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Price Matching and Platform Pricing*

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Abstract

We investigate the effects of Price Matching Guarantees (PMGs) commercial policies adopted by the US NewEgg online platform on prices of a representative sample of consumer electronics products. By applying a Difference-in-Differences (DiD) identification strategy, we find price reductions of about 3% occurring after the policy implementation. Moreover, we control for products characteristics recovered from User Generated Contents (UGCs) and perform heterogeneity analysis based on products appreciation and visibility. Estimates suggest that for high appreciated (and visible) products prices are higher during the policy validity period, while some specifications provide evidence in favour of price reductions occurring after the policy implementation for low appreciated and low visible goods. Results are consistent with the hypothesis that NewEgg's PMGs policies can act as tools for price discrimination.

Keywords. Price Matching Guarantees; Online Sales Platforms; User Generated Contents; Difference-in-Differences.

JEL Classification. L11; L13; L15; L81.

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1 Introduction

Online sales platforms have recently gained increasing importance in both retail and wholesale markets.[1] These ones are characterized by the supply of personalized services, more convenient delivery schedules and the ability to reach a very high number of consumers. In addition, online platforms claim to warrant lower prices with respect to traditional stores through the provision of special offers, promotions, down prices and other price discounting policies. Among these options, online sales platforms often implement Price Matching Guarantees (PMGs) policies, that is the promise to match lower prices offered by competitors.[2]

The announcement to tie prices to those of competitors is surely appealing for customers and can guarantee low prices, increase consumer confidence and brand fidelity. However, the theoretical literature analysing PMGs along various directions has stressed how such policies can reduce competition and sustain high prices in certain markets, thus harming consumers' welfare. In particular, the two most relevant anti-competitive theories consider PMGs as tools for implementing collusive practices (see, among others, Hay, 1981; Salop, 1986; Belton, 1987) or, alternatively, price discrimination (Png and Hirshleifer, 1987; Corts, 1996).

The first strand of literature suggests that PMGs can sustain collusion in oligopoly models and highlights that such clauses might be considered as threats to punishment for firms that lower cartel prices, thus reducing firms' incentive to deviate from agreements.[3] Differently, some other authors argue that sellers can use PMGs policies as a price discrimination tool. Png and Hirshleifer (1987), Belton (1987), Corts (1996) and Nalca et al. (2010) propose theoretical models in which firms rely on PMGs to discriminate between different groups of consumers, who differ in terms of price and warranty information, willingness to pay, loyalty to a specific retailer or the extent of hassle costs.[4] Moreover, as recently suggested by Branco and Brossard-Ruffey (2017) and Townley et al. (2017), it is worth noting that the availability of platform data may be employed by online sellers to have information on consumers' willingness to pay. In particular, the utilization of information released by users on the Internet allows

[1]The term "online platform" identifies a range of digital services that facilitates interactions between two or more distinct but interdependent sets of users (whether firms or individuals) who interact through the service via the Internet (OECD, 2019). Online sales platforms can operate as online retailers, as a marketplace for third-party sellers or they can offer both services.

[2]For example, NewEgg's PMG policy states that "if you purchase an item from Newegg.com which is carrying the Price Match Guarantee badge at the time of purchase, then find the exact same item at a lower price by Newegg or a major retailer, just let us know, and we'll send you a Newegg Customer Care Card to cover the difference". See `https://kb.newegg.com/knowledge-base/price-match-guarantee/`.

[3]Several other papers support the pro-collusive argument by extending the basic oligopolistic setting or applying the Hotelling model (e.g. Logan and Lutter, 1989; Baye and Kovenock, 1994; Lu and Wright, 2010; Hviid and Shaffer, 2010; Pollak et al., 2017; Constantinou and Bernhardt, 2018; Cabral et al., 2018). However, Hviid and Shaffer (1999) highlight that the presence of hassle costs (costs for activating the guarantee) might undermine possible anti-competitive effects of PMGs.

[4]See also Edlin (1997).

online platforms to personalize consumers' digital shopping experience, shopping recommendations, but can also enables for differentiation in prices at which goods are offered to consumers. This then permits the same product to be sold to two different people at the same time, but at different prices, based on an algorithmic assessment of each buyer's willingness to pay (Townley et al., 2017), thus allowing sellers to realize more precise and targeted price discrimination practices. Finally, differently from the most prominent and prevailing anti-competitive theories, the literature also advances somewhat alternative hypotheses. In particular, Jain and Srivastava (2000), Srivastava and Lurie (2004), Moorthy and Winter (2006) and Moorthy and Zhang (2006) suggest that PMGs, under certain conditions, might be a credible signal of low prices, if low cost firms adopt the policy and (high cost) competitors can not match it.[5]

Hence, the theoretical literature suggests that PMGs policies can have different effects on prices, according to markets conditions and consumers characteristics. In particular, should PMGs actually be a tool to carry out collusive practices or price discrimination, such policies could induce higher market prices and a possible loss of consumer welfare. If this is the case, the impact of PMGs on prices can also be a relevant policy issue. Empirically testing the implications of theoretical models is therefore essential. However, applied studies designed to test the effect of such pricing policies are scarce and often inconclusive (Mago and Pate, 2009). Excluding previous analyses of small product groups in narrow local markets, which rely on product catalogs and newspaper advertisements, to the best of our knowledge the only paper that investigate the impact of PMGs leveraging on a wide range of products in a national market is that of Zhuo (2017), who suggests that such policies can generate significantly higher market prices.[6] In addition, it is the only paper that analyses such pricing policies for online platforms; therefore, it seems interesting to further investigate such issue for online markets, that have received less attention with respect to traditional ones, by relying on robust counterfactual impact evaluation methods.

Our work provides empirical evidence on the effect of PMGs policies on daily consumer electronics prices observed on the US NewEgg platform, that exclusively sells consumer electronics products. First, the empirical strategy is based on the analysis of the average change in NewEgg's product prices (the treated sample) before and after a PMGs switch-off.[7] Estimates provide evidence of about 6% lower prices after the PMGs' validity period, consistent with results from the empirical literature (see, among others, Zhuo, 2017; Cabral et al., 2018). Second, we empirically test whether the NewEgg's PMGs switch-off can have an impact on prices of other platforms, thus highlighting the possibility of strategic effects from within-US market non-adopting

[5]See also Mamadehussene (2019).

[6]See Section 2 for details.

[7]Given that our identification strategy is based on a comparison of price levels before and after the policy switch-off, we have excluded platforms that never stop offering PMGs (like Target).

competitors. Indeed, some models (see, among others, Moorthy and Winter, 2006) argue that, under certain conditions, by strategic complementarity PMGs may also be associated to increases in prices for these firms. Moreover, online markets are often interested by price monitoring algorithms adopted by platforms, so that PMGs implemented by NewEgg could affect prices of products sold by competing online sellers. In order to address this issue, following a similar approach to that of Zhuo (2017), we observe the same treated products sold on Amazon US and we analyse their average price change before and after the NewEgg's PMGs switch-off. Estimates do not provide evidence of an impact of NewEgg's PMGs clauses on Amazon US's prices, thus highlighting the absence of strategic effects on the non-adopting platform. Third, in order to have a more refined picture of the issue, we rely on a Difference-in-Differences (DiD) research design in which the pool of NewEgg products affected by PMGs policies is considered as the treated sample; unlike standard DiD studies, we build the control samples with price data for the same treated products observed on a different platform, namely Amazon UK (instead of Amazon US), that never offers PMGs to customers. The rationale for the choice of such a control group relies on the fact that NewEgg's PMGs only apply to purchases within the United States.[8] Moreover, it is worth noting that products sold by Amazon UK are less likely to be affected by the policy; indeed, Amazon US's prices may be not completely independent from NewEgg's PMGs, due to price tracking algorithms frequently implemented in online markets within the same country. Therefore, prices of products sold overseas by Amazon UK (which never applies PMGs and, reasonably, does not compete directly with NewEgg in the US market) represent a valid counterfactual mimicking how prices in the treated sample would have evolved in the absence of PMGs.[9] When the parallel trends assumption is fulfilled, if PMGs actually affect NewEgg's prices, such policies consequently should generate differential price trends between the treatment group and the control one after the treatment. DiD estimates provide evidence in favor of a reduction in NewEgg's prices of about 3% after the implementation of PMGs policies. Finally, we investigate if such effect is heterogeneous and we focus on products features that can be recovered on online markets through the analysis of Users Generated Contents (UGCs).[10] Indeed, online platforms often integrate UGCs, enabling users to rate and comment on products or services. In particular, UGCs in our work include the number of reviews (written texts about products, services or experiences) and the rating received by products (opinions that can be contributed on a given scale, e.g., x out of n "stars"), that are well suited to be a proxy for products' popularity and appreciation respectively. We argue that the distribution of such characteristics across products is likely to be associated to consumers heterogeneity in terms of willingness

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

[9] Such choice is validated in Section 5.2 by an in-depth analysis of parallel trends.

[10] According to Wyrwoll (2014), UGCs are contents published on online platforms by users.

to pay for appreciated items and in terms of price elasticity. Estimates conducted on specific sub-samples suggest that, when PMGs are switched-off, high appreciated NewEgg's products experience prices decreases of about 2%, while low appreciated ones are not affected by the policy. Moreover, since products appreciation is often correlated to products online visibility, as proxied by the time spent on the search engine to discover the specific web-page of a certain product (Google Search Rank), we replicate our analysis after distinguishing low appreciated-visible products from high appreciated-visible ones. Estimates suggest that NewEgg's low appreciated-visible products experience a price increase ranging between 4-6% after the policy implementation, while for high appreciated-visible products a price reduction of about 3% is observed. Similar results arise when we perform heterogeneity analysis based on a Difference-in-Difference-in-Differences (DDD) research design.

Despite being aware of the lack of a theoretical model specifically designed to analyse the impact of PMG policies on online markets, the price discrimination theory, one of the prevailing predictions of the literature, provide some support for our overall empirical findings. In fact, while our baseline results are broadly in line with those of a number of empirical works (see, among others, Zhuo, 2017; Cabral et al., 2018), the estimated heterogeneous impact of PMGs on NewEgg's prices provide novel evidence which cannot be detected in previous empirical literature. In particular, if consumers differ in terms of their willingness to pay for appreciated products and price elasticity, the availability of information from UGCs can enable online sellers to perform discriminating practices, as suggested by Townley et al. (2017). Therefore, buyers characterized by a strong preference for popular items are most likely to be attracted by products with higher ratings in terms of "stars" (high appreciated products) and, according to our results, will pay higher prices during the policy implementation period. Conversely, our empirical evidence seems to be inconsistent with the collusion theory. Indeed, while again lacking a theoretical framework analysing PMGs adopted by online sales platforms, our empirical results somewhat rule out the presence of strategic effects from within-US market non-adopting competitors. Moreover, the setting and predictions of collusive theoretical models often do not fit the context of online markets. Lastly, a collusive outcome is rather inconsistent with the presence of PMGs in markets characterised by a large number of competitors, setting different prices, such as the retail electronics one.

This study enriches the literature on the price effects of PMGs along different lines. First, it provides novel evidence of the impact of PMGs on online markets prices, a topic that has been insufficiently explored so far. Second, our work overcomes various problems in previous research, such as the use of price history charts from price tracking websites or online tools that extracts data from plots and images. In particular, we extend previous works by analysing detailed real-time daily platform data obtained from a Python scraping program; our approach allows us to create a representative sample of consumer electronics, from which we could observe continuous price variations, as well as short and temporary price changes. Third, products characteristics based on platform information and UGCs are employed for the first time in order to study possible heterogeneous effects of PMGs. Fourth, the DiD identification strategy adopted is based on the construction of a control group with a novel approach that guarantees its independence. Finally, our work can provide useful insights to policy-makers in assessing potential consumers' welfare losses from PMGs.

The paper is organised as follows. Section 2 discusses previous empirical literature; Section 3 describes the data extraction process and provides summary statistics; Section 4 explains our identification strategy; Section 5 discusses estimates results and robustness analysis. Section 6 concludes.

2 Empirical Evidence

The empirical literature that studies the effects of PMGs policies on prices focuses on specific markets (tyre, gasoline) and on retailing prices from supermarkets; just one study analyses online markets.

Arbatskaya et al. (2000) recover daily price quotes from the tyre industry advertisements from 61 US Sunday newspapers observed for three months in 1996. Authors find weak evidence of anti-competitive effects of PMGs and show that an increase in the number of firms implementing the policy leads to a 10% increase in prices.[11] Cabral et al. (2018) focus instead on daily pricing policies adopted by the Shell network of gas stations in Germany in 2015. Leveraging on gas stations localization and consumers demographics as sources of identification, they suggest that PMGs can be a collusion enacting policy.[12] Gas station prices have been analyzed also by Byrne and De Roos (2019) for Australia by means of a detailed 15 years time series dataset. Authors argue that the majority of gas stations prices follow a weekly cycle and that dominant firms can use PMGs to coordinate market prices and reduce price competition. Similar results can be found in Chilet (2018), who analyses pricing policies of three big retail pharmacy chains in Chile, observed over the period 2006-2008. The author follows an identification strategy based on the estimation of a demand model, in which quantity sold is a function of price differentials with competitors, around the time period where collusive price increases occurred.

Hess and Gerstner (1991) analyse instead the effect of PMGs on prices by collecting weekly data of 114 goods sold in several US supermarkets and grocery stores, from 1984 to 1986 and provide evidence in favor of higher prices (about 1-2%) when the guarantee is introduced. Different results are provided by Moorthy and Winter (2006),

[11]The same authors in Arbatskaya et al. (2006) confirm their results by analysing the same data with a different approach.

[12]See also Atkinson et al. (2009) and Wilhelm (2016).

who analyse prices of several products sold by 46 Canadian retailers in 2002 and assume the existence of informed and uninformed consumers. Authors argue that the adoption of PMGs policies might be interpreted as a way to signal lower prices to uninformed customers and suggest that PMGs are mainly adopted by low cost/low service chain stores.[13] Similar results can be found in Chung et al. (2016) for three leading hypermarkets in Korea.

Finally, Zhuo (2017) focuses on online platforms and collect US price data from online price trackers for 150 products offered on Amazon in 2012. The author observes prices during and after the implementation of PMGs policies by two big-box stores (Target and Best Buy) targeted specifically on Amazon prices; by applying DiD and RDD methods, the author suggests that prices increase by about six percentage points during the period of validity of the policy. Moreover, the analysis highlights an heterogeneous impact of PMGs, with larger price increases for initially lower-priced goods.[14]

3 Data

3.1 Data Extraction

In order to study the impact of PMGs on prices, we focus on the online consumer electronics market, since it is one of the most widespread sector on online retailing and is often affected by such pricing policies. In particular, electronic products are search goods, whose quality and popularity can be evaluated before the purchase: the advent of online markets has made this process much cheaper and faster and is most likely to affect the impact of such policies, whose outcome depends, among other factors, by the level of search and hassle costs, as well as product quality and appreciation. Moreover, electronic goods are barely affected by seasonal effects, so that prices signals are more stable over time.[15]

Among different online retailing platforms, we choose to focus on NewEgg, a leading online US retailer of consumer electronics products that implements PMGs policies.[16] In particular, NewEgg communicates the period of validity of the price

[13] Authors suggest that firms offering higher prices do not find convenient to apply PMGs as it would imply devolving their pricing decisions to low price competitors (Moorthy and Winter, 2006).

[14] Some other authors analyse the impact of price-beating guarantees, that are less widespread policies with similar terms as price matching ones (in price beating guarantees refund exceeds the price difference). Studies that refer to these policies argue that, with respect to price matching guarantees, they might be serving different purposes in practice and likely be effective in enhancing competition. Experimental literature also focuses on the effect of price matching and price-beating guarantees (see, among others, Deck and Wilson, 2003; Mago and Pate, 2009): however, experimental results often lack the complexity of real interactions between sellers and consumers.

[15] In particular, our sample covers the period May - October 2018 and does not include important dates like Thanksgiving or Christmas.

[16] Given that our identification strategy is based on the comparison of prices before and after a policy's switch-off, we do not consider platforms that apply PMGs to wide groups of products continuously over

guarantee by means of a label that appears on the specific product online page; the customer who purchases an eligible item and discovers the PMG badge has 14 calendar days of time to find the same "title" at a lower advertised price from US competitors belonging to a declared list.[17] Notice that NewEgg's PMGs only apply to purchases within the United States.

In order to build the treated sample we have identified all NewEgg electronics products affected by PMGs on May 2018. We have observed such products (100) from May 2018 to October 2018 and we have collected price data, PMGs information and other UGCs.[18] Different control samples, crucially for our identification strategy, have been built by selecting the same products sold on other platforms, i.e. Amazon US and UK, that never offer PMGs policies; also for control samples we collect information on prices and UGCs.[19] This approach has implied a reduction in the number of observed products, so that the final sample includes 87 products belonging to 19 sub-categories (computer hardware, tablet and computers, mobile phones, printers and scanners, PC accessories, speakers for domotics, screens and audio devices).[20] It is worth noting that NewEgg's PMGs do not apply to products sold by third-party sellers through a major retailer's online marketplace; therefore, we have collected data of products sold directly from NewEgg and Amazon (UK and US) and we did not consider third-party sellers products.[21]

The retrieving of sample data has been a challenging task. Given the absence of ready-made and easy-to-use repositories on price data, we have developed an ad-hoc scraping program (in Python language) able to protect the scraping process from unpredictable changes of the page and capable to recover the data without stressing the site, thus limiting the risk of interruptions due to firewalls. In particular, the scraping process has been supported by several alert tools signalling periodical changes of the internal page structure, given that platforms frequently change the deep structure of the page, in a not visible way by the human reader but in a way that affects the program code and the scraping process. The process of data collection has required the subscription to the Amazon Web Service (AWS) cloud in order to use virtual servers where installing and launching the daily loop process. The scraping code allowed us to navigate among product pages, select the field tags, get the data

time (i.e. Target, among others).

[17]With "title" we refer to a product with the same brand and model number. NewEgg, after checking the validity of the claim, sends a Customer Care Card to refund the price difference (Source: `https://promotions.newegg.com/nepro/16-2624/index.html`).

[18]The average number of treatments occurred in our sample is about 2.38, thus suggesting that, on average, the policy is applied twice to each product during the sample period.

[19]See Section 4 for a rationale on this choice.

[20]In the Appendix C we provide a detailed list of selected products (Tables C.1 and C.2).

[21]This choice allows us to deal with a concern; indeed, both NewEgg and Amazon are platforms in the sense of two-sided markets. In this context, a platform should be concerned with the revenues it receives from both sides of the market. By considering products sold directly by the platform, we alleviate such a concern.

and save on a server disk. Each scraping session run about 20 minutes every day. It is worth noting that this approach allows us to collect real-time high-quality information, and overcomes a number of problems in previous research. Indeed, the use of price monitoring websites does not allow the creation of fully representative samples, as they only track the prices of relatively popular products.[22] Moreover, online tools that extract data from price history graphs found on such price monitoring websites (e.g. WebPlotDigitizer) provide only discrete price points rather than continuous price changes, not allowing the detection of short and temporary price changes (see Zhuo, 2017).

In addition to information on product prices and PMGs, we also have collected some product characteristics available exclusively on online sales platforms, which often integrate UGCs, enabling users to rate and comment on products or services (Wyrwoll, 2014).[23] In particular, data on products provided by the seller may be biased due to his interest to sell them, while products information given by consumers and released on the Internet is free of commercial interests. Since UGCs are considered to be less biased and hence more truthful, they are a valuable source of information for users in their decision making process (Lelis and Howes, 2011), helping consumers to find items that well match their needs (Chen and Xie, 2008).[24] Therefore, we have recovered the number of reviews and products rating given by customers. The absolute number of reviews (written texts about products, services or experiences) is a dynamic information which represents a sort of popularity index, since it is proportional to the product market diffusion. Starting from this information, we have built the relative number of reviews as the ratio between the latter and the amount of reviews received from the most popular product in the same sub-category. This normalized index, that ranges from zero to one, shows the relative popularity of the product with respect to other items of the same sub-category. Another interesting information is the products rating (opinions that can be contributed on a given scale, e.g., x out of n "stars") provided by consumers. We consider the number of stars gained by each product, ranging from zero to five, as a proxy of product (from low to high) appreciation. Finally, we have built a product specific search rank as a proxy of the time spent on the search engine to discover the specific web-page of a certain product. In particular, for each product we have launched, at the beginning of the sample period, the Google query composed by the sentence ("*product name*" AND "*platform name*") and we have recovered its ranking position.[25] Such position has

[22]We deal with this concern in Section 3.2

[23]According to the author, a UGC is content published on online platforms by users.

[24]Scrutinizing consumers opinions in online platforms to understand them is a core goal for online platforms, that analyse UGCs over a given time span with regard to relevant marketing information, including customer preferences and sentiments (Wyrwoll, 2014).

[25]It is worth noting 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. We rank only the product's specific web page.

been normalized in order to interpret the search index as the probability to find the product in first ranked positions of Google. It is worth noting that, although products analysed are sold by Amazon UK and NewEgg in different countries, information on some of considered UGCs maintain their consistency across countries. This property is typical of consumer electronics goods that have a standardized nature. However, we adopt a country-specific search index by launching the Google search engine with specific country settings.[26]

3.2 Descriptive Statistics

The analyzed sample includes 13,542 daily price observations for 87 products observed on the treated sample (NewEgg) and the control ones (Amazon UK and Amazon US), from May 2018 until October 2018. The sample period includes 175 days.

Table 1: Summary Statistics.

Variables	Full Sample	Treated Sample	Control Sample	Control Sample
		NewEgg	Amazon UK	Amazon US
Provider Price ($)	268.32	253.15	298.00	253.81
	(320.77)	(302.39)	(343.85)	(312.63)
Product Popularity (0-1)	0.26	0.20	0.26	0.32
	(0.30)	(0.23)	(0.30)	(0.34)
Search Rank (0-1)	0.78	0.64	0.85	0.85
	(0.27)	(0.36)	(0.17)	(0.17)
Rating (0-5 stars)	4.15	4.15	4.14	4.16
	(0.62)	(0.83)	(0.48)	(0.48)
Observations (#)	13,542	4,514	4,514	4,514

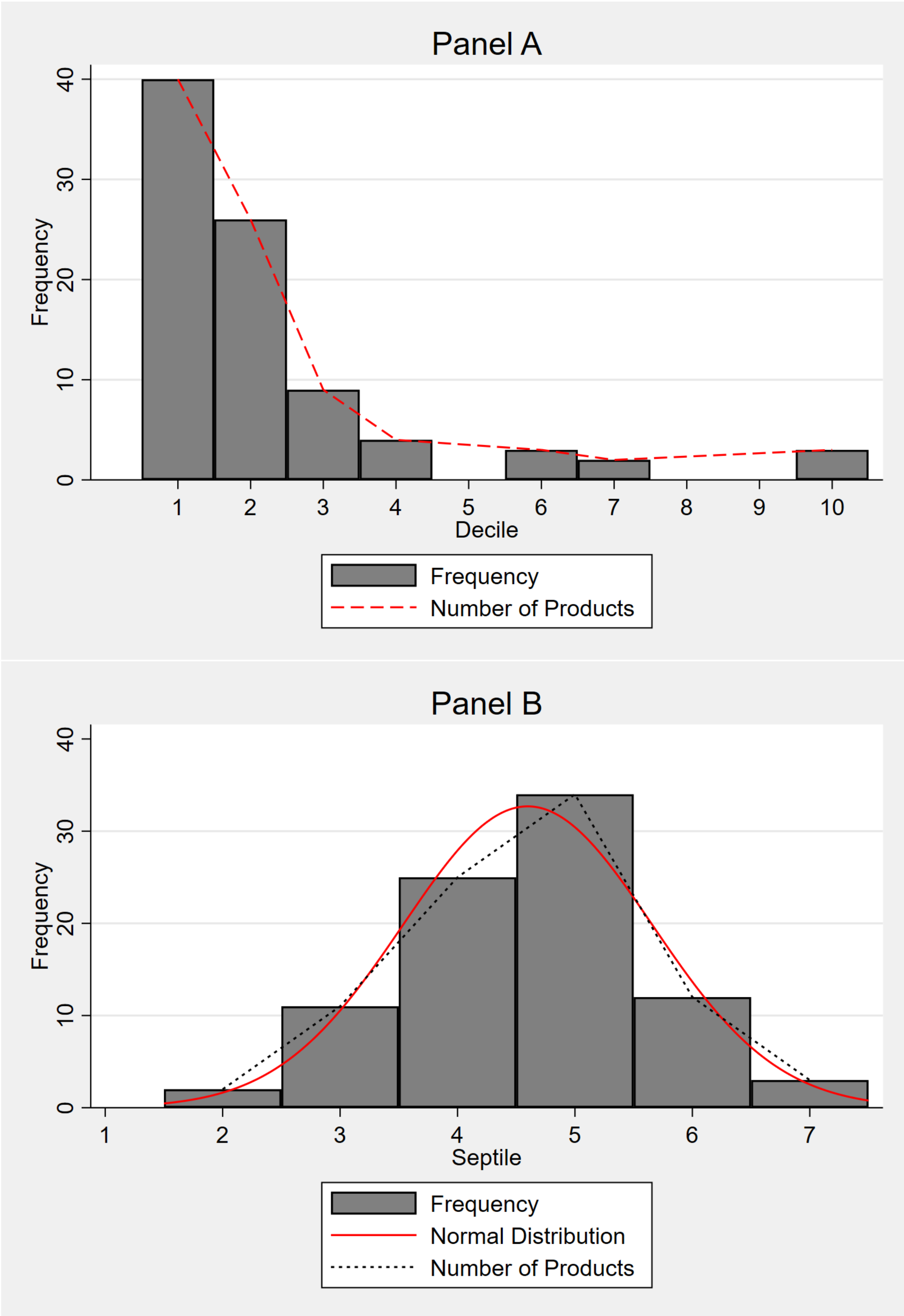
Notes: The treatment of interest is the PMGs switching-off, so that prices observed on the NewEgg platform represent the treated sample, while the control sample has been built by recovering price data for the same products observed on NewEgg but sold on different platforms (Amazon UK and Amazon US). Product popularity is built like the ratio between the absolute number of product's reviews and the amount of ones received from the most popular product in the same sub-category. Products ratings provided by consumers range from zero (low appreciation) to five (high appreciation). The search rank is a proxy of the time spent on search engines to discover the web-page of a certain product. The sample period includes 175 days.

Table 1 shows summary statistics on prices and selected product characteristics for the overall sample and for treated and control ones. Prices show a large variability, being the average for the overall sample \$268.32 and the standard deviation \$320.77. Average prices for Amazon UK are noticeably greater than NewEgg's ones, while Amazon US average prices are very similar than those observed over the treated sample. It is worth noting that such patterns do not represent an issue for our identification strategy as long as the parallel trend assumption is satisfied (see Section 5.2).

Another important issue is related to the representativeness of our sample. The top panel of Figure 1 represents the distribution of products by price classes (10). The histogram shows that 76% of the products belong to the first two price decile, with

[26] Amazon UK prices have been converted into dollars at the daily exchange rate.

Figure 1: Products Distribution by Price Classes and Log-Price Classes.



Notes: The top panel provides the distribution of products by price classes (10). The figure in the bottom panel is obtained by calculating the log-price distribution and mapping the integer part of this value on the x-axis. A septile-partition is shown.

price ranging between 14$ and 309$, and 15% to the third and the fourth decile (prices between 317$ and 523$); the remaining products are ranked from the sixth to the tenth decile, with price ranging between 834$ and 1,574$. This pattern matches typical price distributions observed in several markets (Coad, 2009), often characterized by a large amount of low cost accessories and few luxury goods. Furthermore, calculating the log-price distribution (bottom panel of Figure 1) and mapping the integer part of this value on the x-axis, we obtain a septile-partition. By plotting the distribution of products by log-price classes we obtain a distribution that resembles a Normal one. Such result is in line with those obtained by Coad (2009).

4 Identification Strategy

Our identification strategy first relies on the analysis of the average change in NewEgg's product prices before and after a PMGs switch-off. In particular, we estimate the following equation:

$$\log Price_{i,t} = \alpha_i + \theta Post_{i,t} + X_{i,t}^T \beta + \mu_i + \tau_t + \psi_{i,t} \tag{1}$$

where the price (natural logarithm) of good i, on the NewEgg platform at time t is represented by $Price_{i,t}$, while $Post_{i,t}$ is a binary variable that is equal to 1 for any day since policies are switched-off and $\psi_{i,t}$ is an error term. Equation (1) also contains a set of covariates, $X_{i,t}$, that accounts for product characteristics stemming from UGCs, as products rating and popularity, that might affect the impact of PMGs on prices, and a full set of time and product fixed effects. The θ coefficient reflects the average price change after the PMGs switch-off.

Second, we provide some empirical evidence about the possibility of strategic effects from within-US market competing non-adopting firms. Indeed, PMGs policies, by strategic complementarity can affect prices of the latter, as suggested by Moorthy and Winter (2006) and Zhuo (2017). In addition, NewEgg's pricing policies could affect products sold on Amazon US, due to price monitoring algorithms frequently used in online markets within the same country. To address this issue, we re-estimate Equation (1) by leveraging on the Amazon US sample. Therefore, in this case $Price_{i,t}$ becomes the price (natural logarithm) of good i, on the Amazon US platform at time t. Also the set of covariates, $X_{i,t}$, now accounts for product characteristics stemming from Amazon US's UGCs.

Third, following a similar approach to Zhuo (2017), we apply a DiD research design and we estimate the causal effect of the treatment by comparing the average price change before and after the PMGs switch-off for the treated group (NewEgg products) to the average price change over the same time for the control group (the same treated products sold by Amazon UK).[27] This framework provides a quasi-natural experiment

[27]Notice that Zhuo (2017) observes price changes (on the non-adopting platform) before and after the

that allows us to study the causal impact of PMGs on NewEgg's prices by estimating the following panel FE model:[28]

$$\log Price_{i,l,t} = \alpha_{i,l} + \gamma\big(Treated_{i,l,t} * Post_{i,t}\big) + X^{T}_{i,l,t}\beta + \mu_{i,l} + \tau_t + \epsilon_{i,l,t} \tag{2}$$

The dependent variable, $Price_{i,l,t}$ represents the price (natural logarithm) of good i, on platform l at time t, $Post_{i,t}$ is a binary variable that is equal to 1 for any day since policies are switched-off, $Treated_{i,l,t}$ denotes a binary variable equal to 1 for NewEgg's goods and $\epsilon_{i,l,t}$ is an error term. In order to rise the degree of comparability of the treatment and control groups, the model includes a full set of daily time dummies, τ_t, accounting for unobserved time-varying price determinants that are common to all goods.[29] Products fixed effects, $\mu_{i,l}$, control for any time invariant unobserved heterogeneity at the product and platform level that could be correlated with the included regressors and that could also drive prices. Equation (2) also contains a set of covariates, $X_{i,l,t}$, that accounts for product characteristics (products rating and popularity) derived by UGCs that might affect the outcome of PMGs. The γ coefficient associated to the interaction term ($Treated_{i,l,t} * Post_{i,t}$) represents the DiD estimate of the effect of PMGs switch-off on treated products prices and it measures the average price differential between the treated and the control group.

It should be noticed that the DiD model in Equation (2) leverages solely on Amazon UK (which never applies PMGs) as a control sample. This choice is driven by the fact that NewEgg's PMGs policies only apply to purchases made within the US. Furthermore, it should be emphasised that NewEgg and Amazon UK are not reasonably direct competitors in the US market, strongly alleviating concerns about possible strategic effects from competition.[30] Moreover, despite the analysis resulting from the estimation of Equation (1) on the Amazon US sample, price observed on the latter might not be completely independent from the policy under scrutiny, because of price tracking practices frequently adopted by platforms within the same country. Therefore, prices of identical products sold overseas by Amazon UK are less likely to be affected and well represent a counterfactual sample, mimicking what would have happened to prices of treated products in the absence of PMGs. Notice that this choice is supported by an in-depth analysis of the parallel trends assumption, that is

implementation of PMGs by competitors, while we focus on price changes observed on the adopting platform. Moreover, we innovatively build the control sample with platform price data for the same treated products but observed on another platform (Amazon UK).

[28] In a DiD context, a classic model would be built like $Y = \alpha + \beta_1(Treated) + \beta_2(Post) + \beta_3(Treated * Post) + \varepsilon$. In all models we exclude $Treated$ and $Post$ terms, since they are multicollinear with time and product fixed effects.

[29] As noted in Section 3, the sample does not include important dates, like Thanksgiving or Christmas; moreover daily fixed effects allows to control for possible time effects associated to particular periods like "back to school" days.

[30] According to Statista, in 2021 Amazon US's biggest competitors by market share are Walmart (6.6%), eBay (4.2%), The Home Depot (2.2%), Target (2%) and BestBuy (1.8%), where Amazon led by 41%. See `https://www.statista.com/statistics/274255/market-share-of-the-leading-retailers-in-us-e-commerce/`.

fundamental for the validity of a DiD research design.

Finally, we explore the issue of heterogeneity in the effect of PMGs on NewEgg's prices by splitting the sample according to products features that might affect the outcome of such policies and that can be recovered exclusively on online markets trough UGCs. In particular, platform data allow us to obtain information on products' visibility, ratings and popularity, and the distribution of such product features is likely to be associated to consumers heterogeneity in terms of willingness to pay for appreciation and price elasticity. Indeed, as suggested, among others, by Branco and Brossard-Ruffey (2017) and Townley et al. (2017), the availability of information released by users on the Internet can enable platforms to perform more precise and targeted discriminating practices, an issue that precisely may affect the impact of NewEgg's PMGs on prices. After classifying products according to their appreciation, as measured by the rating assigned in terms of "stars" and described above, we estimate Equation (2) on different sub-samples. In particular, we analyse separately products characterised by high (low) appreciation, namely products whose rating is greater (lower) than 4. Moreover, given that products appreciation and visibility resulted to be highly correlated, we then split the sample according to both characteristics jointly considered.

The heterogeneity issue is also investigated with a different approach by estimating a Difference-in-Difference-in-Differences (DDD) regression on the full sample. In particular, we estimate the following models:

$$\log Price_{i,l,t} = \alpha_{i,l} + \varphi\big(Treated_{i,l,t} * Post_{i,t} * HR_{i,l}\big) + X^T_{i,l,t}\beta + \mu_{i,l} + \tau_t + \omega_{i,l,t} \quad (3)$$

$$\log Price_{i,l,t} = \alpha_{i,l} + \delta\big(Treated_{i,l,t} * Post_{i,t} * HRHV_{i,l}\big) + X^T_{i,l,t}\beta + \mu_{i,l} + \tau_t + \omega_{i,l,t} \quad (4)$$

Equations (3) and (4) include additional components in the interaction term, namely $HR_{i,l}$ and $HRHV_{i,l}$, i.e. dummy variables assuming value 1 for high appreciated products and for high visible and high appreciated products respectively. The coefficients φ and δ of the triple interaction terms measure the average treatment effect of PMGs on prices for high appreciated and high appreciated-visible products respectively.

All specifications are estimated by OLS with robust standard errors. Moreover, following Cameron and Miller (2015), we also compute bootstrapped standard errors allowing for a cluster structure (at product level). In addition, we perform an extensive robustness analysis and placebo tests.

5 Empirical Results

5.1 Main Results

5.1.1 Exploratory Data Analysis

In this Section we provide an exploratory data analysis useful for estimating our DiD and DDD models. In particular, we first scrutinize the correlation between a NewEgg's PMGs switch-off and related price fluctuations for treated products. Then, we analyse possible effects of NewEgg's PMGs on prices of within-US market non-adopting competitors.

In Table 2 are reported estimates of the average change in NewEgg's product prices before and after a PMGs switch-off (Equation 1). All regressions include product dummies and daily time dummies. In particular, results in columns (1) and (2) of Table 2 reveal about 6% higher prices on the NewEgg platform when PMGs are in place. This result is statistically significant at the one percent level, also when including controls. Moreover, if we estimate Equation (1) after splitting the sample according to products' appreciation, as proxied by the rating, heterogeneous results can be detected. In particular, high appreciated products experience about 5% higher prices during the policy implementation period (columns 5 and 6 of Table 2), while low appreciated ones show a somewhat mixed evidence (columns 3 and 4). Heterogeneous estimated results arise also when we split the sample according to both products' appreciation and visibility, as in columns from (7) to (10) of Table 2. Estimates show that, when PMGs are switched-off, low appreciated-visible NewEgg's products experience a price increase of about 3%, while for high appreciated-visible ones a price reduction of about 10% is observed.

Table 2: Average Change in NewEgg's Product Prices Before and After PMGs Switch-Off.

NewEgg's Products Prices (log)	(1) BEFORE AFTER	(2) BEFORE AFTER	(3) LOW RATING	(4) LOW RATING	(5) HIGH RATING	(6) HIGH RATING	(7) LR LV	(8) LR LV	(9) HR HV	(10) HR HV
$Post_{i,t}$	-0.060***	-0.062***	-0.029**	-0.024	-0.051***	-0.057***	0.029**	0.031***	-0.101***	-0.113***
	(0.007)	(0.007)	(0.015)	(0.015)	(0.008)	(0.009)	(0.013)	(0.011)	(0.013)	(0.014)
Controls	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Product Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,514	4,514	1,060	1,060	3,454	3,454	710	710	2,328	2,328
R-squared	0.980	0.980	0.986	0.986	0.979	0.980	0.992	0.992	0.976	0.976
F Test (p-value)	0.000	0.000	0.049	0.000	0.000	0.000	0.030	0.000	0.000	0.000

Notes: This analysis leverages solely on the treated sample. All specifications include time and product fixed effects. Controls include the absolute and the relative number of reviews as well as ratings. High (low) appreciated products have ratings higher (lower) than 4. High (low) visible products have a normalized search index higher (lower) than 0,8. LR-LV are low appreciated and low visible products, HR-HV are high appreciated and high visible products. Robust Standard Errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Such results provide evidence of a strong correlation between a PMGs switch-off and NewEgg's products average price changes; however, does not automatically mean that the latter are caused by a change in the value of the $Post_{i,t}$ term. To give a causal interpretation of such results, we estimate our DiD and DDD models (Equations 2, 3 and 4) in Section 5.1.2.

Finally, we deal with the possibility that strategic effects from non-adopting competitors may arise within the US online consumer electronics market. In particular, according to Moorthy and Winter (2006) and Zhuo (2017), such clauses by strategic complementarity may also increase prices of non-adopting platforms. Moreover, PMGs implemented by NewEgg could affect products sold on Amazon US, due to price monitoring algorithms frequently used in online marketplaces. To address this issue, we rely on the Amazon US sample (see Section 4 for a rationale) and we analyse the average change in Amazon US's product prices before and after the NewEgg's PMGs switch-off. Table 3 shows results from the estimation of Equation (1) over the Amazon US sample. In particular, results in columns from (1) to (6) of Table 3 do not provide evidence of an impact of the NewEgg's PMGs switch-off on Amazon US's prices, thus highlighting the absence of strategic effects on the non-adopting platform. This result is confirmed when including controls and when we interact the term $Post_{i,t}$ with dummies for high appreciated and high appreciated-visible products respectively.

Table 3: Impact of NewEgg's PMGs on Amazon US's Average Price Changes.

	(1)	(2)	(3)	(4)	(5)	(6)
Amazon US's Product Prices (log)	BEFORE - AFTER					
$Post_{i,t}$	0.007	0.002				
	(0.006)	(0.006)				
$Post_{i,t} * HR_i$			0.001	-0.004		
			(0.006)	(0.006)		
$Post_{i,t} * HRHV_i$					0.003	-0.000
					(0.006)	(0.007)
Controls	NO	YES	NO	YES	NO	YES
Product Dummies	YES	YES	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES	YES	YES
Observations	4,514	4,514	4,514	4,514	4,514	4,514
R-squared	0.983	0.983	0.983	0.983	0.983	0.983
F Test (p-value)	0.259	0.000	0.892	0.000	0.634	0.000

Notes: All specifications include time and product fixed effects, relying solely on the Amazon US sample. Controls include the absolute and the relative number of reviews as well as ratings. High (low) appreciated products have ratings higher (lower) than 4. High (low) visible products have a normalized search index higher (lower) than 0,8. HR_i is a dummy equal to 1 for high appreciated products. $HRHV_i$ is a dummy equal to 1 for high appreciated and high visible products. Robust Standard Errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

5.1.2 The Impact of PMGs on NewEgg's Prices

In this Section we provide estimated results from our DiD and DDD models, giving a causal interpretation to the impact of PMGs switch-off on NewEgg's product prices.

Table 4 shows empirical results for the model in Equation (2) that leverages on Amazon UK as a control sample. All regressions include product dummies and daily time dummies. Estimates of our DiD baseline specification performed over the full sample (columns 1 and 2 of Table 4) provide evidence of a price decrease of about 3 percentage points more for products in the treated sample relative to the ones in the control sample after the PMGs switch-off. It is worth noting that the inclusion of control variables into Equation (2) does not significantly affect results. These findings confirms that in Table 2, and they are consistent with those obtained by Zhuo (2017) on a large sample of products observed on Amazon in 2012.[31]

Table 4: DiD Estimates of the Impact of NewEgg's PMGs on Prices.

Products Prices (log)	(1) FULL SAMPLE	(2) FULL SAMPLE	(3) LOW RATING	(4) LOW RATING	(5) HIGH RATING	(6) HIGH RATING	(7) LR LV	(8) LR LV	(9) HR HV	(10) HR HV
$Treated_{i,l,t} * Post_{i,t}$	-0.033***	-0.035***	0.005	-0.001	-0.018***	-0.021***	0.037***	0.056***	-0.030***	-0.031***
	(0.006)	(0.006)	(0.013)	(0.015)	(0.007)	(0.007)	(0.014)	(0.013)	(0.009)	(0.009)
Controls	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Product Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	9,028	9,028	2,896	2,896	6,132	6,132	994	994	4,864	4,864
R-squared	0.986	0.986	0.985	0.986	0.986	0.986	0.980	0.987	0.983	0.983
F Test (p-value)	0.000	0.000	0.722	0.000	0.008	0.000	0.008	0.000	0.001	0.000

Notes: The DiD model leverages on Amazon UK as a control sample. All specifications include time and product fixed effects. Controls include the absolute and the relative number of reviews as well as ratings. High (low) appreciated products have ratings higher (lower) than 4. High (low) visible products have a normalized search index higher (lower) than 0,8. LR-LV are low appreciated and low visible products, HR-HV are high appreciated and high visible products. Robust Standard Errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

In order to explore whether the impact of PMGs on NewEgg's prices is heterogeneous across products, we re-estimate Equation (2) on different sub-samples built according to products' appreciation and visibility. We firstly distinguish products according to the rating as a proxy for products appreciation. Columns from (3) to (6) in Table 4 show results of this analysis and suggest that, when the PMGs are switched-off, products characterised by a low appreciation do not experience price changes, while for high appreciated products NewEgg's prices decrease of about 2% more than Amazon UK's ones, at 1% of significance.[32] This result drives estimates obtained over the full sample, given that about 70% of observations are associated to high appreciated products. Second, since products' appreciation and visibility are correlated in our sample, we estimate Equation (2) after splitting the sample according to both product characteristics jointly considered. Results shown in columns from (7) to (10) of Table 4 suggest that, when PMGs are switched-off, NewEgg's prices for high appreciated-visible products significantly decrease of about 3%, while prices of low appreciated-visible ones raise of about 4-6%.[33] These findings are confirmed when we

[31]Zhuo (2017) observes price changes on the non-adopting platform before and after the implementation of PMGs by competitors, while we focus on the adopting platform. Moreover, we build the control sample with price data for the same treated products but observed on Amazon UK.

[32]Similar results also arise from estimates that include controls. Moreover, the lack of robustness across specifications precludes us from giving too much weight to the result in column (3) of Table 2.

[33]Again, LQ-LV product category represents just 11% of total observations.

perform heterogeneity analysis with a DDD regression approach (Equations 3 and 4), as reported in Table 5.[34]

Table 5: DDD Estimates of the Impact of PMGs on Prices.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Product Prices (log)	BEFORE - AFTER				DDD			
$Post_{i,t} * HR_i$	-0.063***	-0.066***						
	(0.007)	(0.008)						
$Post_{i,t} * HRHV_i$			-0.072***	-0.077***				
			(0.009)	(0.009)				
$Treated_{i,l,t} * Post_{i,t} * HR_{i,l}$					-0.037***	-0.039***		
					(0.007)	(0.007)		
$Treated_{i,l,t} * Post_{i,t} * HRHV_{i,l}$							-0.047***	-0.049***
							(0.008)	(0.008)
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Product Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,514	4,514	4,514	4,514	9,028	9,028	9,028	9,028
R-squared	0.980	0.980	0.980	0.980	0.986	0.986	0.986	0.986
F Test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: All specifications include time and product fixed effects. Estimates in columns from (1) to (4) rely solely on the treated sample, while columns from (5) to (8) leverage on Amazon UK as a control sample. Controls include the absolute and the relative number of reviews as well as ratings. High (low) appreciated products have ratings higher (lower) than 4. High (low) visible products have a normalized search index higher (lower) than 0,8. $HR_{i,l}$ is a dummy equal to 1 for high appreciated products. $HRHV_{i,l}$ is a dummy equal to 1 for high appreciated and high visible products. Robust Standard Errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Furthermore, we investigate the possibility that the effect of the treatment may speed up, stabilize, or mean revert over time. In order to explore this issue, we estimate (over the full sample) a specification of Equation (2) that includes some lags à la Autor (2003). The model relies on Amazon UK as a control sample and takes on the following form:

$$\log Price_{i,l,t} = \alpha_{i,l} + \sum_{j=0}^{3+} \gamma_j \big(Treated_{i,l,t} * P_{i,t+j}\big) + X^T_{i,l,t}\beta + \mu_{i,l} + \tau_t + \epsilon_{i,l,t} \qquad (5)$$

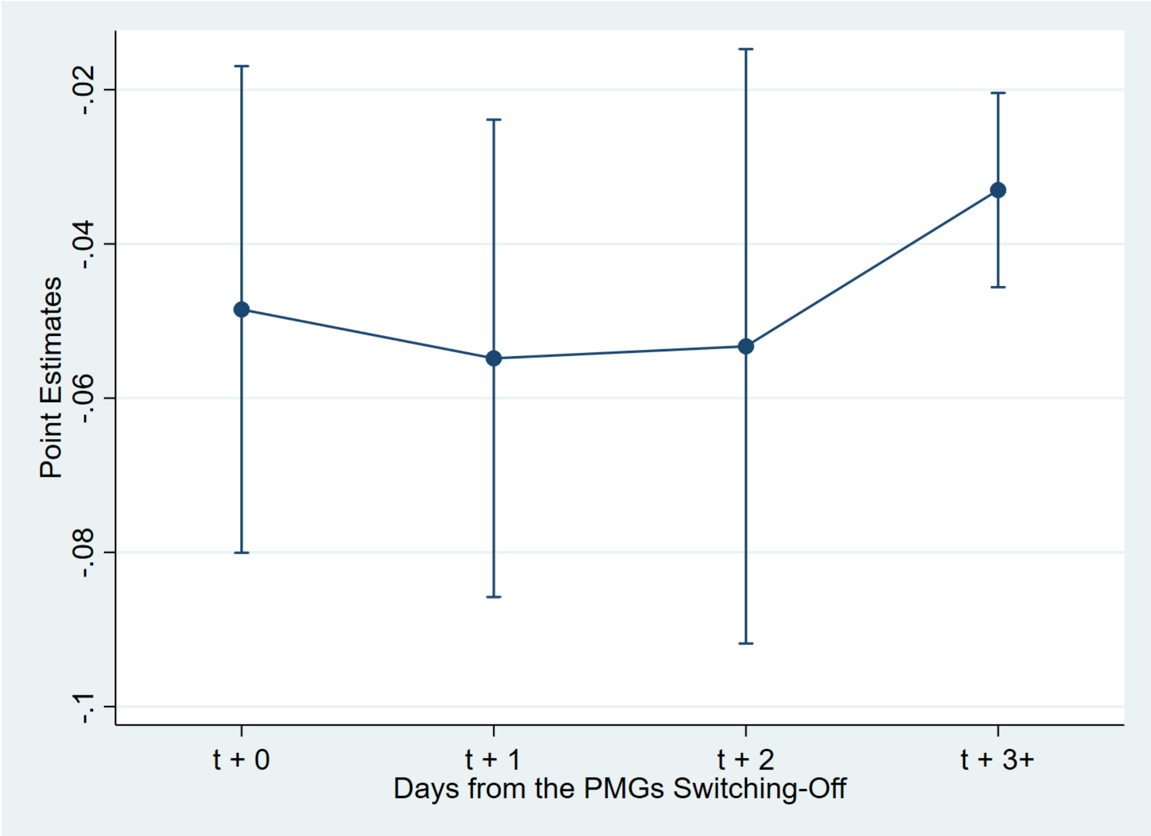
Specification (5), where $P_{i,t+j}$ assumes the value of 1 in day $t+j$, and 0 otherwise, allows the treatment to generate different effects over time. In order to lower the number of parameters of the model, we estimate such effect from the implementation day ($j = 0$) until three days later and onward. Figure 2 graphically shows parameter estimates patterns. According to the latter, coefficients related to lagged variables are always negative and statistically significant. In particular, point estimates suggest that the impact is tangible as soon as NewEgg's PMGs are switched-off, reaches its maximum after one day and starts decreasing afterwards.[35]

Finally, given results in Section 5.1.1, it is worth noting that we can reasonably argue that PMGs adopted by NewEgg do not influence Amazon US's prices, so that we are able to further verify previous results by relying on a different control sample, i.e. products' prices from Amazon US. Therefore, we estimate Equations (2), (3), (4) and

[34]Notice that estimates in columns from (1) to (4) of Table 5 leverage solely on the treated sample, while those in columns from (5) to (8) of Table 5 rely on Amazon UK as a control sample.

[35]Detailed estimates results, not reported, are available upon request.

Figure 2: DiD Estimates of the Impact of PMGs on Prices with lags à la Autor (2003).



Notes: Point estimates and confidence intervals of lagged variables from Equation (5). The specification includes time and product fixed effects. Controls include product popularity, number of reviews and rating. Estimates, not reported, are available upon request.

(5) by leveraging on such a different control sample. Comfortingly, results reported in Appendix B confirm all findings.

5.1.3 Discussion

Overall, our empirical findings obtained on the full sample are in line with those reported by the previous applied literature for different markets (e.g. Cabral et al., 2018; Chilet, 2018; Byrne and De Roos, 2019) and online platforms (Zhuo, 2017). However, one should trace them back to the most prominent predictions of theoretical models, i.e. the collusion theory and the price discrimination one, in order to define if these models are somewhat supportive of our overall baseline results obtained over different specifications.

As far as the collusion theory is concerned, theoretical models require that PMGs should be adopted by all firms in the market, increasing overall market prices (see Moorthy and Winter, 2006). Indeed, under this theory, such clauses lower the incentives of both adopting and non-adopting firms to cut prices, leading to higher prices for both. Moreover, in this context, such policies are not actually invoked in equilibrium.

Given the existence of a non-adopting competitor as Amazon, that never offers PMGs, and the results in Section 5.1.1, that somehow exclude an impact of NewEgg's clauses on this non-adopting competitor, we tend to rule out tracing our results back to the collusion theory. Moreover, the latter is inconsistent with the presence of PMGs in markets characterised by a large number of competitors, setting different prices, such as the retail electronics one, where firms range from small local shops to big chain stores, as well as online platforms, even with the ability to implement potential facilitating practices such as PMGs (which, contrary to the predictions of collusive models, are actually required by consumers).[36]

Conversely, results obtained on different sub-samples provide novel evidence that cannot be compared with the previous empirical literature and which can be partly traced back to price discrimination models. In particular, we believe that the interpretation of such findings can be discussed by considering consumers heterogeneity that is reflected into UGCs. We argue that consumers are heterogeneous in terms of willingness to pay for products' appreciation and price elasticity. Specifically, from the one side consumers characterized by higher taste for appreciated products are most likely to focus on the ones that are characterised by high ratings in terms of "stars" (high appreciated products) and, according to our results, will pay higher prices during the policy implementation period. Moreover, in our sample, such products are likely to have high visibility as proxied by our search index. On the other side, customers that have a lower willingness to pay for products' appreciation are more likely to have higher price sensitiveness so that they manage to pay lower prices by invoking the price matching clause.

Therefore, we argue that results obtained for sub-samples based on products' appreciation/visibility are broadly in line with the hypothesis of price matching motivated by price discrimination. Indeed, the use of information (including UGCs) released on the Internet from users allows platforms not only to personalise digital shopping experiences, but also to set "prices at which goods and services are offered to customers in online environments, making it possible for two individuals to be offered exactly the same product, at precisely the same time, but at different prices, based on an algorithmic assessment of each shopper's predicted willingness to pay" (Townley et al., 2017).[37] Moreover, it is worth noting that NewEgg's PMGs, for low appreciated-visible products, can be a signal of actual low prices for both categories of consumers if actually platforms use UGCs to precisely estimate their willingness to pay.

However, some concerns should be raised. First, the price discrimination hypothesis requires that a significant percentage of customers invoke PMGs rights.

[36] See Moorthy and Winter (2006).

[37] Townley et al. (2017) again state that information released by users on the Internet "substantially enhance the ability of digital retailers to engage in much more precise, targeted and dynamic forms of price discrimination that were not previously possible".

Moorthy and Winter (2006) observe redemption rates ranging between 1% and 25%, on a sample of 46 Canadian retailers and suggest that percentages above 10% are compatible with the aforementioned hypothesis. We believe that it is reasonable to expect higher redemption rates on online markets, given that "hassle" cost should be lower for e-commerce. Second, despite some of the assumptions of theoretical models that interpret PMGs as discriminating tools seem to be satisfied in the analyzed context, platform markets differ from brick and mortar ones along different dimensions. Among others, the process of evaluation of search goods is cheaper and faster thanks to the availability of UGCs, so that commercial policies, like PMGs, are designed according to such features. Indeed, the characteristics of PMGs observed in our sample significantly differ from those described in theoretical models that are more likely to fit brick and mortar markets and it would be interesting to modify such models in order to account for the peculiarities of online markets.

5.2 Robustness Analysis

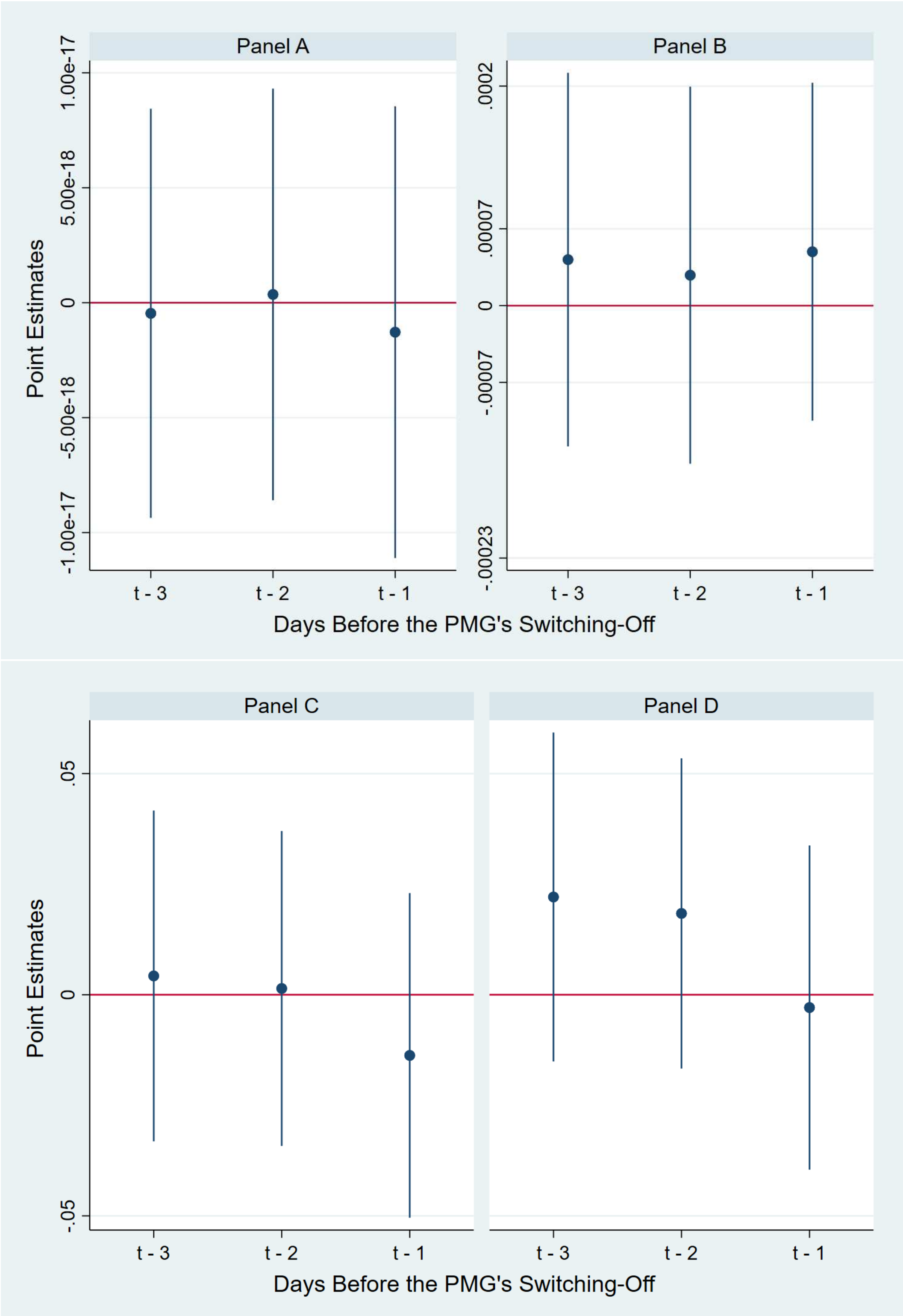
In this Section, we discuss empirical results obtained by conducting an in-depth robustness analysis of our results.

A fundamental concern we tackle is an important issue in a DiD research design, i.e. the presence of pre-treatment common trends for treated and control units. This assumption is indeed fundamental for the validity of the counterfactual policy evaluation analysis. First, in top panels of Figure 3 we show point estimates and confidence intervals of price differentials between treated and control products, from three days before the treatment to the switching day. In order to obtain these values we estimate a panel model where we regress average daily price differences between treated and control samples on relative lead terms. We control for product fixed effects and daily fixed effects. In particular, Panel A of Figure 3 provides results of the comparison between NewEgg and Amazon UK, while Panel B shows point estimates from the analysis that leverages on Amazon US as a control sample. Plotted values in both panels suggest that, before the treatment, price levels for the treated sample do not seem to be significantly different from control sample prices. This result provides evidence in favor of the validity of parallel trends assumption for our samples. Second, in order to further analyse this issue, we follow Autor (2003) and we estimate Equation (5) after including some leads of the treatment interaction variable:

$$\log Price_{i,l,t} = \alpha_{i,l} + \sum_{j=-1}^{-3} \gamma_j \big(Treated_{i,l,t} * P_{i,t+j}\big) + X^T_{i,l,t}\beta + \mu_{i,l} + \tau_t + \epsilon_{i,l,t} \tag{6}$$

In particular, in order to lower the number of parameters of the model, we include leads from one day to three days before the implementation. Indeed, if leads coefficients turn out to be statistically significant, there may be anticipatory effects of the policy and a failure in the parallel trend assumption. Panel C and D of Figure 3 show point

Figure 3: Pre-Treatment Common Trends for Treated and Control Units.



Panel A and B show point estimates values and relative confidence intervals of the difference in the level of prices between treated and control products from three days before the treatment to the day when the policy is switched-off. Panel A provides results of the comparison between NewEgg and Amazon UK, while Panel B shows point estimates from the analysis that leverages on Amazon US as a control sample. Panel C and D show point estimates and confidence intervals from estimations of Equation (6) that leverage on Amazon UK and Amazon US as a control sample respectively. Specifications includes time and product fixed effects. Controls include product popularity, number of reviews and rating. Estimates, not reported, are available upon request.

estimates and confidence intervals from estimations of Equation (6) that leverage on Amazon UK and Amazon US as a control sample respectively. According to plotted values, estimated coefficients of the anticipatory effects are not statistically significant, thus providing further evidence in favor of the existence of a parallel trend between treatment and control sample.[38]

In order to further validate our research design we test for potential treatment endogeneity by leveraging on a regression where the probability of being treated is a function of products prices. Rather comfortingly, results suggest that treatment probability is independent from such a variable.[39]

Treatment exogeneity is also investigated by means of a complete set of placebo tests. First, we randomly assign treatments timing by generating simulated values for the dummy $Post_{i,t}$. In particular, we build a placebo variable $Post_{i,t}^{fake}$ equal to 1 if random numbers drawn from a uniform distribution [0,1] are greater than the sample treatment probability. We therefore estimate Equation (2) after including the new interaction term, $Treated_{i,l,t} * Post_{i,t}^{fake}$ and we iterate such procedure 1000 times in order to obtain a distribution of placebo γ coefficients to compare with the estimated value shown in column (2) of Table 4 ($\gamma = -0.035$). Indeed, a statistically significant treatment effect should be significantly different with respect to placebo estimates. In the top panel of Figure 4 dark bars represent the distribution of estimated placebo coefficients obtained with such iterative method, while the vertical red line shows the γ coefficient value estimated in the baseline specification. It is worth noting that the latter lies outside the density distribution of placebo effects, thus being statistically significantly larger, in absolute value, than those obtained using randomly assigned treatments. Moreover, placebo γ coefficients are normally distributed, with zero mean, thus highlighting no treatment effects under the hypothesis of products and/or treatments *fake* assignments, and supporting the robustness of our main findings. Second, we follow the same procedure to build up another placebo test; in particular, we build *fake* treatments timing as well as *fake* treated products in order to obtain a different placebo interaction term, i.e. $Treated_{i,l,t}^{fake} * Post_{i,t}^{fake}$ (again, placebo dummies are built according to draws from uniform distributions). The bottom panel of Figure 4 shows density estimates for such analysis. Once again, the coefficient inferred from our main specification is significantly different from values obtained from the placebo study, thus confirming the robustness of our previous results.[40]

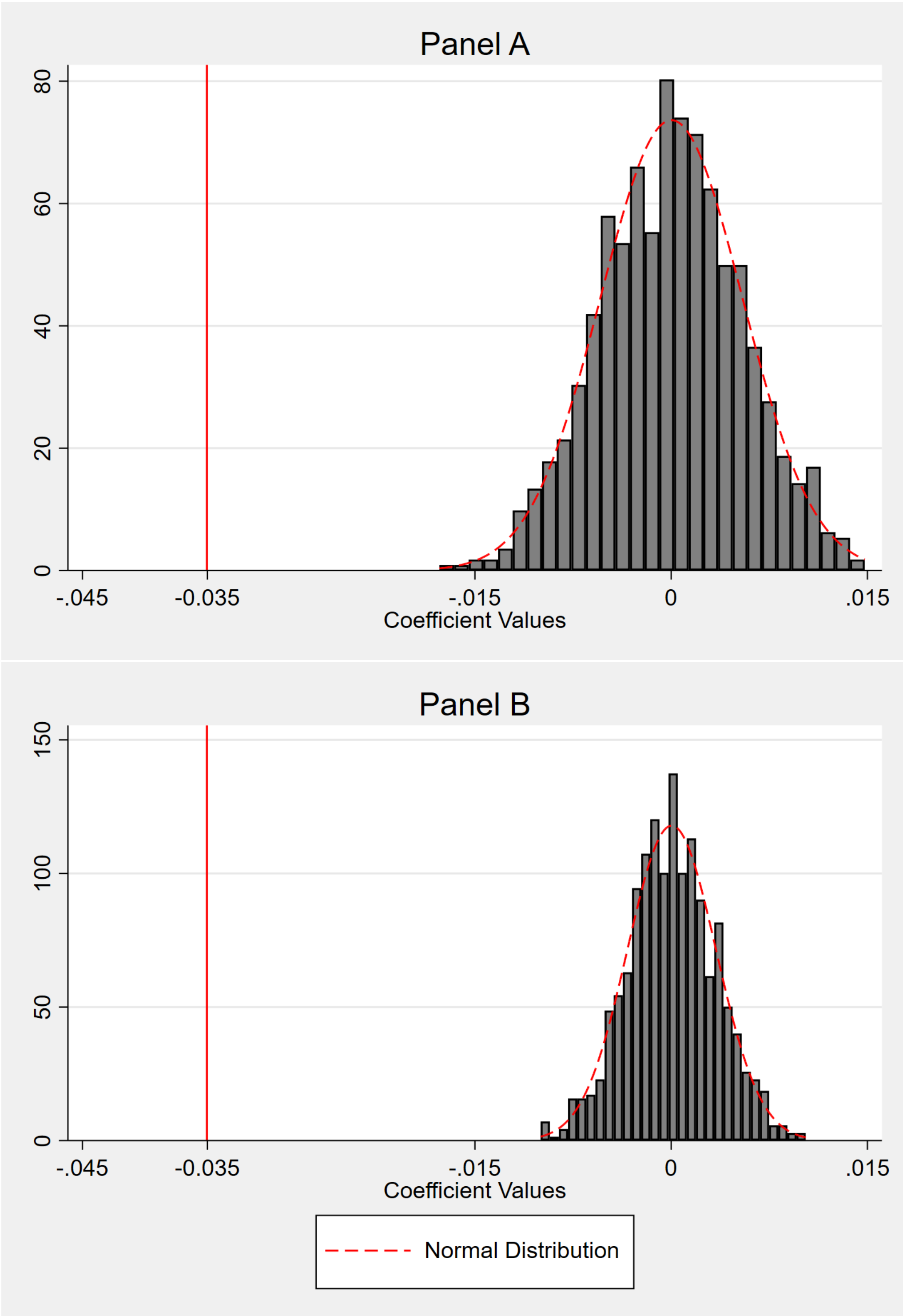
It is worth noting that our results are confirmed when we conduct the aforementioned placebo test relying on Amazon US as a control sample, when we estimate our baseline and DDD specifications after introducing *fake* products and *fake* treatments

[38]Detailed estimates from the parallel trends analysis, not reported, are available upon request.

[39]Results are available upon request.

[40]Once again, the distribution of coefficient values from placebo studies in the bottom panel of Figure 4 resemble a Normal one with zero mean, thus highlighting no treatment effects under the hypothesis of products and/or treatments *fake* assignments.

Figure 4: Placebo Plot Test.



Notes: In the top panel we randomly assign treatments timing by generating simulated values for the dummy $Post_{i,t}$. In particular, we build a *fake* $Post_{i,t}$ equal to 1 if random numbers drawn from a uniform distribution [0,1] are greater than the sample treatment probability. We then estimate Equation (2) after including the new interaction term, $Treated_{i,l,t} * Post_{i,t}^{fake}$ and we iterate such procedure 1000 times in order to obtain a distribution of placebo γ coefficients to compare with the estimated value shown in column (2) of Table 4. The bottom panel reports coefficient estimates' distribution obtained with the same iterative method, where both treatments timing and treated products have been randomly assigned. Dark bars represent the distribution of estimated placebo interaction term coefficients. Vertical solid red lines represent the estimated γ coefficient of $Treated_{i,l,t} * Post_{i,t}$ ($\gamma = -0.035$) shown in Table 4.

randomly drawn from Bernoulli distributions and when we estimate our models after substituting the dependent variable with a *fake* outcome, where product prices are drawn from product specific random distributions resembling sample ones (same mean and variance). Moreover, in order to analyze if our main findings are robust to the exclusion of a particular product, we estimate the baseline Equation (2) after dropping one product at a time and all previous results are confirmed; same conclusions arise when we estimate Equation (2) after balancing the panel and when we compute bootstrapped standard errors allowing for a cluster structure (at product level).[41]

6 Conclusions

In this work we empirically investigate the effects of Price Matching Guarantees (PMGs) commercial policies on daily prices of a representative sample of consumer electronics products observed on the US NewEgg platform, between May and October 2018. We firstly analyse the average change in NewEgg's product prices before and after the NewEgg's PMGs switch-off; second, we apply a Difference-in-Differences (DiD) research design where the control sample is built by recovering price data for the same products affected by PMGs but sold on another platform, namely Amazon UK, that never offers such policies over the sample period.

Estimates provide evidence in favor of an average price reduction of about 3% after the NewEgg's PMGs validity period and such result is confirmed after controlling for products features, retrievable from User Generated Contents (UGCs), that might affect PMGs outcomes, like products' ratings and popularity. Moreover, in order to have a more detailed picture of the issue, we conduct an heterogeneity analysis by distinguishing products according to their appreciation (and platform visibility), as proxied by ratings in terms of "stars" (and the Google search rank). Estimates conducted on specific sub-samples show that, when NewEgg's PMGs are switched-off, low appreciated (and low visible) products experience a price increase ranging between 4-6%, while for high appreciated (and high visible) products a price reduction of about 3% is observed. Similar results arise when conducting a Difference-in-Difference-in-Differences (DDD) regression.

These findings can be considered broadly consistent with the hypothesis of PMGs acting as a tool for price discrimination. In particular, the presence of consumers that differ in terms of price elasticity and willingness to pay for products' appreciation is reflected by UGCs shared on platforms. We argue that high (low) appreciated products are associated to consumers with a high (low) willingness to pay a price premium for products' appreciation, that in turn can be associated to different levels of price elasticity, and these assumptions are consistent with different prices observed for certain classes of products during the policy implementation period. Conversely,

[41] Results are reported in Appendix A and Appendix B.

our results are not consistent with predictions of theoretical collusive models, due to related assumptions that do not fit well in the online market context. Finally, notice that a collusive outcome is somewhat inconsistent with the presence of PMGs in markets characterised by a large number of competitors, setting different prices, such as the retail electronics one.

However, previous models that consider PMGs as price discriminating tools (Corts, 1996; Nalca et al., 2010, among others) have been proposed for brick and mortar retailers and are based on assumptions that do not fully reflect the context of online platform markets. Indeed, the development of a theoretical model, specifically designed to deal with online platform commercial policies, would fill a gap in the literature that has mostly focused on traditional markets.

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Appendix A

Additional Robustness Analysis

In order to further verify our results, we perform a full set of additional robustness tests.

We first estimate our baseline and DDD specifications by leveraging on the Amazon UK control sample and introducing artificially treatments timing and artificially treated products obtained with an alternative distribution. *Fake* assignments are drawn from two Bernoulli distributions with parameters p (probability of success) derived from the sample distributions of $Treated_{i,l,t}$ and $Post_{i,t}$ respectively. Within this setting, we should not observe any significant effect of NewEgg's PMGs switch-off on prices. Comfortingly, results reported in Table A.1 confirm this prediction.

Next, we conduct another falsification test by estimating our models after substituting the dependent variable with a placebo outcome that should not be affected by NewEgg's PMGs switch-off.[1] In particular, we generate *fake* product prices drawn by random distributions resembling sample ones (same mean and variance). Results shown in Table A.2 confirm the absence of any impact of NewEgg's PMGs on the *fake* outcome.

Third, in Figure A.1 we replicate the placebo plot test described for the bottom panel of Figure 4, in the Section 5.2 of the main text, but relying on Bernoulli distributions instead of uniform ones. Rather comfortingly, results in Figure A.1 confirm the robustness of our main findings.

Moreover, we re-estimate the baseline Equation (2) after balancing the panel dataset. Precisely, we drop first 34 days in which we observe only some products and all results are confirmed. Lastly, it is worth noting that results do not change if we compute bootstrapped standard errors allowing for a cluster structure at product level. Table A.3 shows respective results.

[1]Notice that, once again, this exercise is performed relying on Amazon UK as a control sample.

Table A.1: DiD and DDD Estimates of the Impact on Prices of *Fake* Treatments and *Fake* Treated Products.

Product Prices (log)	(1) BEFORE AFTER	(2) BEFORE AFTER	(3) BEFORE AFTER	(4) BEFORE AFTER	(5) BEFORE AFTER	(6) BEFORE AFTER	(7) DiD	(8) DiD	(9) DDD	(10) DDD	(11) DDD	(12) DDD
$Post_{i,t}(Fake)$	0.005	0.004										
	(0.006)	(0.006)										
$Post_{i,t} * HR_i(Fake)$			0.005	0.004								
			(0.007)	(0.007)								
$Post_{i,t} * HRHV_i(Fake)$					0.006	0.005						
					(0.010)	(0.010)						
$Treated_{i,l,t} * Post_{i,t}(Fake)$							-0.003	-0.003				
							(0.003)	(0.003)				
$Treated_{i,l,t} * Post_{i,t} * HR_{i,l}(Fake)$									-0.001	-0.001		
									(0.004)	(0.004)		
$Treated_{i,l,t} * Post_{i,t} * HRHV_{i,l}(Fake)$											0.000	-0.001
											(0.005)	(0.005)
Controls	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Product Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,514	4,514	4,514	4,514	4,514	4,514	9,028	9,028	9,028	9,028	9,028	9,028
R-squared	0.980	0.980	0.980	0.980	0.980	0.980	0.986	0.986	0.986	0.986	0.986	0.986
F Test (p-value)	0.371	0.000	0.441	0.000	0.504	0.000	0.385	0.000	0.891	0.000	0.963	0.000

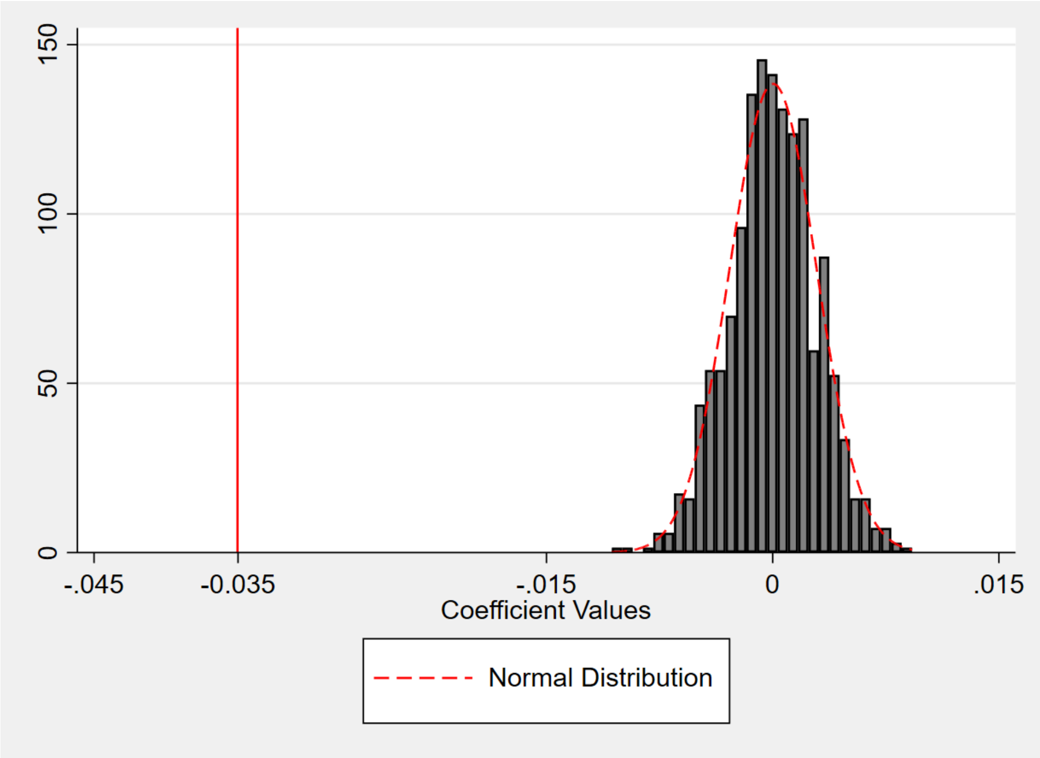
Notes: *Fake* assignments are drawn from two Bernoulli distributions with parameters p (probability of success) derived from the sample distributions of $Treated_{i,l,t}$ and $Post_{i,t}$ respectively. Columns from (1) to (6) rely solely on the treated sample, while those from (7) to (12) leverage on Amazon UK as a control sample. All specifications include time and product fixed effects. Controls include the absolute and the relative number of reviews as well as ratings. High (low) appreciated products have ratings higher (lower) than 4. High (low) visible products have a normalized search index higher (lower) than 0,8. $HR_{i,l}$ is a dummy equal to 1 for high appreciated products. $HRHV_{i,l}$ is a dummy equal to 1 for high appreciated and high visible products. Robust Standard Errors in in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table A.2: DiD and DDD Estimates of the Impact of PMGs on *Fake* Prices.

(*Fake*) Product Prices (log)	(1) BEFORE AFTER	(2) BEFORE AFTER	(3) BEFORE AFTER	(4) BEFORE AFTER	(5) BEFORE AFTER	(6) BEFORE AFTER	(7) DiD	(8) DiD	(9) DDD	(10) DDD	(11) DDD	(12) DDD
$Post_{i,t}$	0.002	0.003										
	(0.002)	(0.002)										
$Post_{i,t} * HR_i$			0.003	0.003								
			(0.002)	(0.002)								
$Post_{i,t} * HRHV_i$					0.002	0.003						
					(0.002)	(0.003)						
$Treated_{i,l,t} * Post_{i,t}$							0.001	0.001				
							(0.002)	(0.002)				
$Treated_{i,l,t} * Post_{i,t} * HR_{i,l}$									0.001	0.001		
									(0.002)	(0.002)		
$Treated_{i,l,t} * Post_{i,t} * HRHV_{i,l}$											0.001	0.001
											(0.002)	(0.002)
Controls	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Product Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,514	4,514	4,514	4,514	4,514	4,514	9,028	9,028	9,028	9,028	9,028	9,028
R-squared	0.998	0.998	0.998	0.998	0.998	0.998	0.999	0.999	0.999	0.999	0.999	0.999
F Test (p-value)	0.211	0.522	0.226	0.546	0.335	0.674	0.408	0.511	0.439	0.525	0.571	0.572

Notes: *Fake* product prices are drawn by random distributions resembling sample ones (same mean and variance). Columns from (1) to (6) rely solely on the treated sample, while those from (7) to (12) leverage on Amazon UK as a control sample. All specifications include time and product fixed effects. Controls include the absolute and the relative number of reviews as well as ratings. High (low) appreciated products have ratings higher (lower) than 4. High (low) visible products have a normalized search index higher (lower) than 0,8. $HR_{i,l}$ is a dummy equal to 1 for high appreciated products. $HRHV_{i,l}$ is a dummy equal to 1 for high appreciated and high visible products. Robust Standard Errors in in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Figure A.1: Placebo Plot Test. Bernoulli Distribution.



Notes: The figure shows the result from a iterative placebo test with artificially timed treatments and artificially treated subjects. Equation (2) is estimated relying on 1000 simulated datasets in which *fake* assignments are randomly reshuffled in each iteration by drawing from Bernoulli distributions with parameters p (probability of success) derived from the sample distributions of $Treated_{i,l,t}$ and $Post_{i,t}$ respectively. The vertical red line represents the effective coefficient of $Treated_{i,l,t} * Post_{i,t}$ ($\gamma = -0.035$) in column (2) of Table 4. Dark bars show the distribution of γ coefficient values from placebo tests.

Table A.3: DiD Estimates of the Impact of PMGs on Prices. Additional Robustness.

Product Prices (log)	(1) BEFORE AFTER	(2) BEFORE AFTER	(3) DiD	(4) DiD	(5) DiD	(6) DiD
$Post_{i,t}$	-0.066***	-0.068***				
	(0.007)	(0.007)				
$Treated_{i,l,t} * Post_{i,t}$			-0.048***	-0.051***	-0.0330*	-0.0355*
			(0.006)	(0.006)	(0.020)	(0.020)
Controls	NO	YES	NO	YES	NO	YES
Product Dummies	YES	YES	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES	YES	YES
Observations	4,118	4,118	8,236	8,236	9,028	9,028
R-squared	0.984	0.985	0.988	0.988	0.986	0.986
Standard Errors	ROBUST	ROBUST	ROBUST	ROBUST	BOOTSTRAP	BOOTSTRAP

Notes: Columns from (1) to (4) show estimates of Equations (1) and (2) on a balanced panel dataset (we drop first 34 days in which we observe only some products). Columns (5) and (6) provide DiD results computing bootstrapped standard errors allowing for a cluster structure at product level on the full sample. All specifications include time and product fixed effects and rely on Amazon UK as a control sample. Controls include the absolute and the relative number of reviews as well as ratings. Robust (Bootstrapped) Standard Errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Appendix B

Alternative Control Sample. Amazon US.

In this Appendix we estimate Equations (2), (3), (4) and (5) by leveraging on Amazon US's product prices as a control sample, instead of Amazon UK's ones. Indeed, given results in Section 5.1.1, we can reasonably argue that PMGs adopted by NewEgg do not influence Amazon US's prices, so that we are able to further verify results in Section 5.1.2 relying on a different control sample (within US market competitor).

Table B.1 shows estimated results from Equation (2) over the full sample and after splitting it according to products' appreciation and visibility. Comfortingly, estimates of the $Treated_{i,l,t} * Post_{i,t}$ term in columns (1) and (2) confirm results obtained in Section 5.1.2. Moreover, the analysis over different sub-samples provides support to an heterogeneous impact of the policy, i.e. that prices of low appreciated and low visible products are higher after the PMGs switch-off, while the ones of high appreciated and high visible products are lower. This heterogeneous impact of PMGs on NewEgg's prices is confirmed also in Table B.2, in which we show parameter estimates from Equations (3) and (4).

Finally, it is worth noting that the impact of PMGs on NewEgg's prices is confirmed to be tangible as soon as NewEgg's PMGs are switched-off and remains significant until three days and onward. Figure B.1 provides graphical evidence of DiD estimates of the specification that includes lags à la Autor (2003) (Equation 5).

It is worth noting that results are robust to usual robustness checks and placebo tests. In particular, parallel trends are analysed in Section 5.2, and comfortingly results provide evidence in favour of this assumption. Moreover, our results are confirmed when we estimate our baseline and DDD specifications after introducing *fake* products and *fake* treatments randomly drawn from Bernoulli distributions and when we estimate our models after substituting the dependent variable with a *fake* outcome, where product prices are drawn from product specific random distributions resembling sample ones (same mean and variance). Tables B.3 and B.4 provide respective results. Finally, we replicate the placebo plot test as in Section 5.2; in particular, we build *fake* treatments timing as well as *fake* treated products in order to obtain a different placebo interaction term, i.e. $Treated^{fake}_{i,l,t} * Post^{fake}_{i,t}$ (again, placebo dummies are built according to draws from uniform distributions). Figure B.2 shows density estimates for such analysis. Once again, the coefficient inferred from our main specification is significantly different from values obtained from the placebo study, thus confirming the robustness of our previous results.[2]

[2]Overall findings are also robust to the exclusion of one product at a time, after balancing the panel and when we compute bootstrapped standard errors allowing for a cluster structure (at product level). Results, not reported, are available upon request.

Table B.1: DiD Estimates of the Impact of NewEgg's PMGs on Prices. Amazon US Control Sample.

Products Prices (log)	(1) FULL SAMPLE	(2) FULL SAMPLE	(3) LOW RATING	(4) LOW RATING	(5) HIGH RATING	(6) HIGH RATING	(7) LR LV	(8) LR LV	(9) HR HV	(10) HR HV
$Treated_{i,l,t} * Post_{i,t}$	-0.062***	-0.066***	-0.019	-0.026	-0.050***	-0.056***	0.062***	0.041***	-0.072***	-0.082***
	(0.006)	(0.006)	(0.014)	(0.017)	(0.007)	(0.007)	(0.017)	(0.016)	(0.009)	(0.009)
Controls	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Product Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	9,028	9,028	2,896	2,896	6,132	6,132	994	994	4,864	4,864
R-squared	0.981	0.981	0.964	0.965	0.984	0.984	0.974	0.984	0.980	0.981
F Test (p-value)	0.000	0.000	0.190	0.000	0.000	0.000	0.000	0.000	0.000	0.000

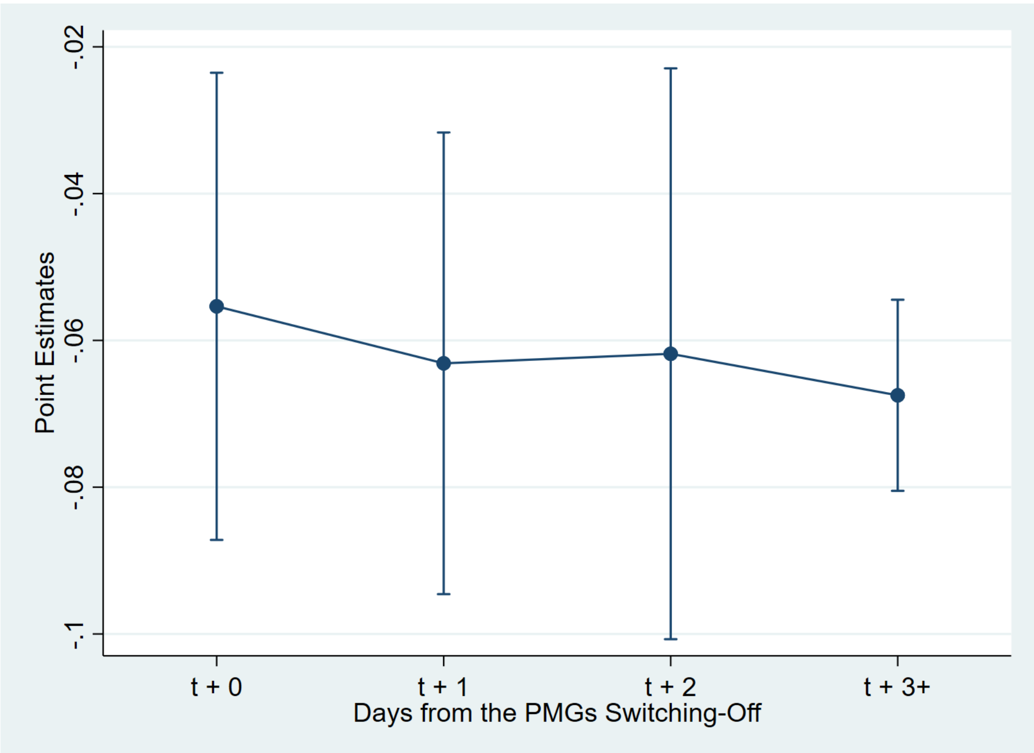
Notes: All specifications include time and product fixed effects and rely on Amazon US as a control sample. Controls include the absolute and the relative number of reviews as well as ratings. High (low) appreciated products have ratings higher (lower) than 4. High (low) visible products have a normalized search index higher (lower) than 0,8. LR-LV are low appreciated and low visible products, HR-HV are high appreciated and high visible products. Robust Standard Errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table B.2: DDD Estimates of the Impact of PMGs on Prices. Amazon US Control Sample.

	(1)	(2)	(3)	(4)
Product Prices (log)	DDD			
$Treated_{i,l,t} * Post_{i,t} * HR_{i,l}$	-0.066***	-0.070***		
	(0.007)	(0.007)		
$Treated_{i,l,t} * Post_{i,t} * HRHV_{i,l}$			-0.075***	-0.079***
			(0.008)	(0.008)
Controls	NO	YES	NO	YES
Product Dummies	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES
Observations	9,028	9,028	9,028	9,028
R-squared	0.981	0.981	0.981	0.981
F Test	0.000	0.000	0.000	0.000

Notes: All specifications include time and product fixed effects relying on Amazon US as a control sample. Controls include the absolute and the relative number of reviews as well as ratings. High (low) appreciated products have ratings higher (lower) than 4. High (low) visible products have a normalized search index higher (lower) than 0,8. $HR_{i,l}$ is a dummy equal to 1 for high appreciated products. $HRHV_{i,l}$ is a dummy equal to 1 for high appreciated and high visible products. Robust Standard Errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Figure B.1: DiD Estimates of the Impact of PMGs on Prices with lags à la Autor (2003). Amazon US Control Sample.



Notes: Point estimates and confidence intervals of lagged variables from Equation (5). The specification includes time and product fixed effects. Controls include product popularity, number of reviews and rating. Estimates, not reported, are available upon request.

Table B.3: DiD and DDD Estimates of the Impact on Prices of *Fake* Treatments and *Fake* Treated Products. Amazon US Control Sample.

Product Prices (log)	(1) DiD	(2) DiD	(3) DDD	(4) DDD	(5) DDD	(6) DDD
$Treated_{i,l,t} * Post_{i,t}(Fake)$	0.004	0.004				
	(0.003)	(0.003)				
$Treated_{i,l,t} * Post_{i,t} * HR_{i,l}(Fake)$			0.006	0.006		
			(0.004)	(0.004)		
$Treated_{i,l,t} * Post_{i,t} * HRHV_{i,l}(Fake)$					0.007	0.007
					(0.005)	(0.005)
Controls	NO	YES	NO	YES	NO	YES
Product Dummies	YES	YES	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES	YES	YES
Observations	9,028	9,028	9,028	9,028	9,028	9,028
R-squared	0.981	0.981	0.981	0.981	0.981	0.981
F Test (p-value)	0.238	0.000	0.160	0.000	0.130	0.000

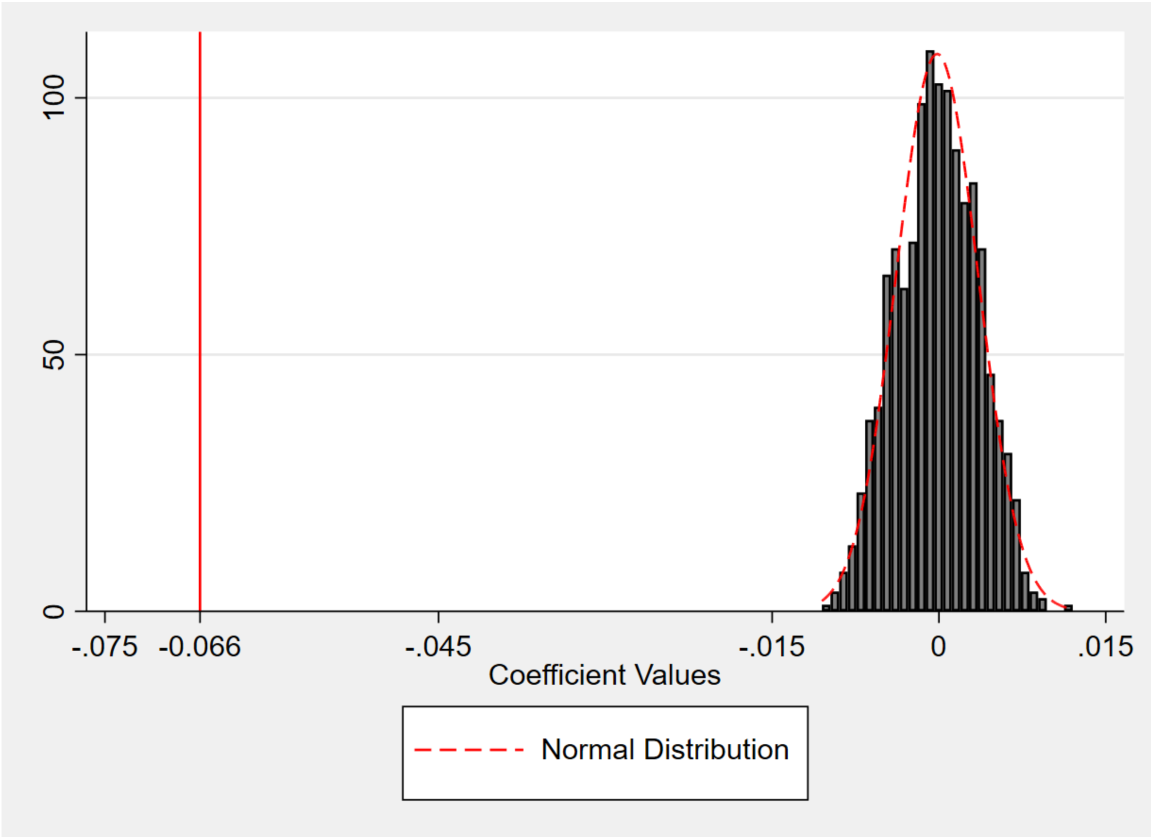
Notes: *Fake* assignments are drawn from two Bernoulli distributions with parameters p (probability of success) derived from the sample distributions of $Treated_{i,l,t}$ and $Post_{i,t}$ respectively. All specifications include time and product fixed effects and leverage on Amazon US as a control sample. Controls include the absolute and the relative number of reviews as well as ratings. High (low) appreciated products have ratings higher (lower) than 4. High (low) visible products have a normalized search index higher (lower) than 0,8. $HR_{i,l}$ is a dummy equal to 1 for high appreciated products. $HRHV_{i,l}$ is a dummy equal to 1 for high appreciated and high visible products. Robust Standard Errors in in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table B.4: DiD and DDD Estimates of the Impact of PMGs on *Fake* Prices. Amazon US Control Sample.

(*Fake*) Product Prices (log)	(1) DiD	(2) DiD	(3) DDD	(4) DDD	(5) DDD	(6) DDD
$Treated_{i,l,t} * Post_{i,t}$	0.001	0.001				
	(0.002)	(0.002)				
$Treated_{i,l,t} * Post_{i,t} * HR_{i,l}$			0.001	0.001		
			(0.002)	(0.002)		
$Treated_{i,l,t} * Post_{i,t} * HRHV_{i,l}$					0.001	0.001
					(0.002)	(0.002)
Controls	NO	YES	NO	YES	NO	YES
Product Dummies	YES	YES	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES	YES	YES
Observations	9,028	9,028	9,028	9,028	9,028	9,028
R-squared	0.998	0.998	0.998	0.998	0.998	0.998
F Test (p-value)	0.466	0.774	0.462	0.775	0.593	0.835

Notes: *Fake* product prices are drawn by random distributions resembling sample ones (same mean and variance). All specifications include time and product fixed effects and leverage on Amazon US as a control sample. Controls include the absolute and the relative number of reviews as well as ratings. High (low) appreciated products have ratings higher (lower) than 4. High (low) visible products have a normalized search index higher (lower) than 0,8. $HR_{i,l}$ is a dummy equal to 1 for high appreciated products. $HRHV_{i,l}$ is a dummy equal to 1 for high appreciated and high visible products. Robust Standard Errors in in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Figure B.2: Placebo Plot Test. Amazon US Control Sample.



Notes: The figure shows the result from a iterative placebo test with artificially timed treatments and artificially treated subjects. Equation (2) is estimated relying on 1000 simulated datasets in which *fake* assignments are equal to 1 if random numbers drawn from a uniform distribution [0,1] are greater than the sample probability. The vertical red line represents the effective coefficient of $Treated_{i,l,t} * Post_{i,t}$ ($\gamma = -0.066$) in column (2) of Table B.1. Dark bars show the distribution of γ coefficient values from placebo tests.

Appendix C

Table C.1: Sub-Categories List.

Sub - Categories	# products
CPU Processor	9
Computer Case	6
Mobile Phone	3
Scanner	6
Speaker	6
Motherboard	3
Monitor	9
Headset	3
USB Flash	3
CPU Cooler	3
Speaker for Domotic	3
Tablet	3
Desktop PC	3
Laptop PC	3
Power Supply	3
Printer	6
Memory Card	6
Hard Disk	3
Smart Thing Domotic	6

Table C.2: Treated Products List.

Treated Products Titles
AMD Ryzen 5 1500X Processor
Corsair Crystal Series 570X RGB - Tempered Glass; Premium ATX Mid-Tower Case
BlackBerry PRIV (32GB) Verizon Factory Unlocked Phone
Fujitsu fi-7160 Color Duplex Document Scanner
Fujitsu ScanSnap S1300i Instant PDF Multi Sheet-Fed Scanner
Philips BT50B/37 Wireless Portable Bluetooth Speaker
Asus ROG MAXIMUS VIII FORMULA DDR4 ATX Motherboards
ASUS VS247H-P 23.6 Full HD 1920x1080 2ms HDMI DVI VGA Monitor
Samsung Hmd Odyssey Windows Mixed Reality Headset
Samsung 128GB BAR (METAL) USB 3.0 Flash Drive
Corsair CW-9060025-WW Hydro Series Liquid CPU Cooler
Echo Dot (2nd Generation) - Smart speaker with Alexa - Black
ASUS VivoMini Mini PC
Dell XF9PJ Latitude 7490 Notebook
Intel Core i7-8700 Desktop Processor 6 Cores
AMD Ryzen 7 2700X Processor Wraith Prism LED Cooler
Corsair RMx Series RM850 x 80 PLUS Gold Fully Modular ATX Power Supply
ASUS 24-inch Full HD FreeSync Gaming Monitor
Brother Monochrome Laser Printer; Compact All-in One Printer
Team 64GB microSDXC UHS-I/U1 Class 10 Memory Card with Adapter
LG Electronics 21.5 Screen LED-Lit Monitor
HP LaserJet Pro M227fdw All-in-One Wireless Laser Printer
Logitech Z313 Speaker System + Logitech Bluetooth Audio Adapter Bundle
PNY CS900 960GB 2.5 Sata III Internal Solid State Drive (SSD)
Samsung SmartThings ADT Wireless Home Security Starter Kit
Samsung SmartThings Smart Home Hub
Rosewill 2U Server Chassis Server Case (RSV-2600)
Corsair Apple Certified 16GB (2 x 8GB) DDR3 1333 MHz (PC3 10600) Laptop Memory
Acer Iconia One 10 NT.LDPAA.003 10.1-Inch Tablet