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Do Online Firms Individualize Search Results? An Empirical Analysis of Individualization on Amazon

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Abstract: Online markets offer sellers access to buyers' information and, thus, the potential to alter prices and products accordingly. In light of this, we undertook an empirical analysis to test for individualization on Amazon.com. We collect data from individuals recruited to shop for household items. Our results indicate evidence of individualization of search results and net prices (via coupons). We found, contrary to what was expected, that demographic, geolocation, and account information play an insignificant role in individualization of search results. Thus, we conclude that individualization is based on more dynamic information, e.g., online browsing behavior. This highlights the fact that sellers' need for (and use of) buyer information goes beyond the simple information accessible from the buyers' accounts to a more rigorous monitoring of buyers' online behavior.

Keywords: individualization; price discrimination; Amazon

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1. Introduction

Recent statistics indicate that, in 2020, online retail accounted for about 21.3% of total retail spending in the U.S., which constitutes a 44% increase from the previous year [1]. The convenience of online shopping, and the health concerns associated with in-store shopping during the pandemic, were major factors in the expansion of online markets. This is happening at the same time that the technology of communication, tracking, data collection, and processing is developing at a fast pace.

There is anecdotal evidence that sellers employ search algorithms that use buyers' demographic and geolocation information to generate the products displayed to users, and to set their prices. It was reported that Staples.com charged buyers different prices based on their location. Buyers who were in close proximity to an Office Depot or Office Max store were charged lower prices for the same products than buyers who had less access to competing stores [2]. Other retailers, for example Home Depot, were also found to alter prices online based on the location of the user [3].

There are several cases where sellers used cookies to collect information on buyers' online behavior. For example, in 2000, Amazon charged people different prices for the same DVD [4]. Similarly, online travel agencies have relied on cookies and more advanced technologies to identify when buyers are most ready to buy [5]. The extent to which user information is used by online sellers to individualize search results and prices is not well understood, as sellers are not explicit about the type of data they collect or the way these data are used. Yet, research indicates that firms have an incentive to excessively track and monitor buyers' online behavior as this results in higher profits. Shiller [6] estimated the demand for Netflix plans and found that using individual web browsing behavior to set prices is more effective than relying on demographic information only.

The purpose of this paper is to take a first step towards understanding the extent of information use and individualization that exists online by analyzing search results on Amazon.com. We investigate whether Amazon's prices and products are (1) standardized across buyers as in brick-and-mortar stores, or (2) individualized based on buyers' information. Since our findings showed that search results are not standardized across buyers, we proceeded to test whether individualization exists and, if so, analyze whether it is based on consumers' demographic and geolocation characteristics.

Literature Review

There is a growing literature on online markets. The advances in the technology that allows firms to obtain buyers' information online raises privacy concerns and highlights the need for policies ensuring transparency pertaining to the use of consumer information and regulating the extent of information use. Borgesius [7], Steppe [8], and Sears [9] outline the extent to which personal information is utilized by online retailers and the role played by the current data-use regulations in Europe. Borgesius [10] found that algorithmic pricing can discriminate against particular groups of people, which is a problem that cannot be fully addressed by the current European competition, data protection, and non-discrimination laws.

Incidences of price discrimination by retailers such as Staples, Home Depot, and Amazon have been identified in which the seller uses the buyer's IP address or location to individualize search results and prices [4,5,10–13]. Several papers in the literature have attempted to track price discrimination practices in online markets more widely, and to identify the variables upon which prices and search outcomes are based. Mikians et al. [14,15] studied the effect of the location, system specifics (operating system and browser), user persona (affluent vs. budget-conscious customers), and originating webpage on search results and prices. Hannak et al. [16] analyzed price discrimination and steering (where product ranking is changed across buyers). They collected information on users' location, the operating system used, and the purchase history. Badmaeva and Hullmann [17] tested for individualization of German online retailers through collecting user information including demographics, operating system, and purchase history.

The techniques for data collection varied across the papers. Mikians et al. [14] used a controlled experiment with PlantLab computing nodes. Mikians et al. [15] used crowdsourcing through a browser extension that enabled them to collect data on 1500 queries of 600 retailers by 350 users across 5 months. They concluded that price and search discrimination may have happened. Hannak et al. [16] recruited 100 users through Amazon's Mechanical Turk, and they collected the results of searches undertaken by these users of a predefined set of retailers. The results obtained from each user were compared to a control account. The user/control difference was compared to the control/control (twin account) to control for noise, which was a significant contribution of their paper. In their study, the price steering was measured through the Jaccard index, Kendall's τ, and nDGG. To study factors that might affect price discrimination and steering, they conducted controlled experiments where they controlled the variables to be analyzed, namely, account information, operating system and browser, and click and purchase history. Similarly, Badmaeva and Hullmann [17] compared search results across students and trained personas, and computed price differences.

In general, there is some evidence of individualization in online markets, yet there is some inconsistency regarding the variables upon which prices are based. Hinderman [13] found that individualization online is exercised by large retailers more than small ones, and when individualization was detected, it was based on either location, operating system, or some consumer characteristics. Mikians et al. [14], Mikians et al. [15], and Hannak et al. [16] found evidence of individualization. Mikians et al. [14] found that individualization is based on the origin URL of the user, location, and the spending behavior of the trained personas, but not on the operating system or the browser used. Mikians et al. [15] found price variability to be in the range of 10 to 30 percent. They found that location plays a role in prices and that some retailers varied prices across the US while others kept US prices constant and varied prices internationally. There was no difference in prices observed by affluent and budget-constrained individuals (unlike in their earlier paper), and some price difference was observed between users who logged in and those who did not when buying Kindle e-books. Hannak et al. [16] found evidence suggesting that individualization is based on operating system, browser, account, and purchase history. On the contrary, Vissers et al. [18] and Azzolina et al. [19] could not find evidence of individualization in the market for airline tickets. Badmaeva and Hüllmann [17] found no evidence of individualization in German online retail.

In this paper we ask whether Amazon individualizes search results. Our goal is to test the following two propositions.

Proposition 1. *Amazon offers a standardized menu, where it does not change the search results across different users.*

Proposition 2. *Amazon individualizes search results based on the user's characteristics.*

We proceeded to test these two propositions using the data we collected.

To test these two propositions, we investigated (1) whether participants reported identical search results, (2) whether products were offered at the same prices, (3) whether there is the relation between the results order and the products' prices, and (4) whether participants observed the same coupon menu. We found that search results varied significantly across participants in terms of content, order, and prices net of coupons. However, we could not find consistent evidence that variation in users' demographic variables, geolocation variables, and account characteristics explained variation in the search results observed after controlling for fixed effects of dynamic pricing through the day. We also found persistence in pricing and search results patterns; for example, users who receive coupons when they search for one product are more likely to receive coupons when they search for other products. The combination of these results suggests that individualization exists and is not simply based on demographic, geolocation, or account information. Instead, it is based on more complex user information e.g., browsing history and online behavior.

2. Materials and Methods

We collected data pertaining to search results on Amazon.com. Participants were recruited on Amazon Mechanical Turk, AMT (https://www.mturk.com/) and were paid USD 1 for their successful participation in the survey. Participants were directed to an online survey, and were instructed to answer some demographic questions, and questions about purchase history and Amazon account information. We instructed participants to conduct three searches, locate the first three search results, click to open each, take screenshots, and upload them to the survey. We used Gravity Forms (https://www.gravityforms.com/) to run our survey. We received 404 responses. Responses were manually checked, and those from outside the United States or having incomplete or bad quality images were filtered out. After filtering, our dataset comprised 324 responses. Filtered responses were then processed for data extraction. We used Google Cloud Platform Vision API (https://cloud.google.com/vision, accessed on 30 July 2022) to perform optical character recognition on the submitted images. The resulting text file for each scanned image was then parsed by custom scripts that we wrote to extract the data described in Section 2.2 Search Results Data.

2.1. Survey Participants' Data

We asked participants to provide personal information that we summarize in Table 1. Specifically, we asked them to provide demographic information regarding their gender, age, race, household size, and income bracket. We collected information regarding the number of hours they work every week. We also collected information regarding shopping patterns and shopping history online. For example, we asked them to report the percentage of grocery shopping undertaken online (referred to as share of online shopping in Table 1).

Table 1. Survey respondents' characteristic summary statistics. For categorical variables, the mean represents the percentage of observations belonging to the indicated category.

Category	Variable	Obs.	Mean	Standard Dev.	Min.	Max.
Gender	Male	324	0.44	0.50	0	1
	Female	324	0.56	0.50	0	1
Age	Age	324	33.75	9.43	18	71
Race	White	324	0.64	0.48	0	1
	Black	324	0.11	0.31	0	1
	Hispanic	324	0.09	0.29	0	1
	Asian	324	0.15	0.36	0	1
Household size	Number in household	324	3	1.49	1	9
	Number below 18	324	0.79	1.10	0	5
Work time	Hours worked per week	324	31	16.92	0	80
Income Bracket	0 to 20,000	324	0.13	0.34	0	1
	20,000 to 40,000	324	0.18	0.39	0	0
	40,000 to 60,000	324	0.18	0.39	0	1
	60,000 to 80,000	324	0.16	0.36	0	1
	80,000 to 100,000	324	0.09	0.29	0	1
	100,000 to 120,000	324	0.06	0.24	0	1
	120,000 to 140,000	324	0.05	0.21	0	1
	140,000 to 160,000	324	0.03	0.18	0	1
	160,000 to 180,000	324	0.04	0.20	0	1
	180,000 to 200,000	324	0.02	0.15	0	1
	Above 200,000	324	0.05	0.21	0	1
Shopping Behavior *	Share of online Shopping	314	25.73	27.48	0	100
Day of Search	January 18	324	0.20	0.40	0	1
	January 19	324	0.07	0.26	0	1
	January 20	324	0.02	0.16	0	1
	January 21	324	0.05	0.21	0	1
	January 22	324	0.07	0.25	0	1
	January 25	324	0.13	0.34	0	1
	January 26	324	0.08	0.28	0	1
	January 27	324	0.02	0.14	0	1
	January 28	324	0.02	0.12	0	1
	January 29	324	0.01	0.08	0	1
	February 8	324	0.15	0.36	0	1
	February 9	324	0.09	0.29	0	1
	February 11	324	0.03	0.18	0	1
	February 13	324	0.03	0.17	0	1
	February 15	324	0.02	0.16	0	1

Table 1. *Cont.*

Category	Variable	Obs.	Mean	Standard Dev.	Min.	Max.
Account Information	Amazon Account Only	324	0.28	0.45	0	1
	Amazon Prime Member	324	0.70	0.45	0	1
	None of the above	324	0.02	0.12	0	1
	Amazon Credit Card	324	0.20	0.40	0	1
Geographic Information *	Miles to fulfillment center	316	61.22	139.27	1.75	2277.30
	Minutes to fulfillment center	316	87.10	367.64	5.29	6515.20
	Median Income of Zip Code	323	70976	29538	6815	213724
	Same Zip Code	324	0.93	0.25	0	1

* Geographic information and shopping behavior were missing for some participants.

We asked participants to provide information regarding the type of Amazon account they had, if any (Amazon Account, Prime membership, or none), and whether they had an Amazon credit card. Finally, we collected geographic information of participants by asking them to provide the zip code of the location where they completed the survey. We then used the Census data to find the median income of the zip code areas provided (Information available at: https://www.incomebyzipcode.com). We also used their location to calculate the distance to the nearest fulfillment center. For data regarding the Amazon fulfillment center network in the US, we used information provided by MWPVL International (Information available at: https://www.mwpvl.com). MWPVL online services provides Amazon Fulfillment locations by state. It also provides fulfillment center classification, e.g., large (small) sortable, large (small) non-sortable, and specialty centers (MWPVL, 2021). We only considered fulfillment centers that process the products analyzed when calculating driving distance using ESRI ArcGIS software. Based on this, we also calculated travel time in minutes. We also collected information on the date that the survey was taken. Ideally, we wanted participants to search for the assigned products within a narrow time period; however, it was difficult to generate a large enough dataset while restricting participation to a narrow time period due to our limited ability to determine daily participation.

Table 1 summarizes the survey respondents' characteristics. On average, our respondents lived in households having a size of 3, and 0.79 members of those households were less than 18 years old. About 50% of the households earned an income less than USD 60,000 and worked 31 h per week on average. It is also interesting to note that 28 percent of the survey participants had an Amazon account, 70% had the paid Amazon Prime membership, and only 2% had none. It is worth noting that survey participants did not necessarily have Amazon accounts. On average, a household bought 25.73% of its groceries online. An average household lived 61 miles from an Amazon Fulfillment center and lived in an area where the median income is USD 71 K. We collected data on miles to the nearest fulfillment center to approximate the cost of servicing. We included this variable in the regression analysis.

2.2. Search Results Data

We asked participants to conduct three searches on Amazon.com for a variety of products that are sold in different sizes and, therefore, at different prices. Specifically, we asked participants to search for toothpaste, Method body wash, and hand sanitizer. The variety of products provided a better opportunity to analyze and detect individualization. For example, two search terms were general, i.e., toothpaste and hand sanitizer, whereas the search for body wash was limited to a particular brand. Moreover, hand sanitizer is a product with a changing demand pattern due to the COVID 19 pandemic. Although there was an increase in demand for hand sanitizer due to the beginning of the pandemic at the end of 2019, there was a significant decrease in January and February of 2021 [20].

For each product, we collected data on the first three search results obtained by each participant. Research suggests that the first three search results on Amazon receive 64% of the clicks [21]. Thus, we believe that limiting data collection to the first three search results provided an adequate representation of the products intended for a given buyer. We used the uploaded screenshots to extract the following variables, for each of the three search results reported by the participants: Amazon Standard Identification Number (ASIN), brand name, product size, price, and coupon value (0 if none). ASIN is a unique number that identifies each product on Amazon by brand and size. In addition, we recorded the order in which products appeared in the search results for each survey participant and the number of "sponsored by Amazon" products in the search results

3. Results

We analyzed the variation in search results across participants. We then identified how these variations correlate with participant characteristics. We found that variation in most consumer characteristics does not explain variation in search results. However, we found correlation in some search variables across the three searches.

3.1. Variation in Search Outcomes

We first considered the price of each search result net of any coupons offered. Coupons are offered as either dollar-off coupons or as percentage discount off the gross price; only 19% of all search results in our data offered a coupon. We observed high standard deviations, as shown in Table 2, when considering the net price of the first search result, the average net price across all three results for a given product, and the net price per ounce of the first search result. Note that the product displayed as a first search result varied across participants, and thus the price of the first search result does not necessarily correspond to a given product.

We also compared prices of a given product ASIN across participants who observed that product in their search results. Figure 1 shows the frequency distribution of the search results by ASIN. It also shows the number of times a given product appeared as first, second, or third in the search results.

Note that there is a large pool of products displayed across all search results (24 ASINs for toothpaste, 34 ASINs for Method body wash, and 46 ASINs for hand sanitizer), which may constitute evidence of individualization. Furthermore, coupons for a given ASIN were not offered consistently. Figure 2 shows the number of participants receiving a given ASIN and the number of participants receiving a coupon for that ASIN, which was smaller. Thus, coupon offering was not consistent across products; some products did not offer coupons, and most of those that offered coupons did so inconsistently across participants, as is clear from Table 3. It is worth noting that the three ASINs in Table 3 that consistently offered coupons to participants rarely appeared in the search results (specifically 1, 2, and 3 times only). We use Figure 3 to illustrate inconsistent coupon offering by showing the gross and net price for a given ASIN across participants that received that product.

To check for correlation between coupon offering and gross price, we compared, for all ASINs offering coupons, the average gross price across the participants who received a coupon and those that did not. The results, included in Table 4, show that, of the 16 ASINs in our data where coupons were offered, 4 had an increase in the gross price for listings with coupons, 4 had a decrease in price, and 8 did not change, suggesting that Amazon does not increase the gross price when they offer coupons to customers.

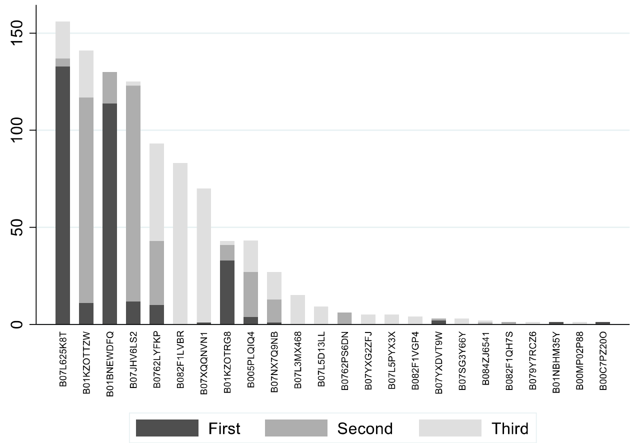
Table 2. Search results summary statistics.

Product	Variable	Obs.	Mean	Standard Dev.	Min.	Max.
Toothpaste	Net price of first search result	324	10.43	3.35	5.44	20.91
	Average Net Price	324	10.74	2.98	5.44	17.28
	Net price/Oz of first search result	324	0.70	0.43	0.20	2.00
	Average Net Price/Oz	324	0.84	0.25	0.41	1.53
	Size of the first search result *	324	21.01	11.18	3	36
	Number of Coupons	324	1.25	1.10	0	3
	Number of sponsored results	324	2.49	1.07	0	3
	Overlap coefficient	46,360	0.32	0.38	0	1
Method Body Wash	Net price of first search result	324	37.74	8.92	0	41.94
	Average Net Price	323	29.15	3.85	10.53	38.28
	Net price/Oz of first search result	324	0.45	0.17	0	1.64
	Average Net Price/Oz	323	0.56	0.14	0.31	1.52
	Size of the first search result *	324	93.50	30.93	16	108
	Number of Coupons	324	0.23	0.43	0	2
	Number of sponsored results	324	1.63	0.85	0	3
	Overlap Coefficient	46,360	0.39	0.30	0	1
Hand Sanitizer	Net price of first search result	321	19.70	12.02	3.49	54.99
	Average Net Price	309	25.40	8.02	13.88	91.87
	Net price/Oz of first search result	321	0.27	0.23	0.02	2.31
	Average Net Price/Oz	309	0.39	0.15	0.17	1.38
	Size of the first search result *	324	78.8	67.17	7.93	1152
	Number of Coupons	324	0.25	0.44	0	2
	Number of sponsored results	324	1.62	0.76	0	2
	Overlap coefficient	46,360	0.25	0.27	0.33	1

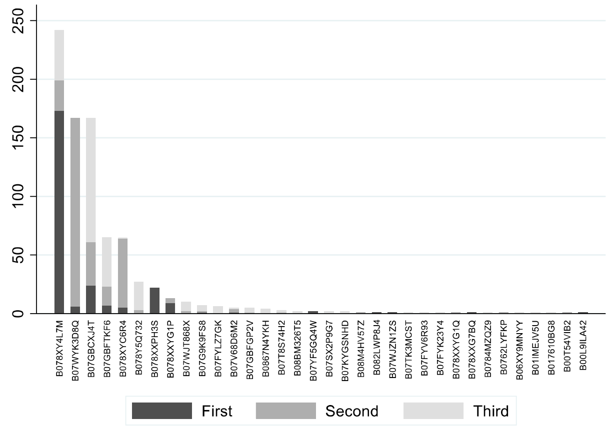
* Size is measured in ounces.

Table 3. Distribution of ASINs by coupon offering. Soap: Method body wash.

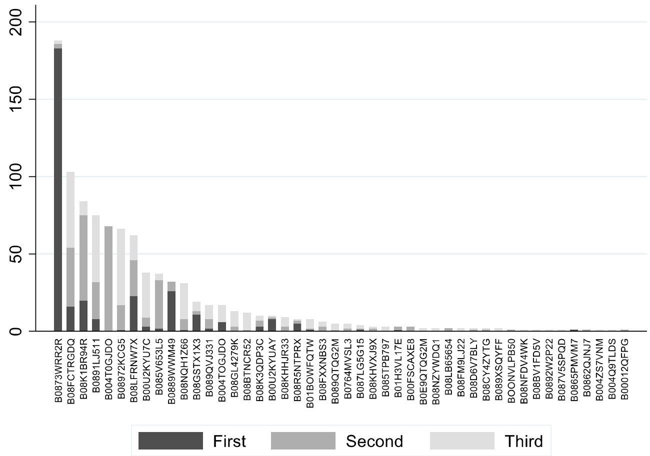
	Toothpaste	Soap	Hand Sanitizer
Number of ASINs with coupons offered	7	3	6
Number of ASINs with coupons offered to all participants receiving that ASIN	1	0	2



(a) Toothpaste



(b) Method Body Wash



(c) Hand Sanitizer

Figure 1. Frequency distribution of search results by ASIN.

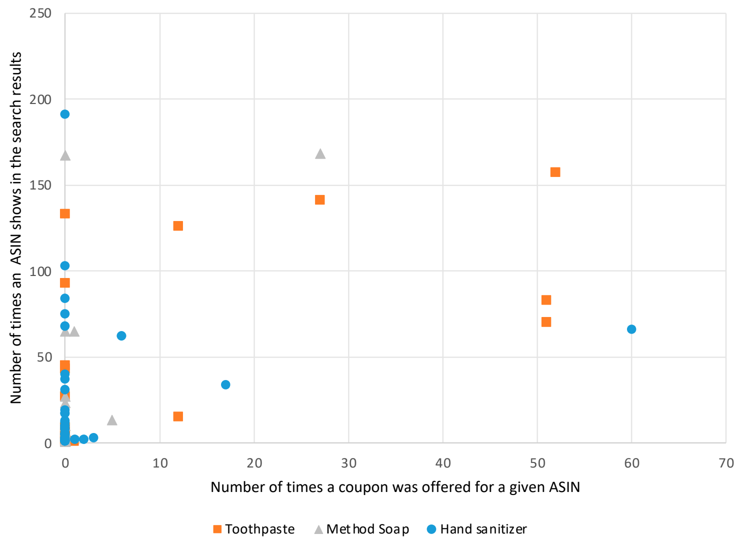


Figure 2. Number of coupons offered by ASIN.

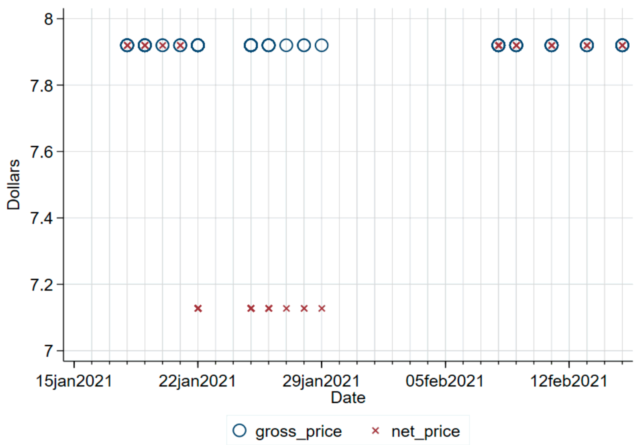


Figure 3. Example gross and net prices for a 6-pack of Colgate Cavity Protection Toothpaste with Fluoride (ASIN B01BNEWDFQ). Keepa (https://keepa.com/) was used to track gross prices. Keepa indicates that gross prices may vary across time but not across participants, which was confirmed by our data.

Table 4. Comparison between gross price for listings with and without coupons.

Product	ASIN	Average Gross Price for Listings with Coupon	Average Gross Price for Listings without Coupon	% Increase for Listings with Coupons
Toothpaste	B07L625K8T	17.99	15.11	19%
	B07XQQNVN1	14.99	14.99	0%
	B082F1LVBR	11.96	11.96	0%
	B01KZOTTZW	16.29	16.72	−3%
	B07L3MX468	6.98	8.96	−22%
	B079Y7RCZ6	16.47	16.47	0%
	B07JHV6LS2	10.32	10.12	2%
Method Body Wash	B07WYK3D8Q	15.96	15.96	0%
	B078XXYG1P	20.81	20.85	0%
	B00FSCAXE8	15.60	15.60	0%
	B08NZYWDQ1	17.74	15.60	14%
	B078XY4L7M	41.88	41.77	0%
	B078XYC6R4	20.31	20.37	0%
Hand Sanitizer	B08972KCG5	29.99	24.99	20%
	B0889WWM49	27.62	28.96	−5%
	B08LFRNW7X	19.77	19.96	−1%

To investigate variation in search results across participants, we used the overlap coefficient. The overlap coefficient is a measure of the similarity between two individual's search results. For each of the three searches, we calculated an overlap index, O_{ij}, for each pair of participants i and j. We define the overlap coefficient to be the number of matches, irrespective of the order, in the search results for a product received by participants i and j divided by 3 (the number of reported results). O_{ij} can takes values of 0 for no overlap, 0.333 or 0.667 for partial overlap, and 1 for an exact match. Table 2 shows significant level of variability for all three products. The highest overlap was observed in the case of the specific brand search relative to the other two general product searches (the average overlap coefficient for Method body wash was 0.39 relative to 0.32 for toothpaste and 0.25 for hand sanitizer). We also investigated if the observed variation was affected by whether searches were undertaken on the same day or on different days. Figure 4 details the distribution of the correlation coefficient divided by this factor. The figure shows that searches undertaken on the same day had a higher percentage of an overlap coefficient of 1 and a lower percentage of a coefficient of 0, compared to their counterparts for searches on different days, for all three products. However, the average overlap coefficient remained low for same-day searches for all three products (results in Table 5)

Table 5. Average overlap coefficient between the search results of each product for pairs of searches undertaken on the same day and pairs of searches undertaken on different days.

	Toothpaste	Method Body Wash	Hand Sanitizer
Same Day Searches	0.45	0.44	0.37
Different Day Searches	0.31	0.39	0.23

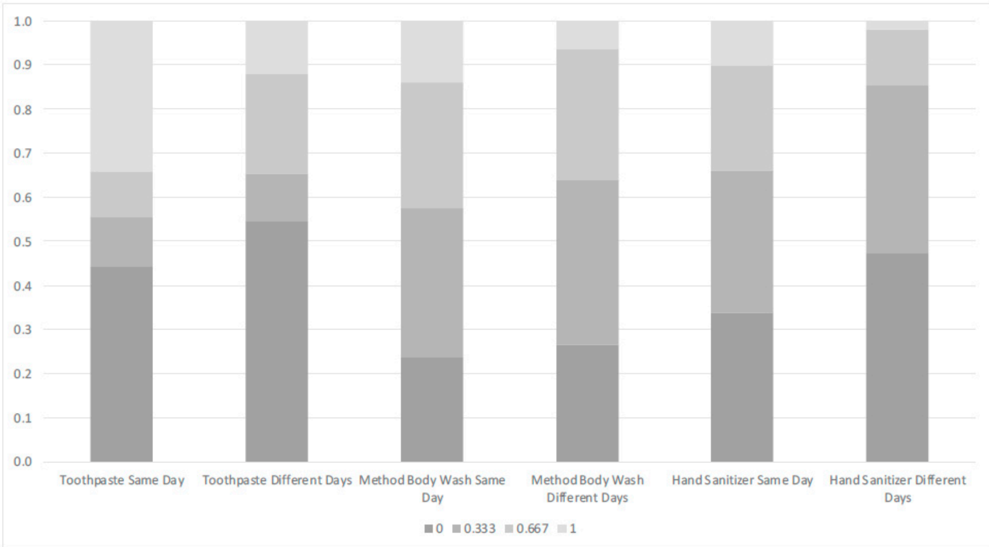


Figure 4. Comparison between the distribution of the overlap coefficient for searches undertaken on the same day and searches undertaken on different days, for each of the three products. Each bar shows the percentages of participant pairs in the specified category (same day/different days) having an overlap coefficient of 0, 0.33, 0.66, and 1. Same-day pairs, n = 5749. Different-day pairs, n = 46,901.

We investigated whether the net price of a product was a factor in deciding the ranking of that product in the search results. For each of the three product categories, we performed pairwise comparisons between the lists of net prices that appeared in each rank (i.e., first search result, second search result, third search result). Table 6 shows the results of the paired one-tail T-test. Although the T-test showed that the difference in the average net price between search results i and j (referred to as rank i and j in Table 6), for i, j = 1, 2, 3 for three product categories, was statistically significant, there was no consistent trend for the change in averages. For example, for toothpaste, the average net price of rank 1 was less than that for rank 2, which was greater than that for rank 3. We found no significant relationship between the price and the rank of the product in the search results.

Table 6. Comparison between the price of a product and where it appears on the search results. * Comparison is performed using the paired one-tail T-test.

	Rank in Search Results	**Rank 1**	**Rank 2**	**Rank 3**
Toothpaste	Average Net Price	10.43	11.07	10.75
	Compare to Rank 2 *	8.7×10^{-5}		
	Compare to Rank 3 *	0.04	0.04	
Method Body Wash	Average Net Price	37.74	19.83	29.98
	Compare to Rank 2 *	8.4×10^{-59}		
	Compare to Rank 3 *	1.2×10^{-19}	7.7×10^{-28}	
Hand Sanitizer	Average Net Price	19.70	30.63	25.73
	Compare to Rank 2 *	1.0×10^{-22}		
	Compare to Rank 3 *	6.1×10^{-8}	9.4×10^{-6}	

3.2. Explaining Variation in Search Outcomes

Variation in search results constitutes necessary, but not sufficient, evidence, to prove that Amazon uses an individualized pricing strategy. To show that Amazon individualizes search results, we need to establish a relationship between the search outcomes and the individual demand level, as stated in Proposition 2. We tested to determine if variation in participant characteristics could explain the variation in search results listed in Table 2. Specifically, we analyzed differences in product prices, sizes, number of coupons, and the number of "sponsored by Amazon" products. We regressed each of those variables on the consumer characteristics summarized in Table 1, in addition to the day fixed effects. Thus, we controlled for gender, age, race, household size, the number of individuals below age 18 that live in the household, the number of hours the individual works per week, the share of online shopping, income, and the type of Amazon account. The day fixed effects allowed us to control for dynamic pricing and, thus, disentangle variation in outcomes that can be attributed to the time a consumer searched for the products, given our data was collected over 15 days. We included the median area income as one of the explanatory variables. We also included distance to the nearest fulfillment center to test if variations in search results, specifically prices, could be explained by shipping cost differences.

The regressions, summarized in Tables S1–S5, showed no consistent significant effect of demographic, geographic, or account information on the search outcome variables. A few exceptions can be noted. For toothpaste, hours worked per week had a negative and significant impact on the number of coupons received (Table S1). For Method body wash, household size had a positive and significant impact on the net price of the first search result, and the package size of the first search result (Tables S2 and S3), suggesting that larger households are offered larger and more expensive products. For hand sanitizer, males received a higher net price (Table S2) and larger households received larger packages as their first search result (Table S3). Moreover, for hand sanitizer, Amazon Prime members received lower average net prices (Table S4), through being offered cheaper products and not through coupon offerings (e.g., the Amazon Prime regression coefficient is not significant in Table S1). For hand sanitizer and Method body wash, households with a larger number of individuals under age 18 were offered more sponsored search results (Table S5).

We also considered the effect of a product not being sold by Amazon on the net price of the first search result and its effect on the size of the first search result (Tables S2 and S3, respectively). For the Method body wash product, not being sold by Amazon had a negative and statistically significant impact on the net price of the first search result. For toothpaste and Method body wash products, not being sold by Amazon had a negative and statistically significant impact on the size of the first search result. These results suggest that products sold by a third party are associated with differences in outcomes observed in the first search result.

Finally, it is also important to emphasize that all our regressions included day fixed effects. Our results indicate some evidence of dynamic pricing since some of the search outcomes we measured depended on the day of the search. More specifically, day fixed effects were statistically significant in several regression specifications. However, day fixed effects were not consistently significant across all products or all search outcome variables.

3.3. Are Search Results Individualized?

The inability of participant characteristics to consistently explain differences in search outcomes across users raises concerns that search results might be randomly generated. To test this, we explored the persistence of particular patterns across searches for a given participant. In particular, we examined whether the search result variables listed in Table 2 were correlated across the different searches. For example, we asked if the number of coupons displayed when searching for toothpaste was correlated with the number of coupons observed when searching for Method body wash or hand sanitizer, for a given participant. We report the results in Tables 7–10.

Table 7. Pairwise correlation matrix for the average net price. Soap is Method body wash. * $p < 0.01$.

	Toothpaste	Soap	Hand Sanitizer
Toothpaste	1		
Soap	0.21 *	1	
Hand Sanitizer	0.10	−0.07	1

Table 8. Pairwise correlation matrix for the size of the first search result. Soap is Method body wash. * $p < 0.01$.

	Toothpaste	Soap	Hand Sanitizer
Toothpaste	1		
Soap	0.33 *	1	
Hand Sanitizer	−0.01	−0.02	1

Table 9. Pairwise correlation matrix for the total number of coupons. Soap is Method body wash. * $p < 0.01$.

	Toothpaste	Soap	Hand Sanitizer
Toothpaste	1		
Soap	0.43 *	1	
Hand Sanitizer	−0.09	−0.04	1

Table 10. Pairwise correlation matrix for the net price of the first search result. Soap is Method body wash.

	Toothpaste	Soap	Hand Sanitizer
Toothpaste	1		
Soap	−0.09	1	
Hand Sanitizer	0.03	−0.08	1

We observed significant correlation in several search variables for toothpaste and Method body wash. We found a positive correlation in the average net price of the two products (Table 7), suggesting that participants who received low net prices for toothpaste were likely to receive low net prices for Method body wash. Similarly, we observed a significant correlation in the size of the first product (Table 8) and the number of coupons received (Table 9). No significant correlation was detected when considering the price of the first search result (Table 10).

However, we did not observe a significant correlation in search results for hand sanitizer and toothpaste, nor for hand sanitizer and Method body wash.

4. Discussion

The analysis showed variation in search results in terms of the products displayed, the ranking of products, the coupon offering, and the value of the coupon offered. As expected, we found larger variability in the search results for the two general products (tooth paste and hand sanitizer), compared to the brand-specific search for Method body wash. We found that coupons were not consistently offered for a given product and that coupon offerings varied across individuals. In short, we did not find support for a standardized menu scenario as described in Proposition 1.

Based on the results of the regression analysis, in general, individual characteristics and demographic, geographic, and account information, did not play a consistent and significant role in explaining search results. Additionally, for all three products, distance to the nearest fulfillment center had no significant impact on the prices observed (or other search variables), which suggests that cost differentials driven by shipping cost play no role in price differentials. We conclude that the data do not provide support for Proposition 2, i.e., that survey respondents' characteristics are the basis for individualization. Since the data do not support the standardized menu suggested by Proposition 1, this implies that either no individualization is implemented, and that search results are generated randomly or possibly through A/B testing, or that individualization is based on variables other than the consumer characteristics reported in Table 1.

The results of the correlation analysis for different variables support the latter statement. The analysis indicates a correlation between toothpaste and Method body wash for the number of coupons the participants received, the size of the first search result, and average net price. This suggests that search results for toothpaste and Method body wash are individualized. In contrast, there was lack of a significant correlation in search results for hand sanitizer and toothpaste, and for hand sanitizer and Method body wash, which suggests that search results for hand sanitizer are not individualized. One probable explanation is that the decline in demand for hand sanitizer during January and February of 2021 caused this lack of individualization, as the search algorithm was going through a process of learning the new demand pattern based on the most recent data of consumer purchases. Thus, individualization may be interrupted as the algorithm collects new information and optimizes accordingly.

It is also worth emphasizing that there are other plausible explanations. For example, a reasonable explanation for the results observed in this study is the existence of stockouts. Stockouts would influence the set of products that consumers are shown. Unfortunately, it is extremely difficult to obtain and collect data that indicate when an item is out of stock. Hence, in this study, we could not test for this dimension in a credible way. Finally, advertising budget constraints can also influence which set of products appears near the top, especially for sponsored listings. In this case, it is also difficult to obtain data.

Our analysis provides some evidence that search results are individualized. However, this individualization is not based on the consumer demographic, geolocation, or account information, as is clear from the earlier regressions. We conclude that individualization is therefore based on other consumer characteristics not captured by our study. It is likely that individualization is based on more dynamic information, e.g., the consumer click history and online browsing behavior.

5. Conclusions

In this study, an empirical analysis was undertaken to investigate individualization in online markets with a focus on Amazon.com. We collected search results data for individuals who shopped for assigned products on Amazon.com. We also collected individuals' information, particularly demographic information, geolocation information, and Amazon account information. We found significant variation in search results across consumers, which is a necessary condition for individualization. However, we did not find significant support for Proposition 2, in which we assumed that the demand level is correlated with consumer demographic, geolocation, and account information. Some evidence of dynamic pricing was found, but this was not sufficient to explain the variation in search outcomes. Thus, we could not explain the variation in search results based on the consumer information we goatherd. However, we found persistence of certain patterns across products for a given participant. For example, participants who received coupons when they searched for toothpaste were likely to receive coupons when they searched for Method body wash. Our results suggest that search results are individualized. This conclusion is further supported by the lack of similar observations when we consider the product that experienced a recent change in demand pattern. This also suggests that some consumer information, other than demographic, geolocation, and account information, is tracked and utilized by online sellers to determine search results. This raises concerns regarding the type of consumer information that online sellers track, and the effect of individualization on search results and prices.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/jtaer17030061/s1, Table S1: Regression of Total Number of Coupons on Survey Respondents' Characteristics; Table S2: Regression of Net Price of First Search Result on Survey Respondents' Characteristics; Table S3: Regression of Size of First Search Result on Survey Respondent Demographic Variables; Table S4: Regression of Average Net Price on Survey Respondents' Characteristics; Table S5: Regression of Spearman's Rho on Survey Respondents' Characteristics.

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References

1. Young, J. *US Ecommerce Grows 14.2% in 2021*; Digital Commerce 360: Gurnee, IL, USA, 2021.
2. Valentino-De Vries, J.; Singer-Vine, J.; Soltani, A. Websites vary prices, deals based on users' Information. *Wall Str. J.* **2012**. Available online: https://www.wsj.com/articles/SB10001424127887323777204578189391813881534 (accessed on 29 March 2022).
3. Venture Beat. Staples, Home Depot, and Other Online Stores Change Prices Based on Your Location. 2012. Available online: https://venturebeat.com/ (accessed on 30 July 2022).
4. Zuiderveen Borgesius, F.; Poort, J. Online price discrimination and EU data privacy law. *J. Consum. Policy* **2017**, *40*, 347–366. [CrossRef]
5. BBC News. Travel Site Orbitz Offers Mac Users More Costly Hotels. Available online: https://www.bbc.com/news/technology-18595347 (accessed on 29 March 2022).
6. Shiller, B. Approximating purchase propensities and reservation prices from broad consumer tracking. *Int. Econ. Rev.* **2020**, *61*, 847–870. [CrossRef]
7. Zuiderveen Borgesius, F. Improving Privacy Protection in the Area Of Behavioral Targeting. 2015. Available online: https://ssrn.com/abstract=2654213 (accessed on 29 March 2022).
8. Steppe, R. Online price discrimination and personal data: A general data protection regulation perspective. *Comput. Law Secur. Rev.* **2017**, *33*, 768–785. [CrossRef]
9. Sears, A.M. The limits of online price discrimination in Europe. *Columbia Sci. Technol. Law Rev.* **2019**, *21*, 1–42.

10. Zuiderveen Borgesius, F.J. Strengthening legal protection against discrimination by algorithms and artificial intelligence. *Int. J. Hum. Rights* **2020**, *24*, 1572–1593. [CrossRef]
11. Kliman-Silver, C.; Hannak, A.; Lazer, D.; Wilson, C.; Mislove, A. Location, location, location: The impact of geolocation on web search personalization. In Proceedings of the 2015 Internet Measurement Conference, Nice, France, 25–27 October 2022; pp. 121–127.
12. Townley, C.; Morrison, E.; Yeung, K. Big data and personalized price discrimination in EU competition law. *Yearb. Eur. Law* **2017**, *36*, 683–748. [CrossRef]
13. Hindermann, C.M. *Price Discrimination in Online Retail*; ZBW-Leibniz Information Centre for Economics: Kiel/Hamburg, Germany, 2018.
14. Mikians, J.; Gyarmati, L.; Erramilli, V.; Laoutaris, N. Detecting price and search discrimination on the internet. In Proceedings of the 11th ACM Workshop on Hot Topics Networks (HotNets-XI), Redmond, WA, USA, 29–30 October 2012; pp. 79–84. [CrossRef]
15. Mikians, J.; Gyarmati, L.; Erramilli, V.; Laoutaris, N. Crowd-assisted Search for Price Discrimination in E-Commerce: First Results. In Proceedings of the Ninth ACM Conference on Emerging Networking Experiments and Technologies, Santa Barbara, CA, USA, 9–12 December 2013; pp. 1–6. [CrossRef]
16. Hannak, A.; Soeller, G.; Lazer, D.; Mislove, A.; Wilson, C. Measuring price discrimination and steering on e-commerce websites. In Proceedings of the 2014 Conference on Internet Measurement Conference (IMC'14), Vancouver, BC, Canada, 5–7 November 2014; pp. 305–318. [CrossRef]
17. Badmaeva, T.V.; Hüllmann, J.A. Investigating personalized price discrimination of textile-, electronics-and general stores in German online retail. In Proceedings of the 14th International Conference in Wirtschaftsinformatik, Siegen, Germany, 24–27 February 2019.
18. Vissers, T.; Nikiforakis, N.; Bielova, N.; Joosen, W. Crying wolf? On the price discrimination of online airline tickets. In Proceedings of the 7th Workshop on Hot Topics in Privacy Enhancing Technologies (HotPETs 2014), Amsterdam, The Netherlands, 18 July 2014.
19. Azzolina, S.; Razza, M.; Sartino, K.; Weitschek, E. Price discrimination in the online airline market: An empirical study. *J. Theor. Appl. Electron. Commer.* **2021**, *16*, 2282–2303. [CrossRef]
20. Bomey, N. Panic Buying? Not Anymore. Suddenly There's a Surplus of Hand Sanitizer. USA TODAY, 2021. Available online: https://www.usatoday.com/story/money/2021/04/08/hand-sanitizer-deals-donations-surplus-panic-buying-pandemic/7120815002/ (accessed on 8 April 2021).
21. Loren, B. Amazon's search engine ranking algorithm: What marketers need to know. *Search Engine J.* **2018**. Available online: https://www.searchenginejournal.com/amazon-search-engine-ranking-algorithm-explained/265173/ (accessed on 29 March 2022).