

ATTENTION AND SALIENCY ON THE INTERNET: EVIDENCE FROM AN ONLINE RECOMMENDATION SYSTEM*

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March 3, 2019

ABSTRACT

Using high-frequency product-level data from an online retail store, we examine whether consumer choices on the internet are consistent with models of limited attention. We test whether consumers are more likely to buy products that receive a saliency shock when they are recommended by new products. We find a sharp and robust 6% increase in the aggregate sales of existing products after they are recommended by a new product. We also establish that the spillover effects of saliency on products further away in the recommendation network are small, suggesting that returns to search via the recommendation network diminish swiftly. Using a structural model we find that saliency has large effects on consumer consideration but a smaller effect on their subsequent choice, conditional on consideration. Counterfactuals suggest that limited attention disproportionately harms top-selling products but recommendation systems can alleviate these search frictions.

KEYWORDS: Limited attention, advertising, online markets.

JEL Classification: D22, M30

*We thank Kim Montalibet and Elango Venkatachalapathy who provided excellent research support; their input was essential and invaluable. We thank also Romain Aeberhardt, Yann Bramouille, Andrew Ching, Jishnu Das, Alessandro Iaria, Yinghua He, Ali Hortacsu, Lian Jian, Bruno Jullien, Thierry Kamionka, Francis Kramarz, Laurent Linnmer, Oliver Linton, Marco Mariotti, Sendhil Mulainathan, Carlos Ponce, Matthew Shum, Anand Srivastava, Catherine Tucker, and seminar/conference participants at Aix-Marseille School of Economics (GREQAM), Cambridge-INET/Cemmap Workshop on Economic and Econometric Applications of Big Data, CREST, ENSAE-Berekely DataLead Conference, Georgetown University, the NBER Summer Institute, 2nd Empirical Microeconomics Workshop Banff, XX LACEA Annual Meeting, TSE 9th bi-annual Postal Economics Conference on E-commerce, the Searle Center 7th Annual Conference on Internet Commerce and Innovation, the Federal Communication Commission, and the 13th Annual International Industrial Organization Conference for their useful comments and suggestions. Financial support from the LABEX ECODEC (ANR-11-IDEX-0003/Labex Ecodec/ANR-11-LABX-0047) and INET is gratefully acknowledged.

1 INTRODUCTION

A standard simplifying assumption about consumer behaviour is that consumers consider all alternatives when making choices. However, exercising choice requires awareness of all available options which may be limited by search costs or by cognitive overload over the number and variety of products available to a consumer (Sims 2003; Caplin et al. 2011; Besedes et al. 2015). Many e-commerce websites offer thousands of products for sale even within narrowly defined sub-categories. For instance, Amazon offers more than 3,000 options for buying a television. Further narrowing of search in this category produces at least 190 options.¹

A growing literature on the nature of consumer search on the internet has documented that despite the low physical search costs associated with internet browsing, there appears to be a prevalence of search frictions due to a scarcity of attention towards the large variety of available choices (Dinerstein et al. 2014). In the face of very large choice sets in these settings, it is plausible that consumers may try to simplify decisions by examining a smaller set of products (Masatlioglu et al. 2012) and product attributes (Bronnenberg et al. 2016). For example, Kim et al. (2010) report that consumers typically only search for 11% of all available options (for camcorders) on Amazon. Experimental evidence too, confirms that limits to attention impose a bottleneck on processing stimuli (Mozer and Sitton 1998).

In view of this, many online marketplaces frequently engage in tactics to attract user attention towards their products. Eliaz and Spiegler (2011) show that marketing devices employed by firms are likely to influence the set of products that a consumer chooses to consider, termed her *consideration set*. Hauser and Wernerfelt (1990) find empirically that consumer consideration sets respond to actions by firms that increase the visibility or salience of products. Advertising as a tool to influence consideration sets has been studied extensively in the marketing literature (Draganska and Klapper 2011; Barroso and Llobet 2012). Another such tool, the product recommendation system, through which a subset of products are selectively highlighted to users, is increasingly used by firms to attract attention and increase awareness towards products (Fleder and Hosanagar 2007). Yet, field evidence on the effectiveness of such recommendations, and indeed how they affect consumer choice, is limited. A small body of experimental studies in the laboratory find that subjects who receive recommendations for a product are more likely to select it relative to those who do not receive them (Senecal and Nantel 2004; Huang and Chen 2006). Kim et al. (2010) use aggregate product search data from Amazon and find in a policy simulation that a recommen-

¹The applied search filters are: Home Entertainment, 50-59 inches, 1080p resolutions, flat screen.

dation system, highlighting popular products, significantly affects their demand and lowers search costs.

In this paper, we examine whether consumer choice online is influenced by impersonal product recommendations. To investigate the question, we use data from an exclusively online retail store, which offers a list of product recommendations for every product available on the website; these recommendations are not personalized and just based on observable attribute similarity. We focus on two objectives: the first is to provide causal evidence on the extent to which recommendations affect aggregate product sales, independent of product popularity or underlying characteristics. Our second objective is to examine whether the saliency effect generated by product recommendations limits consumer attention to a smaller consideration set.

Our identification strategy focuses on product recommendations coming from the arrival of new products. Since new products are highly viewed upon arrival, we focus on the aspect of product *saliency*, that is, the prominence of a product in a consumer's mind. We analyze what happens to the sales of an existing product after it is recommended by new products. Since new products are highly salient, the recommended existing product receives a positive "saliency shock." We exploit both the timing of new product arrivals, which highlight a set of similar products already available on the website (the recommendation set), and regional variation between Europe and the U.S. in recommendation sets to identify our saliency effect. Our double difference-in-difference strategy allows us to difference out both product-by-time and region-by-time unobservables. In addition we are able to employ new-product fixed effects to absorb any possible correlation between characteristics of new products and the products they recommend, ensuring that these saliency shocks are treated as exogenous with respect to the individual existing recommended products.

There is, by now, a large literature on the effect of salience measured via product popularity on sales (see for example, [Sorensen \(2007\)](#), [Carare \(2012\)](#), [Cai et al. \(2009\)](#) and [Tucker and Zhang \(2011\)](#)). However, such evidence cannot rule out the possibility that the visibility of such goods actually imparts information. The effect of being on the first page or being popular also captures latent product quality or price-based relevance. [Narayanan and Kalyanam \(2015\)](#) and [Ursu \(2017\)](#) address this concern in the context of search rankings by relying on quasi-experimental and experimental variation in the data. Our approach differs from the existing literature as we focus on the effect of saliency shocks generated by recommendations from new product arrivals. The saliency of new products is useful because it generates a "spillover saliency" effect for existing products that are recommended by the new product. Our identifi-

cation strategy, therefore, allows us to distinguish between pure saliency and information/popularity effects. In related work, [Oestreicher-Singer and Sundararajan \(2012\)](#) evaluate a product’s recommendation network on Amazon and find that the visibility of the product network can result in up to a threefold average increase in the influence that complementary products have on one another’s demand. Our empirical approach is different in that we evaluate the sales differential of products made salient through the recommendation network over time. [Oestreicher-Singer and Sundararajan \(2012\)](#) rely on various secondary market characteristics as instruments to mitigate bias from endogenous network selection effects and other correlated effects; instead, we identify our effects using shocks to the recommendation system as well as the rich panel and exogenous regional variation in our setting. In addition, we also highlight the mechanism of consumer consideration to explain the recommendation effect on sales.

Our paper also benefits from the feature-rich retail environment, typical of online markets. We use information on the extensive system of product recommendations, separately provided for products that act as substitutes and complements, to examine heterogeneity in the saliency effect as well as to identify externalities generated by the saliency shock on other linked products in the recommendation network. In addition, we are able to understand how such saliency effects diffuse over time based on the dynamic updating of the online product catalogue.

Our results indicate a sharp and robust 6% increase in sales of products after they receive a saliency shock. This saliency effect is short-lived, with the majority of the effect concentrated around the day that the product receives the saliency shock, diminishing rapidly thereafter. The effect completely disappears three days after the saliency shock has been received when the next batch of new products is launched on the platform. Such a pattern of effects, with a prominent spike in a product’s sales on the day that they are recommended, is consistent with the attention-based explanation that products receiving a saliency shock have been previously overlooked by consumers. The lack of persistent long-term effects on sales is in fact incompatible with selection-based explanations which would imply that recommended products would have experienced an increase in sales regardless of the recommendation.² Further, we also find significant (positive) spillover effects. Products recommended by saliency-shock-affected products also see an increase in their sales on the day that new products are launched,

²All our specifications include (panel) leads on the saliency shock variable, as well as their cumulative pre-saliency status, to mitigate the concern of anticipation effects. Our results consistently show insignificant effects for the included leads. In addition, our alternative identification strategy, which exploits regional variation in the composition of recommendation sets, relies only on a common trends assumption between a recommended and non-recommended product *for the same new product*. We show that this assumption is empirically validated in our data.

but to a much lesser extent.

To ensure that the mechanism for the observed effect is indeed product salience and hence a change in a consumer's consideration set, we carry out a range of additional tests. First, we investigate whether the saliency effect depends on the size of recommendation sets. If saliency drives our results, we should see stronger effects the smaller the set of recommended products. We indeed find that the effect of product recommendations is larger for products recommended in smaller sets, suggesting that consumers pay attention to products that are more visible. Next, we test whether the effect depends on the difference between product price of recommended and recommending products. If product recommendations affect consumer choices by changing the consideration set, such price differences should have no effect. This is what we find, price differences do not affect consumer choices.

In addition to these reduced-form checks, we use a random utility model to investigate more directly how consumer demand is affected by recommendations. The random utility model incorporates the formation of a consideration set in the first stage of a consumers' decision making process and therefore allows us to explore directly the mechanics behind the strong, short-lived saliency effect. We find that saliency has a strong, positive effect on the consideration (of existing products) but no further effect on choice, conditional on consideration. We find that the saliency effect is higher within sub-categories where only a few choices are considered. These results should be seen as supportive rather than complete, because we do not have data at the individual consumer-level that would allow the estimation of a full structural model. That said, this analysis – in combination with our reduced-form results – provides compelling evidence that the effect of product recommendations is driven by increased saliency and hence a change in consideration sets.

Finally, we use our random utility model to compare how sales shares for products change when consumers have limited vs. full information. Our results indicate that under the current recommendation system, where all products tend to be equally highlighted, popular products tend to suffer a loss in sales share when consumers have limited attention simply because they are not considered. More popular products, however, stand to gain under limited attention, if the website only recommended more popular products, but this increases the concentration of sales towards popular products in the market. These results are consistent with a “segmentation effect” of improved within-platform search (through for example, recommendation systems) that shifts market participation in favor of some products against others as identified theoretically by [Lewis and Wang \(2013\)](#).

There is some existing empirical evidence to support models of limited attention through the formation of consideration sets. A large literature, mainly in marketing science, uses explicit structural or functional form restrictions to model the formation of consideration sets and its subsequent effect on choice (see for example [Van Nierop et al. \(2010\)](#); [Chiang et al. 1998](#); [Andrews and Srinivasan 1995](#); [Roberts and Lattin 1991](#)). An important part of this literature has focused on how consumer search of product prices and attributes influences consideration set formation ([Mehta et al. \(2003\)](#); [De los Santos et al. \(2012\)](#); [Seiler \(2013\)](#); [Honka \(2014\)](#); [Kim et al. \(2016\)](#); [Honka and Chintagunta \(2017\)](#)). A small but growing literature in economics uses exclusion restrictions to estimate a consumer demand model with limited attention. For example, [Goeree \(2008\)](#) uses advertising expenditure, proxied by media exposure, as an exogenous shifter that affects a consumer's consideration but not her utility. [Draganska and Klapper \(2011\)](#) do not impose such a restriction on advertising but treat it as fully exogenous and assume that the consumer's choice set is limited to only the set of brands that she is aware of. [Kawaguchi et al. \(2014\)](#) propose an alternative methodology that uses product availability as an exclusion restriction to test for attention.

Our approach is similar in spirit but we exploit a richer context, incorporating not just the availability of new products but also variation in product visibility, to identify and estimate the presence of consumer inattention. Additionally, in contrast to some of the existing literature, our paper does not require product saliency, a form of advertising, to be exclusive to the consideration process and allow it to affect consumer utility. Neither do we place any restrictions on the composition of the consideration sets or the process of choice formation. Finally, instead of relying on aggregate proxies, we use a direct measure of product visibility and salience shocks that vary frequently both across products and over time. That said, one of the limitations of our approach is that we are unable to distinguish empirically between awareness and consideration in the process that leads to consumer choices ([Honka et al. 2017](#)). For a product to enter a consumer's consideration set, the consumer needs to be aware of it. Product recommendations affect awareness directly, but they can also affect consideration provided a consumer has become aware of the recommended product. Empirically, however, we are unable to distinguish between these two effects and hence our findings are best interpreted as a combination of recommendations affecting awareness and consideration.

The remainder of this paper is organized as follows. Sections [2](#) and [3](#) describe the setting and data used in our analysis, respectively. Section [4](#) presents our empirical approach to identifying saliency effects in the data. Sections [5](#) and [6](#) present our results and Section [7](#) offers a few concluding remarks.

2 DESCRIPTION OF ONLINE MARKET

We use data from an online luxury fashion retailer, Net-a-Porter, selling top fashion brands such as Burberry, Dolce & Gabbana, Gucci and Dior. Founded in 2000, Net-a-Porter sells fashion, shoes and accessories to 170 countries.³ The company sells almost exclusively to women, the majority of whom have a graduate degree, and claims that its average consumer has an (annual) household income of \$170,000 and expenditure on fashion is \$13,000. It claims 6 million unique users worldwide every month, with a third in the U.S. and 40% in the UK and the rest of Europe, with an average value of an order at \$500. The website is highly successful, with a bounce rate of 34.8% in 2015 and an average of slightly over 6 page views per visitor.⁴

Net-a-Porter is widely considered to have revolutionized retailing luxury fashion because from a customer's perspective it does away with the experience of shopping in an exclusive store and from the fashion label's point of view it dispensed with the need for expensive retail stores. To achieve this, Net-a-Porter undertakes efforts to raise confidence and reduce the risk in online luxury shopping by offering extensive product views (including videos, measurements of products and detailed product description), careful distilling of trends, and an efficient global courier delivery system, with 24 hour delivery service in London and New York.

There are three points about this retailer that make it a useful setting for examining consumer choice.⁵ The first is that the website provides recommendations for every product which are non-personalized. This is ideal for our analysis as we are able to avoid dealing with a large amount of consumer heterogeneity present in most personalized recommendation systems. Second, the only other information provided on each product page, in addition to recommendations, are product attributes (image, price, description, dimensions etc). Importantly, the information does not include any signal on the underlying popularity of the product through reviews or sales-rank or any such instruments.⁶ This ensures that users are not choosing products based on their

³Richemont, a Swiss-based luxury conglomerate, acquired a 93% stake in 2010. When we collected the data in 2014, Net-a-Porter had sales of Eur 550m and was worth Eur 2.5 billion.

⁴The bounce rate is the percentage of users that arrive on the website and leave without viewing a second page on the site. Net-a-Porter's bounce rate is comparable to that of other highly successful online luxury retailers such as Neiman Marcus or Mytheresa. Data from www.alexa.com.

⁵Note that since we scraped the data in 2014, the retailer has changed the site considerably, and set up social media links, added more information on popularity and the live ticker tape is now more a rotation of sets of items. These changes were implemented at the end of 2015 after the retailer was acquired by Yoox Net-a-Porter Group, an Italian online fashion retailer created after the merger between Yoox Group and Net-a-Porter.

⁶As described in Section 3.1 below, our data are obtained from Net-a-Porter "Live" which provides real time data on shopping bag and wish list additions. If a customer watches the live ticker, she would observe individual decisions by other customers to add a product to their shopping bags or wish lists

popularity on the web-site as such information is absent. Finally, the concept of the web-site is innovative, marrying both content and commerce, enabling it to attract a large volume of customers. In brief, the site allows us to examine choice across more than 15,000 products and 530 brands in a setting where consumers are largely fully informed about product and brand attributes including prices and product recommendations are not tailored towards individual customers.

3 DATA

3.1 DATA DESCRIPTION

The data were scraped from the Net-a-Porter website between May and August 2014. The main dependent variable that we use consists of information on additions to the shopping bag and wish lists by anonymous buyers which provides information on potential sales of products. The data consists of several components:

Products: We parsed the entire set of available products from Net-a-Porter’s product catalogue. The catalogue distinguishes between broad categories: clothing, bags, shoes, accessories, lingerie, and beauty. There are a number of subcategories within the broader categories (for example dresses, pants, skirts etc. under clothing). The catalogue presents the products with a number of photos and basic product attributes including the price. Once a customer clicks on the product, a detailed description appears plus more photos and videos.

Product-level sales proxy: Net-a-Porter’s online platform includes a feature called **Net-a-Porter “Live”** which provides real time data at the product-level. The live data feed, updated every second, allows customers to see how many people around the world (and indeed in their particular location) are browsing the site with them, and what they are adding to their shopping bags and wish lists. The data used in our analysis was scraped from this live ticker. That is, we have product-level information

which in principle could offer some information on product popularity. That said, it is highly unlikely that a customer might pick up a reliable signal of product popularity from the availability of the live ticker for at least four reasons: (i) a customer has to access the separate live ticker page during her visit to the site; (ii) products cannot be selected and observed by category or attributes but are simply shown in the order in which they are added to a shopping bag or wish list, e.g. if a customer is interested in buying a handbag, she might in fact not see any handbags being added to a shopping bag or wish list while she is on the page of the live ticker; (iii) a customer would have to observe the live ticker for a considerable amount of time to learn about popular products; (iv) the information displayed on the live ticker is not available on the product pages, i.e. on a given product page it is not possible to find out how often a product was added to a shopping bag or wish list and where the relevant customers are located geographically.

on all items that customers have added to their wish lists and shopping bags, which includes basic information on product attributes including brands and prices as well as the precise time when a customer made these choices and her physical location. In an informal discussion with representatives from the company, we obtained information on the manner in which these data are presented and the implications for our analysis. First, due to the large data volume, the ticker tape does not provide data on every potential transaction. Instead, it shows a random sample which includes around 50% of all live shopping bag and wish list additions that occur at any given point in time. Second, it is possible that some additions to the shopping bag do not result in actual transactions; however, purchases cannot be completed without adding to the shopping bag. We interpret additions to a customer's shopping bag as an intention to buy the corresponding product, whereas additions to the wish list are interpreted as an expression of interest to buy. That said, because not every shopping bag addition results in an actual purchase,⁷ our estimated effects of product recommendations on our sales proxy measure should be interpreted as an upper bound. While the shopping bag and wish list additions are available per minute, we aggregate the data to daily intervals.⁸

New products: Net-a-Porter launches new products three times a week: on Monday, Wednesday, and Friday. We identify all new products from the “What’s New” category on Net-a-Porter’s website, which lists all new arrivals. Supply factors largely determine the timing of these launches. Products are launched on the website as and when they are released by the product’s producer to Net-a-Porter’s warehouses.

Product recommendations “you may also like” (substitutes): In addition to detailed information on a given product, the customer is also provided with product recommendations under the **you may also like** header – see Figure 1. The products under the **you may also like** header form the recommendation sets used in our analysis. These are products that are very similar to the target product, they usually belong to the same product category (Table 1 shows that on average 98.9% of all recommending and recommended product pairs belong to the same product category), a similar price

⁷According to industry **estimates**, fashion has one of the highest conversion rates (defined as the share of shopping bag additions that result in a sale) with around 34%; industry **estimates for Net-a-Porter** which we confirmed in an informal conversation with Net-a-Porter suggest similar albeit slightly higher conversion rates of 30-40%.

⁸There are three main reasons for aggregating at the daily-level even though the aggregation entails a loss of information. First, the major source of variation for our variable of interest, saliency shock, is at the daily level. As such the additional information contained at a lower level of aggregation is not particularly useful for our purposes. Secondly, the minute level data are highly volatile and our aggregation scheme enables us to reduce the impact of non-relevant microstructure effects that induce noise. Finally, daily aggregation reduces the amount of data used for analysis, allowing us to compute our estimates more efficiently.

range (the average price difference between recommended and new recommending products in our sample is close to zero – see Table 1), but not necessarily the same brand/designer (see Table 1). The number of recommended products differs by product. Unlike standard models of product referrals, such as Amazon, Net-a-Porter’s recommended sets are not personalized (as in “if *you* like this, *you* will also like”) and are simply potential substitutes (see Section 5.1 for more details). Moreover, during the time period for which we have data, the set of recommended products remains the same over time.

In conversations with Net-a-Porter we learned that substitutes are chosen through a combination of two tools: one that selects visually similar products and another one that selects products with similar observable attributes. However, no attempt is made to customize the recommendation sets based on some (subjective) perception of product popularity. We also confirmed in our conversations with Net-a-Porter that recommendations are not chosen based on past or expected sales of either the recommending or recommended products. According to them, the goal of providing recommendations is mainly to suggest similar products (substitutes), similar to what a customer would experience in a brick and mortar fashion boutique.⁹

Regional variation in recommendation sets: Net-a-Porter varies its recommendation sets slightly across different geographical areas around the world (see Figure 2). We exploit this feature in our empirical analysis (see Section 4.2). That is, in a few cases, the same new product recommends slightly different sets of products in different regions, say the U.S. and Europe. According to Net-a-Porter this is the result of the attribute matching tool placing different weights on a product’s attributes in attempts to accommodate taste differences across regions. These product- and region-specific taste differences, termed as ‘*style*’ by the merchandise team,¹⁰ concern variation in preferences for designer labels and fashion type (classic vs contemporary etc.) and are fixed over a product’s life-cycle. This means that any observed differences between recommendation sets across regions are due to region-specific market characteristics rather than product-specific demand trends. To obtain the regional data, we parsed the data from locations in the U.S. and the UK. Since the live ticker provides us with the location of customers, we can determine which set of recommended products a given customer in a given region was able to see.

Product recommendations “*how to wear it*” (complements): The website offers

⁹More recently, Net-a-Porter has created apps that allow targeting specific audiences through interaction on social media networks. However, our data pre-date this.

¹⁰The company distinguishes between fixed effects of location, named *style* and time-varying *trends*, which are thought to be the same across locations. We were told explicitly that recommendation sets are not designed as per *trend*.

also product recommendations under a **how to wear it** header (see Figure 1). These recommendations are products that can be worn in combination with the target product. Hence, usually these are products from other product categories (for example if the target product is a dress, **how to wear it** might show shoes, a bag, and earrings). As such we consider these products as complements as opposed to substitutes under the **you may also like** header.

3.2 DATA SUMMARY

Table 2 provides an overview of the shopping bag and wish list additions across product categories. The table also distinguishes between existing and new products and tests for differences in means between those products that were recommended by a new product and those that were not. The tables shows average shopping bag and wish list additions for a given product over the entire time period in our data for which the product is available on the site. For example, the table shows that an existing product that is not recommended by a new product is added to a customer’s shopping bag on average 0.385 times on any given day that it is available. In contrast, an existing product that is recommended by a new product is added on average 0.555 times on any given day that it is available. It is clear that across all product categories and regardless of whether an existing or new product was recommended, recommended products display on average significantly more shopping bag and wish list additions than products that were not recommended. The main purpose of our empirical analysis is, therefore, to demonstrate that this difference is the causal effect of product recommendations.

An important concern in this regard is the potential endogeneity in product recommendations. For example, expensive products could systematically recommend similar cheaper products. In this case, the effect on sales that comes from a product recommendation works through price rather than saliency. However, Table 1 shows that price differences between recommended and recommending products are extremely small across product categories. Moreover, Table 3 shows that neither do we find any significant price differences between products that were recommended and those that were not (except for the relatively small categories lingerie and shoes). Hence, overall we see no evidence for new products recommending cheaper or more expensive products compared to their own price or compared to products that were not recommended.

Our empirical analysis focuses on recommendations by new products. An obvious concern is that recommendation sets associated with new products are systematically different from recommendation sets associated with existing products. Appendix Figure A-1 compares the variation in the size of recommendation sets between new and

existing recommending products. The figure shows no evidence for major differences in the size of recommendations sets across product categories. Moreover, Figure A-2 shows that the size of recommendation sets associated with new products is essentially time-invariant, whereas the number of new products increases over time.

Finally, for our placebo test and double diff-in-diff specification explained in Section 4.2, we rely on differences in recommendation sets between the U.S. and Europe. As explained in detail below, for this part of our analysis we rely only on those products that were recommended in either of the two regions, discarding products recommended in both the U.S. and Europe. Appendix Figure A-3 looks at differences in prices between products recommended in both vs. products recommended in only one of the two regions across product categories. Again, we see no strong evidence for systematic price differences between products which mitigates concerns over sample selection induced by our focus on a subset of recommended products in that part of our analysis.

4 EMPIRICAL SPECIFICATION AND IDENTIFICATION

4.1 NEW PRODUCT ARRIVAL SHOCKS

To consistently estimate the effect of saliency on demand, we use variation from the arrival of new products. Our identification strategy exploits two features of new products. First, new products are more salient on behalf of their novelty. Dedicated web-links and email based advertising to announce the arrival of these products increase their popularity at the time of their arrival. Second, most new products recommend other products that have already existed on the website but have not been recommended before. The in-stock products have a demand history that allows us to control for their latent popularity, thereby eliminating potential selection bias based on past sales.

We therefore make use of the increased popularity of new products that recommend existing products. We treat the arrival of new products as shocks to existing products' saliency and use this to identify the saliency effect. In order to do this, we define the set of new products at every launch date as S . We denote \widehat{s}_{jnt}^N as an indicator for whether product j is included in the set of recommended products for a **new product** n (where $n \in S$) launched at date t . We then sum this variable over the set of all possible new products launched at date t giving us, $\widehat{s}_{jt}^N = \sum_{n \in S, n \neq j} s_{jnt}$. The treatment variable \widehat{s}_{jt}^N measures the intensity of saliency for an existing product j due to the arrival shock of new products at time t .

$$y_{jt} = \alpha + \sum_{\lambda=-\tau}^{\Gamma} \psi_{t-\lambda} \hat{s}_{j(t-\lambda)}^N + \mu_j + \gamma_t + \epsilon_{jt} \quad (4.1)$$

where y_{jt} is the total number of shopping bag or wish list additions for product j during calendar day t . We use a finite distributed lag model to estimate our model allowing saliency effects on product demand to last up to Γ days. For each date, we measure the length of the non-overlapping effect window λ by the number of days preceding the arrival shock τ to the number of days following the arrival shock Γ . The reason for including leads on the treatment variables is to mitigate concerns about potential selection bias due to anticipation effects, if top (or low) selling existing products are endogenously chosen to be part of recommendation sets. We include product fixed effects μ_j to absorb product specific heterogeneity. We also accommodate different time trends in product demand by incorporating calendar day fixed effects γ_t .

To estimate Equation 4.1, we use a fixed effect poisson model, as our dependent variable – the daily *count* of total shopping bag or wish list additions – follows a poisson distribution. For inference, we use cluster-robust standard errors, where each cluster is a product, to account for product specific serial correlation in ϵ_{jt} using the formula derived in Wooldridge (1999).

4.2 REGIONAL VARIATION IN RECOMMENDATION SETS

To further strengthen our identification strategy, in addition to employing product arrival shocks, we exploit regional variation in recommendation sets. One concern with our previously described specification is that new products and products that they recommend share some correlated attributes. If the attributes that make a new product sell well are correlated with the attributes that determine which existing products are recommended, then those existing products will also sell well *post* the introduction of the new product, not because of the recommendation but because of the shared attributes. Alternatively, it could be that the introduction of a new product expands the set of substitutes for the recommended products, reducing its own demand and biasing the coefficient downwards (conversely upwards for complements if the product is recommended through “how to wear it”).

Even though we control for past shopping bag additions of each recommended product in the previous specification, we further strengthen our identification to resolve the issue of correlated effects and expansion of substitute/complements sets by exploiting regional variation in the composition of recommendation sets. This allows

us to include a new product fixed effect which resolves two issues: (i) first, it absorbs all sales-enhancing correlated effects and (ii) second, it captures the decreased (increased) demand effect due to an expansion of a product's set of substitutes (complements). In addition, the strategy allows us to difference out product-by-time unobservable characteristics.

As explained in Section 3, Net-a-Porter provides different recommendation sets across regions for a few products. These differences are a result of regional taste differences that are specific to a product but do not vary over its life-cycle. With that in mind, we decompose the region-specific residual (for each region R), ϵ_{jt}^R into the following components:

$$\epsilon_{jt}^R = \omega_{jt} + \mu_j^R + v_{jt}^R \quad (4.2)$$

where ω_{jt} denotes the time-varying product specific unobservables that are common across all regions, μ_j^R is the time-invariant product specific unobservable that differs across regions and v_{jt}^R is the time-varying product specific unobservable that differs across regions. For example, in our set-up, μ_j^R captures fixed regional differences in preferences for each product while v_{jt}^R captures the differential shift in these preferences.

We now describe how the regional variation in recommendation sets for the same new product allows us to difference out the relevant components of the overall residual. To begin with, we normalize our time variable to event-time days and restrict our analysis to -3/+3 days of product j receiving the saliency shock (day 0). We consider the two regions in which most of the transactions occur - U.S. and Europe - and introduce an additional subscript n which indexes the overall product recommendation set associated with a new product. Therefore y_{jnt}^R is the total shopping bag additions for product j recommended by new product n at time t in region R . For each region, we define the treatment variable, T_{jn}^R , as an indicator taking the value one if product j was recommended by new product n in region R . $Post_t$ is an indicator for the time period following the saliency shock i.e. day 0 to day 3.

$$y_{jnt}^{US} = \beta_1 T_{jn}^{US} + \beta_2 (T_{jn}^{US} \times Post_t) + \mu_j + \gamma_t + \underbrace{\omega_{jnt} + \mu_{jn}^{US} + v_{jnt}^{US}}_{\text{unobservables}} \quad (4.3)$$

$$y_{jnt}^{EU} = \beta_1 T_{jn}^{EU} + \beta_2 (T_{jn}^{EU} \times Post_t) + \mu_j + \gamma_t + \underbrace{\omega_{jnt} + \mu_{jn}^{EU} + v_{jnt}^{EU}}_{\text{unobservables}} \quad (4.4)$$

Now, we can net out the time-varying product specific unobservables that are poten-

tially correlated with a product receiving a saliency shock by taking a difference of Equations (4.3-4.4):

$$y_{jnt}^* = \beta_1 T_{jn}^* + \beta_2 (T_{jn}^* \times Post_t) + \underbrace{\mu_{jn}^* + v_{jnt}^*}_{(4.5)}$$

where y_{jnt}^* denotes the *difference* in demand between the U.S. and Europe for product j recommended by new product n at time t . Similarly, T_{jn}^* denotes the difference in treatment status of product j , i.e. whether it is recommended by new product n , between the U.S. and Europe. Note that our differencing strategy is, implicitly, only relevant for products that were exclusively recommended in either of the two regions; as a result we discard all products that were recommended both in the U.S. and Europe (see appendix Table A-1). For ease of interpretation, we also recode the variable, T^* to take the value 0 if the product was recommended in Europe but not in U.S. (instead of -1 as the differencing suggests).

It is easy to see that first-differencing equation (4.5) allows us to absorb the time-invariant regional unobservables for each product j , μ_{jn}^* , that are crucial in determining the allocation of products to different sets across regions. Further, to deal with the issue of correlated attributes between the new and recommending product we rely on the within (new) product regional variation in recommendation sets. We include, in the differenced equation, a fixed effect (ζ_n) for each new product n that recommends different products in different regions.¹¹

$$\Delta y_{jnt}^* = \beta_2 \Delta(T_{jn}^* \times Post_t) + \zeta_n + \Delta v_{jnt}^* \quad (4.6)$$

Including the fixed effect acts as a synthetic control (Abadie et al. 2010), allowing us to compare the demand differential between product j and product k that are recommended by the *same new product* n but in different regions. Our identifying assumption for this specification is that conditional on being recommended by the same product, product j and product k experience similar trends in product sales before being recommended by the new product.¹² In section 5.7 we empirically test this common trends assumption and show that it is validated in our data.

¹¹88% of the recommended products that experience regional variation are recommended by only one new product. For these products, the new product fixed effect is exactly identified. Therefore, we estimate equation (4.6) dropping products that are recommended more than once (by new products) – 12% of our sample – but also report results from including these products.

¹²For instance, a concern could be that products chosen for recommendation in the U.S. started to experience a higher sales trend before being recommended compared to a non-recommended product in Europe.

5 RESULTS: IMPACT OF SALIENCY ON AGGREGATE SALES PROXY

5.1 IDENTIFYING CONDITIONS

Our identification strategy rests on two assumptions that we can test empirically. First, our strategy requires that new products produce saliency shocks for recommended products. To show that new products are themselves highly salient, Figure 3 plots the novelty effect for new products. The figure shows that new products are highly popular upon arrival and this effect declines over the week. The largest effects are observed over the first four days with the effect tapering off by the sixth day following the arrival. The figure suggests that new products attract an enormous amount of consumer attention and demand immediately when they are launched on the platform.

Second, our empirical approach relies on the fact that recommendation sets for new products are not endogenously selected (although we relax this assumption when we exploit regional differences in recommendation sets). To investigate this assumption in the data with regard to observable product characteristics, as discussed in Section 3.2 above, Table 3 shows average prices for recommended (by new products) and non-recommended products across the different product categories. On average, we do not find any significant differences at reasonable levels of statistical significance. We extend this analysis by testing whether products that are recommended by new products are subject to different demand prior to being recommended. Figure 4 shows the empirical distribution of the difference in shopping bag additions during a 3, 5, and 7 day time period prior to being recommended by a new product and shopping bag additions during the same time period of all other products (each bar displayed in Figure 4 corresponds to the arrival date of a new product). We compute these differences comparing all products (upper graph) and comparing only products within product categories (lower graph). The red colors show that in the overwhelming majority of cases there are no statistical differences in demand for products that are recommended subsequently (3, 5, or 7 days later) by a new product and all other products. Note that while our basic results rely on this conditional independence assumption, our estimations that use differences in recommendation sets across regions difference out any product-by-time unobservables.

5.2 BASELINE SPECIFICATION

For all our specifications and results, we refer to saliency for product j as the number of new products recommending this product at any given point in time (see appendix

Table A-2 for descriptive statistics on the size of recommendation sets). Table 4 reports estimates for the average effect of saliency on total shopping bag additions on the day it received the shock. The sample used consists of a total of 15,398 products from all six product categories (accessories, bags, beauty, clothing, lingerie, shoes) that results in 969,368 observations. First we discuss estimates for the effect of a product being new. Column (1) shows that, upon arrival, new products have on average 96% more shopping bag additions compared to existing products. This confirms our assumption that new products are highly popular and are likely to generate spillover effects from their popularity. We now examine the effect of being recommended by a new product (see appendix Table A-3 for descriptive statistics). Column (1) shows that a one unit increase in saliency, i.e. an additional new product recommendation, increases the total number of shopping bag additions by approximately 6%. To incorporate potential anticipation effects we include the forward lag of saliency in Column (2) and find that our results are still robust to this addition. Further, the coefficient on the forward lag is negative but statistically insignificant suggesting that products exposed to a saliency shock did not experience a differential demand trend prior to receiving the saliency shock. In Column (3) we split the saliency effect between existing products and new products. As described in the data section, new products recommended a mix of existing and (other) new products. We find that the effect of saliency is large and significant for existing products which see a 5.5% increase in their shopping bag additions on the day that they are recommended by a new product. However, this effect is close to zero for new products receiving the saliency shock implying that the novelty effect dominates the sales of new products upon arrival and that there are no added affects of recommendations. In Column (4) we control for the lagged effect (up to 2 weeks) of being a new product addressing the concern that saliency shocks might be picking up lagged new product effects if it were the case that lagged new products were likely to receive the saliency shock. We find that our result is robust to including this control and that the saliency effect is independent of lagged new product effects. Finally in Column (5) we control for past sales, as measured by the seven-day lag of shopping bag additions. We add these lagged demand variables to mitigate concerns that products may have been chosen for recommendation based on their historical popularity and, if so, to net out the effect of pre-trends in sales from recommendations. We find that the coefficient on saliency remains positive and statistically significant, even after controlling for past sales, and is even marginally higher (the effect size increasing by approximately 1%).

Until now we have focused on the immediate short term effect of a saliency shock. To assess whether these saliency effects persist over the days following the arrival of the

product, we report results from estimating the finite distributed lag model presented in Equation (4.1). Figure 5 plots the disaggregated saliency effects for each day following the shock along with their confidence intervals. The figure shows a large increase in total purchases for salient products on the day they receive the saliency shock (7% increase) with the effect positive but declining over the subsequent few days. On average an additional unit of saliency results in a 3-5% increase in shopping bag additions over the three days following the shock. Such a pattern of effects, with a prominent spike in a product's sales on the day that they are recommended, is consistent with the attention based explanation that products receiving a saliency shock could have been previously overlooked by consumers. The lack of persistent long-term effects is incompatible with a selection-based explanation which posits that existing products are endogenously selected to be part of new product recommendation sets in anticipation of their (higher) future sales.

In Figure 6 we break down the daily effects of saliency for existing and new products. The results are mixed. Figure 6(a) shows that existing products see a large increase in their sales on the day that they are recommended by a new product but this effect disappears on day 2, subsequently picking up again over days 3 and 4.¹³ In contrast, we find no additional effect of saliency for new products on the day they are launched *and* recommended by other new products (Figure 6(b)) but we find additional positive and significant effects following the day of the shock. Our results indicate that while the novelty feature of a new product clearly dominates its sales on the day of its launch, the additional saliency effect (relative to the saliency effect for existing products) starts to play a role in increasing its sales once the novelty effect starts wearing off over the subsequent few days.

We undertake the same analysis with total wish list additions (per day) as a dependent variable. Table 5 reports these results. Although additions to wish lists are more noisy, we find strikingly similar results for the effect of saliency. Across all specifications we find that a one unit increase in saliency, i.e., an additional new product recommendation, increases the total number of wish list additions by approximately 6%. This result is robust to controlling for lagged new product effects, anticipation effects and past sales. Further we find strong novelty effects with new products experiencing almost a 118% increase in wish list additions compared to existing products. We find close to zero effects of saliency shocks for new products on the day they receive the shock (Columns (3), (4) and (5)).

¹³A possible explanation for this pattern is that since new products are launched three times a week, recommended products regain a bit of salience on the third day when additional new products are introduced.

Finally, Figure 7 plots coefficients when we use recommendations of complements (“*how to wear it*”) instead of substitutes (“*you may also like*”). The results are similar to those obtained for substitutes in Figure 6; focusing on the effect on existing products, we see a significant, positive effect of the saliency shock on demand on the day of the saliency shock, with the effect pattering out within the first three days. The fact that the coefficient is smaller in magnitude than in the case of substitutes is what we would expect if most consumers choose between substitutes rather than switching to or adding complements to their shopping bags. The effect of the saliency shock on other new products shown in the lower plot is much more lasting, we continue to observe a positive impact up to seven days following the shock.

5.3 ROBUSTNESS

To assess the robustness of our results to lagged novelty effects, we include the two-week lag of whether a product was new in the baseline specification. Figure A-4 shows that the results, both for existing and new products, are robust to the inclusion of this control. We also assess whether our results are sensitive to introducing differential anticipation effects between products that received a saliency shock in the previous week compared to products that did not. *A priori*, one might expect that products that received a saliency shock in the previous week have an upward trending sales curve that makes them more likely to receive another saliency shock. If this were the case, then we would be picking up lagged saliency effects of high-selling products, confounding our estimates of current saliency shocks.

Figure A-5 in the appendix plots the results with the anticipation effects split between products that received a prior saliency shock and those that did not. We see clearly that there is almost no difference in the anticipation effects between these two types of products and that the overall effects are close to zero. Products that received a saliency shock had no differential demand trend 3 days prior to the event. We conduct the same analysis for total wish list additions as a dependent variable. Similar to the results for shopping bag additions, we find that the saliency effects for consumers’ wish list additions are robust to controlling for lagged new product effects (Figure A-6) and differential anticipation effects (Figure A-7).

5.4 SPILLOVER EFFECTS OF SALIENCY

So far, we have measured the direct effect of a saliency shock on products that are recommended by newly launched products. To the extent that these products also

recommend other products, there could exist spillover effects of the saliency shock that potentially bias our estimates downwards. To explore the presence of spillover effects, we build a network of recommendations that allows us to vertically trace the impact of the saliency shock, originating from newly launched products.

We measure, on a given day, the path distance between a product and a new product in the recommendation network. For example, products that were directly recommended by a new product have a one degree separation and are identified by the dummy variable, D^1 . Further, products that are recommended by degree 1 products have a two degree separation between themselves and the new product and are identified by the dummy variable, D^2 . In a similar way we identify degree 3 products (D^3). Note that the variables that identify the degree of a product are mutually exclusive, in the sense that products are identified by their closest degree of separation even if they can be recommended recursively through the network.

$$\begin{aligned}
y_{jt} = & \alpha + \sum_{\lambda=-\tau}^{\Gamma} \psi_{t-\lambda} (\hat{s}_{j(t-\lambda)}^N \times D_{j(t-\lambda)}^1) + \sum_{\lambda=-\tau}^{\Gamma} \psi_{t-\lambda} (\hat{s}_{j(t-\lambda)}^N \times D_{j(t-\lambda)}^2) \\
& + \sum_{\lambda=-\tau}^{\Gamma} \psi_{t-\lambda} (\hat{s}_{j(t-\lambda)}^N \times D_{j(t-\lambda)}^3) + \mu_j + \gamma_t + \epsilon_{jt}
\end{aligned} \tag{5.1}$$

In this specification, $\hat{s}_{j(t-\lambda)}^N \times D_{j(t-\lambda)}^1$ measures the total number of new products recommending product j , i.e., it represents the intensity of saliency for products that are directly recommended by new products (degree 1). The indirect spillover effects are captured by the variables $\hat{s}_{j(t-\lambda)}^N \times D_{j(t-\lambda)}^2$ and $\hat{s}_{j(t-\lambda)}^N \times D_{j(t-\lambda)}^3$. The variable $\hat{s}_{j(t-\lambda)}^N \times D_{j(t-\lambda)}^2$ measures the total number of degree 1 products (those directly affected by the saliency shock) recommending product j for all products at a two degree separation from any new product; $\hat{s}_{j(t-\lambda)}^N \times D_{j(t-\lambda)}^3$ measures the total number of degree 2 products (those indirectly affected by the saliency shock) recommending product j for all products at a three degree separation from any new product.

Table 6 reports results from including spillover effects. The first row of the table presents our baseline results, where we do not account for spillover effects. The subsequent rows report results on both direct and indirect effects of the saliency shock. We find that our baseline results are largely unchanged by the inclusion of the spillover variables. As expected, there is a slight increase in the magnitude of the effect, from 7.4% to 8.2%, after accounting for spillover effects. A comparison of the direct and indirect effects of the saliency shocks reveals that the effects of the saliency shock are strongest for products recommended directly (at degree 1 separation) by new products.

Additionally, we find significant (positive) spillover effects. Products recommended by saliency-shock-affected products see an increase in their sales on the day that new products are launched, but to a much lesser extent (a 2% increase). The results also show that heavily recommended degree 2 products have positive lag effects indicating that these products were popular even before they were recommended by saliency-shock-affected products. This could be explained, perhaps, by a selection effect for degree 2 products. Since the degree 2 spillover effect captures all product recommendations (and not just recommendations from new products), it is possible that frequently recommended degree 2 products are likely also to have higher sales. Even then, despite conditioning on this underlying popularity trend, we find a significant positive spillover effect, on the day of the saliency shock event. The spillover effects are limited to products at a degree 2 separation from new products. We find no significant effects for products that are at a three degree separation from new products.

5.5 ATTENTION AND PRICE EFFECTS

The analysis so far has shown that a product’s saliency has a causal, positive and significant effect on its shopping bag and wish list additions. Yet, our results from this analysis do not necessarily rule out that this effect is driven by consumers’ implicit preference for saliency (thereby affecting their choice) rather than an increase in consumers’ consideration for the recommended product. Next we use heterogeneity in saliency effects across products to provide evidence that the effect on consumer choice can indeed be attributed to changes in a consumer’s consideration set.

The first dimension of heterogeneity we explore is in the size of recommendation sets. For each recommended product j , we compute the display size of the set in which product i was recommended; it equals the total number of other products that were also recommended alongside product j by a new product n . The overall size of the recommendation set may matter if consumers have limited attention and can only focus on a restricted number of products at a time. As a result, products that are recommended in smaller sets may receive more attention, increasing their sales, compared to products recommended in larger sets. To test the display size effect, we include an interaction of the saliency shock to product j and size of the set in which it was recommended. Figure 8 shows results from this specification. We find substantial, negative and significant, display size effects. An additional product in the recommendation set reduces shopping bag additions by 3.2%. To gauge the magnitude of this effect, we note that the average size of the recommendation set in our sample is 7.5. On average, therefore, products recommended with 7 other products see an increase in their sales

by about 8%, similar to the results found in our baseline specification. The maximum effect of saliency is experienced by products recommended in sets of 1-3.

We next turn to exploring the price sensitivity of salient products. To examine this, we interact the saliency shock with the difference in price between product j and the new product n which recommends it. Our null hypothesis is that consumers are less likely to respond to price differences if product recommendations serve only to improve the saliency of a product, thereby drawing consumers' attention. Figure 9 plots the results of the interactions. We fail to reject the null for the interaction effects both on the day of the shock and subsequently. The coefficient on the interaction terms is close to zero suggesting that consumers ignore variation in price differences across recommended products and are influenced only by the number of other competing products.

5.6 SUMMARY

To summarize, we have presented a range of results starting with the baseline specification and extensions in various directions. Table 7 shows the coefficients of interest for all the different models. The table highlights how consistent our results are across specifications – we see a large positive coefficient between 0.74 and 0.82 on the day an existing product receives a saliency shock, with this positive effect lasting for three days. The table also shows that these findings are unaffected by accounting for the price difference between recommending and recommended products. At the same time, we find that the larger the recommendation set, the smaller the saliency effect. These results paint a consistent picture, suggesting that products that have been available to consumers on the platform experience a large surge in demand when they are made more salient through a recommendation by highly salient products.

Finally, Table 8, which presents an overview of the results for wish list additions, suggests an explanation for the lagged effect on shopping bag additions on days two and three: Table 8 shows that the saliency effect on wish list additions is significant only on the event day (the day when the new product is launched). This is consistent with the interpretation that consumers react to the saliency shock not only by adding products to their shopping bag directly but also to their wish list and then 2-3 days later pull these products out of their wish lists into their shopping bags. That said, our data do not allow us to test directly whether the lagged effect is indeed explained by consumers moving products out of their wish list or consumers in fact still add recommended products directly to their shopping bag – the most likely explanation involves a combination of both.

5.7 EXPLOITING REGIONAL VARIATION IN RECOMMENDATION SETS

An identification concern with the results presented so far is that the probability of receiving a saliency shock has an underlying correlation with future sales. In our results so far we have shown that, on average, products receiving a saliency shock did not experience a differential demand trend from non-saliency shock products, prior to receiving the shock. As explained in Section 4.2, we exploit regional variation in the composition of recommendation sets to difference out product-by-time unobservables to consistently estimate the saliency effect.

Our objective is to estimate the effect of a product being made salient in the U.S. on the sales differential between the U.S. and Europe. In estimating equation (4.6), we obtain estimates that – conditional on fixed effects for each new product launched globally – are independent of unobserved (i) time-varying product differences, (ii) time-invariant regional differences for each product and (iii) time-varying regional differences for each product.

Before reporting the results, we test the common-trends assumption implicit in our double difference-in-difference strategy. Figure 10 plots the difference in shopping bag additions between the U.S. and Europe on the y-axis and event time on the x-axis.¹⁴ In the following results table, we undertake a *within new-product* comparison. This means we compare products that receive a saliency shock in the U.S. (treatment) by a new product n with a similar product (control) that is also recommended by n but only in Europe and not in the U.S. While we estimate equation (4.6) over a daily time interval of $\{-3, +3\}$ days, the figure is extended to 12 hour (half-day) intervals over the same sample range.¹⁵ The figure shows that both control (plotted in gray) and treatment (plotted in black) products have a declining sales curve but treatment products lie slightly below control products; however this difference is not statistically significant. On the day that treatment products receive their shock in the U.S., their shopping-bag differential increases by a magnitude of almost two in favor of the U.S. Following the event, the product continues its declining trend but the boost in its shopping-bag additions on the event day puts its sales curve on a higher level compared to control products reversing the pre-event trend gap.

Table 9 now reports results from our double difference-in-difference strategy. All columns condition on new product fixed effects (interacted with the post-shock effect) and a

¹⁴We also test the common-trends assumption conditional on ζ_n , as required by our identification strategy using *predicted* difference in shopping bag additions, i.e., by regressing actual shopping bag differentials on a fixed effect for each new product recommendation set and find similar results.

¹⁵Note that since we require information on shopping bag additions prior to the event, by construction, we are only able to examine saliency effects for existing products.

full set of time effects. Column (1) estimates the difference-in-difference equation and retains the base treatment effect to show that the baseline difference between treatment and control products is statistically insignificant. In Column (2) we report the same specification but now drop all products that are recommended by more than one new product.¹⁶ We find that products recommended by a new product in the U.S. see a 12% increase in their U.S.-Europe sales differential over the 4 event days, compared to similar products recommended exclusively in Europe by the same new product. The magnitude of the effect is larger than the effect obtained in our baseline specification. Column (3) includes a product fixed effect, absorbing the time-invariant treatment differential and finds the same result.

In column (4) we examine whether the treatment effects differ by size of the recommendation sets. We find a 1.5% decrease in sales differential with the inclusion of an additional product in the recommendation set. Finally, column (5) breaks down the effect by event day. As expected, we find a large, positive effect on the day of the event (9.2%) and surprisingly large effects sustained over the days following the event.

6 STRUCTURAL EFFECTS OF SALIENCY ON CONSUMER DEMAND

In this section, we explore further the mechanics behind the impact of saliency that we find in our reduced-form analysis by estimating a structural model of consumer choice that incorporates the process of consideration set formation. Our goal here is to explicitly test how product saliency, through recommendations, differentially affects a consumer's consideration and choice.

6.1 PROBABILISTIC CHOICE MULTINOMIAL LOGIT MODEL

To uncover the effect of saliency on consumer consideration we estimate the Probabilistic Choice Multinomial Logit Model (PCMNL) based on [Manski \(1977\)](#) that allows for sequential decisions with heterogeneous choice sets.¹⁷ A particular advantage of our approach is that we do not need to know the exact choice set formulated by consumers

¹⁶12% of the products in our sample are recommended by more than one new product. To account for the correlation induced by the fact that these products appear multiple times in the estimation sample, in Column (1) we cluster our standard errors at the product-level. For additional robustness, we report all our results by dropping products that are recommended more than once (by new products).

¹⁷We adopt the random constraint-based approach of [Swait and Ben-Akiva \(1987\)](#) where a product is excluded from the choice set if its consideration utility is lower than some threshold consideration utility level. As described by [Başar and Bhat \(2004\)](#), since this threshold utility level is not observed by the econometrician, the exclusion of a product from the choice set becomes probabilistic.

but focus on the potential additions to the choice set created by the increased salience of a subset of products generated by new product arrivals.

We consider the probability that alternative j is considered by consumer i at any time t , where t represents a calendar day.¹⁸ This probability can be written as:

$$C_{ijt} = \frac{1}{1 + e^{-(\phi' \mathbf{w}_{ijt} + \psi_1' s_{jt})}} \quad (6.1)$$

where \mathbf{w}_{ijt} is a column vector of observed attributes for user i and alternative j at time t and ϕ is a corresponding column vector of coefficients which provide the impact of attributes on the consideration probability of alternative j . Our variable of interest, product saliency is captured by s_{jt} which is defined as the number of recommended sets by a new product that product j appears in at time t of the corresponding new products' launch. The coefficient ψ_1 measures the impact of saliency on the consideration probability of alternative j . An important identifying condition that we require for analysis is that, conditional on saliency (and other included attributes, \mathbf{w}), the probability of consideration is independent across alternatives. While slightly restrictive, we justify this assumption in our data based on the fact that all products in each sub-category we analyze are fully substitutable. In addition, apart from saliency, there is very little menu dependence among alternatives i.e, each alternative is presented without any special distinguishing aspects. Allowing for dependence across alternatives is unfeasible in our context as it would yield no observable restrictions on the choice data with which to identify the consideration set as shown by [Manzini and Mariotti \(2014\)](#).

The overall probability of a choice set c_t at time t for user i is given by:

$$P_{it}(c_t) = \frac{\prod_{j \in c_t} C_{ijt} \prod_{k \notin c_t} (1 - C_{ikt})}{1 - \prod_{j=1}^J (1 - C_{ijt})} \quad (6.2)$$

Note that the denominator is normalized to remove the empty choice set. It is also assumed that the randomly-distributed threshold for each alternative is independent of the threshold values of other alternatives. In our setting, the probabilities of the choice set $P_{it}(c_t)$ are described by the random arrival of new products that in turn highlight (or make salient) a subset of older products, or additions to the (unobserved) choice set.

¹⁸Implicitly we make the simplifying assumption that any user i considers purchasing only one unit of a product per day. This is not, however a restrictive assumption, and we can easily re-write the model in terms of a user considering purchasing a product at any given fraction of time.

Conditional on the choice set, a consumer chooses product j at time t based on the following multinomial logit formulation, as:

$$P_{ijt}|c_t = \frac{e^{\beta'x_{ijt} + \psi_2 s_{jt}}}{\sum_{k \in c_t} e^{\beta'x_{ikt} + \psi_2 s_{kt}}} \quad \text{if } j \in c_t \quad (6.3)$$

$$= 0 \quad \text{if } j \notin c_t \quad (6.4)$$

where x_{ijt} is a column vector of exogenous variables that affect the probability of selecting a product conditional on a consumers choice set, β is a column vector of associated coefficients and ψ_2 measures the impact of saliency on the choice probability of alternative j conditional on considering it.¹⁹ Given the conditional choice probability, the unconditional probability of choice of alternative j can be written as:

$$P_{ijt} = \sum_{c_t \in G} (P_{ijt}|c_t) \cdot P_{it}(c_t) \quad (6.5)$$

where G is the set of all non-empty subsets of the comprehensive choice set of all product alternatives, i.e., it includes each possible choice set, a total of $(2^I - 1)$ elements where I is the total number of products in the market.

We estimate the consideration and choice stage parameters by iterating over all possible sets and maximizing the following log-likelihood function:

$$L(\phi, \psi_1, \beta, \psi_2) = \sum_i \sum_j y_{ijt} \cdot \log P_{ijt}(\phi, \psi_1, \beta, \psi_2) \quad (6.6)$$

where y_{ijt} is a dummy variable taking the value 1 if individual i chooses product j and 0 otherwise.

The own and cross elasticities implied by the model²⁰ capture both the impact of a change in the attribute on the consideration of product j as well as the substitution probability at the choice stage conditional on product j being available in the choice set. The total effect of saliency depends, therefore, on the consideration probability for product j as well as its ultimate choice probability from amongst a set of considered alternatives.

¹⁹We later also allow the parameters to be consumer-specific i.e, β_i and ψ_{i2} , incorporating unobserved heterogeneity across consumers.

²⁰The detailed expressions for the elasticities are derived in [Başar and Bhat \(2004\)](#). Note, that the PCMNL model does not display the Independence of Irrelevant Alternatives (IIA) feature of the multinomial/conditional logit model. The cross-elasticities in the PCMNL model depend on the probability information for *both* products j and k . This means that the cross-elasticities will be different across all alternatives.

Our model and method of estimation have a number of limitations, primarily due to the fact that we lack additional data on the consumer search process. First, in our framework, we do not explicitly model the consumer search process. In general, consumers may face heterogeneous search costs that are fixed across all products (De los Santos et al. 2012) or vary by product (Kim et al. 2010), but our consideration stage specification is agnostic about this. In this sense, our results for the consideration effect can be viewed as a mixture of increasing awareness and lowering search costs.²¹ Second, given our data limitation, we rely on the non-linearity of the model’s functional form to separately identify the parameters on saliency for consideration and choice. Despite these limitations, we view this exercise as informative in interpreting our main reduced form results because our setup recovers explicitly the effect of saliency on a consumer’s consideration rather than overall choice.

6.2 RESULTS: EFFECTS OF SALIENCY ON CONSUMER CONSIDERATION AND CHOICE

To estimate this model, we use product-level data on each consumer’s shopping bag additions. Apart from a consumer’s geographic location, we do not identify any other consumer attributes. We thus treat the data as a pooled cross-section as our data does not track individual consumers over time. We are nevertheless able to identify the time period over which a given consumer visited the website and added a product to her shopping bag. This allows us to include product level attributes in our model that vary over time and across consumers, such as saliency and novelty.

The reduced form analysis indicates that the effects of saliency last for a maximum of 4 days. Taking this into account, we define the saliency variable as a dummy variable taking the value one if the product was recommended by a new product at time t and over the 5 days following it. We define the variable “new product” in a similar way.²²

Next in order to make our computation feasible, we estimate our model on a subset of our data: we focus on the “Travel Bags” sub-category, which contains only 12

²¹Honka et al. (2014) model all three stages of a consumer’s decision process, awareness, consideration and choice and find that advertising serves to mainly increase awareness for a product. Their data identifies the list of options considered by the consumers during their search process.

²²Note that although these new products are unavailable to consumers before they were launched, we still include them in our estimation. This is unproblematic because the inclusion of the consideration stage implicitly allows for some options to be irrelevant for some consumers (for example, those who visited the website when the product was not yet launched). For a more formal result, see Crawford et al. (2015) who discuss how the non-availability of products can be incorporated into a demand model with unobserved choice sets.

options.²³ For comparison, and to show that the results are not specific to the chosen product category, we also estimate the model for the sub-category “Watches” (with 25 options), but choosing only the 10 most purchased products that account for over 80% of shopping bag additions. In addition to computational feasibility, we choose these two categories because products within these categories are highly substitutable.

Table 10 reports estimates from the the PCMNL model for both sub-categories (travel bags and watches). All specifications control for the price of the product, although we find the price effect to be insignificant. The majority of products in both sub-categories (more than 80%), receive a saliency shock at least once and vary only in the timing of receipt. Columns (1), (3) and (5) report coefficients from the consideration stage. We find that product saliency has a strong, positive and significant effect on consideration. Consumers, in our context, display a preference for choosing new products. While we find a small, positive and significant effect for saliency at the choice stage (column (2)), this effect disappears when we disaggregate it for existing and new products, as shown in columns (3) and (4). In column (3) we find a strong positive and significant effect of saliency for existing products on a consumers consideration probability. In contrast, new products that are salient are less likely to be considered relative to existing salient products, but, overall benefit from increased consideration due to their saliency. Column (4) shows that, for existing products, saliency has an insignificant effect on the probability of purchase in the choice stage. On the other hand, consumers are less likely to choose new products that are salient (conditional on consideration) relative to new products that are not salient, perhaps because they value new products that are more unique and less substitutable.

Overall, taken together (consideration and choice), the aggregate marginal effects for saliency indicate an average increase in sales of 3% (travel bags) to 15% (watches) after being recommended by a new product (thereby increasing saliency). These effects are consistent with the results obtained from the reduced form analysis where we find that saliency increases product sales on average by approximately 7%. The reason why we find a lower marginal effect for travel-bags compared to watches is because most products in the travel bags category have a high consideration level in the market. Our model estimates imply that the average share of consumers who consider a product within the category travel-bags is a relatively high 78% compared to a low 49% for

²³For this reason, we are also unable to include product dummies in our specification. The inclusion of product dummies (in both the consideration and choice stage) makes the likelihood highly non-convex, resulting often in the non-convergence of our estimator. However we verify that the results from the MNL model are not sensitive to the inclusion or non-inclusion of product dummies. Counterfactual sales shares from either specification in the MNL are approximately the same.

watches.²⁴

We also estimate a PCML specification with unobserved heterogeneity across individuals, which is modeled by allowing the parameters to vary randomly over individuals according to a discrete-continuous mixture distribution (for more details see [Greene and Hensher 2003](#)).²⁵ Unobserved preference heterogeneity is accommodated by a discrete number of separate (and unobserved) classes or segments of individuals with different values for the preference parameters within each class. A set of parameters, which includes individual socio-economic characteristics determines the stochastic assignment into classes.²⁶ The model is estimated for the category travel bags using maximum likelihood and we find broadly similar results as in columns (3) and (4) of Table 10 – the saliency effect is strongly significant at the 1% level with a coefficient of 5.68. The mean (s.d.) of the *Saliency*, *New Product* and *Saliency* \times *New Product* coefficients at the choice stage are -0.15 (0.56), 2.12 (0.83) and -2.60 (0.41) respectively. However we find some heterogeneity of these effects across customers from different locations as shown in Figure A-8 in the appendix which plots the distribution of saliency and new-product coefficients for U.S. and non-U.S. customers. U.S. customers are more sensitive to new-products but less sensitive to saliency effects at the choice stage.

Finally, we present in Table A-4 a sample of estimated own- and cross-price elasticities.²⁷ Each entry j, k , where j indexes row and k column, gives the elasticity of product j with respect to a change in the saliency of k . Note that the products are labelled according to their sales rank (1 corresponding to the top-selling product in the sub-category). Each entry reports the mean elasticity across the 90 consumers who shopped for travel bags. The variation in estimated elasticities (given by the ratio of the maximum to the minimum cross-price elasticity within a column) ranges from -2 to 0. This indicates that the model has overcome the restrictive form imposed by the multinomial logit model which produces proportional substitution elasticities ([Nevo 2000](#)).

²⁴The average share is calculated as the mean of each product's consideration share. The share of consumers who consider a product j is given by: $(1/I) \left(\sum_j \sum_{c_t \in G} \delta_{ijt}^{c_t} P_{it}(c_t) \right)$ where I is the total number of consumers.

²⁵Other ways to incorporate unobserved heterogeneity such as through simulation (see for e.g., [Train 2009](#)), proved to be computationally costly given the two step estimation, and were a poor fit for our application.

²⁶Our results are based on a model with three latent classes and one socio-economic characteristic (whether the individual is located in the U.S. as opposed to any other country in North-, Middle-, or South-America – note that the recommendation sets are the same in all these countries).

²⁷For the elasticities and counterfactuals reported below, we choose the specification where the saliency parameter has not been disaggregated for new and existing products (columns (1) and (2) of Table 10). We do this to examine the overall saliency effect, which simplifies our policy counterfactuals as well as the interpretation of the results.

Most cross-elasticities are negative²⁸ indicating that recommendations generate negative externalities, contracting the market for other products. Some cross-elasticities are positive, indicating positive externalities. This could be a result of spillovers from the saliency effect through cross-recommendations as documented in section 5.4.

Table A-4 also allows us to investigate whether observed increases in demand for more salient products are driven by more customers purchasing these products (extensive margin) or whether customers substitute salient products for products that were not made more salient within product categories (intensive margin). The estimated own- and cross-price elasticities suggest that effects at both extensive and intensive margins are at work. For most products, cross-elasticities are overall negative, which suggests some substitution between products that received a saliency shock and other products which indicates effects are driven by changes at the intensive margin. That said, a comparison between own- and cross-elasticities suggests that for 8 out of 10 products this substitution effect is outweighed by an increase in demand for the more salient product. In other words, the demand increase occurs also at the extensive margin, i.e., new customers purchasing a salient product within a given product category.

6.3 COUNTERFACTUALS

Based on our model estimates, next we simulate counterfactuals to assess how sales shares change when: (1) consumers have full, instead of limited, attention (Kim et al. 2010) and (2) only certain types of products receive recommendations. Lewis and Wang (2013) show theoretically that while recommendation systems help generate a positive surplus for the platform as a result of improved matches, the overall effect may not be Pareto improving, as market participation may shift in favor of some products against others. We investigate this issue empirically, by examining how different types of recommendations systems impact the sales share of popular vs. unpopular products, when consumers have limited attention.

For the full attention case, our model reduces to a standard multinomial logit (MNL) model; we thus use the estimated parameters from the MNL model to calculate sales shares when consumers have full attention. To assess the performance of different recommendation systems, we define the set of “popular products” as those with an observed sales share of more than 10% (products 1, 2 and 3). The remaining products (products 4 to 12) are categorized as “unpopular products.” We then consider two variants of the recommendation system: i) when only popular products are (always)

²⁸Note, that the zero elasticities are a result of the fact that saliency is zero for these (column) products.

recommended (products 1, 2 and 3) and ii) when only unpopular products are (always) recommended (products 4 to 12).

Figure 11 plots the results from the simulations. Each bar in the figure represents the percentage difference in sales share between when consumers have limited attention and when they have full attention. A negative value indicates that the share under limited attention is lower than that under full attention. The x-axis orders products by their sales rank (1 being most popular and 12 being least popular).

The first result is that limited attention disproportionately harms top-selling products. Popular products suffer a loss in their sales share when consumers have limited attention under the existing recommendation system as indicated by the dark grey bars. Intuitively, popular products are chosen less when consumers have limited attention because they enter less frequently in their consideration sets. Under full attention however, they are always in a consumer's consideration set and are frequently chosen based on their superior underlying characteristics. As the actual recommendation system does not disproportionately highlight popular products (Table 10 reports that 10 out of 12 products in this sub-category are recommended by a new product at least once), their share under limited attention is always lower relative to the full attention scenario.

Next, we consider a different recommendation system, whereby, all new products recommend only popular products, namely products 1, 2 and 3. Under this scenario (medium gray bars), we find the difference in sales share for popular products 1 and 2 is still negative but the loss that they suffer is much lower than when all products are equally recommended. Popular product 3 actually reverses the share differential and stands to gain by almost 2% under this system. In contrast, some unpopular products (7, 10, 11 and 12) register a negative difference as a result of only popular products being recommended.

Finally we plot how sales shares evolve under limited and full attention if only unpopular products received recommendations from new products. The light grey bars show that this would, predictably, lead to an increase in the share of unpopular products (under limited attention) and cause the sales share difference to increase by almost about 1.5%. Unpopular products benefit from consumers having limited attention (relative to full attention) because popular products will be even more overlooked under this recommendation system. Popular products in contrast lose up to 4.5% of sales share under this setting.

7 CONCLUSION

In this paper we estimate the effect of product saliency, affected via recommendation sets, on user choice in online markets. We find a sharp and robust 6% increase in the sales of a product when it is recommended by a highly popular new product. This effect is however short-lived, lasting for approximately only four days. On average the daily increase in sales attributable to saliency is around 5%. We also find that products recommended in smaller sets experience larger effects of saliency as they have to compete less for user attention. Finally, our context allows us to build a robust counterfactual to verify our results. We exploit regional variation in recommendation sets whereby we compare regional sales of products that receive recommendations from the same product but over different regions. We find that products recommended by a new product in the U.S. see a 12% increase in their U.S.-Europe sales differential over the 4 event days, compared to similar products recommended exclusively in Europe by the same new product. We offer additional results that confirm that the reduced form effects of saliency on sales are the result of saliency affecting the set of products considered by a consumer. Once we condition on the effect of saliency on the consideration set, saliency has no effect on choice.

Our analysis sheds light on consumer choice in an environment with low search costs but very large choice sets. Our evidence rejects the traditional revealed preference assumption and suggests that consumers make choices consistent with revealed attention. In other words, we find that consumers make choices under limited attention despite having easy access to information. This results in a search friction as consumers do not consider all products available on a given online platform. However, we also show that online platforms operating in these environments can alleviate this friction by helping refine user search by offering product recommendations. We show that such recommendations can temporarily affect the sales and appeal for products by shaping and expanding consumers' consideration sets. Indeed, our counterfactual analysis suggests that different recommendation systems can have large effects on the demand for a given product if consumer choice is subject to limited attention.

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Figure 1: Recommendation sets



VIEW FULL
SIZE IMAGE



CLARE V
Simple coated-leather tote
\$450

Add to Shopping Bag

Add to Wish List

EDITORS' NOTES & DETAILS ▼

Clare V's 'Simple' tote is s made from weathered **cognac-colored leather** and has thick coated stripes. Fit a tablet, wallet and books in its spacious, **chambray-lined** interior. Carry yours by the top handles or detachable shoulder strap.

- Tan leather (Cow)
- Snap fastening at open top
- Designer color: British Tan

How to wear it


SIZE & FIT ▶

SHARE [f](#) [t](#) [g+](#) [t](#) [p](#) [e](#) [✉](#)


VIEW MORE
▶ Clare V
▶ Tote Bags

Product code: 505083 - Need help? [Contact us](#)


HOW TO WEAR IT ▼




J.CREW
Patent-leather loafers
\$230




TOMAS MAIER
Wool sweater
\$475



RAG & BONE
The Dre mid-rise slim
boyfriend jeans
\$200




EDDIE BORGO
Set of three gold-plated,
cubic zirconia and enamel...
\$375




EDDIE BORGO
Set of four gold-plated
multi-stone rings
\$150


YOU MAY ALSO LIKE ▼




MICHAEL MICHAEL KORS
Jet Set textured-leather tote
\$250




OKAPI
Mawu ostrich tote
\$3,910




3.1 PHILLIP LIM
The Pashli large shark-
effect leather trapeze bag
\$975



ALEXANDER WANG
The Rocco textured-leather
tote
\$925



ALEXANDER WANG
The Emile textured-leather
tote
\$925



MICHAEL MICHAEL KORS
Hamilton large textured-
leather tote
\$360

Figure 2: Recommendation sets U.S. vs. Europe

USA

VIEW FULL
SIZE RANGE

CLARE V
Simple coated-leather tote
\$450

[Add to Shopping Bag](#) [Add to Wish List](#)

EDITOR'S NOTES & DETAILS

Clare V's 'Simple' tote is made from weathered cognac-colored leather and has thick coated stripes. It's a bucket, rolled and looks in its spacious, slanting-lined interior. Carry yours by the top handles or detachable shoulder strap.

- Tan leather (Cognac)
- Strap featuring an open top
- Designer color: British Tan

How to wear it

SIZE & FIT

SHARE [f](#) [t](#) [g+](#) [p](#) [e](#) [s](#)

VIEW MORE

- Clare V
- Tote Bags

Product code: 309005 - Need help? [Contact Us](#)

HOW TO WEAR IT

J. CREW
Patent leather oxford
\$230

TOMMY HILF
Wool sweater
\$475

PAUL & BONIE
The One mid-rise slim
boyfriend jeans
\$600

EDDIE BORGO
Belt of three gold points,
cubic zirconia and enamel...
\$275

EDDIE BORGO
Belt of four gold-plated
multi-straps rings
\$180

YOU MAY ALSO LIKE

MICHAEL MICHAEL KORS
Jet Set textured-leather tote
\$460

OKAPI
Monu ocelot tote
\$2,490

3.1 PHILLIP LIM
The Peak® large shark-
effect leather tote bag
\$475

ALEXANDER WANG
The Rocco belted-leather
tote
\$655

ALEXANDER WANG
The Enrie belted-leather
tote
\$605

MICHAEL MICHAEL KORS
Hamilton large textured-
leather tote
\$340

EUR

VIEW FULL
SIZE RANGE

CLARE V
Simple coated-leather tote
€437,51

[Add to Shopping Bag](#) [Add to Wish List](#)

EDITOR'S NOTES & DETAILS

Clare V's 'Simple' tote is made from weathered cognac-colored leather and has thick coated stripes. It's a bucket, rolled and looks in its spacious, slanting-lined interior. Carry yours by the top handles or detachable shoulder strap.

- Tan leather (Cognac)
- Strap featuring an open top
- Designer color: British Tan

How to wear it

SIZE & FIT

SHARE [f](#) [t](#) [g+](#) [p](#) [e](#) [s](#)

VIEW MORE

- Clare V
- Tote Bags

Product code: 309005 - Need help? [Contact Us](#)

HOW TO WEAR IT

J. CREW
Patent leather oxford
€230

TOMMY HILF
Wool sweater
€475

PAUL & BONIE
The One mid-rise slim
boyfriend jeans
€600

EDDIE BORGO
Belt of three gold points,
cubic zirconia and enamel...
€275

EDDIE BORGO
Belt of four gold-plated
multi-straps rings
€180

YOU MAY ALSO LIKE

SOPHIE HILLME
Mini leather tote
€310

MICHAEL MICHAEL KORS
Sultan large textured-
leather tote
€200

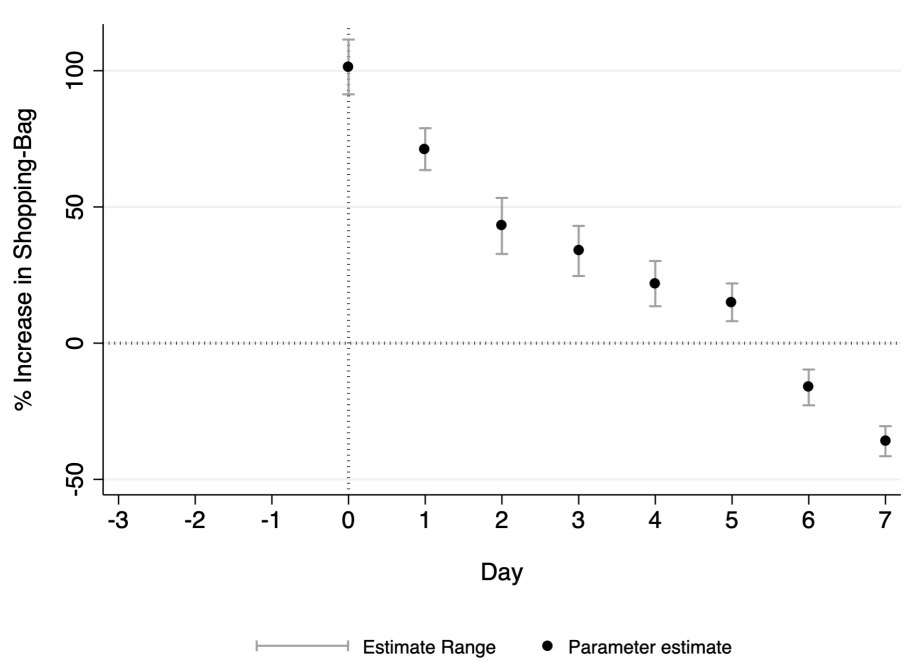
MARC BY MARC JACOBS
In The Green textured-
leather tote
€140

MICHAEL MICHAEL KORS
Selma medium color-block
textured-leather tote
€260

MICHAEL MICHAEL KORS
Jet Set textured-leather tote
€230

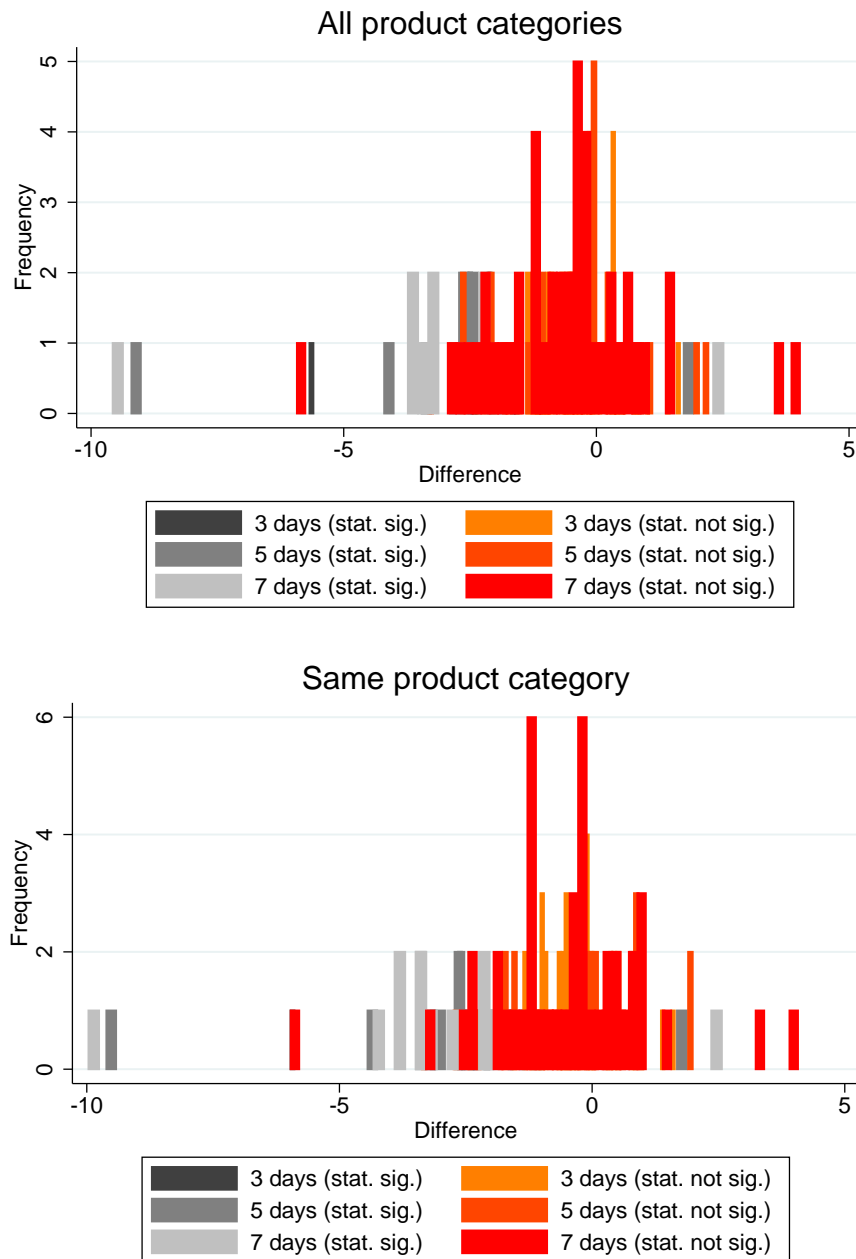
BURBERRY BRICKS &
ACQUAROLES
Crocker belted-leather
and canvas tote
€390

Figure 3: Saliency Shock: New Product



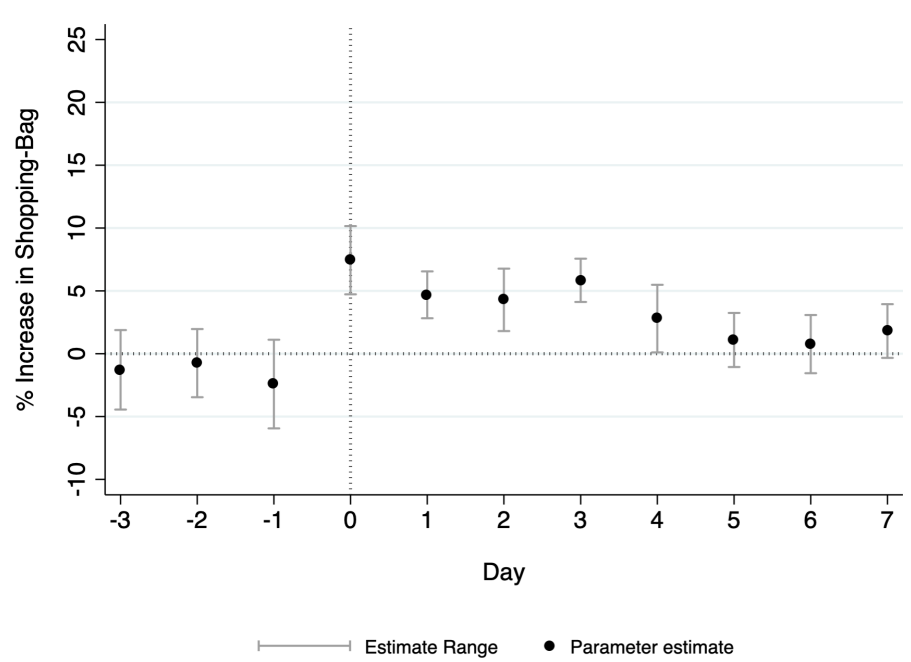
This figure reports coefficient estimates (with 95% confidence intervals) of the effect of entry – being a new product – on the total number of **shopping bag** additions (per day). The sample consists of all daily, product-level, transactions carried out between May 20, 2014 to July 29, 2014. As a result of the thrice-weekly introduction of new products, our database represents an unbalanced panel of products over time. *New Product* is a dummy variable taking the value one is the product was introduced in the catalogue on a given day. The regression specifications controls for time fixed effects, controls for day of the week and weekend.

Figure 4: Differences in shopping bag additions between existing products recommended by new products and all other products



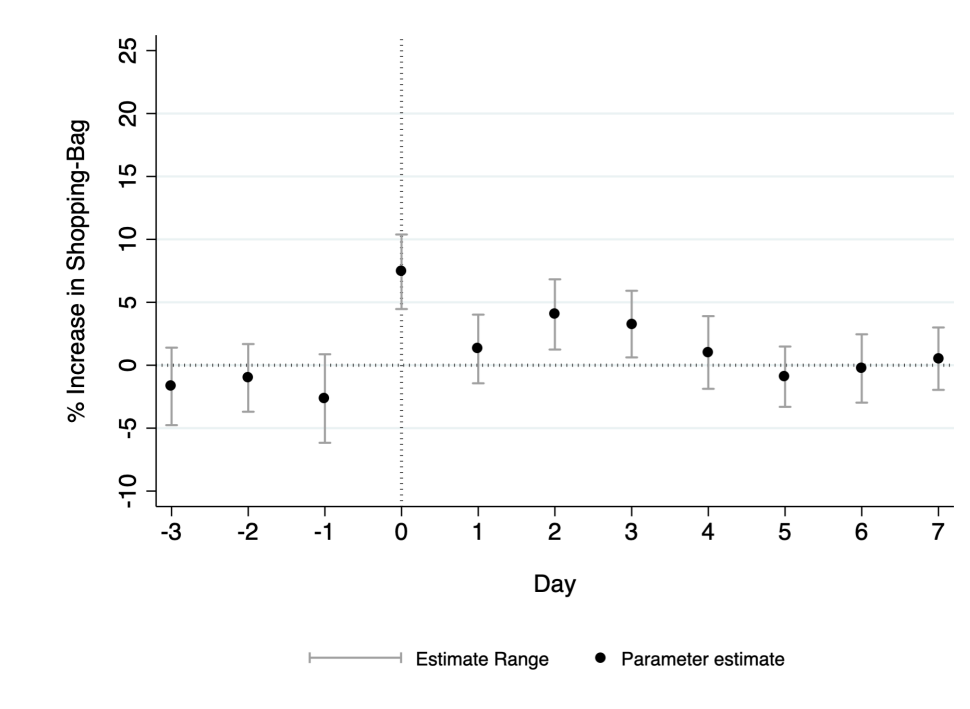
Note: *difference* computed as difference between the number of shopping bag additions for an existing product during 3, 5, or 7 days prior to the recommendation by a new product and the number of shopping bag additions for other existing products that are not recommended by a new product during the same time period. Each bar corresponds to the arrival date of a new product. *Same product category* means we only consider existing products that are recommended by new products that are in the same product category as the existing product.

Figure 5: Staggered Effects of Saliency Shocks

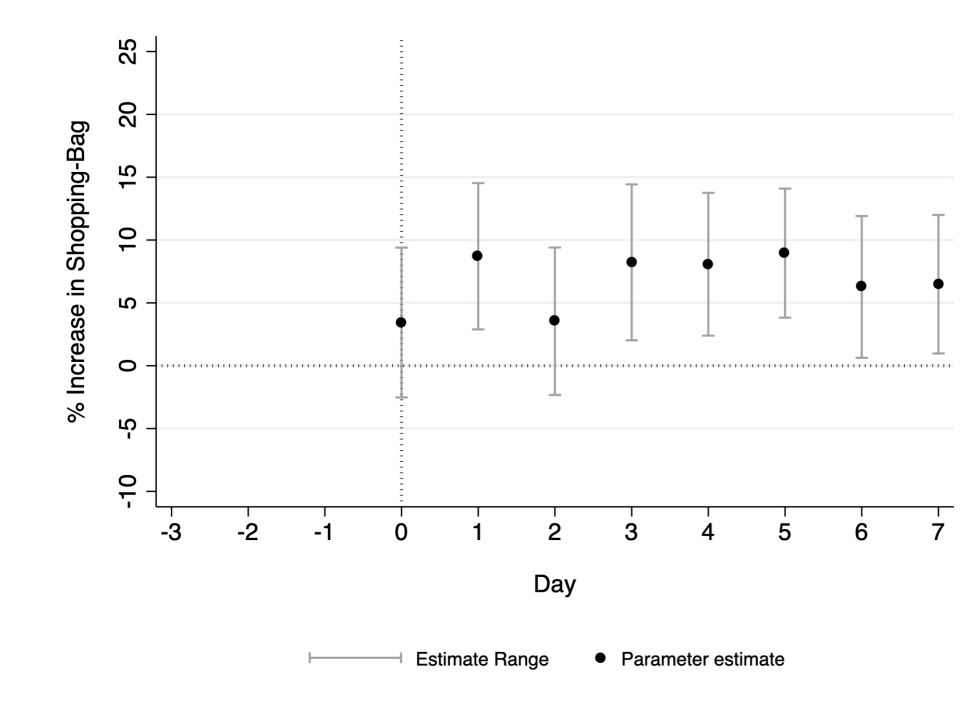


This figure reports coefficient estimates (with 95% confidence intervals) of the effect of saliency on the total number of **shopping bag** additions (per day). The sample consists of all daily, product-level, transactions carried out between May 20, 2014 to July 29, 2014. As a result of the thrice-weekly introduction of new products, our database represents an unbalanced panel of products over time. *Saliency* is defined as the total number of new products that recommend the target product at any given point of time. The regression specifications controls for the entry of a new product, time fixed effects, controls for day of the week and weekend.

Figure 6: Staggered Effects of Saliency Shocks – new vs. existing products



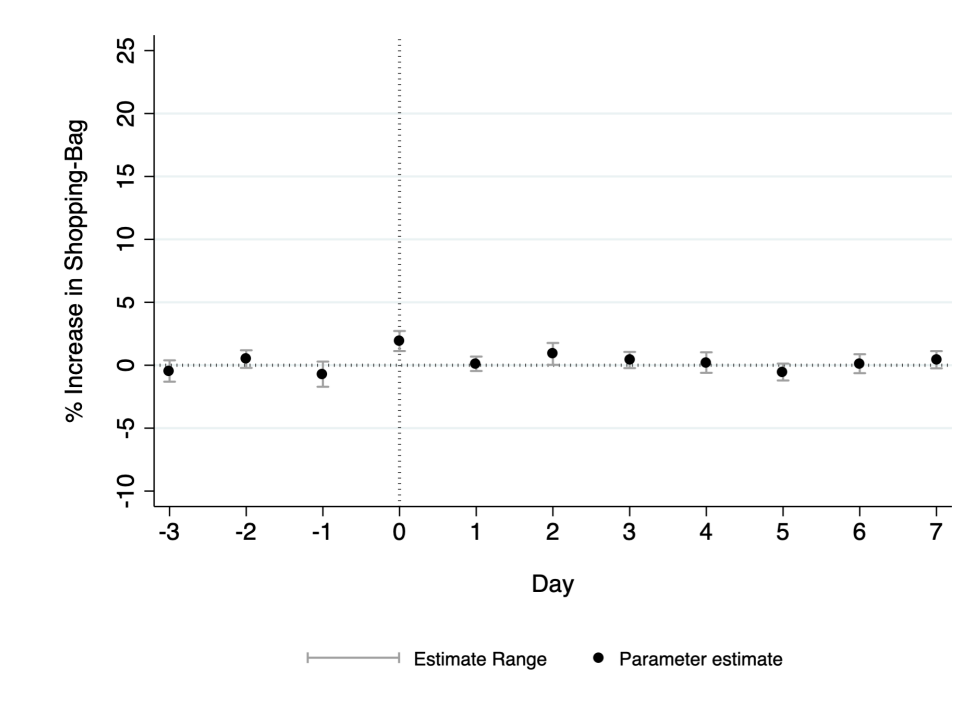
(a) Saliency



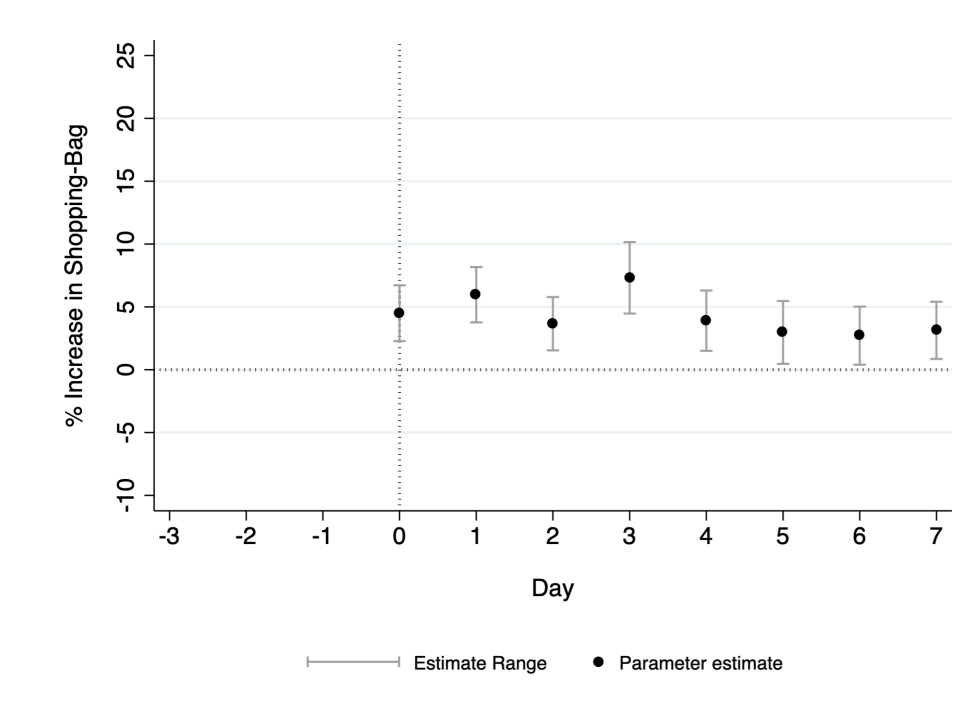
(b) New Product \times Saliency

These figures reports coefficient estimates (with 95% confidence intervals) of the effect of saliency on the total number of **shopping bag** additions (per day). Figure (a) reports the effect of saliency for existing products while figure (b) reports the effect of saliency for new products. The sample consists of all daily, product-level, transactions carried out between May 20, 2014 to July 29, 2014. As a result of the thrice-weekly introduction of new products, our database represents an unbalanced panel of products over time. *Saliency* is defined as the total number of new products that recommend the target product at any given point of time. The regression specifications controls for the entry of a new product, time fixed effects, controls for day of the week and weekend.

Figure 7: Staggered Effects of Saliency Shocks for Complementary Products



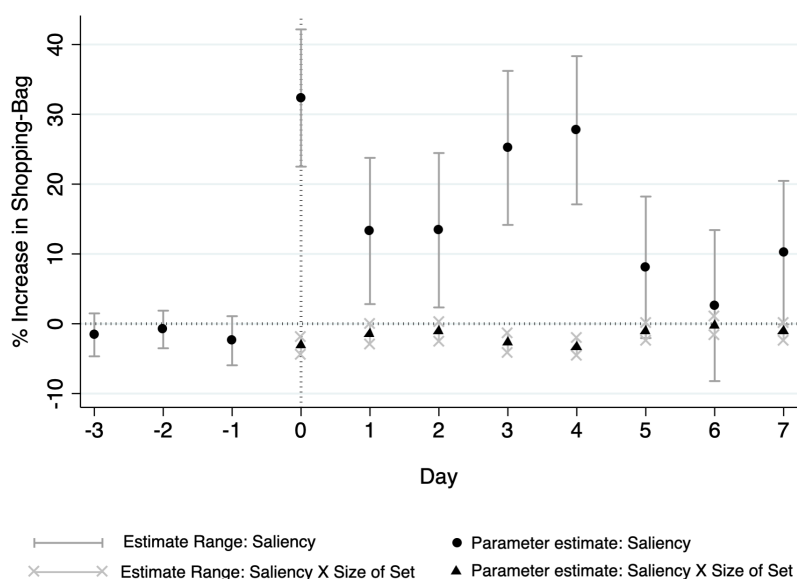
(a) Saliency



(b) New Product × Saliency

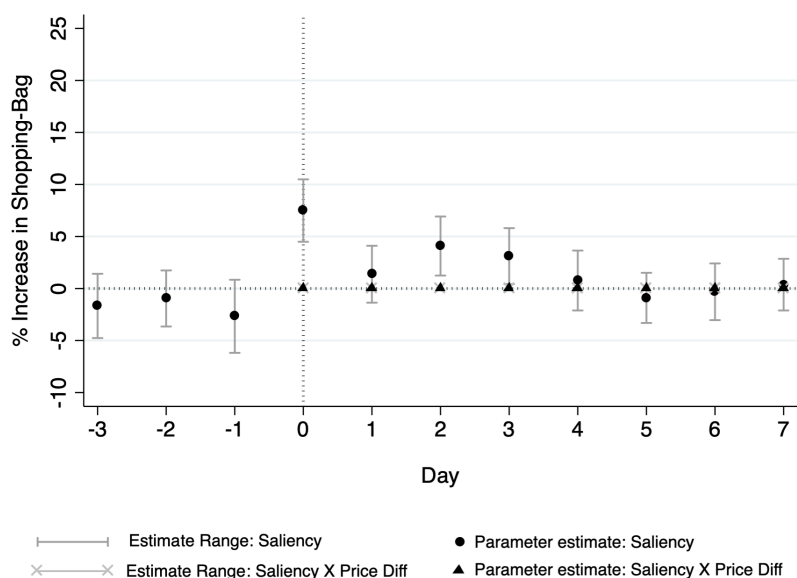
These figures reports coefficient estimates (with 95% confidence intervals) of the effect of saliency on the total number of **shopping bag** additions (per day). Figure (a) reports the effect of saliency for existing products while figure (b) reports the effect of saliency for new products. The sample consists of all daily, product-level, transactions carried out between May 20, 2014 to July 29, 2014. As a result of the thrice-weekly introduction of new products, our database represents an unbalanced panel of products over time. *Saliency* is defined as the total number of new products that recommend the target product **as complementary** at any given point of time under the heading. The regression specifications controls for the entry of a new product, time fixed effects, controls for day of the week and weekend.

Figure 8: Saliency Shocks: Attention Effects



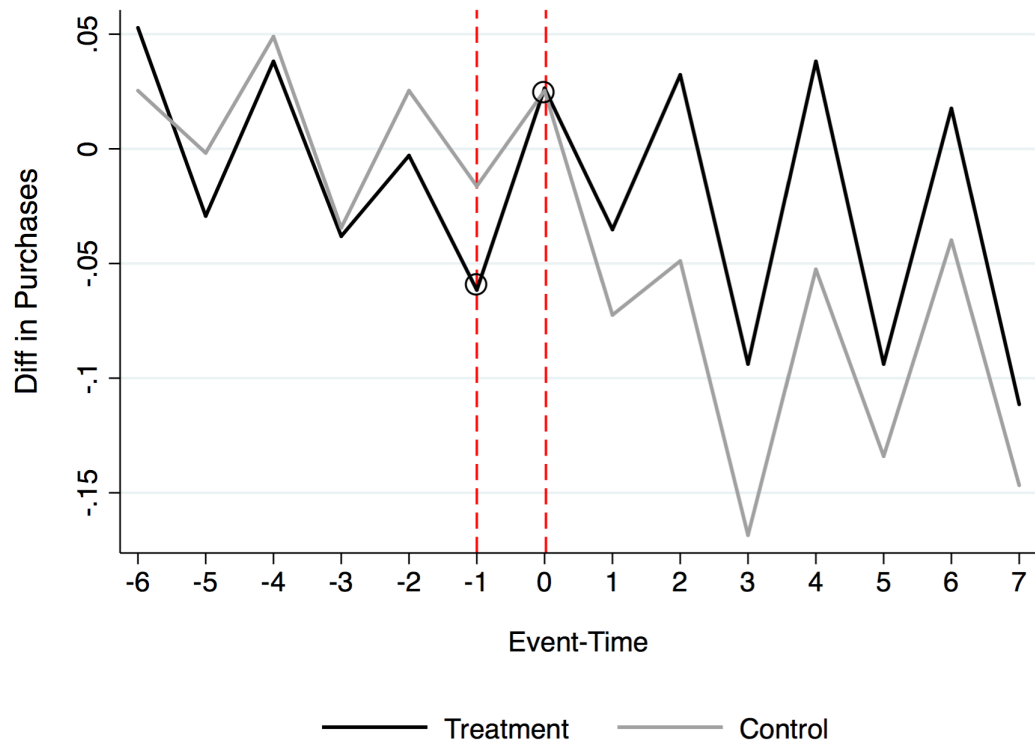
This figure reports coefficient estimates (with 95% confidence intervals) of the effect of saliency and its interaction with 'attention' (size of set) on the total number of **shopping bag** additions (per day). The sample consists of all daily, product-level, transactions carried out between May 20, 2014 to July 29, 2014. As a result of the thrice-weekly introduction of new products, our database represents an unbalanced panel of products over time. *Saliency* is defined as the total number of new products that recommend the target product at any given point of time. Our proxy for attention, the *size of the set* is defined as the average size of new product recommendation sets that include the target product. The regression specifications controls for the entry of a new product, time fixed effects, controls for day of the week and weekend.

Figure 9: Saliency Shocks: Price Effects



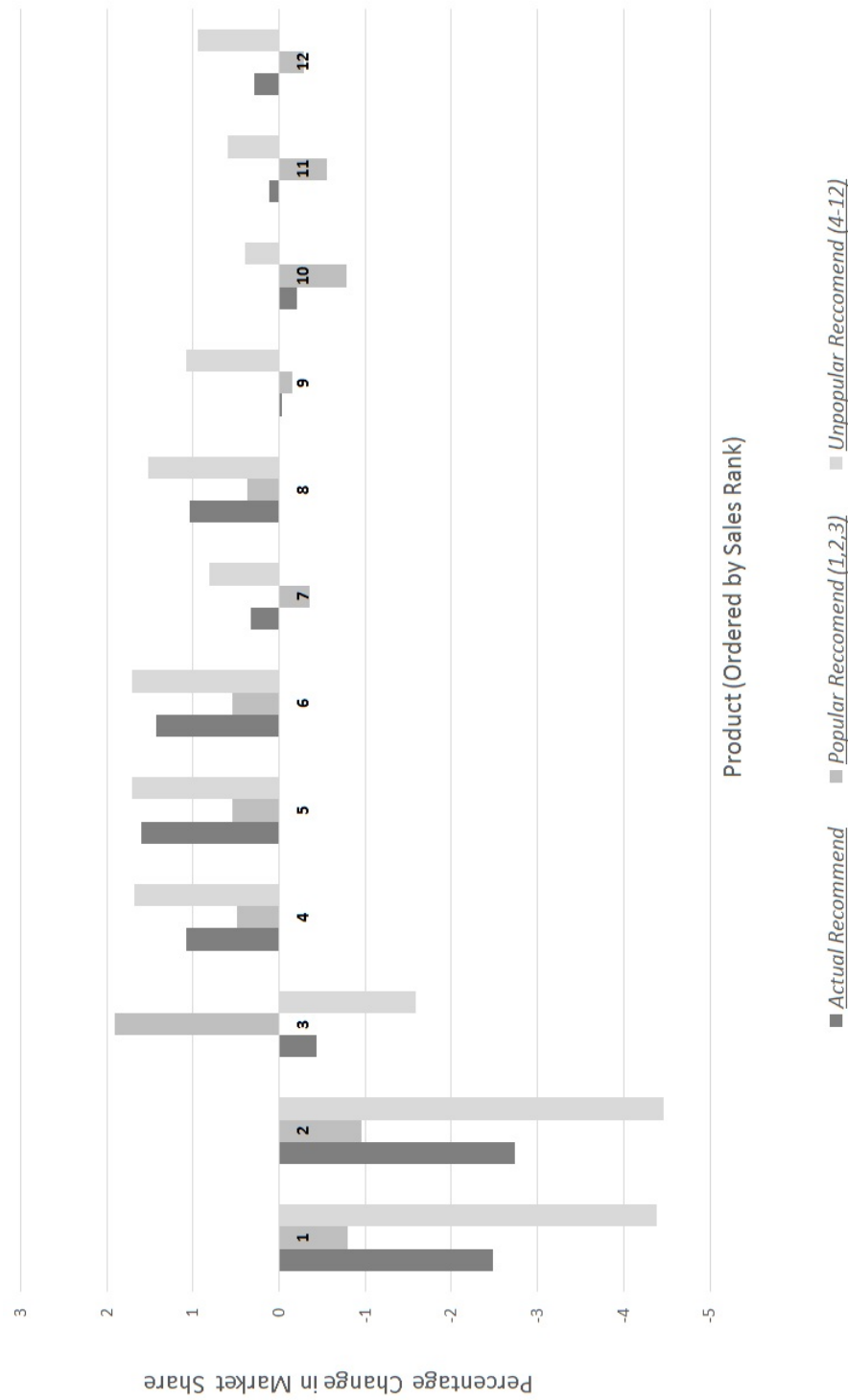
This figure reports coefficient estimates (with 95% confidence intervals) of the effect of saliency and its interaction with the price of the product on the total number of **shopping bag** additions (per day). The sample consists of all daily, product-level, transactions carried out between May 20, 2014 to July 29, 2014. As a result of the thrice-weekly introduction of new products, our database represents an unbalanced panel of products over time. *Saliency* is defined as the total number of new products that recommend the target product at any given point of time. *Price* is the retail price of the product in US dollars. The regression specifications controls for the entry of a new product, time fixed effects, controls for day of the week and weekend.

Figure 10: Double Diff-in-Diff: Common Trends



This figure plots the difference in purchases for the total number of **shopping bag** additions (per day) between the U.S. and Europe.

Figure 11: Counterfactuals - Limited Attention vs. Full Attention Difference in Sales Share



The figure shows results from counterfactual estimations allowing for the following scenarios: (1) consumers have full, instead of limited, attention and (2) only certain types of products receive recommendations. The x-axis orders products by their sales rank (1 being most popular and 12 being least popular). Products 1, 2 and 3 are categorized as 'popular products' (observed sales share > 10%); products 4 to 12 are categorized as 'unpopular products.' Each bar represents the percentage difference in sales share between when consumers have limited attention and when they have full attention. Dark gray bars show results under the existing recommendation system. Gray bars show the difference between limited and full attention when only popular products are (always) recommended (products 1, 2 and 3). Light gray bars show the difference between limited and full attention when only unpopular products are (always) recommended (products 4 to 12).

Table 1: Descriptive statistics: recommended and recommending products

| | Same category | | | Same designer | | | Price difference [†] | | |
|-------------|---------------|-----------|--------|---------------|-----------|--------|-------------------------------|-----------|-----------|
| | Mean | Std. Dev. | Median | Mean | Std. Dev. | Median | Mean | Std. Dev. | Median |
| All | 0.989 | 0.074 | 1 | 0.379 | 0.391 | 0.250 | \$9.210 | \$1,111 | \$-1.666 |
| Accessories | 0.974 | 0.118 | 1 | 0.388 | 0.376 | 0.285 | \$-0.117 | \$1,519 | \$-23.625 |
| Bags | 0.967 | 0.135 | 1 | 0.576 | 0.397 | 0.666 | \$32.987 | \$898 | \$0 |
| Beauty | 0.995 | 0.058 | 1 | 0.665 | 0.397 | 1 | \$1.651 | \$47 | \$0 |
| Clothing | 0.996 | 0.041 | 1 | 0.280 | 0.350 | 0.111 | \$9.116 | \$1,205 | \$0 |
| Lingerie | 0.994 | 0.053 | 1 | 0.695 | 0.385 | 1 | \$-19.873 | \$282 | \$0 |
| Shoes | 0.986 | 0.077 | 1 | 0.441 | 0.392 | 0.400 | \$24.092 | \$370 | \$-5.000 |

Notes: [†] Computed as price of recommended product minus price of recommending product. Averages for *Same category* and *Same designer* can be interpreted as the average share of recommended and recommending product pairs that are in the same product category or by the same designer.

Table 2: Descriptive statistics: Net-a-Porter 'Live'

| Variable | Category | Existing product | | | | t-test | | New product | | | | t-test |
|----------------|-------------|------------------|-----------|----------------|-----------|-----------|-------|-----------------|-----------|----------------|-----------|------------|
| | | not recommended | | recommended | | | | not recommended | | recommended | | |
| | | by new product | | by new product | | | | by new product | | by new product | | |
| | | Mean | Std. Dev. | Mean | Std. Dev. | | | Mean | Std. Dev. | Mean | Std. Dev. | |
| # Shopping bag | All | 0.385 | 1.062 | 0.555 | 1.313 | -0.170*** | | 0.278 | 1.284 | 0.539 | 1.879 | -0.261*** |
| | Accessories | 0.217 | 0.871 | 0.333 | 1.109 | -0.116*** | | 0.203 | 1.105 | 0.395 | 1.507 | -0.191*** |
| | Bags | 0.352 | 1.088 | 0.566 | 1.354 | -0.213*** | | 0.252 | 1.172 | 0.460 | 1.522 | -0.208*** |
| | Beauty | 0.499 | 1.194 | 0.585 | 1.290 | -0.085*** | | 0.474 | 1.597 | 0.549 | 2.198 | -0.075*** |
| | Clothing | 0.359 | 0.948 | 0.532 | 1.217 | -0.173*** | | 0.269 | 1.306 | 0.548 | 1.894 | -0.279*** |
| | Lingerie | 0.529 | 1.140 | 0.706 | 1.280 | -0.176*** | | 0.333 | 1.420 | 0.580 | 1.960 | -0.246*** |
| Shoes | 0.611 | 1.494 | 0.900 | 1.831 | -0.289*** | | 0.387 | 1.412 | 0.763 | 2.370 | -0.376*** | |
| # Wish list | All | 0.179 | 0.677 | 0.246 | 0.674 | -0.067*** | | 0.188 | 1.080 | 0.395 | 1.507 | -0.121*** |
| | Accessories | 0.101 | 0.405 | 0.152 | 0.626 | -0.050*** | | 0.139 | 0.834 | 0.460 | 1.522 | -0.107*** |
| | Bags | 0.236 | 1.388 | 0.248 | 0.662 | -0.012** | | 0.210 | 1.220 | 0.549 | 2.198 | -0.091*** |
| | Beauty | 0.143 | 0.484 | 0.168 | 0.527 | -0.024*** | | 0.177 | 0.860 | 0.548 | 1.894 | -0.041*** |
| | Clothing | 0.182 | 0.533 | 0.251 | 0.648 | -0.069*** | | 0.192 | 1.137 | 0.580 | 1.960 | -0.128*** |
| | Lingerie | 0.157 | 0.461 | 0.205 | 0.527 | -0.048*** | | 0.153 | 0.890 | 0.763 | 2.370 | -0.077*** |
| Shoes | 0.281 | 0.720 | 0.427 | 0.921 | -0.146*** | | 0.260 | 1.198 | 0.310 | 1.382 | -0.163*** | |
| # Users | | 38,437 | 67,620 | 46,561 | 75,658 | -8,124*** | | 63,110 | 164,521 | 91,687 | 198,239 | -28,576*** |

Notes: Product-level data aggregated at the day-level. # *Shopping bag* means number of shopping bag additions; # *Wish list* means number of wish list additions. The table shows statistics computed using product-by-day level data for the entire time period a given product is available for purchase on the website. *** Difference significant at 1%.

Table 3: Descriptive statistics: average prices of products recommended by new products and non-recommended products

| Price (in US\$) | Recommended | Not recommended | Difference |
|-----------------|-------------|-----------------|------------|
| All | 1,075.34 | 1,036.86 | 38.47 |
| Accessories | 989.08 | 1,045.29 | -56.21 |
| Bags | 1,666.98 | 1,732.24 | -65.25 |
| Beauty | 71.65 | 78.99 | -7.34 |
| Clothing | 1,250.59 | 1,281.34 | -30.75 |
| Lingerie | 258.28 | 222.23 | -36.04** |
| Shoes | 800.14 | 873.05 | -72.91** |

** Difference significant at 5%.

Table 4: Effects of Saliency on Total Shopping Bag Additions

| | (1) | (2) | (3) | (4) | (5) |
|-------------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Saliency | 0.059*** (0.013) | 0.057*** (0.014) | 0.055*** (0.016) | 0.054*** (0.016) | 0.069*** (0.016) |
| Forward Lag of Saliency | | -0.027 (0.017) | -0.027 (0.017) | -0.029 (0.018) | -0.017 (0.014) |
| New Product | 0.967*** (0.040) | 0.981*** (0.040) | 0.980*** (0.041) | 0.954*** (0.041) | 1.178*** (0.037) |
| Saliency \times New Product | | | 0.003 (0.022) | 0.004 (0.022) | -0.013 (0.021) |
| 2 Week Lag of New Product | | | | 0.069** (0.027) | -0.189** (0.017) |
| Lagged Demand controls | No | No | No | No | Yes |
| Time and Day F.E | Yes | Yes | Yes | Yes | Yes |
| Observations | 986214 | 969368 | 969368 | 969368 | 854896 |

This table reports results on the effect of the saliency shock on the total number of **shopping bag** additions (per day). The sample consists of all daily, product-level, transactions carried out between May 20, 2014 to July 29, 2014. As a result of the thrice-weekly introduction of new products, our database represents an unbalanced panel of products over time. *New Product* is a dummy variable taking the value one if the product was introduced in the catalogue on a given day. *Saliency* is defined as the total number of new products that recommend the target product at any given point of time. *Lagged Demand* controls comprise 7-day lag of shopping bag additions and are included in specification (5) as a control for possible popularity. All specifications control for time fixed effects, controls for day of the week and weekend. Standard errors clustered by product are reported in parentheses. * indicates significance at 10%; ** at 5%; *** at 1%.

Table 5: Effects of Saliency on Total Wish List Additions

| | (1) | (2) | (3) | (4) | (5) |
|-------------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Saliency | 0.056*** (0.011) | 0.054*** (0.011) | 0.063*** (0.017) | 0.068*** (0.017) | 0.064*** (0.017) |
| Forward Lag of Saliency | | -0.005 (0.018) | -0.004 (0.018) | -0.007 (0.018) | -0.28 (0.018) |
| New Product | 1.181*** (0.029) | 1.187*** (0.029) | 1.192*** (0.030) | 1.130*** (0.029) | 1.172*** (0.032) |
| Saliency \times New Product | | | -0.014 (0.021) | -0.010 (0.021) | -0.025 (0.021) |
| 2 Week Lag of New Product | | | | 0.210*** (0.020) | 0.066*** (0.020) |
| Lagged Demand controls | No | No | No | No | Yes |
| Time and Day F.E | Yes | Yes | Yes | Yes | Yes |
| Observations | 932539 | 915993 | 915993 | 915993 | 792979 |

This table reports results on the effect of the saliency shock on the total number of **wish list additions** (per day). The sample consists of all daily, product-level, transactions carried out between May 20, 2014 to July 29, 2014. As a result of the thrice-weekly introduction of new products, our database represents an unbalanced panel of products over time. *New Product* is a dummy variable taking the value one if the product was introduced in the catalogue on a given day. *Saliency* is defined as the total number of new products that recommend the target product at any given point of time. *Lagged Demand* controls comprise 7-day lag of wish list additions and are included in specification (5) as a control for possible popularity. All specifications control for time fixed effects, controls for day of the week and weekend. Standard errors clustered by product are reported in parentheses. * indicates significance at 10%; ** at 5%; *** at 1%.

Table 6: Spillover Effects of Saliency

| | -3 | -2 | -1 | Event day | +1 | +2 | +4 | +5 | +6 | +7 | +8 |
|-------------------------------------|---------------------|---------------------|-------------------|---------------------|---------------------|--------------------|---------------------|-------------------|--------------------|---------------------|---------------------|
| <i>Without spillovers:</i> | | | | | | | | | | | |
| Direct saliency effect | -0.017 (0.019) | -0.01 (0.016) | -0.026 (0.021) | 0.074*** (0.018) | 0.013 (0.017) | 0.040** (0.017) | 0.033** (0.016) | 0.01 (0.018) | -0.009 (0.015) | -0.003 (0.017) | 0.005 (0.015) |
| <i>With spillovers:</i> | | | | | | | | | | | |
| Direct saliency effect (degree 1) | -0.001 (0.019) | 0.003 (0.017) | -0.018 (0.022) | 0.082*** (0.018) | 0.023 (0.017) | 0.043** (0.017) | 0.038** (0.016) | 0.009 (0.018) | -0.009 (0.015) | 0.01 (0.017) | 0.008 (0.016) |
| Indirect saliency effect (degree 2) | 0.023*** (0.006) | 0.023*** (0.006) | 0.011* (0.006) | 0.019*** (0.006) | 0.024*** (0.006) | 0.013** (0.006) | 0.019*** (0.006) | 0.010* (0.006) | 0.014** (0.006) | 0.029*** (0.006) | 0.015*** (0.005) |
| Indirect saliency effect (degree 3) | 0.006* (0.003) | 0.005 (0.003) | 0.003 (0.004) | -0.002 (0.004) | 0.002 (0.003) | -0.001 (0.003) | 0.0001 (0.004) | -0.005 (0.003) | -0.003 (0.004) | 0.008** (0.003) | 0.002 (0.003) |

This table reports results on the spill-over effects of the saliency shock on the total number of **shopping bag additions** (per day). The sample consists of all daily, product-level, transactions carried out between May 20, 2014 to July 29, 2014. As a result of the three-weekly introduction of new products, our database represents an unbalanced panel of products over time. *Direct Saliency (degree 1)* is defined as the total number of new products that recommend the target product at any given point of time. Products that are recommended by degree 1 products have a two degree separation between themselves and the new product and are identified by the variable *indirect Saliency (degree 2)*. Products that are recommended by degree 2 products have a three degree separation between themselves and the new product and are identified by the variable *indirect Saliency (degree 3)*. All specifications control for time fixed effects, controls for day of the week and weekend. Standard errors clustered by product are reported in parentheses. * indicates significance at 10%; ** at 5%; *** at 1%.

Table 7: Overview of Results - Effect of saliency on shopping bag additions (existing products)

| | Event day | Event day + 1 | Event day + 2 | Event day + 3 | Event day + 4 |
|--|----------------------|--------------------|---------------------|----------------------|----------------------|
| Recommended as Substitutes: | | | | | |
| Saliency Shock | 0.074*** (0.018) | 0.013 (0.017) | 0.040** (0.017) | 0.033** (0.016) | 0.010 (0.018) |
| Saliency Shock with anticipation control | 0.076*** (0.018) | 0.017 (0.017) | 0.043*** (0.017) | 0.034** (0.016) | 0.010 (0.017) |
| Saliency Shock with lagged novelty control | 0.077*** (0.018) | 0.017 (0.017) | 0.043** (0.017) | 0.034** (0.016) | 0.010 (0.017) |
| Saliency Shock Accounting for Spillovers | 0.082*** (0.018) | 0.023 (0.017) | 0.043** (0.017) | 0.038** (0.016) | 0.009 (0.018) |
| <i>Saliency-Price Sensitivity:</i> | | | | | |
| Saliency Shock | 0.075*** (0.018) | 0.014 (0.017) | 0.041** (0.017) | 0.031* (0.016) | 0.008 (0.018) |
| Saliency Shock \times Price | 0.000 (0.000) | 0.000 (0.000) | 0.000 (0.000) | -0.000 (0.000) | -0.000* (0.000) |
| <i>Saliency-Attention Sensitivity:</i> | | | | | |
| Saliency Shock | 0.323*** (0.060) | 0.133** (0.064) | 0.134** (0.067) | 0.252*** (0.067) | 0.277*** (0.065) |
| Saliency Shock \times Size of Recc. Set | -0.032*** (0.008) | -0.015* (0.009) | -0.012 (0.008) | -0.028*** (0.008) | -0.034*** (0.008) |
| Recommended as Complements: | | | | | |
| Saliency Shock | 0.019*** (0.005) | 0.001 (0.003) | 0.009* (0.005) | 0.004 (0.004) | 0.002 (0.005) |

Table 8: Overview of Results - Effect of saliency on wish list additions (existing products)

| | Event day | Event day + 1 | Event day + 2 | Event day + 3 | Event day + 4 |
|--|----------------------|---------------------|----------------------|---------------------|----------------------|
| Recommended as Substitutes: | | | | | |
| Saliency Shock | 0.057*** (0.018) | 0.014 (0.018) | 0.030 (0.019) | 0.014 (0.019) | -0.049** (0.020) |
| Saliency Shock with anticipation control | 0.058*** (0.018) | 0.014 (0.018) | 0.030 (0.020) | 0.013 (0.019) | -0.053** (0.021) |
| Saliency Shock with lagged novelty control | 0.058*** (0.018) | 0.016 (0.018) | 0.031 (0.019) | 0.015 (0.019) | -0.049** (0.020) |
| <i>Saliency-Price Sensitivity:</i> | | | | | |
| Saliency Shock | 0.057*** (0.018) | 0.012 (0.018) | 0.025 (0.020) | 0.009 (0.019) | -0.050** (0.021) |
| Saliency Shock \times Price | 0.000 (0.000) | -0.000 (0.000) | -0.000*** (0.000) | -0.000** (0.000) | -0.000 (0.000) |
| <i>Saliency-Attention Sensitivity:</i> | | | | | |
| Saliency Shock | 0.450*** (0.074) | 0.188** (0.085) | 0.257*** (0.076) | 0.088 (0.079) | 0.193** (0.084) |
| Saliency Shock \times Size of Recc. Set | -0.050*** (0.009) | -0.022** (0.011) | -0.029*** (0.009) | -0.009 (0.010) | -0.030*** (0.010) |
| Recommended as Complements: | | | | | |
| Saliency Shock | 0.017*** (0.005) | -0.003 (0.005) | 0.003 (0.005) | 0.005 (0.005) | -0.010* (0.005) |

Table 9: Effects of Saliency on Difference in Demand b/w the U.S. and Europe

| | (1) | (2) | (3) | (4) | (5) |
|--|--------------------|--------------------|--------------------|--------------------|--------------------|
| Treatment | 0.017 (0.029) | 0.003 (0.035) | | 0.003 (0.035) | -0.018 (0.035) |
| Post | 0.162 (0.106) | 0.142 (0.095) | 0.142 (0.093) | 0.134 (0.091) | 0.138 (0.098) |
| Treatment \times Post | 0.079** (0.038) | 0.121** (0.048) | 0.121** (0.047) | 0.337** (0.141) | |
| Treatment \times Post \times Size of Set | | | | -0.015* (0.008) | |
| Post (Day 0) | | | | | 0.092* (0.053) |
| Post (Day 1) | | | | | 0.164** (0.074) |
| Post (Day 2) | | | | | 0.121** (0.061) |
| Post (Day 3) | | | | | 0.103 (0.065) |
| Sample of once recommended products | No | Yes | Yes | Yes | Yes |
| Controls for product 'age' | Yes | Yes | Yes | Yes | Yes |
| New Product (Block) F.E. | Yes | Yes | Yes | Yes | Yes |
| New Product (Block) \times Post F.E. | Yes | Yes | Yes | Yes | Yes |
| Product F.E. | No | No | Yes | No | Yes |
| Observations | 7154 | 5866 | 5866 | 5866 | 5873 |

This table reports results on the effect of the saliency shock on the difference in total **shopping bag additions** (per day), between America and Europe. The sample consists of a subset of products that are recommended exclusively in the two regions, America and Europe. For this sample of product the specification estimates a double difference-in-difference equation for the sample's daily transactions over a (-3,+3) event window. *Treatment* is a dummy variable that takes the value 1 if the product was recommended in America but not in Europe. *Post* a dummy variable indicating the post-event window (0,+3). Our proxy for attention, the *size of the set* is defined as the average size of new product recommendation sets that include the target product. *Age* of the product is the number of days since the product was released in the catalogue for sale. Standard errors clustered by product are reported in parentheses. * indicates significance at 10%; ** at 5%; *** at 1%.

Table 10: Effects of Saliency on Consideration and Choice on Individual Choice (Shopping Bag)

| | Travel Bags | | Travel Bags | | Watches | |
|--|-------------------------------|-------------------------------|----------------------------|-------------------------|----------------------------|--------------------------|
| | Consideration | Choice | Consideration | Choice | Consideration | Choice |
| Saliency | 0.153*** (1.51e-08) | 0.260*** (2.44e-08) | 6.733*** (0.253) | 0.292 (0.364) | 3.340*** (0.008) | -0.532 (0.712) |
| New Product | -2.539*** (8.96e-08) | 1.228*** (9.92e-08) | -12.223*** (0.470) | 6.422*** (0.280) | -3.284*** (0.797) | 2.347*** (0.393) |
| Saliency×New Product | | | -4.687*** (0.253) | -5.166*** (0.293) | 0.797*** (0.008) | -1.124* (0.637) |
| Aggregate Marginal Effect of Saliency | 0.022 | | 0.030 | | 0.154 | |
| Observations | 1080 | 1080 | 1080 | 1080 | 4430 | 4430 |
| # Products | 12 | 12 | 12 | 12 | 10 | 10 |
| # Products with Saliency Shock (at least 1) | 10 | 10 | 10 | 10 | 8 | 8 |
| # Individuals | 90 | 90 | 90 | 90 | 443 | 443 |

This table reports results on the effect of the saliency shock on the probability of purchase, incorporating both consideration and choice. The sample consists of a subset of products (Travel Bags and Watches), purchased in the region America. All specifications control for the product price. *Saliency* is a dummy variable that takes the value 1 if the product was recommended at time t and 5 days following it. The mean marginal effect of saliency is given by (the mean of) the expression: $\left[(1 - B_{ijt})\psi_1 + \sum_{c_t \in G} \{(P_{ijt}|c_t)(1 - P_{ijt}|c_t)P_{it}(c_t)\psi_2\} \right]$. Standard errors, based on the quadratic approximation to the curvature at the maximum likelihood estimate, are reported in parentheses. * indicates significance at 10%; ** at 5%; *** at 1%.

ONLINE APPENDIX – NOT FOR PUBLICATION

A Appendix: Figures

Figure A-1: Variation in the size of recommendation sets over sample period (new vs. existing recommending products)

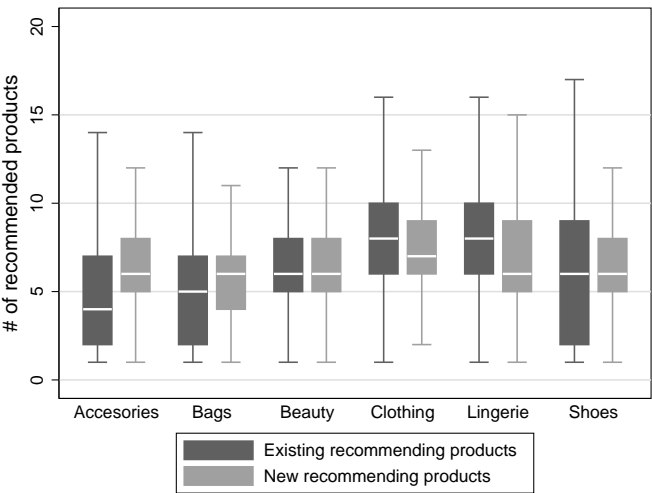


Figure A-2: Variation in the number of new products over sample period

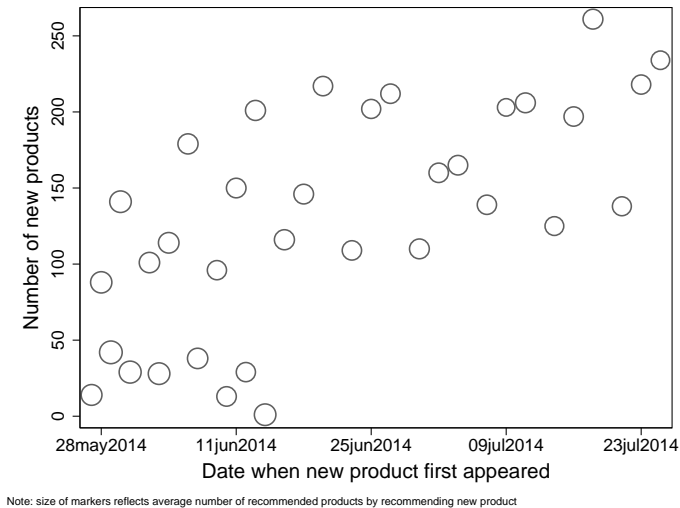
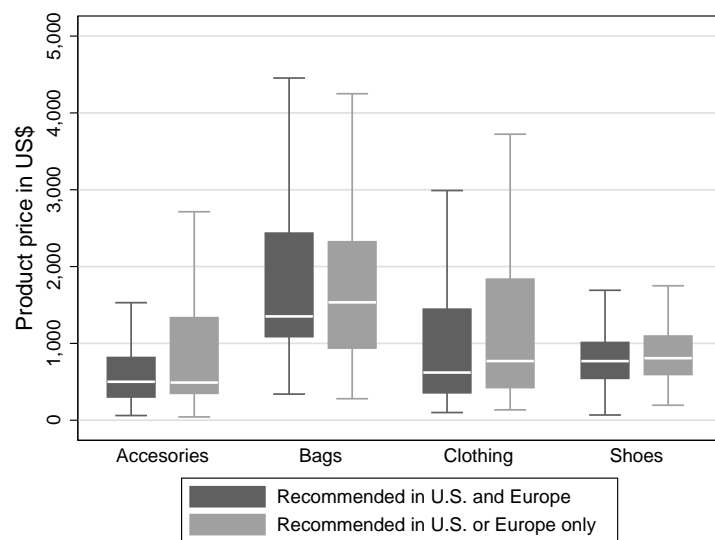
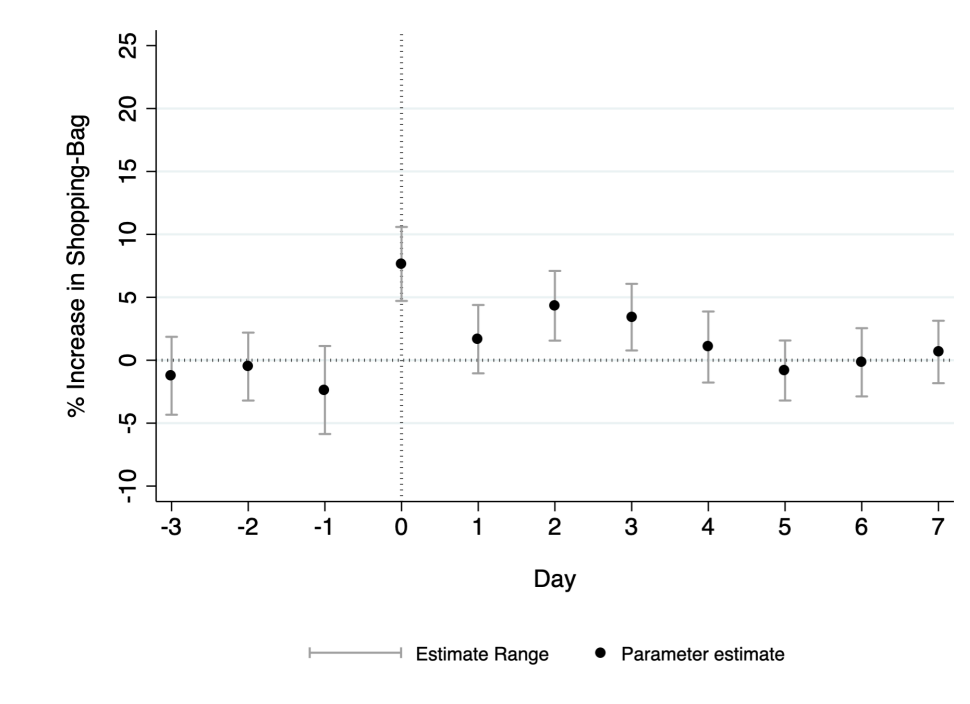


Figure A-3: Variation in regional recommendation sets over sample period: price distribution of products recommended by new products by category

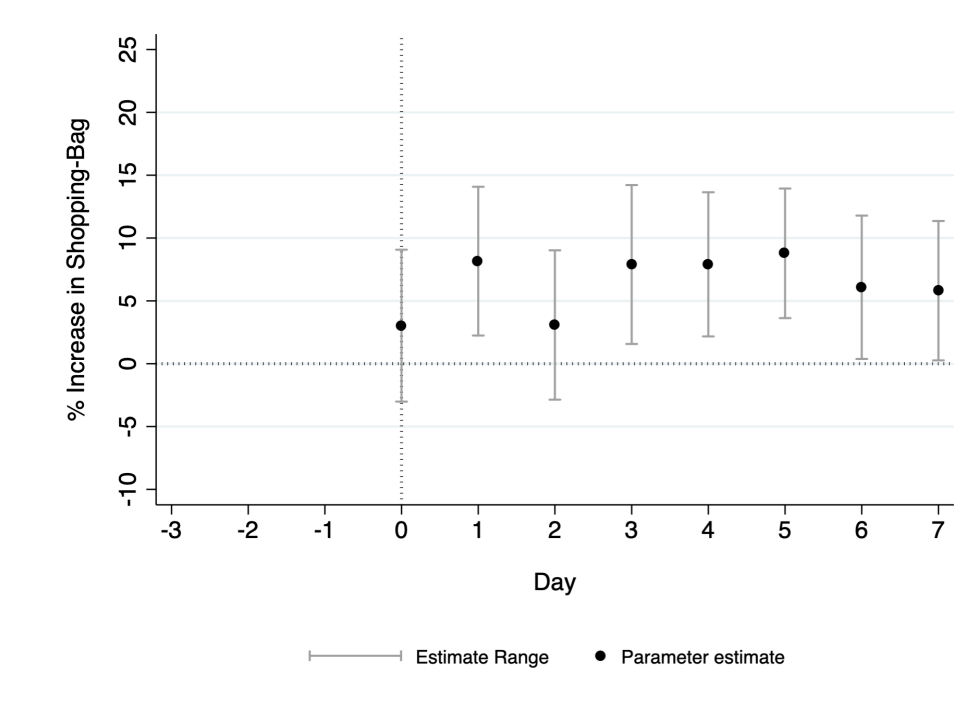


Product categories beauty and lingerie excluded due to small number of observations.

Figure A-4: Saliency Shocks: : Controlling for Lagged Effect of New Product



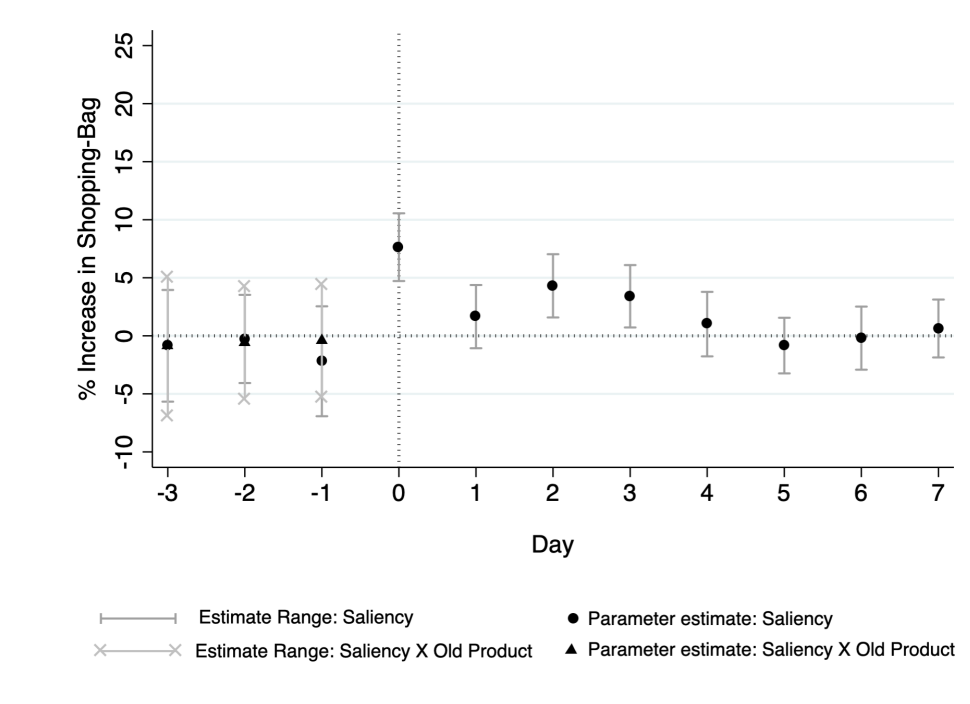
(a) Saliency



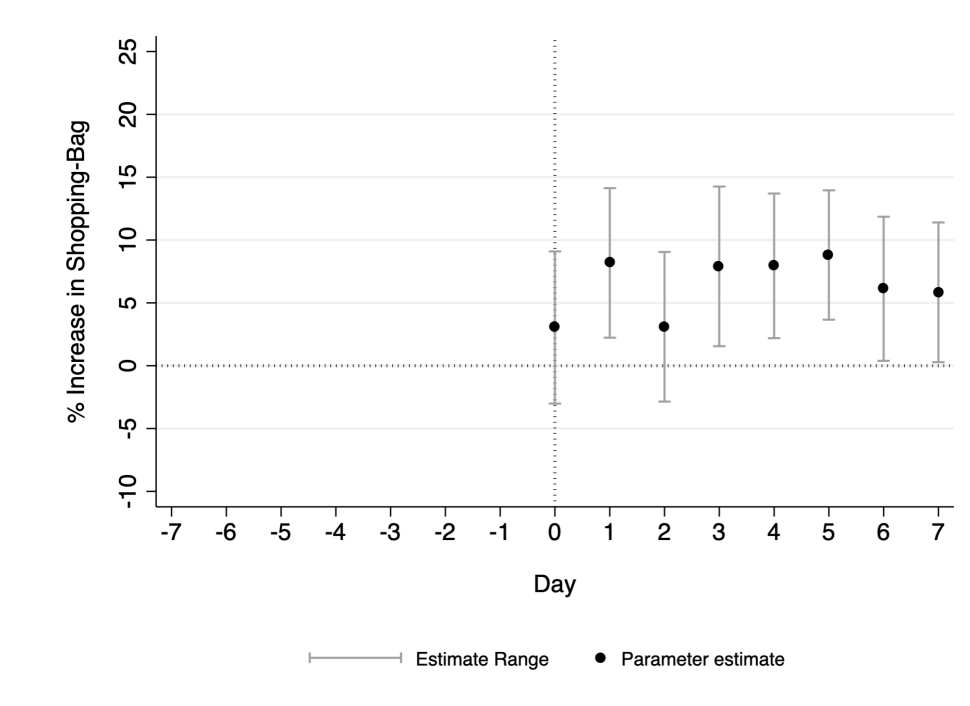
(b) New Product × Saliency

These figures reports coefficient estimates (with 95% confidence intervals) of the effect of saliency on the total number of **shopping bag** additions (per day) controlling for lagged entry effects, i.e, we include the two-week lag of whether a product was new in the specification. Figure (a) reports the effect of saliency for existing products while figure (b) reports the effect of saliency for new products. The sample consists of all daily, product-level, transactions carried out between May 20, 2014 to July 29, 2014. As a result of the thrice-weekly introduction of new products, our database represents an unbalanced panel of products over time. *Saliency* is defined as the total number of new products that recommend the target product at any given point of time. The regression specifications controls for the entry of a new product, time fixed effects, controls for day of the week and weekend.

Figure A-5: Saliency Shocks: Controlling for Differential Anticipation Effects



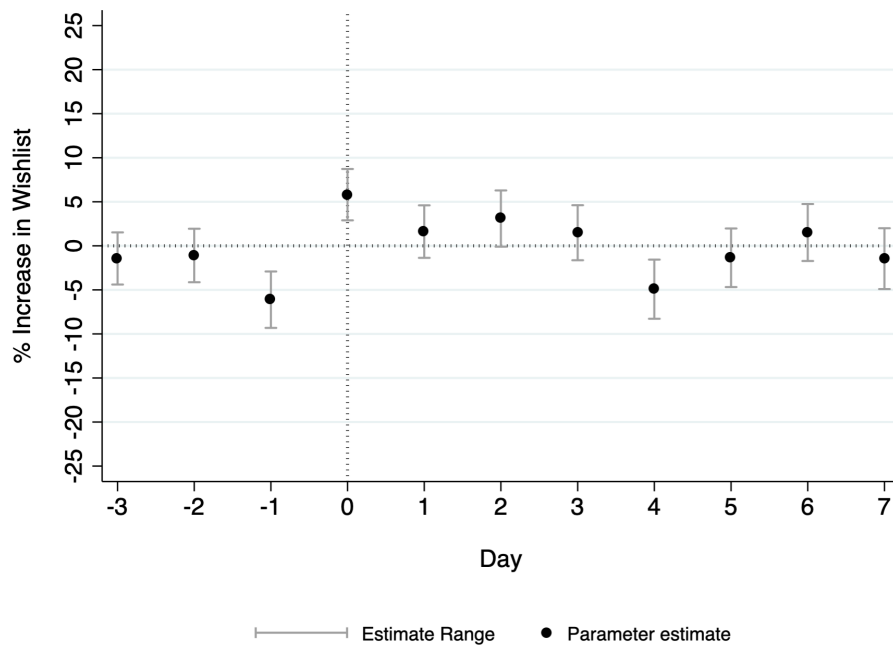
(a) Saliency



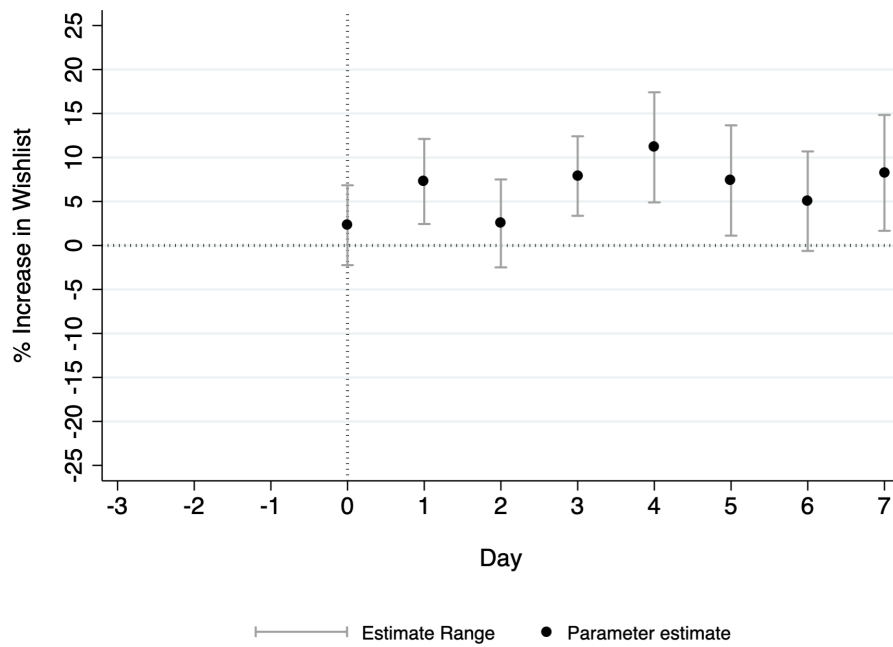
(b) New Product \times Saliency

These figures reports coefficient estimates (with 95% confidence intervals) of the effect of saliency on the total number of **shopping bag** additions (per day) controlling for differential anticipation effects, i.e., we split and include the anticipation effect (forward lags of saliency) between products that received a prior saliency shock and those that did not. Figure (a) reports the effect of saliency for existing products while figure (b) reports the effect of saliency for new products. The sample consists of all daily, product-level, transactions carried out between May 20, 2014 to July 29, 2014. As a result of the thrice-weekly introduction of new products, our database represents an unbalanced panel of products over time. *Saliency* is defined as the total number of new products that recommend the target product at any given point of time. The regression specifications controls for the entry of a new product, time fixed effects, controls for day of the week and weekend.

Figure A-6: Saliency Shocks: Wish list with Controls for Lagged New Product Effects



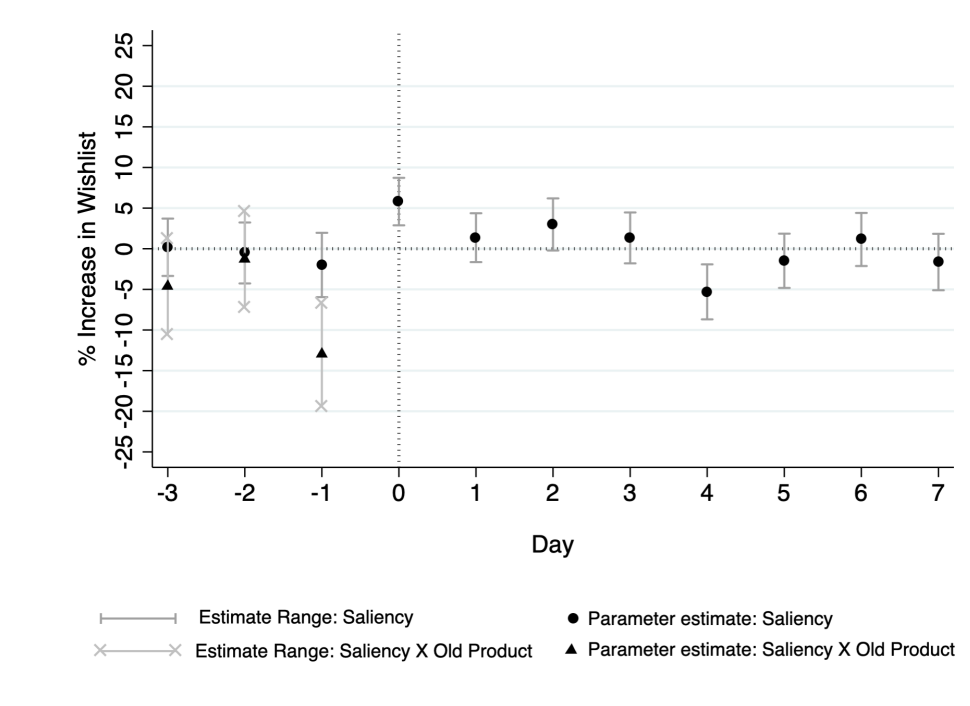
(a) Saliency



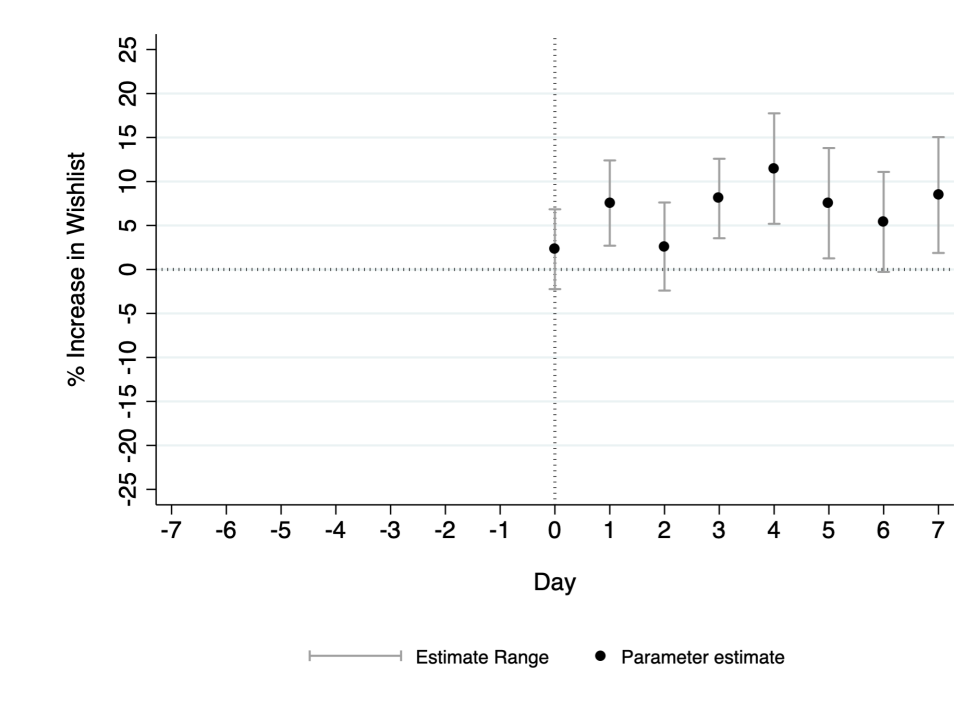
(b) New Product \times Saliency

These figures reports coefficient estimates (with 95% confidence intervals) of the effect of saliency on the total number of **wish list** additions (per day) controlling for lagged entry effects, i.e, we include the two-week lag of whether a product was new in the specification. Figure (a) reports the effect of saliency for existing products while figure (b) reports the effect of saliency for new products. The sample consists of all daily, product-level, transactions carried out between May 20, 2014 to July 29, 2014. As a result of the thrice-weekly introduction of new products, our database represents an unbalanced panel of products over time. *Saliency* is defined as the total number of new products that recommend the target product at any given point of time. The regression specifications controls for the entry of a new product, time fixed effects, controls for day of the week and weekend.

Figure A-7: Saliency Shocks: Wish list with Control for Differential Anticipation Effects



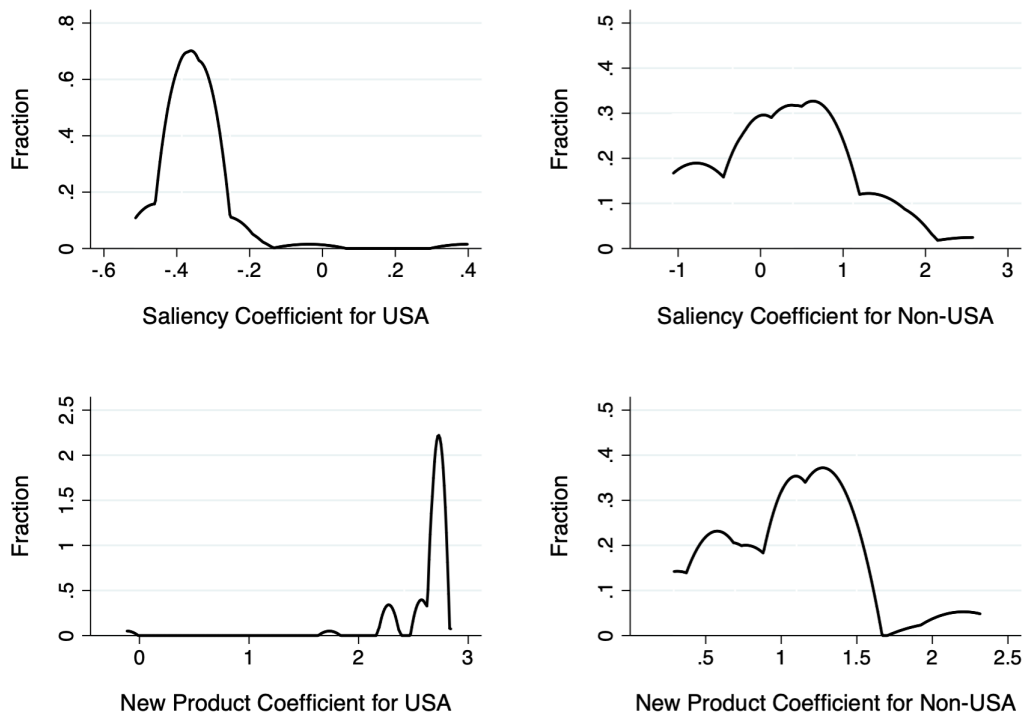
(a) Saliency



(b) New Product \times Saliency

These figures reports coefficient estimates (with 95% confidence intervals) of the effect of saliency on the total number of **wish list** additions (per day) controlling for differential anticipation effects, i.e., we split and include the anticipation effect (forward lags of saliency) between products that received a prior saliency shock and those that did not. Figure (a) reports the effect of saliency for existing products while figure (b) reports the effect of saliency for new products. The sample consists of all daily, product-level, transactions carried out between May 20, 2014 to July 29, 2014. As a result of the thrice-weekly introduction of new products, our database represents an unbalanced panel of products over time. *Saliency* is defined as the total number of new products that recommend the target product at any given point of time. The regression specifications controls for the entry of a new product, time fixed effects, controls for day of the week and weekend.

Figure A-8: Distribution of Saliency and New Product Effects from PCMNL model



This figure shows the distribution of the price and saliency effects from the choice stage estimation for travel bags. The specification for estimation corresponds to that provided in columns (3)-(4) of Table 10. The estimation for the choice stage is based on a latent class multinomial logit model which allows to recover individual-specific coefficients, plotted in the above graph.

B Appendix: Tables

Table A-1: Descriptive statistics: number of recommended products across regions

| | Recommended by | | | | | | | | | | | |
|-------------|------------------|-------|-----------|-------|-------------|-------|-----------|-------|-----------|-------|-----------|-------|
| | existing product | | | | new product | | | | | | | |
| | U.S. & EU | | U.S. only | | E.U. only | | U.S. & EU | | U.S. only | | E.U. only | |
| | # | % | # | % | # | % | # | % | # | % | # | % |
| All | 430 | 35.54 | 520 | 42.98 | 260 | 21.49 | 448 | 28.18 | 574 | 36.10 | 568 | 35.72 |
| Accessories | 107 | 31.66 | 153 | 45.27 | 78 | 23.08 | 122 | 28.50 | 165 | 38.55 | 141 | 32.94 |
| Bags | 36 | 36.00 | 40 | 40.00 | 24 | 24.00 | 35 | 24.65 | 55 | 38.73 | 52 | 36.62 |
| Beauty | 22 | 48.89 | 16 | 35.56 | 7 | 15.56 | 14 | 26.92 | 22 | 42.31 | 16 | 30.77 |
| Clothing | 199 | 37.90 | 228 | 43.43 | 98 | 18.67 | 193 | 28.18 | 233 | 34.01 | 259 | 37.81 |
| Lingerie | 1 | 33.33 | 0 | 0 | 2 | 66.67 | 2 | 33.33 | 2 | 33.33 | 2 | 33.33 |
| Shoes | 65 | 32.66 | 83 | 41.71 | 51 | 25.63 | 82 | 29.60 | 97 | 35.02 | 98 | 35.38 |

The table shows the number of products that are recommended in (a) both the U.S. and Europe, (b) only the U.S., or (c) only Europe.

Table A-2: Descriptive statistics: size of product recommendation sets

| | Recommended by | | | | | |
|-------------|----------------------------|-------|-------|----------------------------|-------|-------|
| | existing product | | | new product | | |
| | # Recommending products | Mean | SD | # Recommending products | Mean | SD |
| All | 13,355 | 6.643 | 3.516 | 8,448 | 6.901 | 2.826 |
| Accessories | 2,315 | 4.666 | 3.077 | 1,585 | 6.564 | 2.846 |
| Bags | 1,333 | 4.954 | 3.275 | 785 | 5.756 | 2.555 |
| Beauty | 1,068 | 6.592 | 2.640 | 282 | 6.485 | 2.664 |
| Clothing | 6,190 | 7.785 | 3.187 | 4,433 | 7.378 | 2.723 |
| Lingerie | 813 | 7.414 | 3.741 | 378 | 6.846 | 3.305 |
| Shoes | 1,636 | 6.142 | 3.946 | 985 | 6.349 | 2.848 |

The table shows the size of recommendation sets by recommending product (existing or new product) across product categories.

Table A-3: Descriptive statistics: product recommendations by new products

| # Products | Recommended by new product | | If recommended # recommendations | | |
|--|-------------------------------|---------|-------------------------------------|------|-----|
| | # products | % Total | Mean | SD | Max |
| By product recommended by new product | | | | | |
| All | 6,693 | 43.46 | 1.50 | 0.91 | 23 |
| Accessories | 1,197 | 52.61 | 1.49 | 0.79 | 8 |
| Bags | 590 | 50.77 | 1.49 | 0.75 | 6 |
| Beauty | 310 | 31.47 | 1.55 | 1.39 | 9 |
| Clothing | 3,523 | 42.24 | 1.53 | 0.84 | 8 |
| Lingerie | 240 | 27.71 | 1.98 | 2.30 | 23 |
| Shoes | 833 | 47.06 | 1.45 | 0.79 | 8 |
| By product recommended by new product and time | | | | | |
| All | 373.57 | 2.95 | 1.27 | 0.68 | 23 |
| Accessories | 64.19 | 3.56 | 1.28 | 0.62 | 8 |
| Bags | 32.63 | 3.57 | 1.27 | 0.58 | 6 |
| Beauty | 6.98 | 0.75 | 1.44 | 1.26 | 9 |
| Clothing | 224.68 | 3.34 | 1.26 | 0.61 | 8 |
| Lingerie | 6.37 | 0.79 | 1.84 | 2.09 | 23 |
| Shoes | 38.68 | 2.62 | 1.24 | 0.61 | 8 |

The upper part of this table reports statistics when we consider whether an existing product was recommended by a new product during the entire period of observation. The lower part of the table, in contrast, reports statistics when we consider whether an existing product was recommended by a new product on a given day during the period of observation. The # of products recommended by new products in the lower part of the table are therefore the average number of existing products recommended by new products on any given day.

Table A-4: Mean Own and Cross-Elasticities from Change in Saliency

| Product | Elasticities | | | | | | | | | | | |
|---------------------------|--------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 1 | 0.079 | -0.021 | 0.000 | -0.005 | -0.004 | -0.009 | -0.007 | -0.007 | 0.000 | 0.010 | -0.006 | -0.019 |
| 2 | 0.007 | 0.068 | 0.000 | -0.005 | 0.012 | -0.007 | -0.006 | -0.006 | 0.000 | -0.005 | -0.005 | -0.017 |
| 3 | -0.007 | -0.006 | 0.000 | -0.005 | 0.005 | 0.014 | -0.005 | -0.005 | 0.000 | -0.005 | -0.005 | -0.017 |
| 4 | -0.007 | -0.021 | 0.000 | 0.044 | -0.010 | 0.005 | 0.015 | -0.006 | 0.000 | -0.005 | -0.007 | -0.019 |
| 5 | -0.008 | -0.020 | 0.000 | -0.005 | 0.098 | -0.009 | 0.007 | 0.015 | 0.000 | -0.005 | -0.007 | -0.019 |
| 6 | -0.008 | -0.020 | 0.000 | -0.005 | 0.004 | 0.081 | -0.007 | 0.007 | 0.000 | -0.005 | -0.007 | -0.019 |
| 7 | -0.008 | -0.021 | 0.000 | -0.005 | -0.011 | 0.005 | 0.062 | -0.007 | 0.000 | -0.005 | -0.006 | -0.019 |
| 8 | -0.008 | -0.021 | 0.000 | 0.010 | -0.003 | -0.009 | 0.008 | 0.062 | 0.000 | -0.005 | 0.015 | -0.018 |
| 9 | -0.009 | -0.021 | 0.000 | -0.004 | -0.010 | -0.001 | -0.007 | 0.008 | 0.000 | -0.004 | 0.007 | -0.004 |
| 10 | -0.002 | -0.021 | 0.000 | -0.005 | -0.010 | -0.007 | -0.006 | -0.007 | 0.000 | 0.044 | -0.007 | -0.005 |
| 11 | 0.013 | -0.020 | 0.000 | -0.005 | -0.011 | -0.009 | -0.006 | -0.006 | 0.000 | -0.005 | 0.062 | -0.019 |
| 12 | 0.007 | 0.002 | 0.000 | -0.005 | -0.010 | -0.008 | -0.006 | -0.005 | 0.000 | -0.005 | 0.009 | 0.048 |
| <hr/> | | | | | | | | | | | | |
| <i>Average Elasticity</i> | | | | | | | | | | | | |
| Spillovers | -0.006 | -0.003 | -0.003 | -0.005 | -0.004 | -0.005 | -0.007 | -0.003 | -0.004 | -0.006 | -0.006 | -0.002 |
| Own+Spillovers | 0.004 | -0.010 | 0.000 | 0.001 | 0.004 | 0.004 | 0.004 | 0.004 | 0.000 | 0.001 | 0.004 | -0.010 |

Cell entries j, k , where j indexes row and k column, give the percent change in sales share of brand j with a one-percent change in the saliency of product kj . Each entry represents the mean of the elasticities from the 90 consumers. The last two rows report the average percent change in sales share of all products due to a one-percent change in the saliency of product j . The penultimate row ('Spillovers') omits self-elasticities in computing this average.