Assessing the Impact of Price-Matching Guarantees and Price Fluctuations on Consumer Feedback: Insights from the Online Consumer Electronics Market

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Assessing the Impact of Price-Matching Guarantees and Price Fluctuations on Consumer Feedback: Insights from the Online Consumer Electronics Market*

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Abstract

Our study investigates the impact of price matching guarantees (PMGs) on consumer behavior in online retail markets. Leveraging a Difference-in-Differences (DiD) approach, we analyze product ratings in response to price changes during PMG policy periods. Results show that PMGs alone have no significant effect on ratings, but price increases during PMG periods lead to lower ratings. Furthermore, the effect strengthens over time, particularly for cheaper and less visible products. These findings suggest that PMGs may serve as effective market signals of pricing strategy, especially for items where price sensitivity is higher or visibility is lower. This underscores the importance of signaling mechanisms in influencing consumer perceptions and responses in online retail settings. From an antitrust perspective, our results highlight the potential for PMGs to influence competition dynamics and consumer welfare. Policymakers may need to consider regulations ensuring pricing transparency and consumer protection in online markets, balancing the benefits of market signaling with the risks of anti-competitive behavior and consumer harm. Overall, our study contributes to the understanding of pricing strategies and consumer behavior in digital markets, with implications for both industry practices and regulatory interventions.

Keywords: Price-Matching Guarantees, Online Retailing, Online Consumers Review, Difference-in-Differences, Signaling Theory, Pricing, Retail Tactics

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1 Introduction

In today's fiercely competitive e-commerce landscape, online retailers continuously strive to gain a competitive edge and capture the attention of discerning consumers. The rapid proliferation of online markets has not only reshaped the consumer shopping experience but has also intensified competition among retailers. In this hyper-connected environment, consumers not only prioritize product quality and features but also closely scrutinize pricing strategies employed by vendors. Among these ones, the implementation of low-price guarantee policies (PMGs), often advertised as promises to match or beat competitors' prices, has emerged as a prominent tactic to enhance price image, signal competitive pricing, and instill consumer confidence.[1] Differently from classic price promotions, PMGs do not advertise a price drop, but rather guarantee a refund, conditional on the availability of incurring a hassle cost associated with engaging in additional price search, providing proof of a cheaper price posted by a competitor, and returning to the seller offering the guarantee.

A significant body of literature has mainly examined the competitive and welfare implications of PMGs, highlighting their potential to reduce price competition and facilitate monopoly pricing [e.g. Hay, 1981, Salop, 1986, Belton, 1987]; differently, some other works have predicted that these policies can be price-discriminating devices [Png and Hirshleifer, 1987, Corts, 1997, Nalca et al., 2010, among others]. In a signalling theoretical environment, instead, some scholars have alleged that consumers are likely to associate PMGs with low store prices, thus being influenced in their price perceptions and enticed to make purchases from sellers who offer the guarantee [see Srivastava and Lurie, 1999, Jain and Srivastava, 2000, Srivastava and Lurie, 2001, 2004, Moorthy and Winter, 2006, Dutta et al., 2007, Mamadehussene, 2019]. Indeed, once a firm implements an PMG, the policy is likely to be maintained for an extended period of time, as opposed to seller price changes, which can occur frequently in an online market. Because PMG decisions are more stable over time than pricing strategies, sellers can promote them more effectively than their posted prices, so it stands to reason that consumers are more aware of firms' PMG practices than their prices. As a consequence, customers that are not informed about firms' prices but that are aware of PMGs may infer that adopting-sellers are posting low prices; in this context, PMGs are signals of low store prices able to attract consumers uninformed about prices [see Moorthy and Winter, 2006, among others].[2]

[1] A PMG would be something like, "If you see a lower price for any model we stock, we will be happy to refund you the difference".

[2] Despite the high level of price transparency in online markets, whereas consumers have access to a vast amount of product information, for many purchases consumers may still not be fully informed about prices, relying instead on the overall price/trustworthiness image of sellers [Simester, 1995]. The latter is indeed a crucial factor influencing consumer buying decisions, so that online sellers employ various strategies to convey this aspect, with PMGs emerging as a prominent tool, among other trust-building strategies, that play a crucial role in shaping consumers' perceptions. Moreover, these policies are also addressed to emphasize the importance of customer satisfaction: specifically, retailers often bundle PMGs with additional perks such as extended warranties or loyalty points, creating a competitive edge that makes consumers to often consider these policies as a key factor in their decision-making process, as well as

However, the presence of an PMG is not proof that the store will offer the lowest price. Consumers can look for lower fares after making a purchase and pay only the lowest available one. Since PMGs may not always result in the lowest prices, analysing under which conditions these policies may signal low shop rates is an interesting topic. Research has often focused on individual and situational variables, such as the opportunity cost of time [e.g. Srivastava and Lurie, 2001], the financial/competitive design of the guarantee [Kukar-Kinney and Walters, 2003], the level of consumers' search costs [Srivastava and Lurie, 2001] and price cues [e.g. Biswas et al., 2002]. Nevertheless, little is known about how market-level factors affect consumers perceptions. Indeed, only few papers explicitly consider whether consumers consider the behavior of other ones in the market as exerting a disciplinary effect on sellers pricing strategies;[3] the latter is likely to deter vendors from sending false signals [Feick and Price, 1987, Wernerfelt, 1988], an issue deserving far-reaching implications for the effectiveness of different sellers' market tactics as PMGs [Bloom, 1989, Ippolito, 1990], as well as for policy-makers called upon to make regulatory actions against such kind of price strategies [Edlin, 1997].[4] Noticeably, in their seminal work Srivastava and Lurie [2004] have been the first to delve into the role of price-matching guarantees as signals of low store prices, shedding light on consumer behavior in response to such policies, suggesting that "market level factors affect consumer beliefs about the extent to which others engage in price search and thereby the effectiveness of price-matching guarantees in lowering perceptions of store prices" [Srivastava and Lurie, 2004, , p. 1].[5]

Building upon this foundational research, this study aims to further explore the impact of PMGs within the context of online consumer electronics retailing, where pricing strategies and consumer behavior are particularly dynamic, and taking into account consumers' behaviour, as proxied by the availability of online consumers' reviews (OCRs), namely ratings and reviews posted by prior customers, which may be a valuable source of information for both consumers and online sellers.[6] Indeed, in the realm of e-commerce

when choosing where to make a purchase. In this context, PMGs actually serve as tangible assurances to consumers that they are receiving the best possible value for their purchases.

[3]Consumer actions such as withholding repeat purchases, spreading negative word-of-mouth, and advocating for regulatory action may trigger market disciplinary mechanisms and punish errant sellers who send false signals [Wernerfelt, 1988, Rao et al., 1999].

[4]From a theoretical standpoint, understanding the process by which PMGs work requires explicitly acknowledging that consumer perceptions of shop pricing are based on witnessing and interpreting a guarantee in the context of market conditions [Stiglitz, 1989].

[5]See also Hamilton and Chernev [2013], which provide a comprehensive framework delineating the key drivers of price image formation and their consequences for consumer behavior. Differently, Pee et al. [2018] suggest that signaling goes beyond the pre-purchase stage of initial purchase to influence repurchase intention. Bergel et al. [2019] investigate the influence of customer satisfaction on four facets of customer engagement, as customer influencer behavior, knowledge behavior, referral behavior and purchase behavior, as well as its indirect influence on affective attitude, price perception and loyalty, arguing that engaged customers develop a more positive affective attitude, which leads to increased future loyalty and positive price perceptions.

[6]The literature has also examined the impact of both price beating guarantees (PBG), which can be defined in very similar terms to PMGs except that the refund exceeds the price difference, and Most Favoured Customers (MFC), which are a contractual arrangement between vendor and customer that guarantees the customer the best price the vendor gives to anyone in a given future time span. As for the

consumer decisions are increasingly influenced by online reviews and ratings, and it is worthwhile analyzing the dynamics between pricing strategies, PMGs and product evaluations from consumers, an issue that have garnered less attention from scholars.[7] The research question we want to answer refers to the possibility that the effectiveness of PMGs in signalling low prices may depend on the degree to which consumers engage in product reviews and ratings, also in relation to the shopping experience and the prices paid. In particular, consumers' engagement with product reviews and ratings can provide behavioral cues that influence their perceptions of PMGs. Positive reviews and high ratings may serve as endorsements of the seller's pricing competitiveness and reinforce the effectiveness of PMGs as signals of low prices. Conversely, negative reviews or the absence of ratings may raise doubts about the validity of the guarantee and its ability to deliver on its promise of competitive pricing.[8]

Products ratings and reviews serve as an effective market disciplinary mechanism in various ways. Firstly, they provide assurance of product quality, with positive reviews indicating high-quality products and negative reviews alerting consumers to potential issues. Secondly, publicly available ratings and reviews hold sellers accountable for their products and services, motivating them to provide satisfactory customer experiences to protect their reputations. This accountability fosters competition based on quality and customer satisfaction. Thirdly, ratings and reviews empower consumers by providing them with a platform to share their experiences and opinions, influencing the purchasing decisions of others and shaping market outcomes. This empowerment reduces information asymmetry and improves market efficiency. Additionally, the feedback loop created by ratings and reviews enables continuous improvement among sellers. Sellers use feedback to identify areas for improvement, address customer concerns, and innovate to meet evolving consumer needs, driving seller improvement and innovation. Lastly, negative reviews and low ratings act as a form of market regulation by penalizing underperforming sellers and deterring others from similar behavior. Sellers are motivated to maintain high standards to avoid negative feedback and maintain positive reputations, promoting

former policy, Desmet and Le Nagard [2005] suggest that a PBG significantly lowers the store price image on the low prices dimension without increasing the intention to search for lower price, compared with a PMG whose effects are positive but rather small. As for the MFC clauses, they may seem pro-competitive, because they offer past customers the same attractive terms as brand-new customers. However, the latter can be employed as tools to maintain higher prices, since they decrease sellers' incentives to cut prices over time [Schnitzer, 1994]. Given the minor relevance of such policies in the online consumer electronics market, we prefer to focus on the much more widely available and analysed PMGs.

[7] We focus on the consumer electronics industry, since it stands as a dynamic and highly competitive sector of e-commerce, characterized by rapid technological innovation, price volatility, and diverse consumer preferences. Within this context, online retailers face considerable challenges in effectively communicating their pricing strategies to consumers and distinguishing themselves from competitors. PMGs offer a potential solution to these challenges by providing visible and tangible assurances of competitive pricing.

[8] The effectiveness of PMGs as signals of low prices may also vary depending on the broader market context and competitive landscape. In markets where consumers are highly price-sensitive and actively seek out the best deals, as in the consumer electronics one, PMGs may carry greater weight as signals of low prices. However, in markets where other pricing cues or promotional strategies dominate consumer perception, the impact of PMGs may be diluted.

fair and ethical business practices in the marketplace.[9]

To address this question, we leverage on a Difference-in -Differences (DiD) identification strategy in which products are considered as treated when subject to PMGs; to this end, we collect prices and related OCRs, as products' ratings and reviews, of PMG-targeted products on a sample of daily consumer electronics observed on the US NewEgg online retailer, which often applies these policies.[10] In addition, during the sample period we also gather information about identical (treated) products, but sold on a different online retailer website, specifically Amazon US (which never provides PMGs).[11] Indeed, this approach enables us to account for both temporal and cross-sectional variations, providing a robust framework to measure the causal effects of NewEgg's pricing interventions. In particular, through a meticulous examination of online reviews, we seek to uncover whether variations in selling prices and the implementation of price matching guarantees engender discernible shifts in consumer sentiment and subsequently influence the trajectory of product evaluations. Moreover, this study seeks to explore how ratings evolve as prices fluctuate during policy activation, providing valuable insights into the dynamics of consumer responses to PMGs over time.[12]

From the one hand, if products' prices increase during the validity periods of PMGs and ratings subsequently decrease, this can indeed be seen as evidence of an effective market disciplinary mechanism. It suggests that consumers are reacting negatively to perceived discrepancies between the advertised price competitiveness implied by PMGs and the actual pricing behavior of the seller. This reaction serves as a form of market discipline, signaling to the seller that consumers are actively monitoring pricing changes and expressing dissatisfaction through ratings. Negative ratings can harm the seller's reputation and credibility, potentially leading to loss of trust and reduced consumer confidence in the seller's pricing strategies. In response to negative ratings and consumer dissatisfaction, sellers may adjust their pricing practices to better align with the expectations set by PMGs. This continuous feedback loop allows sellers to identify and address pricing discrepancies, leading to improved pricing transparency and competitiveness over time.[13]

[9]Overall, products ratings and reviews play a crucial role in shaping market dynamics, promoting seller accountability, empowering consumers, driving seller improvement, regulating market behavior, and enhancing market efficiency and consumer welfare.

[10]See `https://kb.newegg.com/knowledge-base/price-match-guarantee/`.

[11]NewEgg, a prominent player in the e-commerce domain, has garnered attention not only for its extensive product offerings but also for its commitment to competitive pricing through price matching guarantees. This study positions NewEgg products as the treatment group, subjected to the influence of the retailer's pricing policies, while products offered by Amazon US serve as the control group. By adopting a quasi-experimental approach, we aim to discern causal relationships and isolate the true impact of NewEgg's pricing strategies on the online review landscape.

[12]By examining the interplay between PMGs, pricing strategies, and consumer behavior, this research aims to contribute to a deeper understanding of the efficacy of pricing signals in online retailing and offer practical implications for retailers seeking to optimize their pricing strategies.

[13]Overall, if prices increase during PMG validity periods and ratings decrease as a consequence, it underscores the importance of transparency and accountability in pricing practices and highlights the role of consumer feedback in shaping market dynamics.

On the other hand, if the analysis revealed that product ratings were not affected by a price increase during the PMG policy activation period, several implications could be drawn: this may suggest that consumers may not perceive price changes during the activation of the price matching guarantee policy as significant deviations from expected pricing norms, indicating that other factors, such as product quality, brand reputation, or customer service, play a more dominant role in shaping consumer perceptions and ratings. Additionally, it may suggest that consumers are less price-sensitive or more forgiving when prices fluctuate within the context of a pricing policy. This could imply that consumers place greater emphasis on the overall value proposition offered by retailers rather than focusing solely on price levels. Further, if consumers continue to provide favorable ratings despite price increases during the policy period, it could signal a high level of trust and confidence in the retailer's pricing practices. This may indicate that consumers perceive the retailer as transparent and fair, even when prices temporarily deviate from promotional claims. In this context, the absence of a negative impact on product ratings following price increases during the policy activation period could also reflect the competitive dynamics within the industry. If consumers view the retailer's pricing as competitive relative to other market players, they may be less inclined to penalize the retailer for price fluctuations.

Estimates of the static version of our model indicate that changes in product prices and the presence of the PMG policy alone do not significantly impact product ratings. However, the interaction term between prices and PMGs shows a negative and statistically significant coefficient ($\log Prices_{i,r,t} * PMG_{i,r,t} = -0.00796$), suggesting that the relationship between prices and ratings differs depending on whether the PMG is present. Specifically, during the active PMG period, an increase in prices is associated with lower ratings. Furthermore, by leveraging on a different model that allows the effect of the PMG to change over time, the analysis explores the impact of PMG duration on product ratings, finding a significant increase in ratings with each additional day of policy implementation. This suggests that the effect of PMGs on ratings varies over time, potentially reflecting consumers' evolving perceptions of the policy. Similar results arise when we replicate the regressions with observations weighted by a product popularity index, yielding consistent results. Overall findings suggest that consumers are likely to use ratings as a form of market feedback, disciplining retailers that deviate from expected pricing norms associated with PMGs.

To delve deeper, the analysis examines heterogeneous effects based on product prices and online visibility. Results show that PMGs have a more significant impact on ratings for cheaper and less visible products. Cheaper products experience a decrease in ratings with price increases during the PMG period, while the effect of PMGs on ratings amplifies over time for cheaper products. Similarly, PMGs have a stronger impact on less visible products, where the negative effect of price increases on ratings is intensified during the PMG period. The policy may be more effective for cheaper and less visible items due to several reasons. Firstly, consumers tend to be more price-sensitive when purchasing cheaper items, making them more responsive to price signals such as PMGs. Additionally, cheaper items often represent smaller financial investments for consumers, leading them to prioritize obtaining the best value for their money. In highly competitive markets, sellers may use PMGs to differentiate themselves and attract customers, particularly for cheaper items facing greater competition. Moreover, less visible items typically receive less traffic and visibility compared to more prominent products, making consumers navigating to secondary pages of online search engines potentially more price-sensitive and actively seeking cost-effective options. In this scenario, the presence of an PMG policy signals to consumers that despite the product's placement on a less prominent page, the retailer is committed to offering competitive prices. This perception fosters trust and loyalty among consumers, even for products with lower visibility, and encourages them to perceive the retailer as transparent and confident in its pricing competitiveness.[14]

A complete set of robustness tests are conducted to validate the main results. These tests include event study estimates to confirm the parallel trend assumption, placebo regressions with *fake* treatment timings, and random allocation tests to assess the robustness of the estimated coefficients. Overall, the results remain consistent across various specifications and robustness checks, supporting the conclusion that PMGs are likely to act as a market disciplinary mechanism, particularly for cheaper and less visible products, by influencing consumer perceptions and responses to pricing policies.

Our paper is likely to add to the literature for several reasons. Firstly, it contributes to understanding the effectiveness of price matching guarantees as a market disciplinary mechanism, particularly in the context of online retailing, an issue that has been little discussed so far. By empirically analyzing the impact of PMG policies on product ratings, our study sheds light on how pricing strategies influence consumer behavior and perceptions in the digital marketplace. This fills a gap in the literature by providing empirical evidence on the relationship between pricing policies and consumer responses, which is crucial for retailers and policymakers alike. Secondly, our study extends the existing literature on signaling theory, drawing from concepts proposed by Srivastava and Lurie [2004], by empirically testing the signaling role of PMGs in conveying information about a retailer's pricing strategy and commitment to providing competitive prices. By investigating the nuanced effects of PMGs on product ratings, our research offers insights into how consumers interpret and respond to pricing signals, thereby enriching our understanding of signaling mechanisms in retail settings. Finally, our paper contributes to the literature on online consumer behavior by examining heterogeneous effects based on product characteristics such as price and visibility, that have never before been considered. By analyzing how the effectiveness of PMGs varies across different types of

[14]Overall, the effectiveness of PMGs as a market disciplinary mechanism for cheaper and less visible items stems from their ability to address consumer price sensitivity, enhance perceived value, and build trust and confidence in the retailer's pricing strategy.

products, our study provides valuable insights into consumer preferences and decision-making processes in the online marketplace. This nuanced understanding of consumer behavior can inform retailers' pricing strategies and help them tailor their marketing efforts to specific product segments.

To conclude, the study has significant policy implications from both antitrust and policymakers' perspectives. On the one hand, from an antitrust standpoint our findings provide insights into the competitive dynamics of online retail markets. By demonstrating the impact of pricing policies such as PMGs on consumer behavior and product ratings, the research can inform antitrust authorities about the potential anti-competitive effects of such strategies. Specifically, if retailers use PMGs to signal low prices and gain a competitive advantage, this could raise concerns about collusion or exclusionary practices that harm consumer welfare or stifle competition. Antitrust regulators may need to assess the use of pricing policies like PMGs in the context of market power and competition enforcement, ensuring that they do not lead to anti-competitive behavior or market distortions. On the other hand, from a policy-maker's perspective our study highlights the importance of consumer protection and transparency in online markets. If PMGs influence consumer perceptions and purchasing decisions, policy-makers may need to consider regulatory measures to ensure that pricing signals are accurate, truthful, and beneficial for consumers. This could involve guidelines or regulations governing the use of pricing policies in online retailing, requiring retailers to provide clear and accurate information about their pricing strategies and commitments to competitive pricing. Additionally, policy-makers may explore measures to enhance consumer awareness and education about pricing practices in online markets, empowering consumers to make informed choices and protect their interests.

The remainder of the paper is structured as follows: in Section 2 we provide a background literature review. In Section 3 we present the data while in Section 4 we describe our estimation and identification framework. Finally, Section 5 contains both empirical results and the robustness analysis, while Section 6 concludes.

2 Literature Review

This study is related to different strands of literature. First, it generally fits to the wide literature on signalling theory; indeed, the latter has played an important role in characterizing situations where asymmetric information about an unobservable attribute arises between sellers and customers [e.g. Nelson, 1970]. Signaling theory suggests that rational sellers and customers can resolve information asymmetry by communicating unobservable attributes, like product quality, through observable traits as price or advertising level; therefore, consumers can leverage on these observable traits to infer unobservable attributes based on market conditions.[15]

[15] See Boulding and Kirmani [1993] for details.

In this context, some authors have analyzed how customers respond to different kinds of signals under different market conditions; among others, Erdem and Swait [1998] supports the signaling theory's assumptions about the impact of brand names on product quality perceived by consumers, while Boulding and Kirmani [1993] and Kirmani [1990] reach similar results by focusing on warranty terms and advertising expenditures, respectively. It is worth noting that the signalling theory has been utilized also to argue the price-signalling nature of PMGs. In particular, a number of authors have proposed the idea that PMGs are likely to be signals of unobservable prices that can lead to a market equilibrium in which only low-marginal costs firms apply the policy [Jain and Srivastava, 2000, Moorthy and Winter, 2006, Moorthy and Zhang, 2006, Mamadehussene, 2019]. Specifically, Moorthy and Winter [2006] highlight how PMGs can be signals of unobservable prices for uninformed consumers; these signals provide incentives to stop further search, thus allowing adopting-sellers to charge relatively higher prices. In a similar vein, Jain and Srivastava [2000], by hypothesizing different sources of heterogeneity, as size, location, merchandise assortment, and service quality, argue that PMGs signal low prices only when firms are sufficiently asymmetric, whereas Moorthy and Zhang [2006] reach similar results by assuming retailers' heterogeneity in service levels. By contrast, Mamadehussene [2019] has developed a model in which homogeneous sellers may send a signal of low prices through PMGs, in which customers believe that adopting firms offer lower prices not due to anticipation of reduced marginal costs or lower service quality, but solely because they provide a PMG. Noticeably, Srivastava and Lurie [2004] argue that PMGs can act as credible signals of low price stores only when market disciplinary mechanisms are strong, that is when buyers have a high willingness to search and claim refunds. In turn, Yuan and Krishna [2011] explore the effects of PMGs on the behavior of buyers' search patterns and sellers' pricing strategies through an analysis of their strategic interactions. The authors propose that when the demand from searchers is more elastic compared to non-searchers, PMGs can amplify price competition, even in situations where sellers possess symmetrical characteristics. They emphasize that price-matching symmetric sellers are more inclined to employ these policies as tools for price discrimination rather than collusion, implying that they are more likely to vary their prices randomly rather than collude to maintain high price levels. Additionally, experiments conducted by Jain and Srivastava [2000] suggest that PMGs create a perception of lower prices in stores offering them, while Srivastava and Lurie [2001] provide evidence indicating that consumers are less inclined to continue searching after encountering a low-price guarantee.[16] Differently, in the studies conducted by Dugar and Sorensen [2006] and Dugar [2007], the inclusion of buyers experiencing positive hassle costs serves as a mechanism for market discipline, diminishing the motivation for collusion. The authors propose that firms utilize PMGs as a strategy to evaluate buyers based on their readiness to accept the lowest price for the product.

[16] See also Mago and Pate [2009].

It should be noted that, in a signalling theoretical environment, rational sellers are unlikely to leverage on PMGs to convey false price signals if the latter increase costs, reduce immediate/future profits, or harm store's reputation [Nelson, 1970]. Indeed, different market mechanism can discipline sellers sending false price signals [Ippolito, 1990, Kirmani and Rao, 2000], and the strength of these mechanism is likely to impact on the effectiveness of PMGs market signals. From the one hand, if market disciplinary mechanisms are strong a seller is likely to bear significant costs as a result of issuing a false signal. On the other hand, sellers are incentivised to send false price signals if these mechanisms are weak, since the cost incurred by the company in doing so is low. Wrapping up, a PMG policy is likely to be a truthful, credible and effective signal of low prices only when market disciplinary mechanisms are strong. Examples of these mechanisms are buyers' actions, like withholding repeat purchases, engaging in negative word-of-mouth and calling for regulatory actions, that might act as punishments against false price signals [e.g. Wernerfelt, 1988, Rao et al., 1999]. Online consumer reviews and ratings act as a market disciplinary mechanism in online markets by promoting transparency, accountability, and consumer empowerment. They provide transparent feedback about products and sellers, holding sellers accountable for their performance and empowering consumers to make informed purchasing decisions. This feedback loop encourages sellers to continuously improve their products and services, driving market competition and regulating market behavior. Positive reviews and high ratings build trust and credibility, enhancing the overall health and sustainability of online markets. In summary, online consumer reviews serve as a powerful mechanism for ensuring market efficiency, fairness, and integrity in the digital marketplace. Therefore, consumers' activity related to products' reviews and ratings directly affect the strength of market disciplinary mechanisms, and in turn the cost incurred by a seller sending a false signal, so that a PMG policy can be a more effective signal of low store prices as the credibility and depth of recommender systems increase.

A more specialized literature this paper contributes to has focused on the significance of online reviews and ratings in shaping consumer purchasing decisions. Scholars have highlighted the role of social influence and informational cues in guiding consumer choices [Chevalier and Mayzlin, 2006, Dellarocas, 2003]. For instance, Chevalier and Mayzlin [2006] demonstrated that online product reviews influence consumer purchasing decisions, with positive reviews leading to increased sales. Furthermore, Dellarocas [2003] examined the effects of electronic word-of-mouth (eWOM) on product sales and found that positive reviews significantly impact consumer behavior, leading to higher purchase intentions. Moreover, the credibility and reliability of online reviews have been emphasized as crucial factors affecting consumer trust and purchase intentions [Filieri and McLeay, 2014, Zhu and Zhang, 2010]. Filieri and McLeay [2014] found that consumers perceive reviews from other consumers as more trustworthy than information provided by the retailer, thus influencing their purchase decisions. Similarly, Zhu and

Zhang [2010] highlighted the importance of review credibility in shaping consumer attitudes and behaviors. They argued that consumers are more likely to trust and act upon reviews that are perceived as genuine and unbiased. In parallel, the pricing strategies adopted by online retailers have been a subject of extensive research. Dynamic pricing, in particular, has gained prominence as retailers seek to optimize profits in response to fluctuating market conditions and competitive pressures [Ghose and Yang, 2009, Li and Hitt, 2008]. Ghose and Yang [2009] investigated the impact of dynamic pricing on consumer behavior and found that price changes significantly affect demand elasticity and purchase decisions. Li and Hitt [2008] examined the self-selection and information role of online product reviews in influencing consumer perceptions of product value. They found that positive reviews play a crucial role in enhancing consumer perceptions of product quality and value, thus influencing purchase decisions.

The intersection of pricing strategies and consumer reviews has also been explored in the literature. For instance, research has examined how pricing affects consumer perceptions of product quality and value, consequently influencing review ratings and sentiments. Chen and Xie [2008] investigated the relationship between pricing and perceived value, finding that consumers are more likely to leave positive reviews for products perceived as offering high value for the price. Similarly, Jin et al. [2016] analyzed the impact of pricing on consumer sentiments expressed in online reviews, revealing that price changes significantly influence the tone and content of consumer feedback. They argued that price fluctuations can lead to changes in consumer perceptions of product value, subsequently influencing the nature and content of online reviews. More recently, [Carnehl et al., 2023] delve into the effects of strategic pricing on ratings through a theoretical model, positing that higher prices correlate with deteriorating reviews, particularly in scenarios where a monopolist sells a product of uncertain quality. Expanding on this research, Carnehl et al. [2022] scrutinize the influence of prices on ratings using Airbnb data. Their findings echo the notion that elevated prices tend to diminish average ratings, emphasizing the prevalence of the value-for-money effect over the selection effect. Furthermore, Luca and Reshef [2021] explore the relationship between daily menu prices and online customer ratings (OCRs) on an ordering platform, revealing a negative association between higher prices and average ratings. In contrast, Sorokin [2021] presents a divergent perspective by suggesting that producers on the Steam videogame platform leverage discounts to enhance their ratings. This variance in findings underscores the complexity of pricing dynamics and their impact on consumer perceptions across different contexts. In the realm of self-publishing, Zegners [2019] uncovers a counterintuitive trend wherein books provided for free on an online self-publishing platform receive a higher quantity of ratings, albeit with lower average ratings. This observation challenges conventional notions regarding the relationship between price and perceived value, underscoring the multifaceted nature of consumer behavior in digital marketplaces. Moreover, Cabral and Li [2015] shed light on the determinants of ratings, positing that unfavorable feedback is often linked to lower-quality transactions. This insight underscores the importance of transactional quality in shaping consumer evaluations and underscores the interplay between pricing, product quality, and customer satisfaction. Importantly, the aforementioned studies contribute to the broader literature on reputation management, as highlighted by Bar-Isaac et al. [2008].

3 Data

To investigate the influence of PMGs and pricing strategies on OCRs, our study focuses on the consumer electronics retail market, a sector frequently targeted by such pricing policies. Additionally, electronic goods are less susceptible to seasonal variations, resulting in more stable price signals over time.[17] Despite the presence of numerous competitors, ranging from local stores to chain retailers, we concentrate on online retailing. This decision stems from the ability to leverage product information exclusive to online markets, as OCRs. Furthermore, the advent of online markets has expedited and reduced the cost of evaluating search goods, such as electronic products, potentially altering consumers' behaviour in presence of PMGs policies.

Among online sellers, our analysis centers on NewEgg, a prominent US retailer of consumer electronics, known for implementing PMGs policies; NewEgg communicates the validity period of the price guarantee through a label displayed on the product's online page. Customers purchasing an eligible item with the PMG badge have 14 calendar days to find the same product at a lower advertised price from major US competitors listed by NewEgg.[18] To construct our sample, we identified all NewEgg electronics products subject to PMGs in May 2018 and tracked these products (100) from May to October 2018 to retrieve their prices, PMG information, and other OCRs. In addition, an alternative sample has been considered by selecting the same products sold on other retailing website, namely Amazon US, that does not offer these policies. This led to a final sample of 58 products across 19 sub-categories, including computer hardware, tablets, mobile phones, printers, and speakers. It is worth noting that we specifically focus on products directly sold by NewEgg and Amazon US, excluding third-party sellers since PMGs do not apply to them. This allows us to disregard considerations associated with the two-sided nature of online retailing platforms. Despite the reduction in observations due to this approach, we believe it is valuable to concentrate on a significant online retailer like NewEgg. Furthermore, we argue that OCRs provided by reputable online retailers are reliable, as both NewEgg and Amazon enforce guidelines for customer reviews and ratings, prioritizing the integrity of their recommender systems.

The retrieval of sample data presented challenges due to the absence of readily available repositories on price data. To overcome this, we developed a custom scraping pro-

[17] Specifically, our sample encompasses the time-frame from May to October 2018 and excludes significant occasions such as Thanksgiving or Christmas.

[18] See `https://promotions.newegg.com/nepro/16-2624/index.html`.

gram in Python to extract data while safeguarding against changes to the web-page structure. The scraping process was supported by alert tools to detect structural changes, allowing for timely adjustments. Subscription to the Amazon Web Service (AWS) cloud facilitated the scraping process by providing virtual servers. This approach enabled the collection of real-time, high-quality information, circumventing limitations associated with price monitoring websites or data extraction from price history graphs.

In addition to price and PMG information, we collected online-exclusive product characteristics based on customer ratings and reviews. Indeed, OCRs such as ratings and reviews contributed by prior customers, serve as valuable reservoirs of information for both consumers and retailers alike. In example, Timoshenko and Hauser [2019] utilize machine-learning techniques to contrast a dataset derived from customer interviews and focus groups with data sourced from OCRs, demonstrating that the latter hold comparable value as an information source. Specifically, online retailers facilitate buyers in evaluating diverse product offerings that have garnered success or popularity among others, fostering a collaborative exchange of insights among users while ensuring the reliability of the shared information. Moreover, OCRs have the potential to catalyze substantial network effects. As Belleflamme and Peitz [2018] suggest, the active participation of buyers in furnishing and accessing information positions ratings and reviews as integral components of a platform's information-gathering strategy. Furthermore, online retailers employ an information-dissemination strategy by tailoring product recommendations to buyers based on their characteristics and past interactions, a practice discernible through OCRs.[19]

Moreover, buyers' actions, like engaging in negative word-of-mouth and providing low ratings, might act as punishments against false price signals [e.g. Wernerfelt, 1988, Rao et al., 1999]. In an online market environment, OCRs can serve as a market disciplinary mechanism for several reasons; by publicly displaying reviews and ratings, online platforms hold sellers accountable for their actions and performance, so that sellers are incentivized to fulfill their promises, deliver on time, and provide satisfactory customer service to maintain positive reputations and avoid negative feedback. Moreover, online consumer reviews empower consumers by giving them a voice in the marketplace. Consumers can share their experiences, opinions, and concerns, influencing the purchasing decisions of others and shaping market outcomes. This empowerment creates a more balanced relationship between consumers and sellers, reducing information asymmetry and improving market efficiency. In the same vein, OCRs create a feedback loop that encour-

[19]Belleflamme and Peitz [2018] contend that these mechanisms are indispensable for the operational success of digital retail platforms. They assert that prospective consumers face an opportunity cost when assessing the quality of items and their suitability to personal preferences. Consequently, buyers place considerable value on ratings, reviews, and recommendations as they facilitate more informed decision-making. Furthermore, in environments where there is a diverse array of consumer tastes, ratings and reviews play a crucial role in evaluating product quality, providing valuable guidance to customers in their selection process. Moreover, OCRs are often perceived as less influenced by commercial interests compared to product information provided directly by sellers. This lack of bias makes them a valuable resource for consumers when making consumption decisions [Chen and Xie, 2008].

ages continuous improvement among sellers. Feedback from reviews and ratings enables sellers to identify areas for improvement, address customer complaints, and innovate to meet evolving consumer needs and preferences. This iterative process drives market competition and drives sellers to strive for excellence. Additionally, positive reviews and high ratings enhance seller credibility and trustworthiness in the eyes of consumers. Trust is essential for online transactions, as consumers must feel confident in the reliability and integrity of sellers before making purchases. By fostering trust through positive feedback, online consumer reviews contribute to the overall health and sustainability of online markets. Not less important, in the absence of traditional regulatory mechanisms, online consumer reviews can act as a form of market regulation. Negative reviews and low ratings signal subpar products or services, effectively penalizing under-performing sellers and deterring others from engaging in similar behavior. This self-regulating mechanism promotes fair and ethical business practices in the online marketplace.

We have collected data on the ratings and reviews received by each product. Ratings reflect the number of stars awarded by consumers, typically ranging from zero to five, indicating their satisfaction level. Additionally, we have compiled the absolute number of written reviews, encompassing feedback on product features, services, or overall experiences. Utilizing this information, we have developed a normalized index by comparing the number of reviews garnered by each product to the highest-reviewed item within the same sub-category: this allows us to obtain an index of the relative popularity of the product. Indeed, these metrics serve as reliable proxies for gauging the popularity of products within their respective categories. Moreover, we calculate a measure of products' age as the time (days) elapsed since the first date of products' availability on the retailing website, as well as a variable measuring treatment duration, once again expressed in days. Finally, we have developed a specific Google search rank for gauging the time users spend on the search engine to locate specific web pages for products. We posit that this index inversely correlates with the effort required to find these pages. To establish this index, we initiated a Google query for each item in our sample period using the formula ("*product name*" AND "*retailer name*") and recorded its ranking position. In particular, we collect product's ranking positions from the Google search engine research page until the third page (each Google page shows 10 results), so that rankings vary in the range [1 , 30]; it should be noted that such query can provide not only the specific product page, but also a similar product page or a bucket of products that includes the specific object of the search, hence we rank only the product's specific web page.

Ii is worth noting that the influence of PMGs on ratings and reviews is a critical aspect of consumer behavior in the retail market. PMGs are a pricing strategy employed by retailers to assure customers that they will receive the lowest price available for a product. Understanding how these guarantees affect consumer perceptions and evaluations is essential for retailers to strategize effectively. Research has shown that these policies can positively impact ratings and reviews by enhancing customer satisfaction and loyalty. When consumers feel confident that they are getting the best deal possible, they are more likely to have positive perceptions of the retailer and the product. This positive sentiment often translates into higher ratings and favorable reviews. Furthermore, PMGs can contribute to a sense of trust and credibility between the retailer and the customer. By offering a guarantee of the lowest price, retailers signal their commitment to providing value and fair pricing, which can strengthen the retailer-consumer relationship. In turn, satisfied customers are more inclined to leave positive reviews and recommend the retailer to others.

However, the impact of PMG on ratings and reviews may vary depending on various factors, including the effectiveness of the guarantee, the competitiveness of the market, and the overall shopping experience. For instance, if a retailer fails to honor its PMGs or if the process of claiming the guarantee is cumbersome, it could result in negative feedback from customers. Additionally, the presence of the policy may influence consumers' perceptions of product quality. Some consumers may perceive products with the guarantee as being of lower quality or less desirable compared to products without such guarantees. This perception could potentially lead to lower ratings and negative reviews, despite the lower price offered.[20]

Table 1: Summary statistics

	Product Ratings [0,5]	Provider Prices ($)	Product Popularity [0,1]	Search Rank [1,30]	Product Age (days)	Treatment Duration (days)
Full Sample	4.15	253.48	0.26	7.55	865.59	
	(0.68)	(307.53)	(0.30)	(9.08)	(759.07)	
NewEgg	4.14	253.15	0.20	10.74	910.20	
	(0.83)	(302.39)	(0.23)	(10.89)	(853.06)	
NewEgg & $LPG_{i,r,t} = 0$	4.13	253.67	0.19	11.97	786.75	
	(0.86)	(277.81)	(0.23)	(11.48)	(752.62)	
NewEgg & $LPG_{i,r,t} = 1$	4.19	251.01	0.25	5.68	1,417.84	14.47
	(0.70)	(387.59)	(0.23)	(5.77)	(1,035.15)	(15.44)
Amazon US	4.16	253.81	0.32	4.36	820.98	
	(0.48)	(312.63)	(0.34)	(5.08)	(648.69)	

Notes: LPGs adopted by NewEgg are the treatment of interest, so that NewEgg's products are the treated sample; an alternative sample has been built by recovering products' information for the same titles targeted by NewEgg's LPGs but sold on a different retailing website (Amazon US). The sample period includes 175 days, from May 2018 until October 2018.

Table 1 provides summary statistics on selected variables of interest. The studied sample includes 9,028 daily price observations for 58 products collected between May 2018 and October 2018 (175 days) on various retailing websites (NewEgg and Amazon US). As far as the full sample is concerned, products' ratings show a considerable variability, being the average value 4.15 stars and the standard deviation 0.68; by considering the treated sample, namely the NewEgg one, average products' ratings are 4.14 stars ($SD = 0.83$), while Amazon US shows similar scores in magnitude but a lower variability ($SD = 0.48$). Also prices vary greatly, with a sample mean of $253.48 and a standard deviation of $307.53. It is worth noting that both products' popularity and age, as well as the

[20]Overall, while PMGs have the potential to positively impact ratings and reviews by enhancing customer satisfaction and trust, retailers must carefully consider the implementation and communication of these guarantees to maximize their effectiveness and mitigate any potential negative consequences.

relative search rank, show a significant variability over the full sample, being the respective averages values equal to 0.26, 865.59 and 7.55, while standard deviations are 0.30, 759.07 and 9.08, respectively. Finally, when considering the treatment, i.e. PMGs policies adopted by NewEgg, one can observe an average duration of about 14 days ($SD = 15.44$), spanning from a minimum of 1 day to a maximum of 74 days.

It is worth noting that the time-span of our data avoids the confounding effects of COVID-19 pandemic-induced anomalies, as panic buying, increased reliance on e-commerce and fluctuating product availability, thus ensuring that the observed relationships between price guarantees, price fluctuations, and product ratings reflect typical consumer behavior rather than crisis-driven responses, an issue that led to significant shifts in consumer behavior, supply chain disruptions, and changes in online shopping patterns.

4 Identification Approach

We estimate the causal effect of NewEgg's PMGs policies on targeted products' ratings by leveraging on a DiD approach; in particular, we compare the average change in products' ratings, before and after the policy validity period, for treated items to the average change in ratings for the control group, over the same sample period. Hence, our empirical strategy relies on estimating different specifications of the following Equation:

$$\begin{aligned} Ratings_{i,r,t} = \alpha + \beta(\log Prices_{i,r,t}) + \phi(PMG_{i,r,t}) + \gamma(\log Prices_{i,r,t} * PMG_{i,r,t}) + \\ + \iota(X_{i,r,t}) + \mu_i + \tau_t + \psi_{i,r,t} \end{aligned} \tag{1}$$

In Equation 1, $Ratings_{i,r,t}$ is the dependent variable, namely the number of stars gained by product i on retailing website r at time t, while $Prices_{i,r,t}$ represents product i's price (natural logarithm) in day t for retailer r; $PMG_{i,r,t}$, i.e. the treatment of interest, is a dummy variable equal to 1 if items are subject to the price guarantee. Our model includes day time dummies (τ_t) to account for unobserved time-varying price determinants common to all goods, as well as product fixed effects (μ_i) to control for any time-invariant heterogeneity at the product and retailer level that may be correlated with the included regressors and drive ratings. It is worth noting that including individual (product) fixed effects in a DiD research design improves comparability between treatment and control groups. In the same spirit, Equation 1 also includes a set of covariates, $X_{i,r,t}$, aimed to control for products' characteristics (products' reviews, popularity and age) that might be able to affect the outcome of PMGs. All specifications are estimated by OLS, with Huber–White heteroskedasticity-robust standard errors.

The ϕ coefficient is that of interest as it represents the DiD estimate of PMGs on products' ratings: it captures the average differential level of ratings of treated products as compared to control ones, after the implementation of PMGs policies. Moreover, also the γ coefficients should be analyzed with interest; indeed, one can think of the slope estimate for an interaction ($\log Prices_{i,r,t} * PMG_{i,r,t}$) between a continuous and a dummy as the expected difference in the simple slope estimate for the continuous predictor between the group coded as zero and the group coded as one. More generally, a significant γ can be understood to mean that the effect of the the continuous predictor depends on the level of the treatment dummy, namely the rate of increase for each group within the indicator variable is different. Indeed, if product prices rise during the validity periods of PMGs and ratings fall thereafter, this can be seen as evidence of an efficient market discipline mechanism. It shows that consumers are reacting unfavorably to perceived disparities between the promised price competitiveness of PMGs and the seller's real pricing behavior. This reaction serves as a type of market discipline, informing the seller that customers are actively watching pricing changes and voicing discontent through ratings.[21]

Given that a PMG do not advertise an immediate price drop, but rather guarantee a refund, conditional on the availability of incurring a hassle cost associated with engaging in additional price search, providing proof of a cheaper price posted by a competitor, and returning to the seller offering the guarantee, the effectiveness of PMGs as a market disciplinary mechanism may require time. Firstly, consumers need time to become aware of PMGs and understand how they work. Building trust and credibility in PMGs also takes time, as consumers need positive experiences and consistent implementation from sellers. Encouraging behavioral change among consumers to incorporate PMGs into their decision-making process is another time-consuming aspect. Additionally, sellers and competitors may need time to assess the impact of PMGs on pricing strategies and market dynamics. Continuous feedback and iteration are necessary to refine PMG policies and optimize their effectiveness over time. Overall, while PMGs have the potential to be effective, realizing this potential necessitates a gradual process of awareness-building, trust-building, behavioral change, market assessment, and refinement. Hence, to account for this behaviour, in Equation 2 below we estimate a model where we allow the effect of the PMG to change over time:

$$\begin{aligned} Ratings_{i,r,t} = \alpha + \beta(\log Prices_{i,r,t}) + \phi(PMG_{i,r,t}) + \gamma(\log Prices_{i,r,t} * PMG_{i,r,t}) + \\ + \lambda(PMG_{i,r,t} * Treatment\_Duration_{i,r,t}) + \iota(X_{i,r,t}) + \mu_i + \tau_t + \psi_{i,r,t} \end{aligned} \tag{2}$$

Differently from Equation 1, the latter one includes an additional term, $PMG_{i,r,t} * Treatment\_Duration_{i,r,t}$, which allows the effect of the price guarantee to be a linear function of the time span since the PMG has been applied to product i. In fact, $Treatment\_Duration_{i,r,t}$ is equal to zero in the days before the application of the PMG by NewEgg, and it takes the value of 1 in the implementation day, the value of 2 one day after the application, and so on. The time-varying impact of the PMG can therefore be

[21]Negative ratings can undermine a seller's reputation and credibility, potentially leading to a loss of trust and consumer confidence in the seller's pricing policies.

computed as $\phi + \lambda * Treatment\_Duration_{i,r,t}$, which depends on the specific value of the variable $Treatment\_Duration_{i,r,t}$. In other words, we can compute the impact of PMGs on products' ratings for any given day since the application of the policy.

In order to provide further evidence on the investigated issue, we explore the existence of possible heterogeneous effects of PMGs on NewEgg's products' ratings by estimating Equation 1 after splitting the sample according to products' prices at the beginning of the sample period.[22] Indeed, the combination of price sensitivity, perceived value, market dynamics, word-of-mouth effects, and consumer expectations can contribute to a more intense impact of PMGs on ratings for cheaper products. First, consumers tend to be more price-sensitive when purchasing lower-priced items. As such, even small variations in price can significantly influence their purchasing decisions. The presence of PMGs on cheaper products may attract more attention from consumers who are actively searching for the best deals, leading to a heightened impact on their ratings and reviews. Second, cheaper products often have lower perceived value compared to more expensive alternatives. When a PMG is offered on a lower-priced item, it may enhance the perceived value by reassuring consumers that they are getting the best possible price. This positive reinforcement can lead to more favorable ratings and reviews from satisfied customers. Third, in highly competitive markets where price is a primary differentiator, the presence of PMGs on cheaper products can signal a commitment to offering competitive prices. This can help attract price-conscious consumers who are more likely to leave positive ratings and reviews if they perceive the product to be a good value for money. Moreover, cheaper products are often more accessible to a wider range of consumers, increasing the likelihood of word-of-mouth recommendations and referrals. Positive ratings and reviews resulting from a PMG offer on a cheaper product can amplify the product's visibility and desirability among potential buyers, further enhancing its impact on ratings. Finally, consumers may have lower expectations regarding the quality and features of cheaper products. Therefore, when a PMG is offered on such items, it may exceed consumers' expectations and lead to a positive perception of the product, resulting in higher ratings and reviews.

Additionally, in the spirit of some theoretical models that consider search cost as a relevant determinant for the interpretation of PMGs, we test if the policy has different effects on products that result to be more/less easily found on the web, as proxied by the search rank described in Section 3, namely the product's position in the search engine results page at the beginning of the sample period. In particular, we classify products as easily (hardly) found if their initial search rank is lower (higher) than 3.[23] Let us assume the existence of consumers with different search cost. From the one hand, some buyers have low search costs, so that they are willing to conduct further search and make products' ratings and reviews; on the other hand, some other customers are characterized by high search costs, thus being reluctant to search and review products. In this context,

[22]We define cheaper (expensive) products as those with initial prices below (above) the mean.

[23]The rationale behind this threshold relates to the median of the distribution of the visibility index.

PMGs can serve as a more effective market disciplinary mechanism against false price signals for products with high search rank (less popular) compared to those with low search rank (more popular) for a number of reasons. First, for less popular products informed consumers are more likely to encounter PMGs during their search process, and the presence of the latter signals to these consumers that the seller is committed to offering competitive prices, which aligns with their preference for transparency and value; as a result, the effectiveness of PMGs in signaling competitive pricing is amplified for products with high search rank, as informed consumers are more likely to notice and respond positively to these guarantees. At the same time, false signals are likely to be sanctioned by negative word-of-mouth. Second, uninformed consumers may also benefit from PMGs for products with high search rank. While they may not actively search for price information, they may still encounter PMGs during their search process due to the prominence of these guarantees for less popular products; the presence of the policy can serve as a signal of competitive pricing for these consumers, prompting them to consider the product more favorably and potentially leading to positive ratings and reviews.

In contrast, for products with low search rank (more popular), the effectiveness of PMGs as a market disciplinary mechanism may be limited. Informed consumers who actively search for products are less likely to encounter PMGs for popular items, as these guarantees are typically less prevalent or prominent for products that are already in high demand. Additionally, uninformed consumers with higher search costs may be less inclined to invest additional effort in searching for price information for popular products, further reducing the visibility and impact of PMGs. Moreover, products with low search rank often face higher competition and greater price transparency due to their popularity. In this competitive environment, sellers may be less inclined to rely on PMGs as a pricing strategy, as they may perceive less need to signal competitive prices to consumers who are already actively seeking their products. Consequently, the disciplinary effect of PMGs may be diminished for products with low search rank compared to those with high search rank.

It is worth noting that the robustness of our work is confirmed by a full set of falsification tests, whose results are discussed in Section 5.2.

5 Results

Table 2 provides the DiD estimates. In particular, column (1) first shows estimates of the static version of our model, as in Equation 1, without including controls variable, while column (2) displays the replication of the analysis after including controls.

Estimates indicate that changes in product prices, as reflected in the logarithm of the provider's retailing price, do not have a significant direct impact on product ratings. Moreover, on average, the presence of the PMG policy alone does not have a statistically significant impact on our variable of interest. This means that the overall effect of

Table 2: Baseline results

Dep. Var.: Products' ratings	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log Prices_{i,r,t}$	-0.00373	0.00726	-0.00390	0.00691	-0.01008	0.00436	-0.01043	0.00382
	(0.01543)	(0.01614)	(0.01543)	(0.01610)	(0.01619)	(0.01701)	(0.01618)	(0.01695)
$LPG_{i,r,t}$	0.01790	0.01391	-0.00086	-0.00255	0.00813	0.00858	-0.01384	-0.01011
	(0.01619)	(0.01640)	(0.02094)	(0.02108)	(0.02054)	(0.02055)	(0.02656)	(0.02613)
$\log Prices_{i,r,t} * LPG_{i,r,t}$	-0.00821**	-0.00796**	-0.00833**	-0.00807**	-0.00667*	-0.00714*	-0.00678*	-0.00723*
	(0.00373)	(0.00367)	(0.00384)	(0.00377)	(0.00375)	(0.00381)	(0.00388)	(0.00392)
$LPG_{i,r,t} * Treatment\_Duration_{i,r,t}$			0.00158***	0.00140**			0.00188***	0.00160***
			(0.00059)	(0.00055)			(0.00067)	(0.00062)
Observations	9,028	9,028	9,028	9,028	9,028	9,028	9,028	9,028
Controls	✗	✓	✗	✓	✗	✓	✗	✓
Product FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.87206	0.87271	0.87216	0.87278	0.86413	0.86519	0.86426	0.86528

Notes: This Table presents DiD estimates of Equation 1 (columns 1, 2, 5, 6) and Equation 2 (columns 3, 4, 7, 8) on the effect of LPGs on products' ratings. $Ratings_{i,r,t}$ is the number of stars gained by product i on retailing website r at time t. $Prices_{i,r,t}$ represents product i's price (natural logarithm) in day t for retailer r. $LPG_{i,r,t}$ is a dummy variable equal to 1 if items are subject to the LPG in day t. $Treatment\_Duration_{i,r,t}$ captures the number of days since the application of the LPG. All specifications include product and time fixed effects. Controls include the absolute and the relative number of reviews, as well as products' age. Regressions in columns (5), (6), (7) and (8) use observations weighted according to the product popularity index, as described in Section 3, at the beginning of the sample period. All specifications are estimated by OLS. Huber–White heteroskedasticity-robust standard errors are shown in parentheses: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

prices and the PMG on ratings, independently of each other, is not statistically discernible from zero. However, it should be noted that the negative and statistically significant coefficient on the interaction term, namely ($\log Prices_{i,r,t} * PMG_{i,r,t}$), indicates that the relationship between prices and ratings differs depending on whether the PMG is present or not; specifically, when the PMG policy is present ($PMG_{i,r,t} = 1$), the negative coefficient (-0.00821) suggests that an increase in prices is associated with a decrease in ratings, statistically significant at the 5% level. Very similar effects are obtained when repeating the analysis with the inclusion of control variables (Table 2, col. 2).

To explore whether PMGs' duration matters in determining the level of products' ratings, we estimate Equation 2, which allows for a differential impact of PMGs according to the number of days elapsing since the application of the policy. Results of this analysis, reported in column (3) of Table 2, indicate that one additional day of the policy being in place significantly increases products' ratings ($PMG_{i,r,t} * Treatment\_Duration_{i,r,t} = 0.00158$), at the 1% level of statistical significance. This suggests that the effect of the PMG on product ratings varies depending on the duration since the application of the policy.[24] Once again, a very similar estimated coefficient is obtained when we repeat the analysis with the inclusion of control variables (col. 4). It is worth noting that, also in this case, even though the main effect of PMGs is not different from zero, the significant estimated coefficient associated to the ($\log Prices_{i,r,t} * PMG_{i,r,t}$) term suggests that the impact of prices on ratings varies depending on whether the policy is present or not. This highlights the importance of considering the interaction effects and not solely relying on the main effects when interpreting regression results, being again consistent with the expectation that consumers may perceive price increases during the PMG period as a deviation from the expected pricing strategy implied by the policy, leading to lower ratings.

[24]Specifically, the positive coefficient indicates that, as the number of days since the application of the PMG increases, the impact on product ratings becomes more positive. This could imply that consumers' perceptions of the PMG become more favorable over time, leading to higher ratings for products subject to the policy.

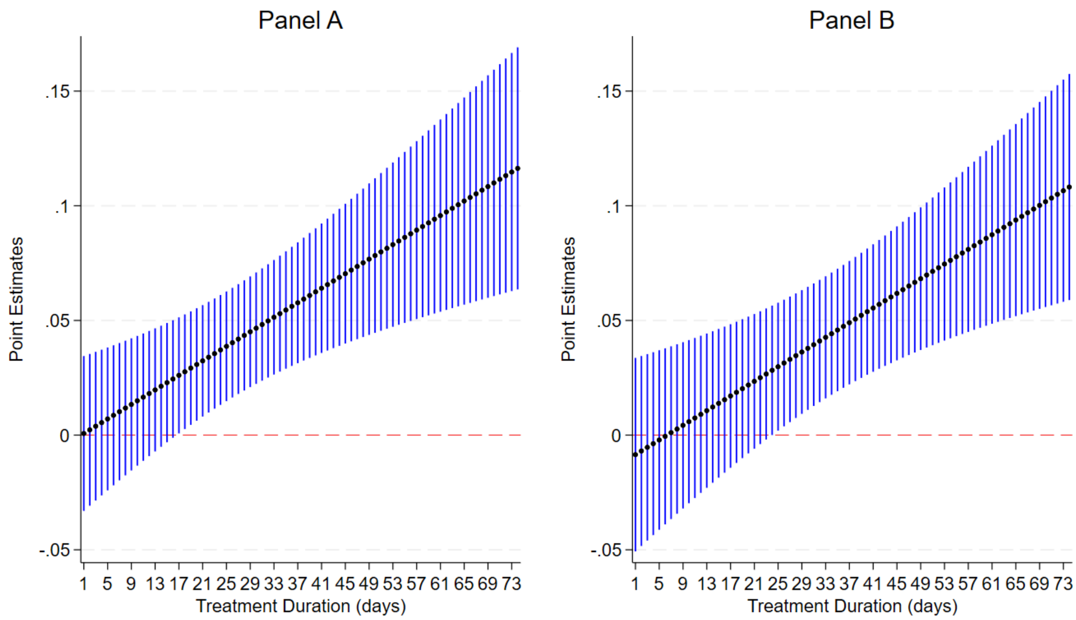
Finally, in columns (5), (6), (7) and (8) of Table 2 we replicate the previous regressions by weighting observations according to the product popularity index, as described in Section 3, at the beginning of the sample period; reassuringly, results do not change. Indeed, the coefficient of both $Prices_{i,r,t}(log)$ and $PMG_{i,r,t}$ are not statistically significant neither in the static specification without control variables (col. 5), nor in the one including controls (col. 6), while estimated point estimates on the (log$Prices_{i,r,t} * PMG_{i,r,t}$) term remain negative and statistically significant; this finding further corroborates the idea that consumers are likely to exert an effective market disciplinary mechanism by engaging in bad ratings when firms use PMG to falsely signal low prices. It can be noticed that neither the inclusion of the $PMG_{i,r,t} * Treatment\_Duration_{i,r,t}$ interaction term without controls, nor the specification including the latter, change the direction and the magnitude of the treatment effect; this result from the weighting procedure suggests that products may not appear to significantly differ in terms of observables, and that the treatment effect is not driven by any particular item in our sample.

Thus far, our results have shown that PMGs policies are associated to an increase in products' ratings, but only after a given period since the application of the latter. To better understand the dynamics of the effectiveness of the policy, we have disentangled the aggregate effect into daily effects. Specifically, for any day after the application of the PMG, we use the estimated coefficient of Table 2 (columns 4 and 8) to compute the following linear combination: $\phi + \lambda * Treatment\_Duration$. The results are reported in Panel A of Figure 1, from which is interesting to observe a statistically significant increase in products' ratings since the 17th day after the application of the policy: indeed, the effect statistically significantly increases from about 0.026 ($SE = 0.02$) to 0.12 ($SE = 0.03$). Similar results are observed after weighting observations according to the product popularity index (Panel B of Figure 1), with the estimated coefficients being slightly smaller in magnitude.

Aforementioned findings are likely to align with the signaling interpretation of PMGs proposed by Srivastava and Lurie [2004]. In particular, a signaling mechanism occurs when one party conveys information about its characteristics or intentions to another party. In the case of retailers offering PMGs, the provision of such guarantees can be seen as a signal to consumers about the store's pricing strategy and commitment to providing competitive prices. Reasonably, most rational sellers are likely to be not willing in sending false price signals if the latter increase costs as immediate or future profits, reputation and overall price image. Indeed, "the disciplinary mechanisms are the key in signaling theory because the effectiveness of market signals depends on the prevailing strength of such mechanisms. When disciplinary mechanisms are strong, the cost that a firm is likely to incur or forfeit by sending a false signal is relatively high." [Srivastava and Lurie, 2004, , p. 119]

In our setting, the negative coefficient on the interaction term can be precisely interpreted as evidence of market discipline exerted by consumers. Indeed, in competitive

Figure 1: Effect of LPGs on products' ratings according to the days since the application of the policy.



Notes. This Figure presents DiD estimates of the effect of the LPG policy on the level of products' ratings according to the number of days since the application of the policy. Estimates in Panel A and B are based on the estimated coefficients of columns (4) and (8) of Table 2, respectively. The following linear combination, $\beta_2 + \lambda * Treatment\_Duration$, is applied. 90 percent confidence intervals are reported. Huber–White heteroskedasticity-robust standard errors are computed.

markets as the online consumer electronic one, buyers have access to various sources of information, can quickly assess whether a retailer's pricing practices align with its promotional claims, such as PMGs, and often engage in reviewing and rating products. When consumers perceive a disconnect between a store's pricing and its promotional messaging, they may respond by expressing dissatisfaction through lower ratings or reduced patronage. Thus, the negative coefficient reflects consumers' use of ratings as a form of market feedback, effectively disciplining retailers that deviate from expected pricing norms associated with PMGs, so that the latter can effectively act as a signal of low prices. Specifically, products' ratings and reviews can act as an effective market disciplinary mechanism due to several key factors. Firstly, they provide transparent information about product quality and satisfaction, allowing potential buyers to make informed decisions based on the experiences of others. Positive ratings and reviews serve as social proof, indicating a product's reliability and worthiness, while negative feedback signals potential issues or dissatisfaction. Moreover, ratings and reviews hold sellers and manufacturers accountable for product quality and customer satisfaction. Negative reviews can damage a company's reputation, incentivizing businesses to maintain high standards and address consumer concerns promptly. This creates a feedback loop between consumers and businesses, fostering continuous improvement and enhancing overall product satisfaction. Finally, ratings and reviews contribute to market competition by differentiating products based on quality and performance. Positive feedback can give companies a competitive advantage, while negative feedback highlights areas for improvement that competitors may exploit.

Overall, these results underscore the nuanced effects of pricing policies on consumer behavior, particularly in the context of signaling theory as elucidated by Srivastava and Lurie [2004] and discussed above. Results in both columns (3) and (4) of Table 2 confirm the idea that consumers are likely to punish deviations from the expected sellers' behavior implied by the PMG by means of bad ratings, and this finding aligns with the notion that consumers perceive these policies as signals of low store prices. Moreover, the positive coefficient on the interaction between the PMG and treatment duration implies that consumer perceptions of the policy may become more favorable over time, potentially reflecting the establishment of trust and credibility in the retailer's pricing practices. Thus, through the lens of signaling theory, the observed interactions between prices, PMGs, and treatment duration shed light on how pricing policies serve as signals that influence consumer perceptions and ultimately shape their responses, highlighting the importance of considering signaling mechanisms in understanding consumer behavior in retail settings.

5.1 Heterogeneous Effects

In order to further investigate the analyzed issue, we perform additional analyses to verify if the impact of PMG and pricing policies is heterogeneous depending on products' prices at the beginning of the sample period. Indeed, the effectiveness of PMGs as a market disciplinary mechanism may be stronger for cheaper items compared to expensive ones for several reasons. Firstly, consumers tend to be more price-sensitive when purchasing cheaper items, making them more responsive to price signals such as PMGs. Additionally, cheaper items often represent smaller financial investments for consumers, leading them to prioritize obtaining the best value for their money. In highly competitive markets, sellers may use PMGs to differentiate themselves and attract customers, particularly for cheaper items facing greater competition. Moreover, the higher sales volume associated with cheaper items means that even small improvements in pricing strategies, such as the implementation of PMGs, can have a significant impact on overall revenue. Lastly, consumers may perceive the risk associated with purchasing cheaper items differently, being more inclined to take a chance on a cheaper item if they believe they are getting a good deal with an PMG.

Table 3 presents the regression results for an analysis investigating those possible heterogeneous effects. Across all specifications, the estimated coefficients associated to products' prices are not different from zero, suggesting the absence of a direct impact of pricing policies on ratings. Conversely, and differently from results in Table 2, PMGs have a positive and statistically significant impact on product ratings, with estimated coefficients ranging from 0.28 (SE = 0.09) to 0.037 (SE = 0.02) with statistical significance between 1% and 5%. The ($\log Prices_{i,r,t} * PMG_{i,r,t}$) interaction term, once again, assesses whether the impact of prices on ratings differs between products sub-

Table 3: Heterogeneous results. Cheaper/expensive products.

Dep. Var.: Products' ratings	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Expensive Products				Cheaper Products			
$\log Prices_{i,r,t}$	-0.02610	0.00706	-0.02591	-0.02591	-0.01496	-0.00427	-0.01579	-0.01579
	(0.02923)	(0.02852)	(0.02925)	(0.02925)	(0.01881)	(0.01959)	(0.01876)	(0.01876)
$LPG_{i,r,t}$	0.03176**	0.02963**	0.03700**	0.03700**	0.30957***	0.29211***	0.28043***	0.28043***
	(0.01447)	(0.01447)	(0.01652)	(0.01652)	(0.10394)	(0.09647)	(0.09418)	(0.09418)
$\log Prices_{i,r,t} * LPG_{i,r,t}$	0.00018	-0.00182	-0.00041	-0.00041	-0.07693***	-0.07291***	-0.07593***	-0.07593***
	(0.00203)	(0.00207)	(0.00223)	(0.00223)	(0.02853)	(0.02683)	(0.02814)	(0.02814)
$LPG_{i,r,t} * Treatment\_Duration_{i,r,t}$			-0.00011	-0.00011			0.00219**	0.00219**
			(0.00010)	(0.00010)			(0.00085)	(0.00085)
Observations	2,606	2,606	2,606	2,606	6,422	6,422	6,422	6,422
Controls	✗	✓	✗	✓	✗	✓	✗	✓
Product FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.99220	0.99295	0.99220	0.99220	0.81804	0.81920	0.81820	0.81820

Notes: This Table presents DiD estimates of Equation 1 (columns 1, 2, 5, 6) and Equation 2 (columns 3, 4, 7, 8) on the heterogeneous effect of LPGs on products' ratings, based on products' initial prices. $Ratings_{i,r,t}$ is the number of stars gained by product i on retailing website r at time t. $Prices_{i,r,t}$ represents product i's price (natural logarithm) in day t for retailer r. $LPG_{i,r,t}$ is a dummy variable equal to 1 if items are subject to the LPG in day t. $Treatment\_Duration_{i,r,t}$ captures the number of days since the application of the LPG. All specifications include product and time fixed effects. Controls include the absolute and the relative number of reviews, as well as products' age. Cheaper (expensive) products are those with initial prices below (above) the average value. All specifications are estimated by OLS. Huber–White heteroskedasticity-robust standard errors are shown in parentheses: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

ject to the PMG policy and those that are not. Interestingly, it is worth noting that, when the PMG policy is applied ($PMG_{i,r,t} = 1$), negative and statistically coefficients are associated with cheaper products, suggesting that an increase in prices is likely to generate a decrease in cheaper products' ratings; moreover, estimated coefficients are slightly higher in magnitude with respect to those in Table 1, and statistically significant at the 1% level. It should be noted that expensive items are not affected by either pricing policies, nor the PMG policies: moreover, also ($\log Prices_{i,r,t} * PMG_{i,r,t}$) and $PMG_{i,r,t} * Treatment\_Duration_{i,r,t}$ interaction terms' coefficients are statistically not different from zero. Lastly, we examine whether the duration of the PMG policy implementation affects the relationship between prices and ratings. Again, statistically significant positive coefficients are associated to cheaper products, while the expensive ones are not affected; this suggests that the effect of PMGs on ratings is amplified over time for cheaper products subject to the policy, differently from expensive items. Specifically, when we include the interaction term, $PMG_{i,r,t} * Treatment\_Duration_{i,r,t}$, the estimated coefficient related to cheaper products turns out to be positive and statistically significant, both in the specification without controls and in that including controls (0.00219, columns 7 and 8, respectively).

In a similar vein, we also explore whether the impact of PMGs and pricing is different on products that require different search efforts at the beginning of the sample period. Indeed, if PMGs serve as signals of low store prices (conveying valuable information about a retailer's pricing strategy and commitment to providing competitive prices), when applied to products that are relegated to secondary pages of search engines, those requiring higher search effort, these guarantees can become even more potent as market discipline mechanisms for several reasons. Firstly, products featured on secondary pages typically receive less visibility and traffic compared to those on primary pages. Consumers navigating to secondary pages may exhibit higher price sensitivity, actively seeking cost-effective options. In this scenario, the presence of a PMG policy signals to consumers that despite the product's placement on a less prominent page, the retailer is committed to offering competitive prices. Secondly, consumers exploring secondary pages may be more inclined to conduct price comparisons across multiple retailers. The presence of a PMG encourages consumers to perceive the retailer as transparent and confident in its pricing competitiveness. This perception fosters trust and loyalty among consumers, even for products with lower visibility. Thirdly, consumers navigating to secondary pages may be more discerning and deliberate in their purchasing decisions, often motivated by specific product attributes or price considerations. The presence of a PMG on these pages reassures consumers that they are making informed choices and receiving the best possible value for their money.[25]

Table 4: Heterogeneous results. More/less visible products.

Dep. Var.: Products' ratings	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	More Visible Products				Less Visible Products			
$\log Prices_{i,r,t}$	-0.01211	-0.00529	-0.01349	-0.01349	-0.01370	0.02348	-0.01191	-0.01191
	(0.03383)	(0.03333)	(0.03392)	(0.03392)	(0.01450)	(0.01998)	(0.01476)	(0.01476)
$LPG_{i,r,t}$	0.04860*	0.04076	0.07418**	0.07418**	0.17310***	0.26235*	0.17483**	0.17483**
	(0.02857)	(0.02872)	(0.03423)	(0.03423)	(0.06390)	(0.15758)	(0.06805)	(0.06805)
$\log Prices_{i,r,t} * LPG_{i,r,t}$	-0.00325	-0.00260	-0.00496	-0.00496	-0.06257***	-0.06311*	-0.07583***	-0.07583***
	(0.00412)	(0.00413)	(0.00444)	(0.00444)	(0.02077)	(0.03490)	(0.02412)	(0.02412)
$LPG_{i,r,t} * Treatment\_Duration_{i,r,t}$			-0.00130***	-0.00130***			0.00529***	0.00529***
			(0.00036)	(0.00036)			(0.00135)	(0.00135)
Observations	4,405	4,405	4,405	4,405	4,623	4,623	4,623	4,623
Controls	✗	✓	✗	✓	✗	✓	✗	✓
Product FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.86941	0.86978	0.86961	0.86961	0.86817	0.89716	0.86879	0.86879

Notes: This Table presents DiD estimates of Equation 1 (columns 1, 2, 5, 6) and Equation 2 (columns 3, 4, 7, 8) on the heterogeneous effect of LPGs on products' ratings, based on products' initial online visibility. $Ratings_{i,r,t}$ is the number of stars gained by product i on retailing website r at time t. $Prices_{i,r,t}$ represents product i's price (natural logarithm) in day t for retailer r. $LPG_{i,r,t}$ is a dummy variable equal to 1 if items are subject to the LPG in day t. $Treatment\_Duration_{i,r,t}$ captures the number of days since the application of the LPG. All specifications include product and time fixed effects. Controls include the absolute and the relative number of reviews, as well as products' age. More (less) visible products are those with an initial search rank below (above) the median value. All specifications are estimated by OLS. Huber–White heteroskedasticity-robust standard errors are shown in parentheses: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4 shows the results of aforementioned analysis. PMGs policies are confirmed to exert a positive and statistically significant impact on products' ratings across almost all specifications; however, the effect is noticeably greater for less visible items, with point estimates in the range 0.17–0.26, depending on whether we consider the specification without or with controls (columns 5 and 6, respectively). It is worth noting that when we include the duration interaction term (point estimates of Equation 2 in columns 3, 4, 7, 8), i.e. $PMG_{i,r,t} * Treatment\_Duration_{i,r,t}$, the PMG policy has a smaller effect on product ratings as the duration increases for more visible products, whereas the opposite holds true for less visible ones. This pattern suggests that the visibility of products plays a crucial role in shaping consumer responses to pricing policies like PMGs. More visible products may already enjoy a higher level of consumer awareness and trust, making them less sensitive to changes in pricing policies over time. In contrast, less visible products may rely more heavily on pricing signals, such as PMGs, to attract consumer attention

[25] Moreover, in the competitive landscape of e-commerce, where consumers have access to a plethora of options and information, retailers must differentiate themselves to stand out. By offering price-matching guarantees, especially for products on secondary pages, retailers signal their commitment to customer satisfaction and competitiveness, thereby enhancing their brand reputation and attracting discerning consumers.

and compete effectively. Therefore, the diminishing effect of the PMG policy on ratings for more visible products could be attributed to factors such as consumer familiarity, brand reputation, and trust, which mitigate the influence of pricing policies over time. Conversely, the increasing effect of the policy on ratings for less visible products suggests that pricing signals become more influential as consumers actively seek cost-effective options, especially for products with lower visibility.

A further aspect to be considered in the heterogeneity analysis based on online visibility provided in Table 4 refers to the fact that the estimates of the ($\log Prices_{i,r,t} * PMG_{i,r,t}$) term are negative and statistically significant in all specifications pertaining to the sample of less visible products, as opposed to those referring to the more visible products one. In particular, the coefficient on the interaction term is negative and often highly statistically significant across all specifications (columns 5-8), indicating that the PMG policy amplifies the negative effect of price increases on ratings for less visible items. Indeed, if we assume that the presence of a PMG policy can signal to consumers the retailer's commitment to providing competitive prices, the effectiveness of this signal may vary depending on the visibility of the product in online search results. For more visible products, consumers may already have higher expectations regarding pricing competitiveness due to their prominence in search results. Thus, the presence of a PMG policy may serve as reinforcement of the retailer's commitment to competitive pricing, mitigating the negative impact of higher prices on consumer ratings. Conversely, for less visible items, consumers may have lower initial expectations regarding pricing competitiveness. In this case, the presence of the policy may be a more salient signal of the retailer's pricing strategy, amplifying the negative impact of increasing prices on consumer ratings. This aligns with the findings of our analysis, where the interaction between prices and the PMG policy has a more pronounced effect on ratings for less visible products.

5.2 Robustness Analysis

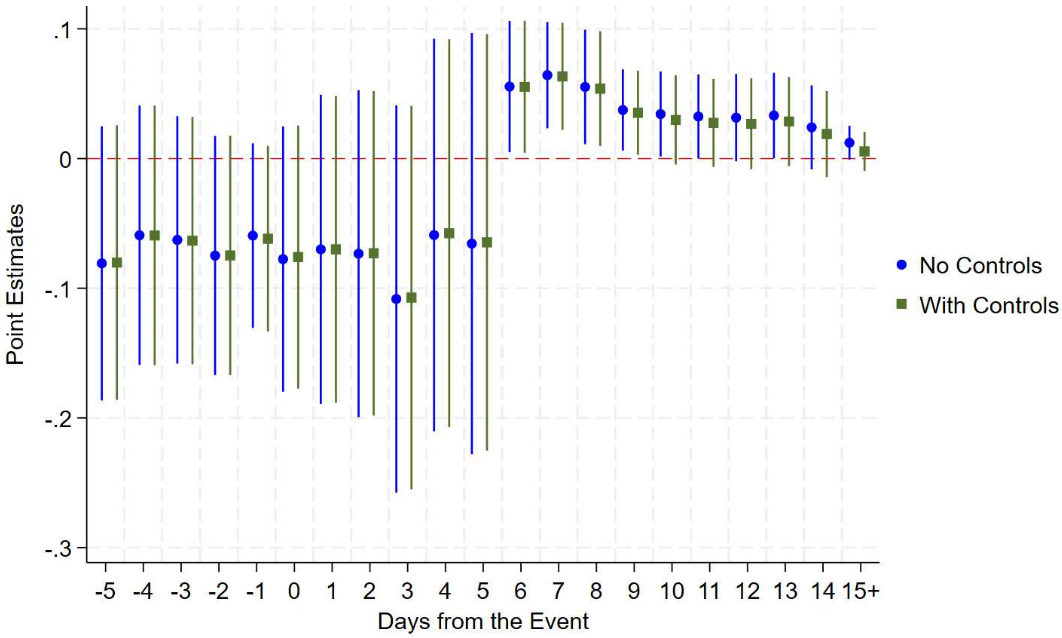
In this Section, we assess the validity of our main results by performing a set of robustness tests.

First, it is worth noting that one potential concern when estimating Equation 2 is related to the linearity assumption, i.e. we have assumed that the effect of prices and PMGs is a linear function of the time span since the policy is applied. Hence, we relax this assumption by leveraging a more general specification which includes leads and lags à la Autor [2003] and that takes the following form:

$$Ratings_{i,r,t} = \sum_{\xi=-K}^{-1} \Gamma_\xi \left(PMG_{i,r,t+\xi}\right) + \sum_{\xi=0}^{M} \delta_\xi \left(PMG_{i,r,t+\xi}\right) + X_{i,r,t}^T \beta + \mu_{i,r} + \tau_t + \epsilon_{i,r,t} \tag{3}$$

Differently from Equation 2, in the latter one the K leads of the treatment indicator span from 5 to 1 days before the treatment and the Γ's represent pre-trends coefficients. The M lags of treatment variable span from the treatment day ($t = 0$) to 15 days after the treatment and onwards; the δ's represent the DiD coefficients of interest, reflecting dynamic average treatment effects, i.e. this specification allows PMGs to have a differential effect over time. Moreover, fundamental for the validity of a DiD research design, this specification allow us to test the existence of a parallel trend between treated and control groups, since it contains different leads of the treatment. Indeed, a statistically significant coefficient for leads terms might be indicative of possible anticipatory effects, namely that the parallel trend assumption might be violated.

Figure 2: Event study representation of the effect of LPGs on products' ratings



Notes. Event study estimates of Equation 3. All specifications include product and time fixed effects. Controls include the absolute and the relative number of reviews, as well as products' age. 90 percent confidence intervals are reported. Huber–White heteroskedasticity-robust standard errors are computed.

Figure 2 provides event study estimates of Equation 3 and suggests that the parallel trend assumption required by DiD research designs is satisfied; in fact, pre-trends coefficients of the treatment K leads, spanning from 5 to 1 days before the application of the PMG, are individually and jointly not statistically different from zero, thus confirming the absence of any anticipatory effect and the validity of the research design.[26] Moreover, the estimated specification allows us to investigate the possibility that the effect of the treatment may speed up, stabilize, or mean revert over time, since it includes M lags of the treatment, ranging from the implementation day ($t = 0$) until 15 days later and onward. Estimated coefficients, graphically shown in Figure 2, suggest that PMGs exert a positive effect on products ratings, starting six days after the treatment and lasting

[26] We conduct an F test of leads' joint significance for both the specification without controls [$F(5;8791) = 1.26$ - $Prob > F = 0.2775$] and the one including controls [$F(5;8789) = 1.29$ - $Prob > F = 0.2649$], that highlight the absence of anticipatory effects.

up to the 9^{th} day, after which they become non-statistically different from zero. Comfortingly, if we replicate the above analysis after including controls, we find very similar results. Taken together, these findings confirm the results from the linear specification in Equation 2: this suggests that imposing a linear structure does not lead to biased results.

Second, we estimate the more extended specification (including control variables) of both Equation 1 and 2 over the full sample and the sub-samples of cheaper products and less visible ones, after introducing *fake* treatment timings. The latter are drawn from Bernoulli distributions, with parameters p (probability of success) derived from the $PMG_{i,r,t}$ sampling distribution. In this setting, we should not observe any significant effect of *fake* PMGs on products prices: comfortingly, results reported in Table 5 confirm this prediction.

Table 5: Effect of *fake* LPGs on products' ratings.

Dep. Var.: Products' ratings	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample		Cheaper Products		Less Visible Products	
$\log Prices_{i,r,t}$	0.00342	0.00257	-0.00445	-0.00506	0.01360	0.01343
	(0.01505)	(0.01512)	(0.01822)	(0.01839)	(0.01663)	(0.01668)
$LPG^{fake}_{i,r,t}$	0.01294	0.01444	0.04596	0.05032	0.00821	0.00829
	(0.02137)	(0.02212)	(0.06218)	(0.06135)	(0.04168)	(0.04195)
$\log Prices_{i,r,t} * LPG^{fake}_{i,r,t}$	-0.00338	-0.00349	-0.01138	-0.01190	-0.00081	-0.00079
	(0.00345)	(0.00346)	(0.01648)	(0.01636)	(0.00687)	(0.00688)
$LPG^{fake}_{i,r,t} * Treatment\_Duration_{i,r,t}$		0.00010		-0.00033		0.00047
		(0.00041)		(0.00056)		(0.00102)
Observations	9,028	9,028	6,422	6,422	4,623	4,623
Controls	✓	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
R^2	0.87263	0.87264	0.81866	0.81867	0.89684	0.89685

Notes: This Table presents DiD estimates of Equation 1 (columns 1, 3, 5) and Equation 2 (columns 2, 4, 6) on the effect of *fake* LPGs on products' ratings. $Ratings_{i,r,t}$ is the number of stars gained by product i on retailing website r at time t. $Prices_{i,r,t}$ represents product i's price (natural logarithm) in day t for retailer r. $LPG^{fake}_{i,r,t}$ are drawn from Bernoulli distributions, with parameters p (probability of success) derived from the $LPG_{i,r,t}$ sampling distribution. $Treatment\_Duration_{i,r,t}$ captures the number of days since the application of the LPG. All specifications include product and time fixed effects. Controls include the absolute and the relative number of reviews, as well as products' age. Cheaper products are those with initial prices below the average value. Less visible products are those with an initial search rank above the median value. All specifications are estimated by OLS. Huber–White heteroskedasticity-robust standard errors are shown in parentheses: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Third, main results are confirmed when we estimate Equations 1 and 2 after substituting the dependent variable with a *fake* one, in which products' *fake* ratings are drawn from product specific random distributions resembling sampling ones (same mean and variance). Once again, we should not observe any significant effect of NewEgg's PMGs on *fake* products' ratings. Results shown in Table 6 confirm the absence of any impact of PMGs on the *fake* outcome.

Fourth, we provide a random allocation test, in which we build a *placebo* treatment variable taking on value 1 if random numbers drawn from a uniform distribution [0,1] are greater than the sampling treatment probability. We then estimate the most extended specification of Equation 1, leveraging on this new *fake* treatment indicator, and iterating such procedure 1,000 times, in order to obtain a distribution of *placebo* average treatment

Table 6: Effect of LPGs on *fake* products' ratings.

Dep. Var.: Fake products' ratings	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample		Cheaper Products		Less Visible Products	
$\log Prices_{i,r,t}$	0.00927	0.00923	0.01145	0.01130	0.01232	0.01244
	(0.01124)	(0.01123)	(0.01397)	(0.01393)	(0.01838)	(0.01839)
$LPG_{i,r,t}$	-0.01169	-0.01392	-0.01185	-0.01590	-0.04038	-0.04033
	(0.01097)	(0.01379)	(0.03807)	(0.03295)	(0.03091)	(0.03105)
$\log Prices_{i,r,t} * LPG_{i,r,t}$	0.00167	0.00166	0.00121	0.00134	0.00369	0.00156
	(0.00143)	(0.00143)	(0.01067)	(0.01050)	(0.00777)	(0.00885)
$LPG_{i,r,t} * Treatment\_Duration_{i,r,t}$		0.00019		0.00031		0.00085
		(0.00033)		(0.00049)		(0.00069)
Observations	9,028	9,028	6,422	6,422	4,623	4,623
Controls	✓	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
R^2	0.92600	0.92600	0.88978	0.88978	0.91144	0.91145

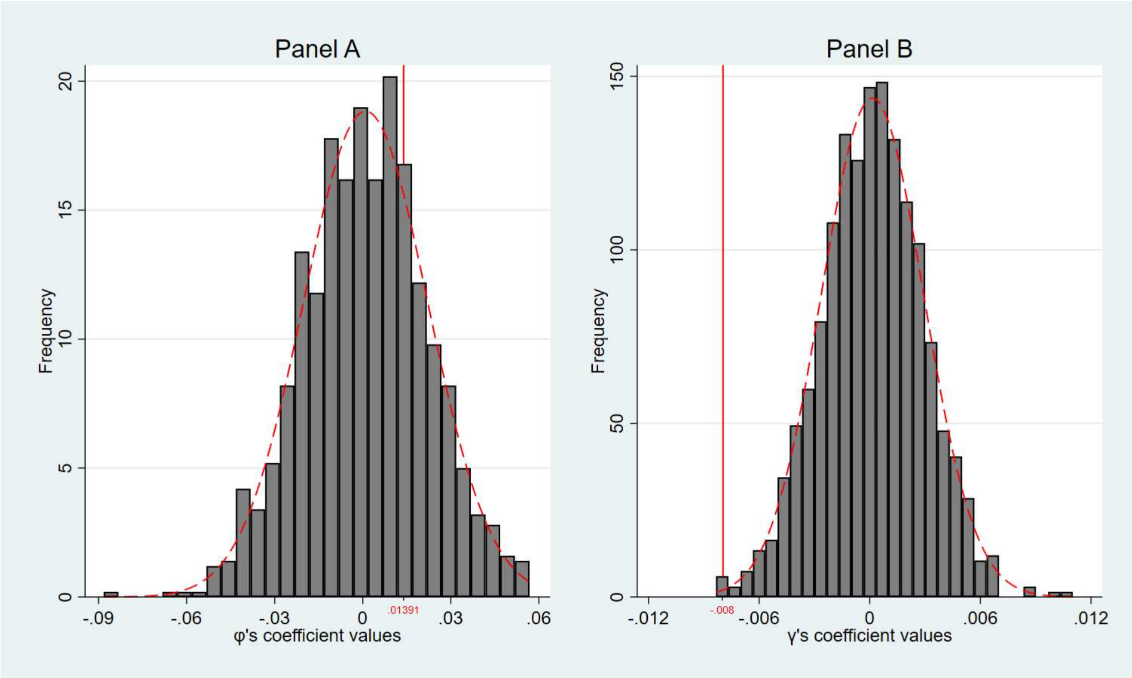
Notes: This Table presents DiD estimates of Equation 1 (columns 1, 3, 5) and Equation 2 (columns 2, 4, 6) on the effect of LPGs on *fake* products' ratings. *Fake* ratings are drawn from product specific random distributions resembling sampling ones (same mean and variance). $Prices_{i,r,t}$ represents product i's price (natural logarithm) in day t for retailer r. $LPG_{i,r,t}$ is a dummy variable equal to 1 if items are subject to the LPG in day t. $Treatment\_Duration_{i,r,t}$ captures the number of days since the application of the LPG. All specifications include product and time fixed effects. Controls include the absolute and the relative number of reviews, as well as products' age. Cheaper products are those with initial prices below the average value. Less visible products are those with an initial search rank above the median value. All specifications are estimated by OLS. Huber–White heteroskedasticity-robust standard errors are shown in parentheses: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

effects to compare with the estimated average values observed in column (2) of Table 2, namely $PMG_{i,r,t} = 0.01391$ ($S.E. = 0.02$) and $\log Prices_{i,r,t} * PMG_{i,r,t} = -0.00796$ ($S.E. = 0.004$). Indeed, a statistically significant average treatment effect should be different with respect to those obtained with placebo estimates. In both Panel A and B of Figure 3 the grey bars represent the estimated placebo coefficients' distribution obtained with the aforementioned iterative method, while the vertical red lines highlight the estimated average treatment effects based on actual treatments for $PMG_{i,r,t}$ and $\log Prices_{i,r,t} * PMG_{i,r,t}$ terms.

One should notes that placebo coefficients are almost normally distributed, with estimates centered at zero, thus highlighting no treatment effects under the hypothesis of *fake* treatment assignments. From the one hand, evidence reported in Panel A suggest that $PMG_{i,r,t}$ is confirmed to be not statistically different from zero while, on the other hand, the test for $\log Prices_{i,r,t} * PMG_{i,r,t}$ term, reported in Panel B, suggests that the actual γ estimate lies outside the density distribution of placebo effects, thus being statistically significantly larger, in absolute value, than those obtained using randomly assigned treatments. Overall, this random allocation test supports the robustness of our main findings.

Finally, given that our dependent variable refers to products' ratings, namely a direct measure of consumer satisfaction, it is interesting to verify if our results are robust to different but correlated alternative measures for positive/negative customers' feedback. To this end, we leverage on the number of good reviews, namely the total number of reviews multiplied by the share of 4 and 5-star rating, as an alternative measure of positive/negative customers' feedback possible correlated with market disciplining mech-

Figure 3: Placebo plot test. Random treatment allocation.



Notes. In this test we randomly assign treatments timings by generating simulated values for the dummy $LPG_{i,r,t}$. In particular, we build a *fake* $LPG_{i,r,t}$ equal to 1 if random numbers drawn from a uniform distribution [0,1] are greater than the sample treatment probability. We then estimate the more extended specification of Equation (1) after including the new treatment indicator, $LPG^{fake}_{i,r,t}$ and we iterate such procedure 1,000 times in order to obtain a distribution of placebo coefficients to compare with the average estimated values shown in column (2) of Table 2, namely $LPG_{i,r,t} = 0.01391$ ($S.E. = 0.01640$) and $\log Prices_{i,r,t} * LPG_{i,r,t} = -0.00796$ ($S.E. = 0.00367$). Panel A and B show this iterative test for ϕ and γ coefficients, respectively. Dark bars represent the distribution of estimated placebo coefficients. The vertical solid red line represents the estimated average treatment effect shown in column (2) of Table 2.

anisms.

It is worth noting that ratings capture the immediate sentiment of consumers regarding their experience with a product: a higher rating directly correlates with better consumer satisfaction. Moreover, the latter measure offers a more granular view of customer sentiment: for instance, a 4-star rating is quantitatively different from a 5-star rating, which provides more nuanced data than just counting, for example, a total number of reviews. However, using a measure of "good reviews" (as the total number of reviews multiplied by the share of 4 and 5-star reviews) can be an alternative, but it has limitations. First, this measure combines the quantity of reviews with the quality: while it reflects both aspects, it can be less precise because it conflates two different dimensions of feedback. Second, a product might have many 4 and 5-star reviews initially, but if recent reviews are negative, the share might not decrease quickly enough to reflect this change: ratings, on the other hand, would drop more immediately in response to negative feedback. Third, products with a very high number of reviews might dominate the analysis, overshadowing trends in products with fewer reviews: ratings are less likely to be skewed in this manner because they normalize the feedback irrespective of the number of reviews.

Given that, we estimate the causal effect of NewEgg's PMGs policies on the number of good reviews ($Good_{i,r,t}$) received by targeted products by leveraging on a DiD approach as in the following Equations, in which we use the same notation from both Equation 1 and 2:

$$\begin{aligned} Good_{i,r,t} = \alpha + \beta(\log Prices_{i,r,t}) + \phi(PMG_{i,r,t}) + \gamma(\log Prices_{i,r,t} * PMG_{i,r,t}) + \\ + \iota(X_{i,r,t}) + \mu_i + \tau_t + \psi_{i,r,t} \end{aligned} \tag{4}$$

$$\begin{aligned} Good_{i,r,t} = \alpha + \beta(\log Prices_{i,r,t}) + \phi(PMG_{i,r,t}) + \gamma(\log Prices_{i,r,t} * PMG_{i,r,t}) + \\ + \lambda(PMG_{i,r,t} * Treatment\_Duration_{i,r,t}) + \iota(X_{i,r,t}) + \mu_i + \tau_t + \psi_{i,r,t} \end{aligned} \tag{5}$$

Table 7: Alternative dependent variable: good reviews.

Dep. Var.: Good Reviews	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log Prices_{i,r,t}$	-287.37***	-287.99***	-287.40***	-288.02***	-180.28***	-182.43***	-180.36***	-182.55***
	(43.67)	(41.14)	(43.67)	(41.12)	(29.26)	(27.82)	(29.25)	(27.80)
$LPG_{i,r,t}$	139.84***	138.56***	136.81***	137.12***	120.18***	119.80***	115.20***	115.62***
	(33.93)	(33.32)	(34.58)	(34.23)	(25.55)	(25.61)	(26.01)	(26.30)
$\log Prices_{i,r,t} * LPG_{i,r,t}$	-29.40***	-28.65***	-29.42***	-28.66***	-26.40***	-25.90***	-26.42***	-25.92***
	(5.81)	(5.81)	(5.80)	(5.80)	(4.56)	(4.58)	(4.55)	(4.57)
$LPG_{i,r,t} * Treatment\_Duration_{i,r,t}$			0.26	0.12			0.43	0.36
			(0.43)	(0.44)			(0.34)	(0.35)
Observations	9,028	9,028	9,028	9,028	9,028	9,028	9,028	9,028
Controls	✗	✓	✗	✓	✗	✓	✗	✓
Product FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.997	0.99798	0.997	0.997	0.997	0.997	0.997	0.997

Notes: This Table presents DiD estimates of Equation 4 (columns 1, 2, 5, 6) and Equation 5 (columns 3, 4, 7, 8) on the effect of LPGs on good reviews received by treated products. $Prices_{i,r,t}$ represents product i's price (natural logarithm) in day t for retailer r. $LPG_{i,r,t}$ is a dummy variable equal to 1 if items are subject to the LPG in day t. $Treatment\_Duration_{i,r,t}$ captures the number of days since the application of the LPG. All specifications include product and time fixed effects. Controls include the absolute and the relative number of reviews, as well as products' age. Regressions in columns (5), (6), (7) and (8) use observations weighted according to the product popularity index, as described in Section 3, at the beginning of the sample period. All specifications are estimated by OLS. Huber–White heteroskedasticity-robust standard errors are shown in parentheses: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 7 provides results of this analysis. The variable $\log Prices_{i,r,t}$ consistently shows a negative and highly significant coefficient across all model specifications (Columns 1 to 8). This suggests that an increase in provider retailing prices is associated with a decrease in the number of good reviews, given that the coefficients range from approximately -287 to -180, thus indicating a substantial negative impact on consumer feedback as prices rise. The precision of these estimates is confirmed by the small standard errors, so that the results are significant at the 1% level. In addition, results in Table 7 indicate that the application of the PMG pricing policy by Newegg significantly increases the number of good reviews, with the $PMG_{i,r,t}$ indicator variable showing positive and highly significant coefficients across all specifications. What is more, the interaction term for the latter two variables is also negative and highly significant in all models, with coefficients ranging from about -29. to -26. This indicates that the interaction between the PMG policy and provider price further exacerbates the negative impact on good reviews. The results are insensitive to both the inclusion of controls and the use of observations weighted according to the product popularity index.

These results strongly align with findings in the main analysis, except for the point estimates on the $PMG_{i,r,t} * Treatment\_Duration_{i,r,t}$ terms that are always not statistically different from zero. This suggests that the duration of the PMG policy does not have a statistically significant impact on the number of good reviews. The economic rationale for this difference hinges on how these metrics capture consumer sentiment. From the one hand, ratings reflect a continuous measure of satisfaction that can steadily improve with a longer PMG policy duration, as consumers perceive long-term price fairness. On the other hand, good reviews combine volume and positivity, but extended PMG duration may not significantly boost review counts, as initial satisfaction captures most of the positive sentiment. Overall, ratings better capture the sustained positive sentiment resulting from both a short and a long-term PMG policy, while good reviews are less sensitive to these prolonged effects, so that we prefer to rely on the former measure for our main analysis.[27]

6 Conclusion

In our study, we meticulously explore the intricate dynamics surrounding price matching guarantees (PMGs) and consumer behavior within the realm of online retail. Through rigorous empirical analysis, we unearth nuanced insights into the efficacy of PMGs as market signals and their implications for consumer welfare. To do so, we focus on the consumer electronics retail market and we leverage on a Difference in Difference (DiD) research design in which products' sold by NewEgg, a leading US online player for this market, are considered as treated when targeted by its PMG policy, while the same titles sold on Amazon US, that never offers price matching guarantees, act as the control group. Our study represents a significant addition to the existing literature by untangling the intricate interplay between pricing signals, consumer perceptions, and market outcomes in the digital age.

Our findings resonate with the complexity inherent in PMGs, revealing that while these policies alone may not exert a direct impact on consumer ratings, they wield significant influence over consumer responses to price fluctuations during PMG periods. Of particular note is our observation that price increases during PMG periods precipitate declining ratings over time, indicative of consumer perceptions of pricing deviations during such periods as misleading or unfavorable. Moreover, our study illuminates the differential impact of PMGs across various product categories, emphasizing their heightened effectiveness for cheaper and less visible items. This nuanced observation suggests that PMGs may serve as potent signaling mechanisms, especially in markets characterized by heightened price sensitivity or products facing visibility challenges. This observation carries profound implications for market participants, highlighting the need for tailored pricing strategies that account for product characteristics and market dynamics.

[27] Our main results are confirmed when including products' category fixed effects. Results available upon request.

From an antitrust perspective, our findings raise important considerations regarding the competitive implications of PMGs in digital markets. While PMGs can foster pricing transparency and consumer welfare, there is a pressing need to guard against potential anti-competitive behavior or consumer harm arising from misleading pricing signals. Policymakers face the formidable task of designing regulatory frameworks that strike a delicate balance between fostering market competition, safeguarding consumer interests, and promoting innovation in digital marketplaces.

In conclusion, our research represents a seminal contribution to the burgeoning literature on online retail pricing strategies and consumer behavior. By unraveling the complex interplay between pricing signals, consumer responses, and market outcomes, we provide valuable insights that inform strategic decision-making for industry stakeholders and policymakers alike. As digital commerce continues to evolve, our study serves as a timely reminder of the importance of understanding and navigating the intricacies of pricing dynamics in the digital landscape.

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