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"TRUST, REPUTATION AND QUALITY IN ONLINE MARKETPLACES"

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ABSTRACT

Questo elaborato scritto tratta dei mercati online, quali, ad esempio, eBay, Aliexpress, Taobao e Airbnb, e in particolare del problema delle asimmetrie informative che caratterizza questo tipo di mercati. Gli e-markets sono piattaforme in cui compratori e venditori che provengono da tutto il mondo possono interagire tra di loro attraverso transazioni a due parti. In questo contesto, coloro che si occupano di progettare e regolamentare queste piattaforme devono cercare di mitigare il rischio di comportamenti opportunistici e promuovere la fiducia e la collaborazione tra i vari utenti.

Vi sono vari strumenti che i mercati online utilizzano per raggiungere questi obiettivi, ad esempio le certificazioni di qualità ai venditori e l'utilizzo degli "user generated contents", ovvero i contenuti quali i commenti, i feedback e le recensioni che gli utenti lasciano sulla piattaforma una volta concluso un acquisto.

Questo scritto offre un quadro generale delle politiche più significative ed efficaci implementate dai mercati online e esplora in dettaglio, attraverso la raccolta di studi empirici, gli effetti economici e comportamentali dell'implementazione di tali meccanismi, sia sulle imprese che sui consumatori.

A conclusione dell'elaborato è presente una mia riflessione, fatta alla luce di tutto ciò che viene presentato di seguito, su come un'ipotetica autorità antitrust potrebbe redigere una regolamentazione valida per tutti i mercati online che possa consentire ai consumatori di mantenere, almeno in parte, il proprio surplus, e di poter contare su venditori di qualità anche in questo tipo di mercati in cui il rischio di comportamenti opportunistici è molto elevato.

INTRODUCTION

Today online marketplaces are widespread and have been defined as one of the greatest success of the internet over the past two decades. They usually consist of e-platforms in which sellers and buyers can interact between them in order to trade goods and services. These platforms can be a great vehicle for firms which want to expand their business or to sell out their inventories fast, but also for consumers who want to buy specific goods that can be found only in other countries or that are rare to find in physical stores.
Every single online marketplace is focused on some product (or service) categories.
Actually, the main categories on which platforms focus are: Food & beverage, Homeware, Health & beauty, Clothing and accessories, Toys and games, Electrical appliances, Books, Games & consoles and Sports. On the one hand, Amazon.com, the biggest global online platform, with 304 millions of active users, offers a very wide range of product categories, but, for example, Airbnb, one of the most successful marketplaces for lodging and house rentals, with 150 millions of active users, focuses only on this specific sector.
Globally, more than 50% of ecommerce sales were made through online marketplaces in 2018, and that is forecast to grow to about two-thirds within five years.
Following there's a list of the major 5 generic online marketplaces which offer nearly all the product categories I've mentioned before; apart from Mercado Libre, which is characteristic of the South America, the other are global platforms.
In the third column of the table is showed the average number of visits per months; data are updated at February 2019.

Name	Region	Visits per month
Amazon	Global	4,6 billions
eBay	Global	1,8 billions
Aliexpress	Global	865,2 millions
Mercado Libre	South America	634,7 millions
Rakuten	Global	384,9 millions

The list of e-markets that actually exist all over the world is really long: according to Webretailer.com, they are 146. In 2017, retail e-commerce sales worldwide amounted to 2.3 trillion US dollars and e-retail revenues are projected to grow to 4.88 trillion US dollars in 2021, moreover, the electronic commerce is expected to cover a share of 17,5% of sales of the global retail commerce in 2021.

In designing online marketplaces, there are some typical problems that must be taken into account. The biggest issue is the fact that, unlike in a physical transaction in a store, where the buyer can touch and feel the good he or she is buying, this close contact is absent in electronic commerce (Tadelis 2016). Therefore, marketplace designers have to adopt mechanisms which can ensure trust among buyers and sellers. Trust in online marketplaces means that consumers and sellers can act in two-sided transactions with no risks of opportunistic behaviours, gaining each one their own surplus when the transaction has occurred.

In this paper I will illustrate in detail the most relevant issues affecting online marketplaces and I will examine the mechanisms that platform designers have adopted, with the aim of guaranteeing trust among users.

In the remaining of this study, Section 1 presents the theory behind the risk of opportunistic behaviours in marketplaces, Section 2 offers an overview of the most common and successful reputation mechanisms adopted by platforms and examine through empirical analysis the economic and behavioural consequences of these mechanisms, exploring also the problem of rating biases. Section 3 concludes the paper, offering some ideas to an antitrust institution that is interested in the issue of trust in online trades, about designing a set of rules that will help consumers to be protected from opportunistic behaviours.

1. THEORY BEHIND REPUTATION MECHANISMS

1.1 – MORAL HAZARD AND ADVERSE SELECTION

The main concept behind the risk of opportunistic behaviours in transactions is the one of information asymmetry. Information asymmetry occurs when one of the two parts of a transaction has more or better information than the other.
This can happen when one of the two parts knows something about the item traded that the other part doesn't know, or instead it knows something about the other part, while the latter doesn't.

The two main forms of information asymmetry are the concepts of adverse selection and moral hazard; they are relevant for our study because they actually affect the vast majority of transactions in e-markets.
Adverse selection occurs when one of the two parts (usually the seller) has more information than the other on the item traded. This is obviously an advantage for the former, that can set the price for the good or service knowing that the other part, due to the lack of information, may accept that price also when is too high if compared to the effective quality of the product.
The concept of adverse selection is well explained by George Akerlof (1970) in his work "The Market for Lemons: Quality Uncertainty and the Market Mechanism". In the American slang, the world "lemon" defines a car that it is found to be a bad quality one only after it has been bought. In his paper, Akerlof in fact studies the concept of information asymmetry applied to the market for used cars.
Suppose that, in this specific market, two types of cars are sold: high-quality cars and low-quality cars; sellers know, for each of their cars, if they are high or low quality, but consumers can't know that, because of information asymmetry.
So, there's a risk of opportunistic behaviour by the sellers, that can sell low-quality cars (lemons) at the price of an high quality car. This is, in practice, the concept of adverse selection.
In his work, Akerlof then shows that this market setting, characterised by the adverse selection problem, can lead to the failure of the market, with consumers that, because of the fear of buying a bad car at the price of a good one, are willing to pay a maximum price equal to the price of lemons. The result is that only low-quality cars are sold in the market.

“It has been seen that the good cars may be driven out of the market by the lemons. But in a more continuous case with different grades of goods, even worse pathologies can exist. For it is quite possible to have the bad driving out the not-so-bad driving out the medium driving out the not-so-good driving out the good in such a sequence of events that no market exists at all.” (Akerlof 1970, p.490)

Moral hazard is the situation in which one of the two parts of a transaction, after it has agreed to the contract, changes its behaviour in order to gain more benefits, taking advantage of the fact that the other part can’t do nothing to prove its unfair behaviour.
The typical setting in which moral hazard can take place is the insurance sector. Insurance contracts are situations in which one of the two parts, the insurance company, in change of regular payments, takes responsibility for all the economic risks linked to the “hazardous behaviours” of the insured.
An individual, in general, pays a lot of attention to avoid behaviours that can deal damage to other people or things, if the risk of dealing that damage is (at least partly) in charge of him. So, when an insurance company takes responsibility for the damage that an individual can deal, the latter pays less attention to its “hazardous behaviours” and this because it is very difficult for the insurance company to monitor its customer’s actions and verify its unfair behaviour. This is a practical example of moral hazard.

Following Tadelis (2016) we escribe now a couple of examples highlighting asymmetric information issues in online markets. First, let’s consider a seller on eBay: suppose that this seller knows that the good it’s offering it’s defective and that he chooses not to reveal the defect. In this case we have an adverse selection problem, because the seller knows something more about the object of the transaction than the buyer.
Suppose now that the seller, instead of selling a defective item, sells an high-quality item but, once the transaction has been completed, it chooses to skimp on the wrapping material used for the item’s delivery, increasing the likelihood that the good arrives damaged. This is an example of moral hazard in e-markets.

These examples show that in online marketplaces quality uncertainty is a very common problem, given the usual incomplete information settings in which agents operate: “For a marketplace to flourish, therefore, it is necessary that both sides of the market feel comfortable trusting each other, and for that, they need to have safeguards that alleviate that problems caused by asymmetric information” (Tadelis 2016, p. 2).

1.2 – THE TRUST GAME MODEL

The difficulty in supporting anonymous online trade can be easily explained using a simple game theoretic example, which is a version of the "trust game".

Trust game is a game theory model in which two players, in each stage of the game, have to choose if to honor trust, or instead to abuse trust. Following Tadelis (2016), we describe a simple trust game.

In an online marketplace where the two players are a seller and a buyer, the buyer finds an item listed online by the anonymous seller at a price of 30. Imagine that the buyer values the product at 50 (the net surplus for the buyer is 20) and that the seller has no alternative use of the good, implying that if it doesn't sell the item it will gain a profit of 0.

Shipping and handling expenses cost a total of 10 to the seller, meaning that at a price of 30, it gains a net surplus of 20.

Now suppose that the seller can be of two types: an honest seller, who will always honor trust and will ship the item once the transaction has been completed, or an opportunistic seller, who will maximize its net profit.

In an anonymous marketplace, the buyer doesn't know which type the seller is, but it knows that it is an honest seller with a probability $\rho \in (0,1)$.

In this game model we have both adverse selection (the type of seller is known only by the seller) and moral hazard (the choice of the opportunistic seller is not controllable by the buyer).

Imagine that the game is played only once: in this case an opportunistic seller will always abuse trust, choosing not to ship the item and gaining a total profit of 30 instead of 20; so, the buyer will trust and buy only if the expected benefit for either getting 20 of surplus or losing 30 is not negative:

$$20\,\rho + (-30)(1-\rho) \geq 0 \quad \rightarrow \quad \rho \geq 0{,}6.$$

But if the game is played more than once, the opportunistic seller may have incentive to honor trust, and this choice is based on how much it values future rewards.

Suppose that the seller discounts future payoffs at a discount factor $\delta \in (0,1)$.

We also have to take into account that with a multiple stage game, the buyer can use the seller's behaviour in the first transaction as a proxy to identify the type of seller. This means that, if the seller has abused trust in the previous transaction, the buyer would not trust it anymore, nullifying future rewards for the seller.
"Equipped with these beliefs, if future is important enough, then an opportunistic seller would not find in its best interests to abuse trust in the first transaction". (Tadelis 2016, p.5)

So, assuming we are in a two-stage game and that the buyer too uses δ as discount factor, it will be happy trusting the seller only if:

$$\rho\,(20 + 20\delta) + (1-\rho)(-30) \quad \rightarrow \quad \rho \geq \frac{30}{50+20\delta},$$

If: $\delta \approx 1 \rightarrow \rho \geq 0{,}4.$

The result shows that as δ approaches to 1, the likelihood that the buyer will trust the seller is higher, in the sense that the former will be happy to transact also for lower values of ρ.
With more stages than two, this effect is larger, and trade will occur also for much lower values of ρ.

The key idea here is that actions of sellers will lead to future consequences that will affect their future payoffs; as Tadelis (2016) affirms, if the performance of sellers will be shown not only to single buyers but to all buyers in the platform, in a sort of "transaction history", the reputation of the seller (to be an honest-type or not) will be clear to all potential buyers, and this may be a great incentive for sellers to behave well.

2. ECONOMIC AND BEHAVIOURAL CONSEQUENCES OF REPUTATION MECHANISMS IN ONLINE MARKETPLACES

2.1 – FEEDBACK SYSTEMS AND ONLINE REVIEWS

Two types of mechanisms are usually used to create a transaction history of sellers and to provide future buyers a portrait that can help them deciding if to trust a seller or not.

The so called feedback systems are standardized processes designed by marketplaces that allow users (both buyers and sellers in a two-sided feedback system) to leave comments, usually in form of a "star rating" about the seller's (buyer's) performance and behaviour in the transacting and delivering phase.
Online reviews are instead comments and valuations, created by buyers, about the items traded in the marketplace, not dealing with the buying experience. They contribute to create a seller's past reputation focusing on quality of products or services which the latter offer.

2.1.1 – EWOM AND USER GENERATED CONTENT, AN OVERVIEW

Word-of-mouth (WOM) is defined as oral, person-to-person communication between a receiver and a communicator, whom the receiver perceives as non-commercial, regarding a brand, product, or service.
The Internet has enabled new forms of communication platforms that further empower both providers and consumers, allowing a vehicle for the sharing of information and opinions both from business to consumer, and from consumer to consumer. EWOM (electronic Word-of-mouth) refers to any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institution (Yang, Li et al. 2016, p. 272).

According to Tadelis (2018) and King et al. (2014) the great success of eWOM today is due to the possibility for users to maintain anonymity, a fact that make them more comfortably in making their opinions public, and to the great pervasiveness of this type of UGCs (User Generated Contents); through eWOM in fact, opinions become available to a much larger audience and for a much longer time.

Before online feedback and reviews systems were introduced, people were highly skeptical about their adoption by marketplaces, as mentioned also by Jeff Bezos (CEO of Amazon) in his "Letter to stakeholders" in 2003. This skepticism was supported also by the economic theory: in fact leaving a feedback or a review supplies a public good and we know that, because of the free riding problem, people are not encouraged to supply public goods that can give benefits to other people. However, the rise of eWOM shows that in online marketplaces such a pro-social behaviour has become a trend; this probably because of factors like the possibility to maintain anonymity and so not being judged by others and like the possibility to become "opinion leaders" for other consumers and gain some moral satisfaction. Another reason for the raise of the pro-social behaviour mentioned above is the fact that, even if eWOM is a public good, there are no monetary costs (in addition to the purchase cost of the item traded) to leave a feedback or a review: costs exist only in terms of time and therefore it is easy to sustain.

As Tadelis studies show, in 2016, 65% of users left feedback on eBay and in the earlier days of that platform, this percentage was even higher (nearly 80%).

2.1.2 – <u>TAOBAO AND THE "RFF" SYSTEM</u>

Taobao marketplace (www.taobao.com) was launched in 2003 and it has become the most popular Chinese consumer-to-consumer marketplace. On an average day, about 600 millions of users visit Taobao to search for some products. (Data from https://www.similarweb.com/website/taobao.com)

Taobao is part of the Alibaba group, a large Chinese public company which operates in the e-commerce sector, and, like eBay, Taobao intermediates between buyers and sellers, but unlike eBay, it doesn't earn from charging listings or from commission fees, it gains from advertising and other services that the platform provides to users.

In the present analysis I will treat Taobao separately from other marketplaces because of its particular feedback system, called "Reward-for-feedback" (RFF).

The RFF system was introduced in 2012, and it consists in a feedback mechanism in which sellers can set, for each item they sell, a rebate amount, in form of cash or a store coupon, as a reward for a buyer's feedback (review) after purchasing the item. If the seller chooses the RFF feature, the rewards for feedbacks are given only to those customers who leave high-quality reviews. The quality of reviews doesn't depend on whether they are favorable or not, but it is determined by a machine learning algorithm that examines feedback's content and length, finding if the key features of the item are mentioned.

The introduction of this feedback system was based on the economic theory, which predicted that the RFF system would have improved the overall quality in the marketplace.
Nelson (1970) was the first to introduce the concepts of experience goods and search goods: an experience good is a product or service where product characteristics are difficult to observe in advance, but this characteristics can be ascertained upon consumption; a search good is a product or service which characteristics can be easily evaluated before purchase. The economic literature has established a theory for which the adverse selection problem concerning experience goods can be solved through advertising: only high quality sellers will spend money to promote their experience goods, because only high quality sellers can be confident that they will receive positive returns for their expenditures.
So, advertising would act as a signaling device, attracting buyers towards high quality sellers; therefore, on Taobao, only high quality sellers will adopt the RFF feature and reward buyers for their feedbacks, because, like in the advertising case, only high quality sellers will gain from their expenditures; in this sense RFF acts as a signaling device.
Li et al. (2018) studied the implications of this RFF mechanism, using data from transactions that involved 13018 randomly selected sellers on Taobao between September 2012 and February 2013, in four product categories: cell phones, memory cards, cosmetics masks and jeans. They found out a confirm to the RFF-as-signal theory.
In fact, their results showed that high quality sellers use the reward-for-feedback feature to send signals to customers, and the latter respond rationally to these signals: sales of an item are 30% higher when the seller chooses to adopt RFF.
The RFF also help new sellers to solve the "cold start" problem: it is normally difficult for a seller with no feedback history to show that it is an high quality one, but adoption of RFF is an immediate and effective signal to buyers, that creates reputation faster.
Furthermore, people now are paid to supply feedbacks, that are public goods, so they are obviously encouraged to post more reviews and also to spend more time on writing them, resulting in more detailed and complete product reviews.

2.1.3 – TWO-SIDED VS ONE-SIDED FEEDBACK, THE RETALIATION PROBLEM

Analyzing feedback systems of online marketplaces, we have to distinguish between "two-sided" and "one-sided" feedback systems. The former are mechanisms in which, after a buyer and a seller have completed a transaction, both of them can leave feedback to each other. The latter instead are mechanisms in which only buyers can leave feedback to sellers after the completion of a transaction.

Before 2008, eBay feedback system was of a “two-sided” type, but then the platform decided to switch to a “one-sided” system; why eBay decided to make this change?

In the earlier days of eBay, payments were made through checks or money orders to sellers, and these payments methods made it clear that also sellers had to decide if to trust or not buyers, because also the latter could, referring to the trust game we analyzed in the previous section, “behave bad” and do not send the payment to the seller.

Then, in 2002, eBay acquired Paypal, the famous online payment system, making the problem of buyers not paying all but disappeared; this obviously made feedback from sellers less useful.

However, the reason of the switch to the “one-sided” system lies in the so called *retaliation problem*. The general definition of retaliation is the act of responding with an harmful action to someone who hurt us with an harmful action too.

Bolton et al. (2013), using data from eBay in the period of the “two-sided” feedbacks, show in their studies that sellers, before giving feedback to buyers, waited to get feedback from them. Let’s consider a simple model in which a buyer (B) and a seller (S) have completed a transaction; the transaction then will end with the feedback setting (FB,FS), where FB is the feedback from the buyer and FS is the feedback from the seller. Both FB and FS can be a negative feedback (-), or a positive one (+). Bolton et al. (2013) show that practically all transactions ended with (+,+) or (-,-) and then the authors show that the vast majority of (-,-) transactions were characterized by the seller leaving feedback on the same day or the day after the buyer did, while the (+,+) transactions happened with less correlation between the buyer’s and the seller’s day of leaving feedback.

Hence, as Tadelis (2016) states, seller’s negative feedback scores were primarily retaliatory, which in turn made it painful for buyers to leave negative feedback.

So, today it’s generally accepted that “one-sided” feedback systems, combined with online instant payments methods, can avoid opportunistic behaviours from buyers and can also avoid the retaliation problem, but this statement it’s not true for all online marketplaces.

In fact, if we consider a platform for lodging and house rentals like Airbnb, it’s not true that the best feedback system is of a “one-sided” type. In this type of marketplaces, owners can mispresent the home they are renting, leave it dirty, not give renters the key at a specific time and more, but also renters can leave the home damaged or dirty, disturb

neighbours, and behave opportunistically in the period of their sojourn. So, in this setting, both the owner and the host "performance/behavior" matter, way more than the "performance/behavior" of the consumers on eBay or Amazon. So it is relevant to leave a feedback on the host too. For this moral hazard problem affecting both the two parts of the transactions, here it's preferable to adopt a "two-sided" feedback system.
"Each marketplace, therefore, must weigh the cost and benefits from one- versus two-sided feedback systems". (Tadelis 2016, p.13)

2.1.4 – CONSEQUENCES OF ONLINE REVIEWS ON FIRM'S ECONOMIC PERFORMANCE

"By bridging the informational gap between buyers and sellers, online user reviews can help make a product worth purchasing." (Tadelis 2018, p.5)
This statement can help us realizing that online product reviews have become a fundamental tool not only for buyers who want to know more about the effective quality of goods and services offered in marketplaces, but also for firms, because a lot of studies on this topic have demonstrated that online user reviews impact the economic performance of sellers, in terms of sales.
The two relevant dimensions of online reviews are volume and valence; volume is the number or reviews that a product detains, valence instead is defined as the average rating of those reviews. The studies of Chen et al. (2004) and Chevalier and Mayzlin (2006) are the first that had investigated the relationship between online reviews and product sales; they showed, analyzing data from Amazon and Barnes and Noble online bookstores, that valence and volume of reviews were always positively correlated with sales. Dellarocas et al. (2007) and Liu (2006) used in their studies data from Yahoo movies, an online marketplace for movies, and found that, in the movie industry, ratings per se do not affect sales directly, but they do through volume. The relationship went also in the opposite direction for the movie industry: higher sales led to an higher volume of reviews; in this case, valence doesn't play a large role.
Exploring the value of valence, Chevalier and Mayzlin (2006) had found that negative reviews have a much larger impact on sales than positive reviews. Regarding valence of the content (and not of the rating score) of reviews, Cui et al. (2010) found out that

reviews with a negative content might even have a positive impact on sales, as long as the average user rating is positive, because they raise product awareness among consumers.
Some studies have been carried also on the impact on sales of another dimension of online reviews: the variance, that can be defined as how much valence of reviews vary from its average value, for a specific item. About that, Clemons (2006), analyzing data from the craft beer industry, shows that variance, in markets for hyperdifferentiated products, has an even larger role than valence in affecting sales: the higher the variance in the ratings, the more negative the impact on sales. However, apart from the context of hyperdifferentiated and niche markets, variance seems not to have a relevant role.
Online user reviews are characterized also by the fact that they (usually) embody a textual content. Ghose and Ipeirotis (2011), investigated the impact of textual content of reviews on the economic performance of sellers and found, using text mining techniques on Amazon product reviews, that if a review was characterized by subjectivity, the impact on sales was positive for search goods; for experience goods, the correlation between subjectivity and sales was not clear, but Ghose and Ipeirotis (2011) showed that sales for these goods were affected negatively by the proportion of spelling mistakes.
In sum, online user reviews affect sales in different ways, and through different dimensions: the most important "drivers" of sales are volume and valence of reviews, which positively affect sales for nearly all types of markets, instead variance drives sales only in niche markets. It has been found out that also textual content of reviews affects firm's economic performance, but research on this aspect is still new and the only results show that this dimension of reviews affects in different ways experience goods and search goods.
Now, let's examine the studies that investigated how firms incorporate eWOM into their marketing strategies, in particular in their pricing decisions. Using data from Shopzilla, a shopping comparison website, Grover et al. (2016) showed that a greater variance in ratings, which means a more heterogeneous consumer willingness to pay for the same good, leads sellers to raise prices.
Yacouel and Fleischer (2012) were interested in studying how feedbacks posted on Online Travel Agencies impact the price decisions of hotels; they analyzed data from Bookings (the actual Booking.com) and found out that if reviews signaled an high quality, firms seems to be allowed to ask for a premium price. One interesting result concerning hotels on Bookings was that when hotels gained high scores even just in the rating of the staff performance, they charged higher prices. An exception to the positive correlation

between high quality signaled by reviews and higher prices charged by sellers was found by Kocas and Akkan (2016), who considered data from Amazon bookstore and demonstrated that in this specific market, booksellers charged lower prices when the average quality was higher. Kocas and Akkan explained this result stating that a lower price combined with high ratings can help patronize customers.

2.1.5 – CONSEQUENCES OF ONLINE USER REVIEWS ON CONSUMERS' BEHAVIOUR

The "funnel metaphor" that the traditional marketing literature had adopted to describe the consumers' decision-making process, has been challenged by the "Consumer decision journey" model, theorized by McKinsey in 2009. The former model was theorized by E. St. Elmo Lewis in 1898 and it represents the consumer decision-making process through a funnel, divided in 5 parts, that starts from the awareness about a product or brand, then it passes through the opinion, consideration and preference phases, and finally ends with the purchase decision. The model of McKinsey instead provides us a view of the consumer in which it is constantly exposed to advertisement, recommendations and other marketing activities, and, during its decision making process, it may add or subtract brands at any time. In fact, today, consumers, as De Langhe et al. (2016) state, are empowered agents, as they can share opinions with a larger audience and become active users evaluating their experience with products and informing others. In the era of eWOM, therefore, firms have to take into account that consumers are not as "loyal" to the brand as they were in the past, because they finally can compare various products without excessive search costs, and they have access to the opinions of customers that already purchased the product they are looking for. Hence, reviews has also an impact on the behaviour of consumers, considering both the purchasing phase and the rating phase itself.

Chatterjee (2001) studied the different effects of online reviews on two types of consumers: consumers that are familiar with a specific e-retailer and consumers who instead were attracted by lower prices. Through a laboratory experiment, in which he divided the two groups and analyzed their behaviour in the browsing and purchasing phase, he was able to show that the former are less likely to search for peers' opinions, while the latter are more influenced, in making their purchase-choices, by eWOM. Results of Chatterjee (2001) demonstrate that the "lowest price" advertising strategy is not so profitable, because it attracts the less-loyal type of consumers.

Vermeulen and Seegers (2009), by means of a laboratory experiment, analyzed the effect of the exposure to online reviews on hotel awareness, attitude and consideration.

Their results showed that both positive and negative reviews increase awareness; attitude to the hotel instead was improved by positive reviews and worsen by negative reviews. Interestingly, consideration was not affected by negative reviews, because, as the authors suggest, the positive effect on awareness was high enough to compensate the negative effect on consideration. In line with the studies of Chatterjee (2001), the two authors showed that familiarity with the hotel makes consumers less willing to rely on eWOM, while lesser known hotels were more susceptible to online reviews. Studies of Forman et al. (2008), using a dataset based on ratings and reviewers characteristics from Amazon, found that people are more willing to rely to online reviews when the platform provides some information about the identity of reviewers. "Community members process information heuristically, using source of characteristics as a convenient and efficient heuristic device on which to base their product purchase decisions" (Forman et al. 2008, p. 308). Exploring the role of textual content of reviews, Hu et al. (2014) found out, using a sample of Amazon reviews, that ratings of reviews is usually adopted to skim through the many available alternatives, while textual reviews are used to actually make the choice.

2.2 – RATING BIASES

Rating biases are those phenomena in which the rating behaviour of consumers is influenced by other exogenous factors, and therefore, it may not correspond to the true valuation of a product/service/purchase experience.

When eWOM is biased, it might lead the users of a marketplace to make inefficient purchase decisions. Biases in reputation of e-retailers can exist due to a "natural" heterogeneity of consumers, who can be more prone to submit positive (or negative) feedbacks, but they can exist also due to attempts of sellers to strategically manipulate feedbacks. The latter are cases studied by Mayzlin et al. (2014), who were able to demonstrate that sellers in travel sites manipulated feedbacks and reviews to compete with local competitors for the business of travelers. The authors showed that, in travel sites in which to leave a review or feedback it was needed to have purchased a room through the website, the reviews seem to be less biased than in those sites in which there were no costs to sustain in order to leave a review. In the former, the distribution of ratings in fact was bunching at extreme values, probably because of fake reviews left by hotels to compete with rivals.

Another example that can explain this phenomenon of bias in eWOM is the eBay's switch to the one-sided feedback system in 2008, a topic covered in chapter 2.1.3 of the present study: before the switch, users tended to post reviews that could be not true, due to the fear of retaliation.

Today, platform designers have adopted mechanisms that have made the problem of fake reviews by sellers all but disappeared, but rating biases due to consumers' psychology continue to exist.

2.2.2 – RATING BUBBLES

Studies of Chevalier and Mayzlin (2006) and Godes and Mayzlin (2004) have shown that online rating distributions are, typically, concentrated around extreme positive or negative values; in many websites, as Tadelis (2018) states, moderate ratings are almost non-existing. This is the phenomenon of rating bubbles.

Rating bubbles have been object of various studies, in primis by Hu et al. (2009), who compared the rating distributions of randomly chosen Amazon products and the rating distributions of the same products but in a controlled laboratory setting. The results of the experiment show that online ratings followed a J-shaped distribution, with ratings concentrated on extreme values, instead laboratory ratings were more moderate.

The authors suggested that this "extreme-rating-trend" was due to the problem of early adopters enthusiasm, a topic that will be covered in the next paragraph, and to the fact that people tend to conform to previous ratings when they have to leave a review.

Li and Hitt (2008) found that rating data followed a decreasing trend over time, a result supporting the explanations of Hu et al. (2009).

2.2.1 – EARLY ADOPTERS ENTHUSIASM

Li and Hitt (2008) studied the phenomenon of bias in ratings, analyzing data from Amazon bookstore and they found out that there might exist self-selection due to heterogeneous consumer attitudes towards products.

In particular, they focus on the difference in the rating behaviour of two types of consumers: early adopters and late-comers. The former are people who are in general more enthusiastic about a product, and they usually buy it almost immediately when it's launched in the platform. The first reviews of the product therefore will be very positive, because of this early adopters enthusiasm. It's not always true that early adopters would assign an high rating to the products they are enthusiastic for, but this happens very often in markets for items like books, videogames, films, and tv series, which are goods that engage customers at a more psychological level, and their perceived quality is highly subjective.

Li and Hitt (2008) were able to demonstrate that this self-selection due to heterogeneous consumer attitudes greatly impacts consumer behaviour during browsing and these biased signals might push users to sub-optimal choices. A natural consequence of this early adopters enthusiasm is the fact that average rating of products tend to worse over time, because late-comers obviously would leave reviews that are less enthusiastic and positive than those of early reviewers.

2.2.2 – ONLINE SOCIAL INFLUENCE

Another explanation that the economic literature gave for the rating bubble problem is "online social influence", that is defined by Cicognani et al. (2016) as the tendency to imitate peers during the rating phase. Analyzing social influence, Moe and Schweidel (2012), studied the behaviour of two types of reviewers: frequent and infrequent posters. The former tend to differentiate themselves and being critical when they have to review something, infrequent posters instead tend to be influenced by previous peers' opinions. So, for these authors, rating bubbles are due to heterogeneity in the reviewer pool, and about that, they found another result: "individuals with either high or low postpurchase evaluations are more likely to contribute, whereas individuals with moderate postpurchase evaluations are less likely to contribute".

Ma et al. (2013) focus on personal characteristics of reviewers and found out that when these are geographically mobile, socially connected and female, they are less likely to be influenced by previous reviews.

Cicognani et al. (2016), to investigate the relationship between the level of familiarity/loyalty of a consumer to a brand or product and its rating behaviour, conduced an experiment in the accommodation industry; they found out that usual customers tend to be less influenced by previous ratings than other customers.

Lee et al. (2015) studied if opinions from a generic crowd have a different impact on the rating behaviour of consumers than opinions from friends. To do this, the authors used data from a social movie-website and they found out that prior ratings from friends have a great impact on subsequent reviews, triggering a sort of "herding behaviour"; prior ratings from a generic public instead, according to Lee et al. (2015), tend to influence subsequent ratings only if volume of this prior ratings is high. So, results of this study show that if the product is largely adopted by people, future reviewers tend to imitate peers' opinions, but if the product is a niche one, users tend to differentiate themselves from the crowd opinion.

In conclusion, rating bubbles are a generic trend of marketplaces, though they impact differently generic and niche markets, and they might lead to inefficient choices in terms of purchase decisions, but they are really difficult to avoid, because they exist due to heterogeneity in the reviewers pool. Market designers can instead intervene when bias in ratings in due to online social influence, for example mitigating the exposure of consumers to prior ratings.

2.3 – CERTIFICATION POLICIES

Warranties, reliance on past reputation and regulated certifications by trusted institutions are some of the instruments that have emerged to mitigate the problem of asymmetric information in markets. Online platforms adopt all three, in the form of buyer protection policies, sellers' reputation score, and certification badges. The latter are quality certification given to sellers who meet some minimum quality threshold determined by the marketplace (Tadelis 2019).

For example, on eBay there exist the "TRS" badge (Top Rated Seller), on Airbnb there exists the "Superhost" badge and on Upworks (a freelance marketplace) there are the "Top Rated" freelancers. All the badges, though having different names, signal a certain quality threshold for a seller, a lessor or a freelancer, determined on the basis of the average rating of their performance in the marketplace, therefore determined by eWOM. Usually, in addition to all the advantages in terms of reputation that such a badge gives to sellers, these gain also in terms of discounts on shipping fees or on commission fees and, last but not least, it is a common practice for online marketplace designers to show first the certified sellers, when a user is browsing for an item in the webpage.

2.3.1 – THE EBAY CASE AND THE POLICY CHANGE OF 2009

The feedback system of eBay consists on the possibility for buyers to leave a positive, neutral or negative feedback. We already know that before 2008 that system was two-sided but then it became one-sided. In addition to that, buyers can also express their opinion in the "detailed seller rating", a mechanism in which they can give sellers anonymous ratings between 1 to 5 stars along four dimensions: item as described, communication, shipping speed and shipping rate.

Before 2009, eBay had a certification policy based on the "Powerseller" badge, which qualified sellers with at least 100 items or at least 1000 dollars worth of items every month for three consecutive months, in addition to the obligation to maintain at least 98% of positive feedbacks and 4.6 out of 5.0 detailed seller ratings.

In September 2009 the "Top Rated Seller" badge became effective and replaced the "Powerseller" one. The new badge has more stringent certification requirements, in fact, to gain it a seller must have all the features required by the "Powerseller" and, additionally, it must have at least 100 transactions and sell at least 3000 dollars worth of items over the previous 12 months, it must have less than 0,5 % of transactions with a DSR lower than one star and it must have less than 0,5% of transactions with complaints from buyers.

Let's consider a simple model proposed by Hui et al. (2019), who studied the eBay policy change; in this model there is a continuum of sellers and each of them can produce with zero marginal costs and fixed costs $k \in [0, +\infty)$.

In this continuum, sellers are of three types: μ^l (low-quality sellers), μ^h (high-quality sellers), μ^s (strategic sellers). The latter are sellers who can produce both medium quality (M) and high quality (H), but if they choose to produce high quality they have to exert an extra effort with a cost e.

Each of a continuum of buyers demands one unit of good and it's willing to pay up to the expected quality of the good, but they can't observe the quality of any seller.

A marketplace regulator produces an observable badge B that denotes a quality between high and medium:

$$B \in \{M, H\}.$$

Since prices depend on the quality and buyers can only ascertain if a seller is badged or not, strategic sellers will always choose to shirk and produce medium quality, that is comprised in the badge as high quality. The equilibrium prices in this setting are p_m, which is the price that a badged seller can ask, and p_l, that is the price that a non-badged seller can ask.

Now we will introduce a change in the badge requirements, simulating the eBay change of September 2009.

In our model, a more stringent badge means excluding medium quality from it, hence, the new badge will be: $B = H$.

With this new badge, μ^s sellers must exert effort e and produce high quality if they want to gain (or maintain) the certification.

Now suppose that the price that a badged seller can ask is p_h, and the price that a non-badged seller can ask is p_l; strategic sellers will choose to exert effort and produce high quality only if the costs of doing that are lower than p_h.

The cost function of μ^s sellers is: $F = f(k, e) = k + e$.

Hence, strategic sellers will produce high quality if and only if: $p_h > k + e$.

The results of this model are that when $B = H$ there exists a new equilibrium, with a price p_h and a price p_l. Market prices and cost functions of strategic sellers determine for each of them their choice to work.

The model of Hui et al. (2019) shows also that, because $p_l < p_m$, strategic sellers who lost their badge are hurt facing a lower price (before the change they were able to ask p_m with the same effort), and those with high enough entry and effort costs will not enter the market after the change. Another evidence is that now unbadged sellers include both μ^l and μ^m sellers (before the change they include only μ^l), so the overall quality of unbadged sellers increases.

In sum, the policy change, according to this model, will give benefits to high and low quality sellers: the former benefit from the ability to ask for a price p_h, the latter benefit from being pooled with medium quality sellers, which probably means a price p_l that might be slightly bigger than the price of non-badged sellers in the “lax badge” setting. As a direct consequence, market entry increases for low and high quality sellers and decreases for strategic sellers.

In their studies, Hui et al. (2019) used data from October 2008 to September 2010, which include all listings and transaction data on eBay in the year before and in the year after the policy change. To measure quality of sellers in their empirical analysis, the authors used a measure proposed by Nosko and Tadelis (2015): the EPP (Effective Percentage Positioning), which is the number of positive feedback transactions divided by the number of total transactions. Results of the studies of Hui et al. (2019) show that the policy change caused in all markets a decrease in the share of badged sellers, however, the entity of this decrease varies a lot across different markets, and in those markets that are more affected, the entrant ratio is bigger and the average quality of entrants too.

Studying the quality distribution of entrants, the authors were able to demonstrate that after the policy change it exhibits “fatter tails”, which means that entrant ratio is higher for high and low quality sellers and exit ratio is bigger for medium quality sellers.

Regarding the policy effect on prices, Hui et al. (2019) found evidence that overall prices increase for those sellers who were unbadged before the change and then remained unbadged (NN). Sellers who lost their badge after the policy change (BN) experienced a decrease in prices and sellers who maintain their badge (BB) or who were unbadged before the change but were able to gain the badge (NB) experienced a larger increase in prices than NN sellers.

In conclusion, empirical studies of Hui et al. (2019) found confirmations to their theoretic model that predicted the effects of the policy change.

3. DISCUSSION AND CONCLUSION

In this study, I illustrated the most successful reputation mechanisms of online marketplaces and I discussed how they work to guarantee trust among users. As we can see from the various empirical studies that I collected in this work, online platforms have become a very interesting topic for the economic literature: platforms – on the one hand – have great economic value, and – on the other hand – suffer of specific issues which are actually affecting them and are difficult to solve for market designers.

The study has been organized in 3 parts. In Part 1 I provided an overview of the information asymmetry problem, discussing both adverse selection and moral hazard. In Part 2, I showed how this problem affects online markets and how could be reduced through different mechanisms like eWOM, Rebate systems (like the one of Taobao) and certification policies. Indeed, eWOM acts as a repository of ratings left by buyers about a seller's performance in its various transactions, with feedbacks concerning the purchase experience offered by the seller and reviews concerning the quality level of items sold. Trusted certification badges given by marketplaces are another mechanism that contributes to create a sort of seller reputation, therefore mitigating the first major problem of e-markets, that is information asymmetry. Certification policies are based on average ratings, hence they are a derivation of eWOM.

The second major problem of online platforms is the one of rating biases. As I showed in section 2 of this paper, bias in ratings is a problem common to nearly all online marketplaces and it's very difficult to solve, because it is due mainly to heterogeneity in the reviewers psychology and to online social influence. The latter is the phenomenon of people who imitate other people (seen as opinion leaders) in their rating phase. Rating biases' more alarming problem is the fact that reviews and feedbacks may not correspond to the true consumers' valuations about a product or a purchase experience.

Another issue typical of the online platforms is the one of retaliation: normally, if a user leaves a negative feedback to another user, if possible, the latter will retaliate and rate negatively the former. We've seen that marketplace designers have been able to solve the retaliation problem through adopting a one sided feedback system instead of a two sided one. However, we also saw that one sided feedback systems are not optimal for all types of marketplaces.

In the aim of allowing consumers to maintain at least part of their surplus, in what follows I discuss a set of rules that an antitrust authority can implement for online platforms. In this perspective, I present 8 points:

- First, taking into account information asymmetry, an antitrust institution should state that eWOM, composed by feedbacks and reviews, must be incorporated to all online platforms. In fact it's clear that eWOM is a fundamental tool to make consumers empowered agents and to make them able to form an idea about the reputation of a generic seller.
- The feedback system should be one sided, unless the marketplace is a house-rental type or a marketplace with similar characteristics; this will guarantee that the problem of retaliation will be solved and users will be able to leave more true and less biased reviews.

  For house-rental markets like Airbnb, or marketplaces with similar characteristics, the system should be a two sided type. However, I think that there should be a customer service addressed to both lessors and renters, that can intervene in case of disputes for feedbacks that are supposed to be retaliatory by examining their textual content and the past reputation of the two parts: this customer service may alleviate the retaliation issue also in these particular platforms.
- Following the Taobao path, I think that the Reward-for-feedback system should be adopted as a rule by all marketplaces, because of the great advantages in terms of reduction of information asymmetry that it provides, but also because it helps increasing the overall quality of the marketplace and helps new sellers to bypass the cold start problem.
- To leave a feedback or a review, I think that should be compulsory that before rating a seller or a product, the buyer has to purchase something, to avoid the problem of fake reviews.
- Regarding bias in ratings, we've seen that this problem is articulated in various forms.

  The first form is the one of early adopters enthusiasm: early adopters normally are very enthusiastic about a product, and therefore their reviews will be more positive than the one of late comers. The consequent downtrend of ratings hence is not justified by a concrete decrease in the item's performance.

  The second form is the one of online social influence. Empirical evidence highlights the phenomenon of rating bubbles: reviewers tend to conform their opinion to the one of previous reviewers and this happens very often when the latter are seen as opinion leaders. I also showed in section 2 of this paper that online social influence affects consumers in different ways and with different levels of pervasiveness, and this depends on the psychological characteristics of individuals.

Though it's not possible to eliminate bias in ratings, I think that an antitrust institution can design some rules to alleviate that problem. We've seen that early adopters enthusiasm impact more those markets where consumers are engaged at a more psychological level, like markets for books or tv series; therefore, for these markets, together with markets for which the valuations by consumers tend to be highly subjective (i.e. videogames, films, music…) should be treated separately and should embody only textual reviews. In the latters, people can give their subjective explanation for why they liked or not the product, without being obliged to leave a rating score.

A rating score is much more impactful on peers valuation than the content itself of a review, because the former is a direct and easy way to express the valuation of an item, that can be copied without excessive effort, therefore it is more prone to work as a proxy to which the subsequent reviews may conform.

With a system in which only the review content is showed, buyers, when browsing for reviews about, for example, a videogame, will see only textual reviews in which are listed, according to each reviewer, their thought about pros and cons of the item.

The same treatment should be adopted also for niche markets: as showed by studies of Lee et al. (2015) when the product is a niche one, people tend to differentiate themselves from the crowd in the rating phase; I think that if reviews are free from rating scores, it will be more difficult for reviewers to imitate or differentiate themselves in respect to peers, driving them to post more truthful reviews.

- As reported in paragraph 2.2.2, studies of Moe and Schweidel (2012) found out that individuals with extreme post purchase valuations are more likely to contribute with eWOM than those with moderate post purchase evaluations, and this is another reason for the problem of rating scores which are concentrated on extremely positive or negative values; in this case I think that the adoption of the Reward-for-feedback system, which I proposed to alleviate information asymmetry, can be very effective, giving more incentives to contribute with feedbacks and reviews also to those people who normally are less likely to contribute due to their moderate valuations.

In fact, as we already said, eWOM is a public good, and this implies that not all consumers are encouraged to provide it; maybe those that are more encouraged to post a feedback or a review are people who are very disappointed about their experience, or, o the other hand, are very enthusiastic. Those who have a moderate valuation of their purchase experience find no incentive to provide information to future buyers. Here comes the RFF system, that rewards people to supply that public good, encouraging also "moderate consumers".

- Regarding quality certifications given by platforms to sellers, as we've seen in paragraph 2.3 of this paper they can be a very effective tool to alleviate information asymmetry and to improve the quality of the marketplace. In fact, a certification badge is a very impactful signal of a seller's reputation, that a generic buyer can always trust. The point here, for our antitrust institution, is to determine the quality threshold for each certification of each marketplace.

  Following the studies of Hui et al. (2019) on the eBay certification policy change of 2009, we've seen that setting a threshold that is a medium one is not the best practice, because sellers who offer medium quality take advantage of continuing to provide that medium quality; if we set the threshold at a higher quality level, for a medium quality seller it's necessary to make more efforts and improve its quality to gain the badge and exploit all the advantages that it provides.
- In line with the studies of Chu and Wu (2018) on Chinese online platforms designed for offline services (O2O), for example baby sitting, wedding planning or food delivery, I propose another point that our hypothetical Antitrust authority can include in its regulation for e-markets. Chu and Wu (2018) showed that, in China, O2O platforms are characterized by a fierce competition because of the excessive number of sellers; for this reason it is probable that firms will tend to concentrate on the short time period: service providers may shirk in early transactions, producing a quality level which is not the one they advertised, to achieve faster the reputation level they need to be competitive and to not being pulled out of the market.

  The authors present a model in which the platform restricts the number of service providers below a certain threshold, excluding those which deliver low quality outcomes to consumers (quality of outcomes is measured through eWOM): they found out that doing so can improve the overall quality offered on the platform, making competition more lax than in the setting in which the number of providers is unlimited. So, another point of my hypothetical regulation is that, if the market is characterized by a severe competition, to protect consumer surplus and improve the quality of items traded online platforms should set a restriction on the number of sellers, excluding those sellers who, according to reviews and feedbacks left buy buyers, are low-quality sellers.

In conclusion, these are my ideas about how an antitrust authority should "regulate" online marketplaces; indeed, such new markets should be designed to guarantee trust among their users. I know that the problem of rating biases is not yet solved even with those hypothetical rules that I proposed in this paragraph, but the information asymmetry problem is very much reduced and eWOM has had the greater role in this process. Changing the behaviour of consumers and making them more powerful and comfortable when comparing the products that the market offers to them, eWOM has created the need for sellers to differentiate themselves, improve their quality and delight customers. Competition among online marketplaces is an evolving phenomena, and new research should be addressed to investigate it, in particular considering consumer surplus and the role of Antitrust Authorities in protecting it.

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