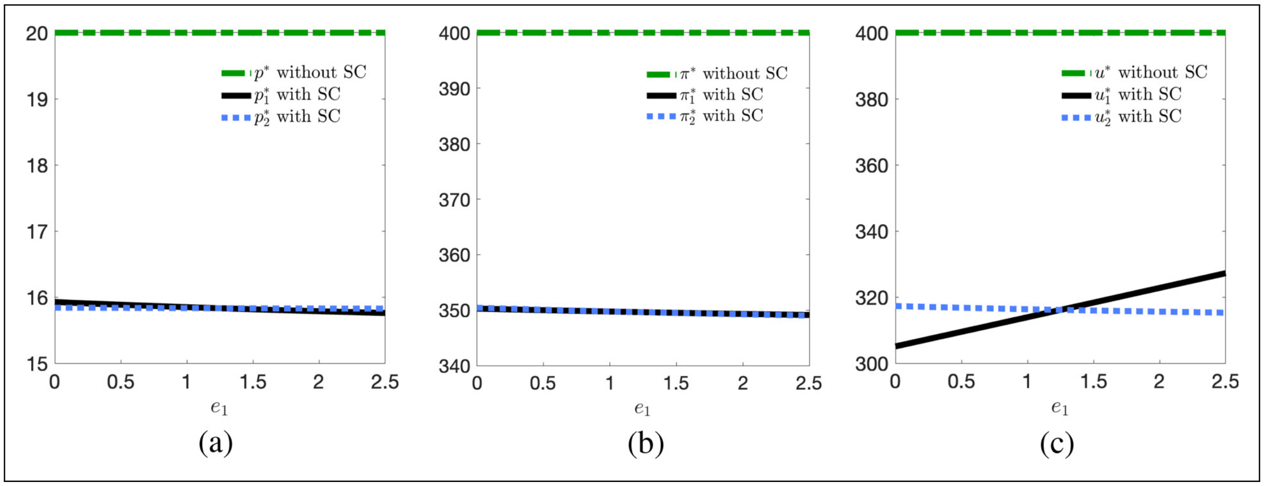

Figure 7. Implications of sellers' peer comparison (SC) under asymmetric Ahead-Seeking and low uncertainty ($m = 30$, $\gamma = 0.5$, $\ell = 5$, $e_2 = 1.25$, $\epsilon \sim$ *Truncate* $\mathcal{N}(0, 1)$ *on* $[-10, 10]$). (a) Equilibrium price. (b) Profit. (c) Utility.

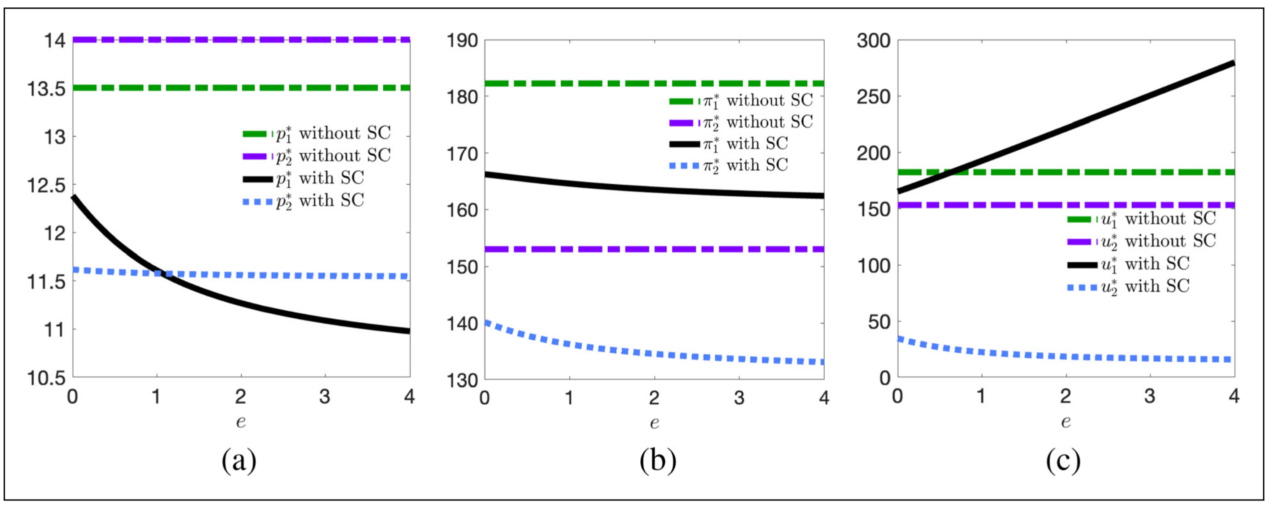

Figure 8. Implications of sellers' peer comparison (SC) under asymmetric marginal costs and low uncertainty ($m = 20$, $\gamma = 0.5$, $\ell = 4$, $c_1 = 0$, $c_2 = 2$, $\epsilon \sim$ *Truncate* $\mathcal{N}(0, 1)$ *on* $[-6, 6]$). (a) Equilibrium price. (b) Profit. (c) Utility.

parameter e increases. The driving force is that the competitor (seller 2), who is facing extra market uncertainty, is raising the price as e rises and thus alleviates the intensity of competition.

6.3 Biased Believes About Competitor's Market Uncertainty

To account for the possibility that sellers know more about their own operations than their competitors', here we study an extension in which sellers may underestimate or overestimate each other's market uncertainty but hold unbiased beliefs toward their own. This is consistent with the *naive realism* approach adopted in the literature (see, e.g., Fan et al., 2023; Li et al., 2017).

Suppose both sellers still face an identical amount of uncertainty, ϵ. The difference from the base model is that they perceive their own market uncertainty unbiasedly as ϵ but guess that for their competitor to be some $\tilde{\epsilon} \neq \epsilon$. Sellers overestimate (underestimate, resp.) the market uncertainty for their competitor if $\tilde{\epsilon}$ is more (less, resp.) uncertain than ϵ in the sense of our Lemma 1.

We can verify that the sellers' expected utility function is still concave. Following similar arguments for the base model, we can derive the equilibrium price as $p^* = \bar{p} \wedge p^{\max}$, where

$$\bar{p} \equiv \frac{(2 + \ell + e)m + 2(\ell - e)\tilde{\sigma}}{2(2 + \ell + e - \gamma)}, \tag{8}$$

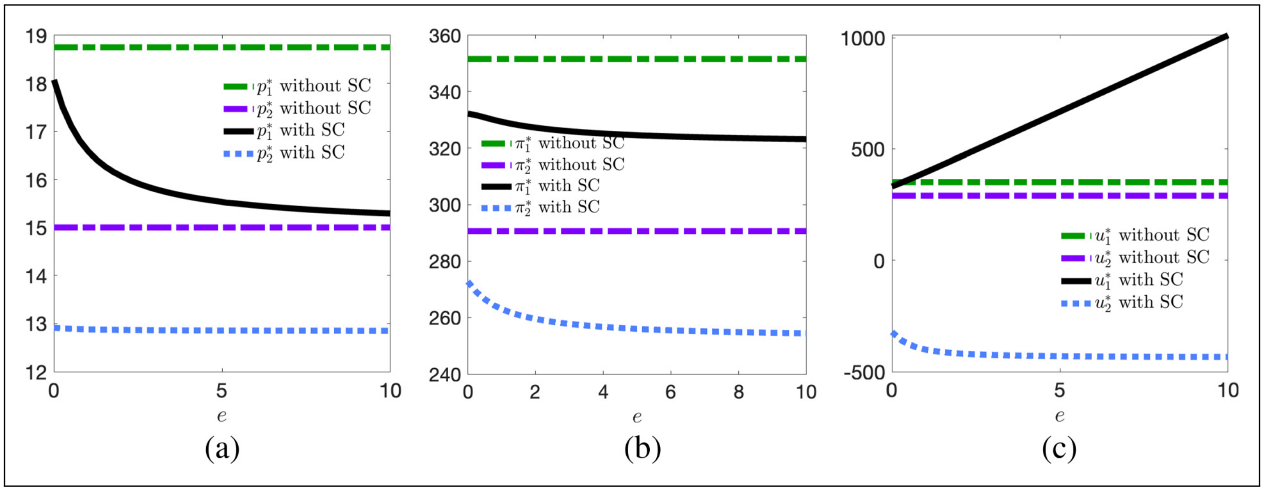

Figure 9. Implications of Ahead-Seeking under asymmetric market sizes and low uncertainty ($m_1 = 30$, $m_2 = 25$, $\gamma = 0.5$, $\ell = 10$, $\epsilon \sim Truncate\ \mathcal{N}(0, 1)$ *on* $[-10, 10]$). (a) Equilibrium price. (b) Profit. (c) Utility.

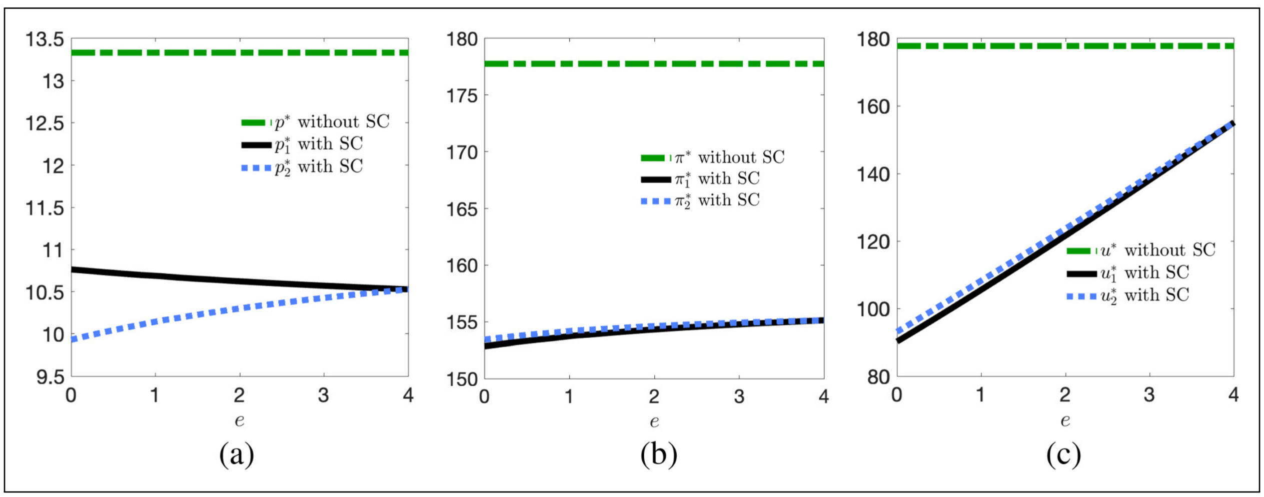

Figure 10. Implications of sellers' peer comparison (SC) under asymmetric demand shock distributions ($m = 20$, $\gamma = 0.5$, $\ell = 4$, $\epsilon_1 \sim Truncate\mathcal{N}(0, 1)$ *on* $[-6, 6]$, $\epsilon_2 \sim U[-6, 6]$). (a) Equilibrium price. (b) Profit. (c) Utility.

and $\tilde{\sigma} \equiv E[\epsilon 1_{\{\epsilon<\tilde{\epsilon}\}}]$. By a similar analysis as in the proof of Proposition 1, we can show that the equilibrium defined in (8) is unique if $e > -1$. One can see that (8) differs from the benchmark equilibrium price (4) only in how the relative market uncertainty is measured (i.e., $\tilde{\sigma}$ versus σ). Lemma 5 below shows the monotonicity of the term $\tilde{\sigma}$ and its counterpart $\check{\sigma} \equiv E[\tilde{\epsilon} 1_{\{\tilde{\epsilon}<\epsilon\}}]$ in the market size distributions ϵ and $\tilde{\epsilon}$.

LEMMA 5. *The terms $\tilde{\sigma}$ and $\check{\sigma}$ satisfy the following monotone properties:*

(i) *$\tilde{\sigma}$ is nonpositive, decreasing in the uncertainty of ϵ, and increasing in the uncertainty of $\tilde{\epsilon}$;*
(ii) *If the density functions of ϵ and $\tilde{\epsilon}$, namely $f_\epsilon(x)$ and $f_{\tilde{\epsilon}}(x)$, are unimodal on $[-\bar{\alpha}, \bar{\alpha}]$, then $2\tilde{\sigma}+\check{\sigma}$ is decreasing in the uncertainty of $\tilde{\epsilon}$ and $\tilde{\sigma} + 2\check{\sigma}$ is decreasing in the uncertainty of ϵ.*

The following result shows how a seller's own market uncertainty and the perceived competitor's uncertainty affect the equilibrium price, expected profit, and expected utility.

PROPOSITION 8 (Equilibrium with Biased Beliefs). *In equilibrium:*

(i) *The price p^* and the expected profit $\pi(p^*, p^*)$ are decreasing in the seller's own market uncertainty and are increasing in the perceived market uncertainty of the competitor;*
(ii) *If the density functions $f_\epsilon(x)$ and $f_{\tilde{\epsilon}}(x)$ are unimodal on $[-\bar{\alpha}, \bar{\alpha}]$, then the expected utility $u(p^*, p^*)$ is decreasing in the seller's own market uncertainty and the perceived market uncertainty of the competitor.*

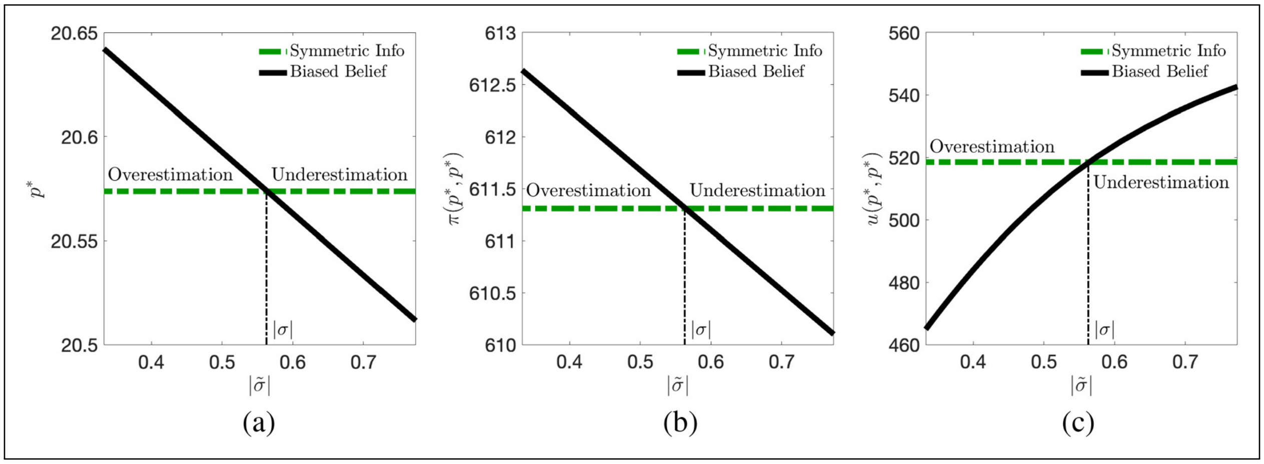

Figure 11. Implications of biased uncertainty belief ($m = 40$, $\gamma = 0.5$, $\ell = 8$, e = 4, $\epsilon \sim$ *Truncate* $\mathcal{N}(0, 2)$ *on* $[-8, 8]$, $\tilde{\epsilon} \sim$ *Truncate* $\mathcal{N}(0, 2 + \Delta)$ *on* $[-8, 8]$, $\Delta \in [-1.5, 3]$). (a) Equilibrium price. (b) Profit. (c) Utility.

Proposition 8(i) implies that the price competition will be relaxed as both sellers tend to overestimate their competitor's market uncertainty. To intuit, first consider how sellers' biased beliefs about their competitor's uncertainty affect the outcomes of peer comparison. When a seller is caught by a negative demand shock, he or she is likely to lag behind if the competitor either receives a positive shock or is hit by a milder negative shock. However, as the perceived competitor's uncertainty increases, the focal seller would expect that the competitor is more likely to encounter rather extreme negative shocks. As a result, the seller becomes slightly more optimistic,[21] and this helps relieve the pressure for him or her to lower the price.

When the focal seller experiences a positive demand shock, opposite to what we have just discussed, he or she may anticipate a higher chance of lagging behind in light of a more unpredictable market for the competitor since it is also more likely that the competitor will receive rather extreme positive shocks. Interestingly, though, the focal seller may instead raise the price to close the performance gap because a positive shock has fallen upon the seller, and it is better to tap into that already expanded market demand. Combining both scenarios (the focal seller experiencing a negative shock and a positive shock ex post), we see that sellers' overestimation of their competitor's uncertainty can indeed increase the equilibrium price (Figure 11).

Also note that, at first glance of Proposition 8(ii), the result seems to suggest that sellers should intentionally underestimate the uncertainty faced by their competitors to improve utilities. Yet no sellers may wish to do so unilaterally; our analysis in Section 4 implies that if the competitor is unbiased and has set the price as p^*, distorting one's own belief and charging $p \neq p^*$ does not ensure a higher utility for any focal seller.

That said, Proposition 8(ii) does offer a behavioral account for why sellers may not have the incentives to acquire too much information about their competitors. Consider a case where sellers tend to underestimate the uncertainty of their competitor. Suppose at some point in time they realize this fact of underestimation and also the possibility to (partially) correct such biases via, e.g., consulting market experts. Then, according to Proposition 8(ii), sellers may not even bother to take such an extra step since more precise knowledge about the competitor only hurts their utilities, not to say that the process of information acquisition is itself costly. This negative value of market information has been studied in various contexts (see, e.g., Wang and Hu 2014: §4.3, for a possible negative value of information about the competitor's inventory level).

6.4 Reference-Dependent Consumers

Finally, we examine the case where consumers are comparing sellers' offerings while sellers themselves are not comparing with each other; That is, we attempt to understand how the market will unravel when the sellers' comparison takes place indirectly through the mental accounting of their reference-dependent consumers. Based on the framework in Zhou (2011), we develop the following consumer demand model:

$$\begin{aligned} D_i(p_1, p_2) = {} & \frac{m}{2} G\left(\frac{1}{2} + \frac{(1+\ell_c)(p_{-i} - p_i)}{2(1+e_c)}\right) \\ & + \frac{m}{2} G\left(\frac{1}{2} + \frac{(1+e_c)(p_{-i} - p_i)}{2(1+\ell_c)}\right) \\ & + \epsilon_i, \ i \in \{1, 2\}, \end{aligned} \tag{9}$$

where $G(\cdot)$ is the cumulative distribution function of a symmetric random variable on $[0, 1]$,[22] and ϵ_i is an independent zero-mean random shock. To intuit, consider a mass m of consumers in the market, each of whom has a random taste X on

$[0, 1]$. Sellers (exogenously) sit on the ends of that unit taste line. Consumers evaluate sellers' offerings sequentially; They take the first seller they view as the reference point, against which the next seller encountered is then compared. In particular, half of them will first view seller 1 and then seller 2, and the other half will do the opposite. ℓ_c (e_c, resp.) represents a customer's per-unit utility loss (gain, resp.) for purchasing from the seller they view later, if that seller sets a higher (lower, resp.) price or is less (more, resp.) attractive for the customer's taste than the reference seller. See Section OA5 in the e-companion for details.

Suppose consumers' tastes are uniformly distributed (i.e., $G(x) = x$ for $x \in [0, 1]$). One can verify that the equilibrium price is $p_1^* = p_2^* = 2(1 + \ell_c)(1 + e_c)/((1 + \ell_c)^2 + (1 + e_c)^2)$, which decreases in consumers' loss-averse parameter ℓ_c and increases in their gain-seeking parameter e for $e \leq \ell_c$, and so is sellers' equilibrium profit $\pi_1^* = \pi_2^* = m(1 + \ell_c)(1 + e_c)/((1 + \ell_c)^2 + (1 + e_c)^2)$. These comparative statics align with the insights from our base model, and the intuition is also similar: ℓ_c serves to aggravate the competitive pressure between sellers as consumers become more sensitive to paying higher prices, while e_c helps alleviate the tension since a larger e_c boosts consumers' pleasure given the same amount of price cut. Also note that because consumers mainly pay attention to sellers' prices and product designs (but not their sales records) when making the purchase decision, sellers' market performance disparity ex post is not relevant to themselves or the sellers. As a result, the equilibrium is independent of the market uncertainty.

7 Conclusions

In this paper, we take a behavioral perspective to study small sellers' operations in modern online marketplaces. Motivated by the observation that online platforms' marketplace design tools have stimulated the peer comparison among sellers, we develop and analyze a model of price competition in which sellers not only care about their own profitability but also factor in their relative performances ex post against each other. Countering the common beliefs, we find that peer comparison is not always pro-competitive. Indeed, we show that while the behind-aversion aspect of peer comparison fosters competition, the ahead-seeking aspect can be anti-competitive when the market uncertainty is sufficiently large. Overall, peer comparison can intensify the competition between sellers, and such a negative effect will be amplified as market uncertainty aggravates. We examine the implications of sellers' peer comparison for consumers and an online platform, reveal the tension between consumers' welfare and sellers and the platform's profits, and discuss how an online platform should fine-tune its marketplace design algorithms (regarding information sharing, etc.) to maximize the total surplus of the ecosystem.

As we have mentioned throughout, in reality, sellers' competition also takes place over quantity and quality. Our main insights can be applied there as well. In particular, from a technical point of view, we can similarly characterize the equilibrium as long as sellers' utility functions preserve quasi-concavity, and the comparative statics of equilibrium outcomes with respect to peer comparison and market uncertainty shall behave similarly to what we have analyzed in this paper.

We offer a parsimonious framework to study the strategic interactions among small sellers in modern online marketplaces. Many other directions are worthy of further exploration. One is to investigate more complex games between sellers, such as competitive price discriminations (e.g., Cohen et al., 2023). Another promising direction is to investigate the scenario of a general number of sellers with potentially heterogeneous pairwise peer comparison. It will be interesting to explore how market outcomes depend on the total number of sellers as well as the network structure of peer comparison (i.e., strong and weak links of comparison between any two sellers). Moreover, one may study the coordination between sellers over their peer comparison behavior. We may introduce stage 0 to our model and let the sellers coordinate by themselves whether to let the profitability information circulate ex post. Though Proposition 3 in our paper implies that sellers shall become better off without the peer comparison, the caveat is that preventing the leakage of profitability information between sellers can be costly in reality (e.g., sellers might need to update their internal codes of conduct, retrain their employees, etc.); as a result, it is not clear *a priori* whether sellers will coordinate effectively, and thus the question merits further investigation.

We have discussed platforms' marketplace designs at a rather high level in Section 5.2. Future research may consider more specific operational problems faced by online platforms and incorporate sellers' behavioral regularities into platforms' marketplace designs. For a concrete example, both Taobao and eBay would reward sellers with animated badges for their overall operational progress (see, e.g., Zhong, 2022), which is essentially a discretized fashion to display sellers' performances. We have touched upon the issue of informational granularity when introducing the model in Section 3. Researchers may further investigate whether a more (or less) granular performance indicator, e.g., sellers' total revenue (or whether they are among the top 1000 sellers), could better orchestrate sellers' interactions and ultimately boost marketplace efficiency.

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Supplemental Material

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Notes

1. Referred to as the "gross merchandise sales," or GMS in the industry.
2. Analytics companies such as Helium 10 offer sellers detailed information about their relative performances and advice for improving operations. See Liu and Long (2024) for related managerial issues.
3. We include workers in the general concept of "sellers" as they are essentially sellers of certain intangible products (i.e., services).
4. Note that Uber has allowed independent drivers to set their own rates in some markets, and there have been price competitions among drivers. See, e.g., https://therideshareguy.com/set-your-own-rates-uber-feature/.
5. See, e.g., https://help.shopify.com/en/manual/reports-and-analytics/shopify-reports/report-types/using-reports/benchmarks_in_reports.
6. To see this, notice that for any seller i, $e'[\Pi_i(p_1,p_2,\epsilon_i) - (\alpha\Pi_1(p_1,p_2,\epsilon_i)+(1-\alpha)\Pi_{-i}(p_1,p_2,\epsilon_{-i}))]^+ - \ell'[\Pi_i(p_1,p_2,\epsilon_i) - (\alpha\Pi_1(p_1,p_2,\epsilon_i) + (1-\alpha)\Pi_{-i}(p_1,p_2,\epsilon_{-i}))]^- = ((1-\alpha)e')[\Pi_i(p_1,p_2,\epsilon_i) - \Pi_{-i}(p_1,p_2,\epsilon_{-i})]^+ - ((1-\alpha)\ell')[\Pi_i(p_1,p_2,\epsilon_i) - \Pi_{-i}(p_1,p_2,\epsilon_{-i})]^-$ for any weight parameter $\alpha \in (0,1)$ the platform uses when aggregating sellers' peformances. Define $e = (1-\alpha)e'$ and $\ell = (1-\alpha)\ell'$ and we can analyze the model in the same way.
7. In the duopolistic case, such a scheme is to inform the sellers if they are ahead/behind, and we can formulate sellers' utility of peer comparison as $S_i(p_1,p_2,\epsilon) = e1_{[\Pi_i(p_1,p_2,\epsilon_i)\geq\Pi_{-i}(p_1,p_2,\epsilon_{-i})]} - \ell 1_{[\Pi_i(p_1,p_2,\epsilon_i)\leq\Pi_{-i}(p_1,p_2,\epsilon_{-i})]}$, where $1_{[\cdot]}$ is the indicator function.
8. The platform's optimal information policy (regarding what information to show sellers, the level of informational granularity, etc.) is an interesting direction for future research. See Chen and Roels (2024) for an in-depth discussion in different settings.
9. See, e.g., https://www.reddit.com/r/AmazonSeller/.
10. The set ordering in this lemma is induced by the usual ordering relation $\leq$ on $\mathbb{R}$.
11. That is, for any seller i, we have $\partial\Pi_i^*/\partial p_i|_{p_i=p^*} = 0$ and $\partial^2\Pi_i^*/\partial p_i^2|_{p_i=p^*} < 0$ (for quasi-concave and differentiable profit Π_i).
12. Since $\frac{(1+\ell)m}{2(1+\ell)-\gamma} \leq \frac{[1+(\ell+e)/2]m}{2[1+(\ell+e)/2]-\gamma} \leq \frac{(1+e)m}{2(1+e)-\gamma}$ by the monotonicity of the function $\frac{(1+x)m}{2(1+x)-\gamma}$ in x.
13. The expected utility $u(p^*,p^*)$, in general, does not have any monotone property in e.
14. To understand this better, consider why there is no such an effect in the case without market uncertainty. Similarly transforming any seller i's expected total utility there, we obtain $s_i(p_1,p_2) = e(\pi_i(p_1,p_2)-\pi_{-i}(p_1,p_2))-(\ell-e)(\pi_i(p_1,p_2)-\pi_{-i}(p_1,p_2))^-$. One can see that the term $(\pi_i(p_1,p_2)-\pi_{-i}(p_1,p_2))^-$ and $\pi_i(p_1,p_2) - \pi_{-i}(p_1,p_2)$ are essentially on the same scale.
15. In the case of $e > \ell$, the closed-form expression (4) will continue to be the unique equilibrium price under additional conditions that guarantee the quasi-concavity of sellers' utility functions; one can then verify that the equilibrium price will be *higher* with peer comparison than without if and only if $\sigma < (\ell+e)\gamma m/(2(2-\gamma)(\ell-e))$. Following our proof of Proposition 3, one can further verify that peer comparison will increase sellers' expected utility in equilibrium if $\sigma \in [\gamma(1+\ell+e)m/(2(\ell-e)(1-\gamma)), (\ell+e)\gamma m/(2(2-\gamma)(\ell-e)))$. In general, the case of $e > \ell$ can have multiple and asymmetric equilibria (see, e.g., Avcı et al. 2014), which requires separate rigorous treatment.
16. A lower equilibrium price leads to a higher overall demand. Given that more customers make a purchase at a lower price, we conclude that the total consumer welfare is higher.
17. For more formal treatment, suppose there are N representative consumers. Each of them $j = 1,\ldots,N$ will purachse from two sellers 1 and 2. Consumer j has the following utility function $U_j(q_{j1},q_{j2}) = (a+\xi_{j1})q_{j1} + (a+\xi_{j2})q_{j2} - (bq_{j1}^2 + 2dq_{j1}q_{j2} + bq_{j2}^2) + q_0$, where (1) ξ_{ji} is a zero-mean idiosyncratic shock in the marginal utility $\partial U_j/\partial q_{ji} = a + \xi_{ji} - 2bq_{ji} - 2dq_{j,-i}$, and (2) q_0 is the Hicksian composite commodity with a price normalized to 1 (Belleflamme and Peitz, 2015). One may show that consumers maximizing such utility functions will lead to our linear demand form in (1). Given the equilibrium prices (p_1^*,p_2^*), consumers' expected welfare will be $CS^* = E[\sum_j(U_j^* - \sum_{i=1,2}p_i^*q_{ji}^*)] = E\{\sum_j[(a+\xi_{ji})q_{j1}^* + (a+\xi_{ji})q_{j2}^* - (b(q_{j1}^*)^2 + 2dq_{j1}^*q_{j2}^* + b(q_{j2}^*)^2)] - (p_1^*q_{j1}^* + p_2^*q_{j2}^*)\}$, where q_{ji}^* denotes the optimal quantity purchased from seller i; see Choné and Linnemer (2020) for details. Given that $E[\xi_{ji}] = 0$ for any j and i, clearly the random shocks $\{\xi_{ji}\}$ will not *directly* affect the consumer welfare.
18. Such equivalence is clearly an artifact of our zero-cost assumptions for both sellers and the platform. With non-zero cost on the sellers' end, the equilibrium price p^* will increase in the platform's commission rate θ (rather than staying constant). Yet still, we would expect that our main insights on sellers, consumers, and the platform will continue to hold.
19. For micro-foundations, additive shocks may apply to markets where the size of the consumer pool and each consumer's price sensitivity are fixed, but their valuation for a product fluctuates. In contrast, multiplicative shocks may be applicable when both consumers' price sensitivity and their valuation are fixed, but the consumer pool size scales up and down randomly; as such, the aggregate market demand, which integrates each individual consumer's demand, would feature a stochastic price sensitivity.
20. There is evidence suggesting that in modern online marketplaces, well-established brands are constantly challenged by and have to compete with emerging players (see, e.g., Hagiu and Wright, 2020). As such, we believe that the simultaneous (rather than sequential) pricing model is still valid for studying sellers' strategic interactions when they have different market sizes.

21. Note that, at the same time, the seller would also expect his or her competitor to more likely receive rather extreme positive shocks. That said, this may only have a marginal effect on the likelihood of the seller falling behind given that he or she has already run into a negative shock anyway.
22. in the sense that $1 - G(x) = G(1 - x)$.

References

Adida E and Özer Ö (2019) Why markdown as a pricing modality? *Management Science* 65(5): 2161–2178.

Allon G, Cohen MC and Sinchaisri WP (2023) The impact of behavioral and economic drivers on gig economy workers. *Manufacturing & Service Operations Management* 25(4): 1376–1393.

Avcı B, Loutfi Z, Mihm J, Belavina E and Keck S (2014) Comparison as incentive: Newsvendor decisions in a social context. *Production and Operations Management* 23(2): 303–313.

Baron O, Hu M, Najafi-Asadolahi S and Qian Q (2015) Newsvendor selling to loss-averse consumers with stochastic reference points. *Manufacturing & Service Operations Management* 17(4): 456–469.

Belleflamme P and Peitz M (2015) *Industrial Organization: Markets and Strategies*. Cambridge, UK: Cambridge University Press.

Belleflamme P and Peitz M (2021) *The Economics of Platforms*. Cambridge, UK: Cambridge University Press.

Bhargava HK (2022) The creator economy: Managing ecosystem supply, revenue sharing, and platform design. *Management Science* 68(7): 5233–5251.

Bojd B, Song X, Tan Y and Yan X (2022) Gamified challenges in online weight-loss communities. *Information Systems Research* 33(2): 718–736.

Bolton GE and Ockenfels A (2000) ERC: A theory of equity, reciprocity, and competition. *American Economic Review* 91(1): 166–193.

Burtch G, Carnahan S and Greenwood BN (2018) Can you gig it? An empirical examination of the gig economy and entrepreneurial activity. *Management Science* 64(12): 5497–5520.

Castellanos S and Shah A (2019) Small businesses aren't rushing into AI. *WSJ*.

Castillo JC (2020) Who benefits from surge pricing? https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3245533.

Chen L, Desir A and Roels G (2023) Fairness concerns in heterogeneous teams: Optimal team formation and contract. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4503491.

Chen L and Roels G (2024) Transparent or not? Optimal performance feedback in games and gamified services. Working Paper.

Chen Y-J, Dai T, Korpeoglu CG, Körpeoğlu E, Sahin O, Tang CS and Xiao S (2020) OM forum—innovative online platforms: Research opportunities. *Manufacturing & Service Operations Management* 22(3): 430–445.

Choné P and Linnemer L (2020) Linear demand systems for differentiated goods: Overview and user's guide. *International Journal of Industrial Organization* 73: 102663.

Cohen MC, Jacquillat A and Song H (2023) Price discrimination and inventory allocation in bertrand competition. *Manufacturing & Service Operations Management* 25(1): 148–167.

Cong LW and Li S (2023) A model of influencer economy. https://www.nber.org/papers/w31243.

Connolly B (2022) *How to Handle Amazon Quantity Limits in 2022*. Jungle Scout. https://www.junglescout.com/resources/articles/amazon-quantity-limits.

Cui TH, Raju J and Zhang ZJ (2007) Fairness and channel coordination. *Management Science* 53(8): 1303–1314.

Debreu G (1952) A social equilibrium existence theorem. *Proceedings of the National Academy of Sciences* 38: 886–893.

Dinerstein M, Einav L, Levin J and Sundaresan N (2018) Consumer price search and platform design in internet commerce. *American Economic Review* 108(7): 1820–59.

Fan X, Wu Q, Chen Y-J and Tang CS (2023) The implications of pay transparency in the presence of over- and underconfident agents. *Production and Operations Management* 32(7): 2304–2321.

Farronato C, Fradkin A and MacKay A (2023) Self-preferencing at Amazon: evidence from search rankings. Tech. rep., National Bureau of Economic Research.

Fehr E and Schmidt KM (1999) A theory of fairness, competition, and cooperation. *Quarterly Journal of Economics* 114(3): 817–868.

Guda H, Dawande M and Janakiraman G (2023) The economics of process transparency. *Production and Operations Management* 32(6): 1812–1829.

Hagiu A and Wright J (2020) Platforms and the exploration of new products. *Management Science* 66(4): 1527–1543.

Hallanan L (2019) Live streaming 101: Understanding the battles or PK feature. *Medium*.

Ho T-H, Su X and Wu Y (2014) Distributional and peer-induced fairness in supply chain contract design. *Production and Operations Management* 23(2): 161–175.

Hoffmann S, Lannes B and Dai J (2012) *China E-commerce: Heading Toward RMB 1.5 Trillion*. Bain & Company. https://www.bain.com/contentassets/84dc567f81eb48ad9cd979ca30d71287/bain_brief_china_e-commerce.pdf.

Hydari MZ, Adjerid I and Striegel AD (2023) Health wearables, gamification, and healthful activity. *Management Science* 69(7): 3920–3938.

Jain S and Qian K (2021) Compensating online content producers: A theoretical analysis. *Management Science* 67(11): 7075–7090.

Kahneman D and Tversky A (1979) Prospect theory: An analysis of decision under risk. *Econometrica* 47(2): 263–292.

Knight B, Mitrofanov D and Netessine S (2022) The impact of AI technology on the productivity of gig economy workers. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4372368.

Langkamp D, Beckett M, Brégé C, et al. (2023) *Resilient Pricing for An Uncertain World*. Boston Consulting Group. https://www.bcg.com/publications/2023/resilient-pricing-for-uncertain-world.

Lellouche K, Candelon F, Reichert T, et al. (2020) *The New Consumer Conversation in An Era of Uncertainty*. Boston Consulting Group. https://bcghendersoninstitute.com/wp-content/uploads/2020/11/The-New-Consumer-Conversation-in-an-Era-of-Uncertainty.pdf.

Leung ACM, Santhanam R, Kwok RC-W and Yue WT (2023) Could gamification designs enhance online learning through personalization? Lessons from a field experiment. *Information Systems Research* 34(1): 27–49.

Li J, Pisano G, Xu Y and Zhu F (2023) Marketplace scalability and strategic use of platform investment. *Management Science* 69(7): 3958–3975.

Li L, Chen J and Raghunathan S (2018) Recommender system rethink: Implications for an electronic marketplace with competing manufacturers. *Information Systems Research* 29(4): 1003–1023.

Li M, Petruzzi NC and Zhang J (2017) Overconfident competing newsvendors. *Management Science* 63(8): 2637–2646.

Liu C-W, Wang W, Gao G and Agarwal R (2024) The value of virtual engagement: Evidence from a running platform. *Management Science* 70(9): 6179–6201.

Liu D, Santhanam R and Webster J (2017) Toward meaningful engagement. *MIS Quarterly* 41(4): 1011–1034.

Liu Q and Shum S (2013) Pricing and capacity rationing with customer disappointment aversion. *Production and Operations Management* 22(5): 1269–1286.

Liu Y and Long F (2024) Data and algorithm: Designing marketplace analytics for platform sellers. Working Paper.

Liu Z, Zhang DJ and Zhang F (2021) Information sharing on retail platforms. *Manufacturing & Service Operations Management* 23(3): 606–619.

Loch CH and Wu Y (2008) Social preferences and supply chain performance: An experimental study. *Management Science* 54(11): 1835–1849.

Long F and Liu Y (2024) Platform manipulation in online retail marketplace with sponsored advertising. *Marketing Science* 43(2): 317–345.

Long X and Nasiry J (2020) Wage transparency and social comparison in sales force compensation. *Management Science* 66(11): 5290–5315.

Lu S (2023) *China-founded Rivals Shein and Temu Ramp Up War for American Shoppers*. WSJ. https://www.wsj.com/articles/china-founded-rivals-ramp-up-war-for-american-shoppers-77c55650.

Lui V, Sun J, Mo S, et al (2021) *Winning in E-commerce Through a Consumer-centric Approach*. Boston Consulting Group. https://web-assets.bcg.com/a4/9b/7c25a12b4d69a008ba8a4f4aa0ed/bcg-x-tmall-fashion-and-apparel-report-apr-2021-en.pdf.

Mason S (2018) *High Score, Low Pay: Why the Gig Economy Loves Gamification*. The Guardian. https://www.theguardian.com/business/2018/nov/20/high-score-low-pay-gamification-lyft-uber-drivers-ride-hailing-gig-economy.

McKinsey & Co. (2023) What is e-commerce? McKinsey & Company. https://www.mckinsey.com/~/media/mckinsey/featured%20insights/mckinsey%20explainers/what%20is%20e%20commerce/what-is-e-commerce_final.pdf.

Momot R, Belavina E and Girotra K (2020) The use and value of social information in selective selling of exclusive products. *Management Science* 66(6): 2610–2627.

Niewoehner RJ and Staats BR (2022) Focusing provider attention: An empirical examination of incentives and feedback in flu vaccinations. *Management Science* 68(5): 3680–3702.

Pavlov V, Katok E and Zhang W (2022) Optimal contract under asymmetric information about fairness. *Manufacturing & Service Operations Management* 24(1): 305–314.

Pierce L, Wang LW and Zhang DJ (2021) Peer bargaining and productivity in teams: Gender and the inequitable division of pay. *Manufacturing & Service Operations Management* 23(4): 933–951.

Popescu I and Wu Y (2007) Dynamic pricing strategies with reference effects. *Operations Research* 55(3): 413–429.

Roels G and Su X (2014) Optimal design of social comparison effects: Setting reference groups and reference points. *Management Science* 60(3): 606–627.

Senate Banking, Housing and Urban Affairs Committee. (2024) Brown demands answers on Amazon and Walmart's use of so-called "dynamic pricing".

Smith B (2021) *How TikTok Reads Your Mind*. The New York Times. https://www.nytimes.com/2021/12/05/business/media/tiktok-algorithm.html.

Song H, Tucker AL, Murrell KL and Vinson DR (2018) Closing the productivity gap: Improving worker productivity through public relative performance feedback and validation of best practices. *Management Science* 64(6): 2628–2649.

Su X (2007) Intertemporal pricing with strategic customer behavior. *Management Science* 53(5): 726–741.

Tan TF and Netessine S (2019) When you work with a superman, will you also fly? An empirical study of the impact of coworkers on performance. *Management Science* 65(8): 3495–3517.

Topkis DM (1998) *Supermodularity and Complementarity*. Princeton, NJ: Princeton University Press.

Ursu RM (2018) The power of rankings: Quantifying the effect of rankings on online consumer search and purchase decisions. *Marketing Science* 37(4): 530–552.

Wang M, Fang X, Wang Z and Chen Y-J (2023) Impacts of distributive comparison behavior on corporate social responsibility in supply chains: The role of small firms. *Manufacturing & Service Operations Management* 25(2): 686–703.

Wang Z and Hu M (2014) Committed versus contingent pricing under competition. *Production and Operations Management* 23(11): 1919–1936.

Yang L, de Véricourt F and Sun P (2014) Time-based competition with benchmark effects. *Manufacturing & Service Operations Management* 16(1): 119–132.

Yang L, Guo P and Wang Y (2018) Service pricing with loss-averse customers. *Operations Research* 66(3): 761–777.

Yang V (2024) JD.com unveils ambitious plans for 618 grand promotion: Aiming to more than double high-performing merchants. JD.com Corporate Blog.

Ye Z, Zhang Z, Zhang D, Zhang H and Zhang RP (2023) Deep learning based causal inference for large-scale combinatorial experiments: Theory and empirical evidence. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4375327.

Yu P, Zhang ZJ and Li Q (2023) Traffic channeling under uncertain conversion rates on e-commerce platforms. *Naval Research Logistics (NRL)* 70(1): 34–52.

Zhong ZZ (2022) Chasing diamonds and crowns: Consumer limited attention and seller response. *Management Science* 68(6): 4380–4397.

Zhou J (2011) Reference dependence and market competition. *Journal of Economics & Management Strategy* 20(4): 1073–1097.

Zhou R, Ren F and Tan Y (2021) Stimulating intrinsic and extrinsic motivation in online learning: The role of incentive design. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3326319.

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