STUCK ONLINE: WHEN ONLINE ENGAGEMENT GETS IN THE WAY OF OFFLINE SALES

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Abstract

In recent years, billions of marketing dollars are spent, by both online and offline retailers, on website design aimed at increasing consumers' online engagement. We study the relationship between online engagement and offline sales, utilizing a quasi-experimental setting whereby a leading luxury automobile brand launched a new interactive website gradually across markets, allowing for a treatment-control comparison. The paper finds surprising evidence that increased online engagement reduces (offline) car sales. Comparing markets where the website was launched to control markets, we find that the high-engagement website led to a decline of approximately 12% in car sales. This negative effect is due to substitution between online and offline engagement, as the high-engagement website decreased users' tendency to submit online requests that lead to personal contact with a car dealer. We further show that the result is not due to decreased website usability or efficiency, and perform several robustness tests to establish our main result. For pure offline products, hands-on engagement is a necessary step toward purchase, and thus increasing consumer engagement online may halt progression down the sales funnel and may not be an optimal strategy.

Keywords: online engagement, online-to-offline, sales funnel, e-commerce, natural experiment.

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Introduction

Could a highly engaging and informative brand website be bad for business? Studying the relationship between online user engagement at a brand website and its offline sales, we find that the answer is a surprising 'yes.' We exploit a quasi-experimental setting, examining the impact of the launch of a new interactive website by a leading luxury automaker in four (out of 12) markets, on the brand's offline car sales. We find a negative impact of the high-engagement website on sales, with an average decline in sales of approximately 12% in markets where the website was launched compared to control markets. Further examining the Online-to-Offline (O2O[1]) sales funnel, we identify the mechanism leading to the decrease in offline sales. Namely, higher online engagement at the automobile brand website decreased users' tendency to submit requests for personal contact with car dealers, resulting in a loss of opportunities to persuade potential buyers.

This work relates to ongoing efforts to understand the interaction between online and offline retail channels (1–6). Over a decade ago, when e-commerce was in its infancy, it sparked questions and concerns as to the future of brick-and-mortar stores. Many wondered whether physical stores would become showrooms for e-retail, and whether and to what extent consumers would shift from offline to online shopping (7–9). While about half of consumers do use physical stores as showrooms, the reverse, online product research followed by an offline purchase is actually more common (10). Online-to-offline purchase journeys have become the norm for *pure offline products* such as cars, real estate, and healthcare services, that are (largely) not available online. Specifically, in the automobile market, consumers shopping for a new car have been

[1] http://www.innovationiseverywhere.com/o2o-why-china-leads-the-online-to-offline-revolution/

substituting dealership visits with online information gathering, leading to a decline in their average number of dealership visits from 5 to 1.6 in just ten years[2] (11, 12). In this new landscape, it is increasingly important to understand and measure the end effect of web presence on offline sales, and how it is mediated by online consumer behavior. Studying this question for the online-to-offline sales funnel, we fill a gap in the existing literature that has examined settings where an actual purchase was not limited to the offline channel (1–6).

We focus on the impact of increased online engagement on offline sales. Online engagement metrics represent consumers' level of web activity using different features of website visit, including bounce rate, number of pages viewed, number of events per page-view, session duration, average page-view duration, and return rate (13–15). Consumers' online engagement has been shown to increase website efficiency (16), by inducing more positive consumer opinions, reviews and comments. Moreover, engagement stimulates online word of mouth, which, in turn, increases online sales (e.g., 17–19). Relating to the online-offline purchase funnel framework, online engagement moves consumers from the initial consideration level down to the decision-making level, and eventually leads to purchase (1).

With this in mind, both online and offline retailers have been focusing their efforts on improving their online presence and enhancing firm websites, and website spending is commanding the lion share of marketing budgets (20). These efforts are aimed at increasing traffic and consumer engagement on brand websites, and ultimately at increasing purchase probability (21–23). Our natural experiment setup, coupled with the context of a pure offline

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[2] The dealership visit remains a necessary step towards purchase, with 90% of American consumers surveyed report having conducted at least one test drive prior to purchase.

product, provides a unique opportunity to identify a causal effect of online engagement on offline sales. We demonstrate that for pure offline products, high online engagement can be a double-edged sword, as substituting the offline hands-on experience with increased online engagement has the potential to decrease sales.

Evidence from a Quasi-experiment

We partnered with a leading luxury automobile manufacturer with a substantial global presence to estimate the effect of increased online engagement on local brand websites on the company's offline car sales, between 2011 and 2014. Increased online engagement, in our setting, is due to the manufacturer's launch of new interactive brand websites, replacing the previous less-interactive websites at the same URLs.

The auto-maker's stated goal for the new website was to increase consumers' engagement with the brand and their awareness of different car models and features. The main change compared to the previous website is a substantially improved car customization experience under the "Build Your Own" tab. This tab is designed to engage users as they test out different configurations of car models, interactively displaying the full set of customizable options, accompanied by detailed information and price for each option.

To evaluate the impact of high online engagement generated by the upgraded website, we utilize the quasi-experimental setting arising from its staggered launch, whereby the website was upgraded only in some countries, and at different times. This gradual launch strategy was possible since the brand's websites are centrally designed and deployed, yet maintained at local, country-specific URLs, such that all traffic from a specific country, or *market*, is automatically directed to the local URL. Specifically, between 2011 and 2014, the auto-manufacturer launched the upgraded *high engagement (HE)* website in four markets in our data-set, labelled T1-T4 – in T1 in December 2011, and in T2-T4 in December 2012. Other markets were left unaffected by the *HE* treatment in the above time period. These markets, where the website remained in its previous *low engagement (LE)* format[3], serve as our control group. We obtained data for eight such control markets, labelled C1-C8.

We estimate the effect of the *HE* treatment by comparing pre- and post- launch engagement, sales, and user activity, for treatment vs. control markets. This is the difference-in-differences (DID) empirical strategy, whereby the effect of the treatment is measured as the change in the differences between treatment and control groups that is due to the onset of treatment (see 24 for further details and discussion).

Our main data set has been made available by the leading luxury auto-manufacturer. We analyze quarterly sales data for the four-year period from 2011 to 2014, for T1-T4 and C1-C8. Further analyses of the effects of launch on engagement and user activity utilize additional data sets, and are based on subsets of these treatment and control groups, as well as subsets of the four-year period, due to constraints in data availability as detailed below.

Manipulation Check: The *HE* Website Launch Increased Online Engagement

The starting point of our analysis is to confirm that the launch of the interactive brand website indeed resulted in higher online user engagement, as planned. This manipulation check is performed using data from Alexa.com, which tracks and measures global online activity.

We study the impact of the upgraded website on two variables, *Time-On-Site* and *Traffic Rank*. *Time-On-Site* is our proxy for user engagement, and is measured as time spent on the

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[3] At least in our period of analysis.

brand website.[4] *Traffic Rank* is a measure of website popularity, determined by Alexa.com based on global internet traffic, such that a lower rank indicates greater popularity.

Alexa.com measures engagement only for the 100,000 most popular websites worldwide, and therefore *Time-On-Site* is available only for two treatment markets (T2-T3) and three control markets (C3, C4, C7). *Traffic Rank* for the brand's market-specific websites is available for all treatment markets, and for seven control markets (all but C8). Both metrics are available at a monthly level for September 2012-December 2014, i.e., starting three months before the T2-T4 launch.

The launch of the interactive website was not accompanied by any related promotions designed to attract more users to the brand's market-specific websites. The launch was aimed only at increasing engagement for website visitors, and not at increasing website traffic. Hence, we expect to find a positive impact of launch on *Time-On-Site*, with no effect on *Traffic Rank*.

Figure 1 shows that indeed this is the case. Comparing the pre- and post-launch three-month periods, average monthly *Time-On-Site* did not significantly differ between treatment and control markets pre-launch, substantially increased for the T2-T3 launch markets in the post-launch months, and slightly decreased for control markets (where this decrease is not statistically significant). For *Traffic Rank*, we observe that both treatment and control markets suffer an increase in rank (i.e., decreased traffic) in the post-launch months.

(a) Time-On-Site	**(b) Traffic Rank**

[4] Number of pageviews per visit is also measured by Alexa.com, yet pageviews before and after the new website launch are incomparable, due to changes in the definition of a pageview event resulting from the upgrade.

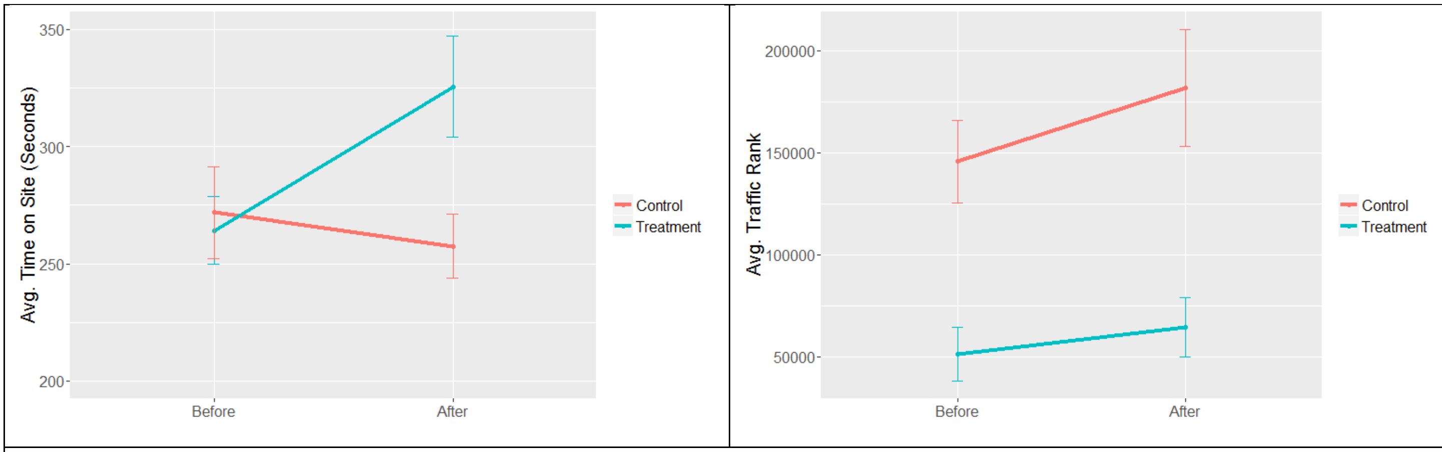

Figure 1. The Effect of Launch on Online Engagement. (a) Average Time-On-Site three months before and after launch: T2-T3 vs. three control markets; (b) Average Traffic Rank three months before and after launch: T2-T4 vs. seven control markets.

We estimate the effect of launch on engagement using the following DID regression model:

$$(1) \qquad TimeOnSite_{cym} = \alpha_c + \beta_y + \gamma_m + \boldsymbol{\delta} \cdot Launch_{cym} + \epsilon_{cym}$$

where cym represents $country - year - month$. The model thus has a full set of country, year, and month fixed effects represented by $\alpha_c, \beta_y,$ and γ_m, to control for differences between countries, and for the trend and seasonality in the car market. The idiosyncratic error term is ϵ_{cym}. We define the binary variable *Launch* to equal 0 until the new website is launched (in each market), and 1 from the month of launch onwards. We are interested in estimating δ, which is the effect of $Launch$. Estimation results are reported in column (1) of Table 1, where column (2) presents estimation results for the effect of Launch on *Traffic Rank* (with the same model specification). Standard errors, clustered at the country level, are bootstrapped using the "wild bootstrap" method due to the small number of clusters (25).

The results show a significant increase in consumers' engagement in the upgraded local websites and no significant change in the traffic to these websites. Specifically, launch of the interactive website increased *Time-On-Site* for the average user by approximately 63 seconds (p=

0.003***). These results are in line with the manufacturer's stated goal for the website's redesign, namely – higher engagement.

Table 1: The Effect of *HE* Website Launch on Time-On-Site and Traffic Rank

	Dependent variable:	
	Time-on-Site	*Traffic Rank*
	(1)	(2)
Launch	62.67^{***}	-4,950.67
	(19.78)	(22792)
Observations	139	308
Adjusted R^2	0.43	0.80
Note:	Fixed effects for country, year and month included.	
	Standard errors (shown in parentheses) are clustered at the country level, and estimated using the wild bootstrap method.	
	*** p<0.01, ** p<0.05, * p<0.1	

The Negative Effect of the *HE* Website Launch on Sales

We turn to our main DID analysis - examining the impact of the *HE* website launch on sales, employing country-level quarterly panel data of the number of cars sold, available from the manufacturer for T1-T4 and C1-C8, in 2011-2014. The DID analysis hinges on the parallel trend assumption stating that treatment and control groups follow a similar pre-intervention trend, and thus any divergence in trend for the treatment group in the post-intervention period is due to the treatment. We employ three tests to validate the parallel trend assumption, following the presentation of our main results.

As a first visual inspection, figure 2 plots the average quarterly sales, in terms of numbers of cars sold, before and after the December 2012 launch for T2-T4 and all control markets. The dashed light blue line represents the parallel trend assumption, by showing the hypothetical change in sales for treatment markets had they continued to follow the same trend as control markets (i.e., absent treatment). The "Launch effect" marked in figure 2 is the change in the differences between control and treatment markets' average quarterly sales, comparing the post- to pre-launch period. We observe a negative effect, as the *HE* launch group exhibits a smaller increase in average quarterly sales compared to control markets.

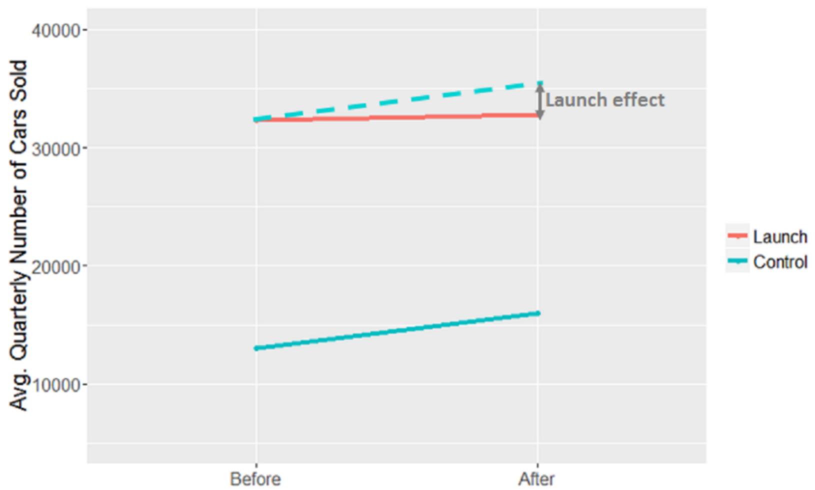

Figure 2. The Effect of the *HE* Launch on Sales. Average quarterly sales for T2-T4 launch markets and all control markets, one year before and after the December 2012 launch.

To formalize this result, we estimate the launch effect using the following model:

$$(2) \qquad \log(Sales_{cyq}) = \alpha_c + \beta_y + \gamma_q + \boldsymbol{\delta} \cdot Launch_{cyq} + \epsilon_{cyq}$$

Where $\log(Sales_{cyq})$ is the natural logarithm of quarterly number of cars sold in country c in year y and quarter q. The variables $\alpha_c, \beta_y,$ and γ_m represent fixed effects for country, year and quarter, controlling for these sources of variation. As both launches occurred towards the end of a quarter, we define the binary variable *Launch* to equal 0 until the quarter in which the new website launched (in each market), and 1 from the quarter following launch onwards. This further accounts for the pace of the market for new cars, where typically 1-3 months pass from initial inquiry to the supply of a new vehicle (26, 27). Due to this supply lag, we test a second model specification where the dependent variable is the one-quarter lead of sales, considering the possibility of a delayed impact. To these base specifications, we add the variable

TotalRegistered, which provides the total quarterly number of non-commercial vehicles registered in each country, allowing for better control for country-level trends in automobile sales. Estimation results for these four specifications are reported in Table 2 below. As before, standard errors, clustered at the country level, are bootstrapped using the wild bootstrap method due to the small number of clusters (25). We focus our attention on δ, the effect of $Launch$.

Our results show a significant negative effect of the *HE* launch on sales, such that post-launch quarterly sales were, on average, approximately 12-13% lower in treatment compared to control markets, using same-quarter sales (models (1) and (3), $p < 0.05$), and approximately 11% lower using next-quarter sales (models (2) and (4), $p < 0.05$).

Table 2: The Effect of the *HE* Website Launch on Sales

	Dependent variable:			
	$\log(Sales_q)$	$\log(Sales_{q+1})$	$\log(Sales_q)$	$\log(Sales_{q+1})$
	(1)	(2)	(3)	(4)
Launch	-0.14^{**}	-0.12^{**}	-0.13^{**}	-0.12^{**}
	(0.07)	(0.06)	(0.07)	(0.07)
TotalRegistered			0.0000	-0.0000
			(0.0000)	(0.0000)
Observations	192	192	192	192
Adjusted R^2	0.98	0.98	0.98	0.98

Note: Fixed effects for country, year and quarter included.
Standard errors (shown in parentheses) are clustered at the country level, and estimated using the wild bootstrap method.
*** p<0.01, ** p<0.05, * p<0.1

Validity of the Control Group

The manufacturer chose to deploy the *HE* website gradually, and continued its roll-out in the same manner in other markets after our period of analysis. Reportedly, the order of launch markets was chosen based on internal considerations, and was not based on previous web activity or sales in these markets. This supports the soundness of our treatment-control comparison, in our quasi-experimental setting. However, to ensure the validity of our DID empirical strategy, we directly test the parallel trend assumption, and examine whether a common sales trend exists for treatment and control markets prior to the launch of the *HE* website (if these groups follow different pre-launch trends then the estimated effect may simply be due to the difference in trends). Two additional robustness tests follow, offering further support of the validity of our empirical strategy.

Analyzing pre-launch trends. Figure 3 allows us to visually inspect the sales trend, and shows parallel pre-launch trends for T2-T4 and all control markets. Post-launch, we observe a small downward vertical shift in treatment markets' sales, and a difference in trends, as the treatment group's growth rate is now slower compared to that of the control group.

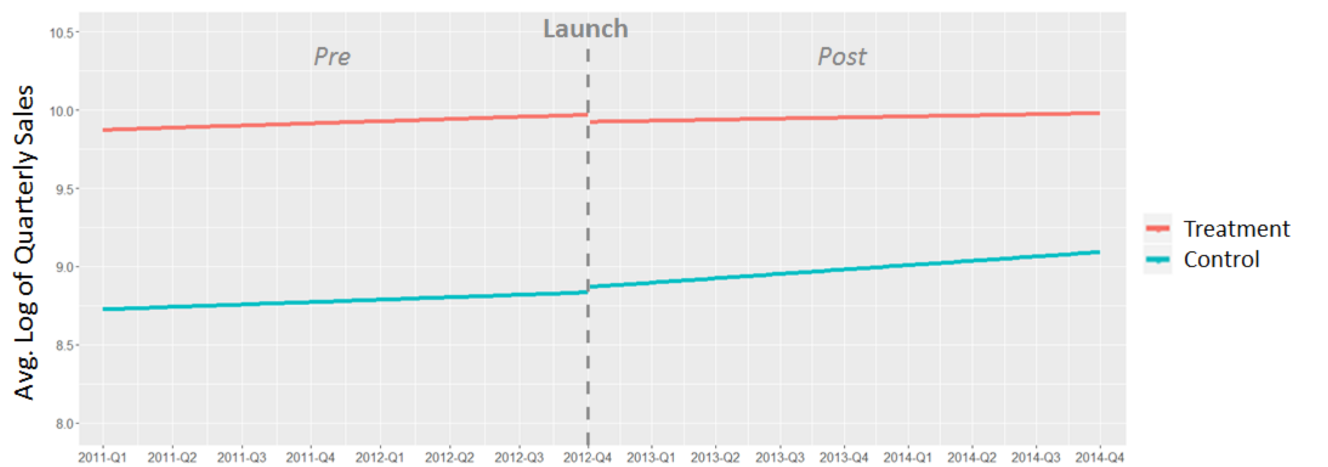

Figure 3. Linear Trend of $Log(Sales)$ for Treatment (T2-T4) vs. Control Markets (C1-C8), Pre- and Post-Launch.

Formally, we estimate the following model as a direct test for differences in pre-launch trends:

$$(3) \qquad \log(Sales_{cyq}) = \alpha_c + \beta_1 \cdot Trend_{yq} + \boldsymbol{\beta_2} \cdot Trend_{yq} \cdot Treatment_c + \epsilon_{cyq}$$

Where $Trend_{yq}$ is the index of quarter q in year y, and $Treatment_c$ is an indicator variable that equals 1 if country c is in T1-T4, and 0 otherwise. Other variables are defined as in equation

(2). We also test a second specification that includes $TotalRegistered_{cyq}$ as an additional control. In both specifications, β_2 is not statistically significant ($p > 0.1$; see Table S1 in the SI), implying that there is no difference in pre-launch trends between the treatment and control groups.

Granger-causality test. We conduct a second robustness test, as in (28). This test of Granger causality (29), checks that *HE* launch status predicts sales only after- and not before- launch, where a finding of no pre-treatment effect provides further evidence of no pre-launch differences in trends for treatment and control markets. For this test, we create a set of dummy variables, indicating the quarter relative to the *HE* launch. Specifically, we use indicator variables for 1-3 quarters before launch, and 0-4 quarters after launch, labelled $RelLaunch_{c,t}$, where $t \in \{-3, -2, .., +4\}$; and an indicator for the 5th quarter and onwards after launch, labelled $RelLaunch_{c,+5onwards}$. These variables allow for a possible effect of launch before and after the actual *HE* launch, and further allow us to examine the dynamics of the *HE* impact – whether the effect increases over time or remains stable.

The following model (4) incorporates these variables, that replace $Launch$ in (2), and further includes country and quarter fixed effects (α_c and γ_q) as well as control for market specific trends in car sales, represented by $TotalRegistered$.

$$\text{(4)} \qquad \log(Sales_{cyq}) = \alpha_c + \gamma_q + \sum_{t\in\{-3,..+4\}} \delta_t \cdot RelLaunch_{c,t} + \delta_{+5onwards} RelLaunch_{c,+5onwards} + TotalRegistered_{cyq} + \epsilon_{cyq}$$

Estimation results are reported in Table S2. The results confirm that there are no anticipatory effects, that is, the differences between treatment and control markets do not appear prior to the *HE* launch, in support of the parallel trends assumption. Furthermore, we observe the negative impact of the *HE* website increasing in magnitude in the periods following launch.

Placebo treatment model. As a final robustness test of the DID results, we estimate a placebo treatment model to demonstrate that the observed effect on sales cannot be attributed to chance. For this exercise, we use pre-launch data for T2-T4 and control markets, and estimate the effect of a placebo (fake) launch starting December 2011, using the same specifications as in Table 2. The effect of the placebo treatment is not statistically significant, as expected ($p > 0.1$; estimation results are reported in Table S3).

Mechanism: Higher Online Engagement Decreased Personal Contact with Dealers

The automobile brand's website is designed to affect sales via sales leads – online requests for information, requests for dealership offers, and test drives — following which the interested consumer is contacted by a car dealer. This is the case for the pre- and post-launch website. If the *HE* launch is indeed the cause of the decline in sales in treatment markets, then we expect to find a negative effect of launch on online sales leads, to establish the mechanism through which higher online engagement led to lower offline sales.

We study the effect of launch on sales leads using a panel of monthly sales leads for T3 and four control markets, between January 2012 and December 2014.[5] Online sales leads are captured by the following three variables: (1) *BD* – brochure downloads, where a brochure includes all possible options for model configuration along with their price (for a single chosen model); (2) *RFO* - requests for an offer; and (3) *TDA* - test drive applications.

Requests for test drives (*TDA*) are performed by customers with a strong purchase intent, as they demonstrate a commitment to arrive at a dealership. On the other hand, brochure downloads (*BD*) represent an earlier stage in the car purchase journey, when the customer is still gathering

[5] The automaker provided limited data for online sales leads.

information and deliberating, and a request for offer (*RFO*) is an intermediate stage, in which the deliberating customer seeks out personal contact with a dealer.

Figure 4 illustrates the effect of launch on these three variables. Comparing the difference between control markets to T3 in *BD*, *RFO*, and *TDA* in the year before T3's *HE* launch to the year after, we observe a positive effect of launch on *BD* and *TDA*, and a large negative effect on *RFO*.

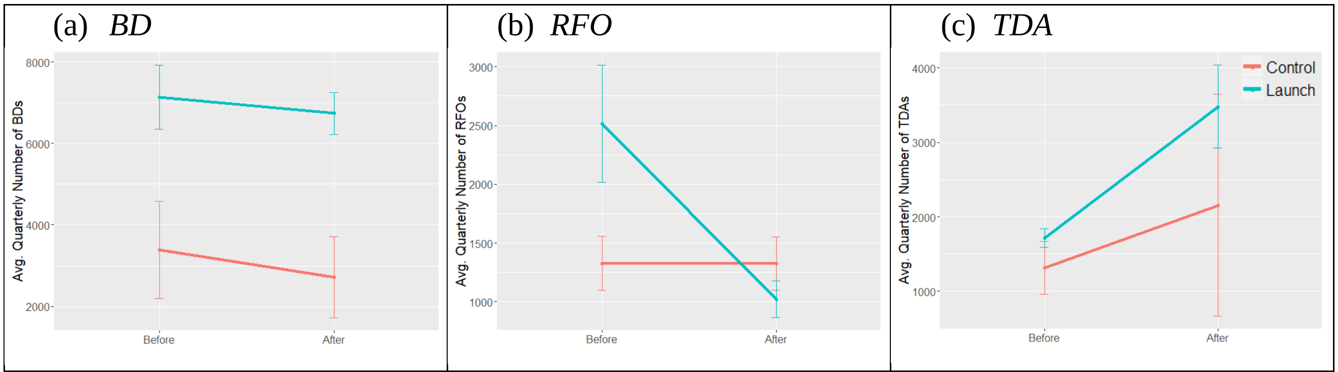

Figure 4. The Effect of *HE* Launch on Online Sales Leads: (a) *BD*; (b) *RFO*; (c) *TDA*. Comparing T3 to control markets, a year before and a year after the T3 launch, we observe a positive effect of launch on *BD* and *TDA*, and a negative effect on *RFO*.

The effect is estimated in the following DID model:

$$\text{(5)} \qquad \log\left(SalesLead_{cym}\right) = \alpha_c + \beta_y + \gamma_m + \boldsymbol{\delta} \cdot Launch_{cym} + \epsilon_{cym}$$

where $SalesLead$ is one of $\{BD, RFO, TDA\}$ and the remaining variables are the same as in specification (2). Estimation results are reported in Table 3.

Table 3: *HE* Launch effect on Online Sales Leads

	Dependent variable:		
	$\log(BD)$	$\log(RFO)$	$\log(TDA)$
	(1)	(2)	(3)
Launch	0.23^{***} (0.05)	-0.89^{***} (0.09)	0.95^{***} (0.20)
Observations	24	24	32
Adjusted R^2	0.98	0.75	0.77
Note:	Fixed effects for country, year and quarter included. Cluster robust standard errors shown in parentheses (Clustered on country). *** p<0.01, ** p<0.05, * p<0.1		

The results indicate that the launch of the *HE* website increased the number of brochure downloads and test drive requests, while reducing the number of requests for offers.[6] The results continue to holds when we further control for total car registration in each market (Table S4).[7]

Our results suggest that higher online engagement led to increased information gathering online, as represented by the increase in brochure downloads. Furthermore, *HE* helped move customers with a strong purchase intent down the purchase funnel, by increasing test drive applications. Yet, higher online engagement also resulted in fewer, pre-test drive, dealership contacts, represented by the decrease in requests for offers (likely due to improved availability of comprehensive pricing information). This reduction in personal offline contacts with customers who are still in the deliberation stage, is the driver of the decrease in sales.

The mechanism by which online engagement impacts offline sales is further discussed in the Model section in the SI, where we present a formal model of the online to offline purchase funnel, for purely offline products. The model highlights two roles of online engagement, in the

[6] We refrain from comparing the magnitude of these effects to the magnitude of the effect on sales, as this analysis is based on a more limited dataset.

[7] The DID parallel trends assumption holds, as for the three type of sales leads, there was no difference in pre-launch trends between the treatment and control groups (see Table S5 in the SI).

spirit of those attributed to traditional advertising: providing product information and persuasion (30). The first is modelled as uncertainty reduction regarding consumers' fit with the product, and the second as the introduction of a non-negative product bias. These effects counteract when consumers' uncertainty regarding product fit is relatively high and their match probability with the product is low. Within this framework, we derive conditions for which online engagement will have a negative impact on offline sales.

We find that the overall effect of high online engagement on offline sales will be negative when the share of consumers who match with the product is relatively low[8] and uncertainty levels regarding product fit are high, on average. In this case, lower online engagement, which maintains high uncertainty levels, is a stronger driver of movement down the sales funnel than high online engagement, which biases toward purchase, yet reduces uncertainty (further discussed in the SI).

Comparison to Major Competitors

We now compare sales for our luxury brand to two close competitors in the treatment markets, before and after launch, as another robustness test of the negative effect of *HE* launch on sales identified in the market-level DID analysis. This comparison will rule out the possibility that the negative effect we find is due to some exogenous negative shock to the luxury segment in the treatment countries, which is not related to the launch of the *HE* website.

The brand's two closest competitors were identified by the company. We use new vehicle registration data as a close proxy for sales, as we do not have access to internal sales data for the competing brands. We thus analyze a brand-level panel of monthly vehicle registrations, for three

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[8] Quite likely for luxury cars, with the segment comprising approximately 13% of total car sales, http://www.thecarconnection.com/news/1104264_do-ugly-may-car-sales-mean-a-recession-is-coming.

brands — the focal brand and its two main rival brands — focusing on the two largest markets T2 and T3, in which registration data is publicly available.

We estimate a DID model similar to specification (2), where the control groups are competing brands. The soundness of this comparison is ensured, as we find no difference in pre-launch trends between the treatment and control groups (Table S6). We study the effect of launch on both a one- and two-month lead for sales, to account for the pace of the car market as well as a possible lag between purchase and registration.

The results reported in Table 4 and Figure 5 show a significant decrease of approximately 9-10% ($p < 0.01$***) in sales following the *HE* website launch, compared to the control brands. We therefore reaffirm our main finding that high online engagement led to a decrease in car sales.

Table 4: The Effect of *HE* Launch on Sales – Comparison to Competing Brands

	Dependent variable:					
	$\log(Sales_{t+1})$			$\log(Sales_{t+2})$		
	Control Brand1	Control Brand2	Both	Control Brand1	Control Brand2	Both
	(1)	(2)	(3)	(4)	(5)	(6)
Launch	-0.09***	-0.11***	-0.10***	-0.09***	-0.09***	-0.09***
	(0.003)	(0.01)	(0.01)	(0.001)	(0.002)	(0.003)
Observations	192	192	288	192	192	288
Adjusted R^2	0.78	0.83	0.80	0.78	0.83	0.80
Note:	Fixed effects for brand, country, year and month included.					
	Cluster robust standard errors shown in parentheses (Clustered on brand).					
	*** $p < .01$,** $p < .05$,* $p < .1$					

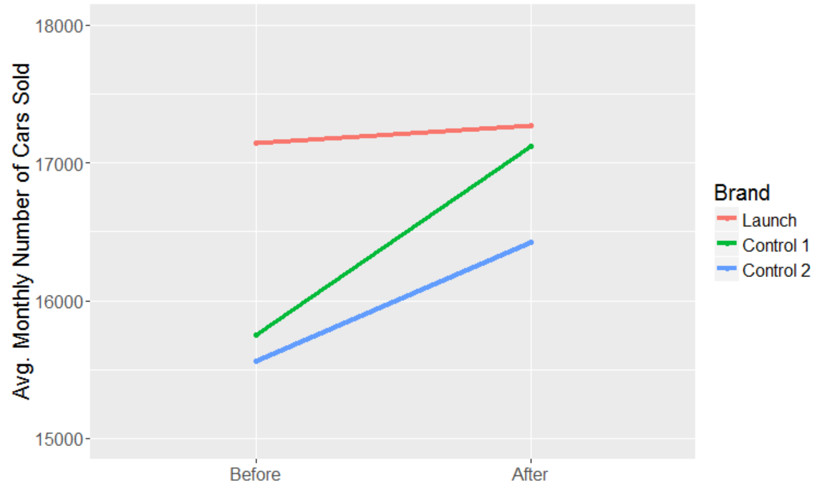

Figure 5. The Effect of *HE* Launch on Sales – Comparison to competing luxury brands, two years before, and two years after the *HE* launch in T2 and T3.

The Effect of Website Launch on Online Engagement – Online Lab Experiment

An alternative explanation for the negative impact of the *HE* website could be faulty web-design that influenced key user-experience parameters, such as site usability, information quality, and interactivity features (31–34). To test this alternative explanation, we conducted an online lab experiment where 335 participants were randomly assigned to either the *HE* or *LE* version of the brand website to complete three tasks, and then answered a survey reporting on different aspects of their online experience. Specifically, participants were asked to browse the manufacturer's website and perform the following three tasks, associated with purchase intention: (a) design their own car using the "Build your own car" feature of the website (BYO); (b) locate and download a brochure of their selected model (BD); and (c) locate and complete the test drive application form (TDA). The experiment was carried out on the brand's live local websites (in one treatment market and one control market) that are in the same language.

Following task completion, participants answered a ten-item survey on website perceived usefulness and ease of use (35, 36), with responses on a seven-point Likert scale.

The experiment tasks were submitted as human intelligence tasks (HITs) to Amazon Mechanical Turk (MTurk). Each participant was required to complete the entire set of website tasks and the survey in order to receive a payment (of $1).

We compare users' experience on the *HE* (post-launch) and *LE* (pre-launch) websites using both completion times for each website task and survey responses. Comparing tasks' completion times, we find that participants assigned to the *HE* website spent more time customizing their "own car" than the *LE* participants (BYO: 446 seconds vs. 364 seconds, $p < 0.01$***). Furthermore, *HE* participants could locate and download brochures and submit test drive requests significantly faster than their *LE* counterparts (BD: 99 seconds vs. 214 seconds, $p < 0.01$***; TDA: 50 seconds vs. 112 seconds, $p < 0.01$***). These results are presented in Figure 6 below.

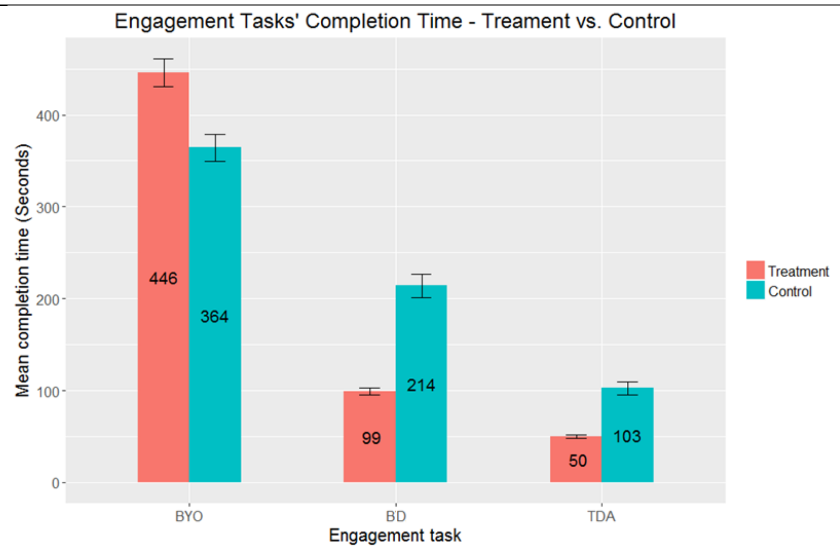

Figure 6. Comparison of the *HE* (post-launch) and *LE* (pre-launch) websites efficiency using different tasks completion times.

The *HE* website continues to dominate in usefulness and ease of use evaluations, based on participants' survey responses. Namely, participants ranked the post-launch version of the brand website significantly higher than its pre-launch version in all survey items, except for one (the only exception was appearance attractiveness, where there was no significant difference in the scores). Figure 7 shows the comparison of mean survey scores for each item, for the *HE* (treatment) and *LE* (control) website versions.

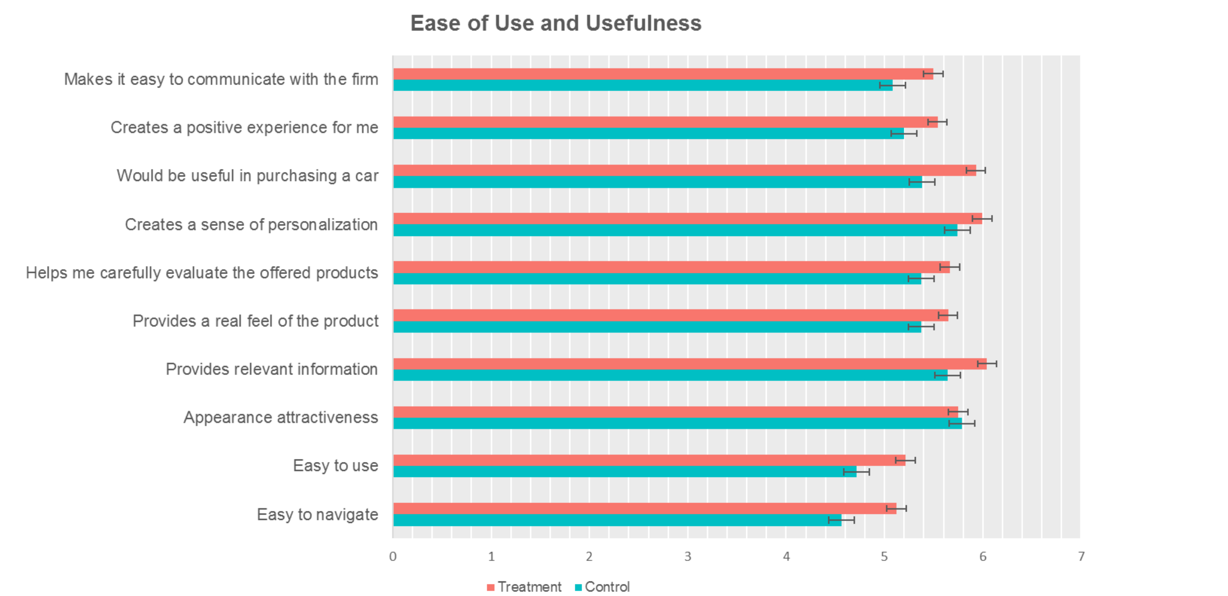

Figure 7. Online lab survey results - comparison of the *HE* (post-launch) and *LE* (pre-launch) websites ease of use and usefulness

These findings rule out the alternative explanation that the upgraded website was (unintentionally) inferior. In fact, the above online experiment demonstrates that the *HE* website enhanced consumers' online experience and facilitated user actions related to purchase intent (online sales leads).

To supplement these findings, we also estimate the effect of the launch on the effectiveness of the online sales leads, i.e. the conversion rate of each type of sales lead, before and after the launch of the *HE* website. We perform a correlational analysis based on user-level data, available from the manufacturer's CRM system in one treatment market (T3). The results (reported in the SI) show a significant negative effect of the launch on the probability of car purchase, in line with our previous findings. Yet, we find an increase in the conversion rate of both types of sales leads following the launch (from 7.6% to 8.6% for BDs, and from 13.7% to 16.1% for TDAs). This suggests that these online requests became more effective in creating conversions following launch.

Concluding Remarks

The consumption process has changed significantly in recent years, with online product search and engagement on brand websites playing an increasingly important role. Website design, communication channels, and level of interactivity have been shown to influence consumers' online behavior and purchase intent. Yet, the effect of online tools and services on offline sales remains ambiguous, especially for products that are only sold in physical stores.

Using a unique natural experiment, we study the online-to-offline funnel in the automobile market. Our results provide evidence of strong substitution between online and offline engagement, that led to a decrease in offline sales. The brand suffered from a loss of opportunities to persuade undecided shoppers, as the *HE* website reduced these shoppers' personal interaction with sales persons.

Our work contributes to the research on the relationship between consumer behavior in online and offline channels. Our results provide the first evidence of a causal effect of online engagement on offline sales. The negative effect we identify suggests that setting high online engagement goals is not a “one size fits all” strategy, and must be carefully considered, especially when a hands-on experience is a necessary step toward purchase.

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Supporting Information

Quasi Experiment – Robustness Tests

Table S1: Pre-Trend Comparison

	Dependent variable:	
	$\log(Sales)$	
	(1)	(2)
Trend	0.02	0.01
	(0.02)	(0.02)
*Trend * Treatment*	-0.002	0.004
	(0.02)	(0.02)
TotalRegistered		0.0000
		(0.0000)
Observations	92	92
Adjusted R^2	0.98	0.98
Note:	Fixed effects for country included. Cluster robust standard errors shown in parentheses (Clustered on country). *** p<0.01, ** p<0.05, * p<0.1	

Table S2: Anticipated effects test (Granger-causality test)

	Dependent variable:
	$\log(Sales)$
TotalRegistered	0.0000 (0.0000)
d_PreLaunch3	0.11 (0.10)
d_PreLaunch2	-0.08 (0.07)
d_PreLaunch1	-0.07 (0.06)
d_PostLaunch1	-0.05 (0.08)
d_PostLaunch2	-0.15^{*} (0.09)
d_PostLaunch3	-0.17^{**} (0.08)
d_PostLaunch4	-0.13^{*} (0.07)
d_PostLaunch5	-0.11 (0.07)
LaunchLag6	-0.25^{***} (0.08)
Observations	192
Adjusted R^2	0.98
Note:	Fixed effects for country and quarter included.
	Cluster robust standard errors shown in parentheses (Clustered on country).
	*** p<0.01, ** p<0.05, * p<0.1

Placebo treatment model:

The following table reports estimation results for a placebo treatment model. We use pre-launch data for T2-T4 and control markets, and estimate the effect of a placebo launch starting from December 2011. The effect of the placebo treatment is not statistically significant, as expected.

Table S3: Placebo treatment model

	Dependent variable:			
	$\log(Sale_q)$	$\log(Sales_{q+1})$	$\log(Sales_q)$	$\log(Sales_{q+1})$
	(1)	(2)	(3)	(4)
Placebo	0.05	0.07	0.09	0.06
	(0.09)	(0.09)	(0.10)	(0.09)
TotalRegistered			0.0000*	-0.0000
			(0.0000)	(0.0000)
Observations	88	88	88	88
Adjusted R^2	0.98	0.98	0.99	0.98
Note:	Fixed effects for country, year and quarter included.			
	Cluster robust standard errors shown in parentheses (Clustered on country).			
	*** p<0.01, ** p<0.05, * p<0.1			

Table S4: Launch effect on Website Activity Variables (Controlling for Total Registered)

	Dependent variable:		
	$\log(BD)$	$\log(RFO)$	$\log(TDA)$
	(1)	(2)	(3)
Launch	0.22^{***} (0.04)	-0.92^{***} (0.15)	0.89^{***} (0.19)
TotalRegistered	0.0000 (0.0000)	0.0000 (0.0000)	0.0000^{*} (0.0000)
Observations	24	24	32
Adjusted R^2	0.98	0.73	0.77
Note:	Fixed effects for country, year and quarter included. Cluster robust standard errors shown in parentheses (Clustered on country). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$		

Table S5: Pre-Trend test for Website Activity Variables

	Dependent variable:		
	log(BD)	log(RFO)	log(TDA)
	(1)	(2)	(3)
Trend	-0.20^{***} (0.03)	-0.20^{*} (0.10)	0.03 (0.18)
*Trend * Treatment*	0.03 (0.03)	-0.14 (0.10)	-0.13 (0.18)
Observations	12	12	16
Adjusted R^2	1.00	0.82	0.84
Note:	Fixed effects for country, year and quarter included. Cluster robust standard errors shown in parentheses (Clustered on country). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$		

Table S6: Pre-Launch Trend - Comparison to Major Competitors

	Dependent variable:
	log(Sales)
Trend	0.002*** (0.0003)
*Trend * Treatment*	0.01 (0.005)
Observations	144
Adjusted R^2	0.63
Note:	Fixed effects for country, year and quarter included. Cluster robust standard errors shown in parentheses (Clustered on country). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Launch Effect on Sales Leads Effectiveness - Analysis of User-Level Data One Market (T3)

To further examine the effect of the new *HE* website on offline sales, we estimate the effectiveness of sales leads. i.e. the conversion rate of each type of sales lead, before and after the launch of the *HE* website.

We present the results of a correlational analysis based on user-level data, available from the manufacturer's CRM system in one treatment market, T3. The company's CRM data is managed at the market level and includes data on different aspects of online and offline interactions[9] with its current and prospective customers.

For this analysis, we constructed a dataset of potential customers' *consideration windows*, and their outcome (whether or not the customer purchased a vehicle). A consideration window is defined as the timeframe between a customer's initial online sales lead and a purchase event, where a purchase is attributed to the initial lead if it occurs within the following 12 months. For

[9] Interactions are at both market headquarters and dealership level, and include, for example, online requests, dealership visits, email promotions, maintenance and service visits, vehicle registration date.

context, over 97% of users had exactly one consideration window within our period of analysis and 8.6% of these consideration windows ended with a purchase.

In this dataset, there are two types of sales leads, BDs and TDAs,[10] and all initial leads were submitted on the brand website between January 2012 and December 2014. For each sales lead the company recorded the purchase outcome (sale/no sale) during the consideration window. The effect of launch and the different types of sales leads on purchase is estimated using the following logistic regression model:

$$(6) \quad logit(dPurchase_i) = \alpha + \boldsymbol{\delta} \cdot Launch_i + \beta_1 dBD_i + \beta_2 dTDA_i + \beta_3 dBD_i \times Launch_i + \beta_4 dTDA_i \times Launch_i + \gamma \cdot Year_i + \lambda \cdot Month_i + \epsilon_i$$

Where $dPurchase_i$ is a dummy variable indicating whether or not consideration window i ended with a purchase, dBD_i, $dTDA_i$ are dummies that equal 1 if consideration window i includes a BD or a TDA sales lead, respectively. $Launch$ is defined in the previous specifications. We further include interaction terms for each type of sales lead and $Launch$, to capture the change in the effect of each lead on purchase probability following launch.

The results, reported in Table S8, show a significant negative effect of the launch on the probability of car purchase. However, the positive coefficients of the interaction terms indicate that performing an online request after launch is positively correlated with a higher purchase probability. We found an increase in the conversion rate of both types of sales leads following the launch (from 7.6% to 8.6% for BDs, and from 13.7% to 16.1% for TDAs).

This suggests that online sales leads became more effective in creating conversions following launch.

[10] RFOs were not recorded in this market's CRM system in the pre-launch period, and therefore are not included in this analysis.

Table S7: The Effect of Launch on the Propensity to Purchase a Vehicle and on Sales Leads' Efficiency

	Dependent variable:
	$dPurchase$
Launch	-0.51*** (0.13)
dTDA	0.03 (0.06)
dBD	-0.12 (0.07)
$dLaunch \times dTDA$	0.64*** (0.08)
$dLaunch \times dBD$	1.01*** (0.09)
Constant	-1.92*** (0.08)
Observations	134,181
Log Likelihood	-39,042.51
Akaike Inf. Crit.	78,123.01
Note:	Year and month dummies included.
	*** $p < .01$,** $p < .05$,* $p < .1$

Online Lab Experiment – Website Evaluation Questionnaire

Please tell us how much you agree or disagree with the following statements about the site you visited:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly Agree
The website is easy to navigate	○	○	○	○	○	○	○
The website is easy to use	○	○	○	○	○	○	○
The website has an attractive appearance	○	○	○	○	○	○	○
The website provides relevant information	○	○	○	○	○	○	○
The website provides a real feel of the product	○	○	○	○	○	○	○
The website helps me carefully evaluate the offered products (cars)	○	○	○	○	○	○	○
The website creates a sense of personalization	○	○	○	○	○	○	○
The website makes it easy to communicate with the firm	○	○	○	○	○	○	○
The website creates a positive experience for me	○	○	○	○	○	○	○
The website would be useful in purchasing a car.	○	○	○	○	○	○	○

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Figure S8. Website evaluation questionnaire, completed by experiment participants following the experimental tasks on the live brand websites.

Model: From Online Engagement to Offline Purchase

We model the purchase process for a purely offline product that begins with online information gathering and engagement in the brand or product website, and may proceed to offline engagement and purchase. We specifically consider products for which offline search costs are high (e.g., cars, real-estate) such that all purchase processes effectively begin online.

The model considers imperfectly informed consumers who enter the purchase funnel by visiting the product website. These consumers' online experiences shape their perceived fit with the product, thereby determining whether or not they proceed down the funnel to engage offline, as well as their (offline) purchase probability.

The model highlights two roles of online engagement, in the spirit of those attributed to traditional advertising: providing product information and persuasion (Bagwell 2005). The first is modelled as uncertainty reduction regarding consumers' fit with the product, and the second as the introduction of a non-negative product bias. These effects counteract when consumers' uncertainty regarding product fit is relatively high and match probability with the product is low. When the share of consumers who match with the product is relatively low,[11] lower online engagement, which maintains high uncertainty levels, is a stronger driver of movement down the sales funnel than high online engagement, which biases toward purchase, yet reduces uncertainty.

The next subsection presents the details of our modelling framework, and the following subsection presents the analysis and derives conditions under which higher online engagement will lead to lower offline sales.

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[11] Quite likely for luxury cars, with the segment comprising approximately 13% of total car sales, http://www.thecarconnection.com/news/1104264_do-ugly-may-car-sales-mean-a-recession-is-coming.

The Model. There is a mass 1 of consumers with unit demand interested in the product (or brand). These interested consumers are characterized by the value of their match with the product, denoted $m \in \{0,1\}$, where $m = 1$ (0) represents a match (no match) with the product, such that given perfect information on product attributes, including price, they will always (never) buy it. The probability of a match for an interested consumer is $\Pr[m = 1] = \tau,\ \tau \in (0,1)$. Since the mass of consumers is 1, τ also represents the share of interested consumers who match with the product.

Interested consumers are imperfectly informed about their match with the product, such that they are uncertain regarding m and assign probability σ to the opposite type, where $\sigma \sim U[0, \overline{\sigma}]$ is iid across consumers and $\overline{\sigma} < 1$. Consumers thus enter the market with a *perceived match value* defined as:

$$\tilde{t}_m^0 = (1 - \sigma)m + \sigma(1 - m)$$

where superscript 0 represents the initial perceived match value *before* online engagement has taken place. The initial perceived match value is therefore $\tilde{t}_1^0 = 1 - \sigma$ when $m = 1$, and $\tilde{t}_0 = \sigma$ when $m = 0$. We refer to σ as consumers' *uncertainty* parameter.

Consumers begin their product search online, visiting the product or brand website to gather information and reduce their uncertainty regarding m.

Online engagement: Consumers engage online at the brand's website. Their online engagement level depends on the website, and can be either high or low, denoted $e_{on} \in \{L, H\}$. High engagement allows the consumer to learn about his match value by reducing σ, while also creating a non-negative bias towards the product. Low engagement does not improve consumer information, and does not introduce a bias. Formally, let $\sigma_{e_{on}}$ be the revised uncertainty parameter, such that $\sigma_H = 0$ and $\sigma_L = \sigma$,[12] and let $b_{e_{on}}$ denote the bias created by online engagement, where $b_L = 0$ and $b_H \sim U[0, \bar{b}]$ is *iid* across consumers, with $\bar{b} < 1$.

We thus write the updated perceived match value following online engagement, which depends on the engagement level and true match value, $\tilde{t}_m^{e_{on}}$, for $m \in \{0,1\}$ as -

$$\tilde{t}_0^{e_{on}} = \min(\sigma_{e_{on}} + b_{e_{on}}, 1)$$

$$\tilde{t}_1^{e_{on}} = \min(1 - \sigma_{e_{on}} + b_{e_{on}}, 1)$$

This revised perceived match value determines the probability that a consumer moves down the sales funnel to the next stage of offline engagement (e.g., physically examining real-estate, arriving at a car dealership). Specifically, assume that when the perceived match value exceeds some threshold $T \geq 0.5$, the online consumer seeks offline contact with the product, such that $\Pr[\tilde{t}_m^{e_{on}} \geq T]$ is the probability of offline engagement for a consumer with true match value m and online engagement level e_{on}.

Offline engagement and purchase: The product can only be purchased offline following some offline interaction (e.g., meeting with a car dealer or other sales representative). The probability of purchase equals $\tilde{t}_m^{e_{on}}$, the consumer's perceived match value following online engagement. This represents the final impact of online engagement on the offline purchase decision. Note that we have made no assumptions regarding the impact of offline engagement, other than it is a necessary step toward purchase. While real world interactions with seasoned sales professionals may have an incremental impact on purchase probability, incorporating such effects is not necessary to obtain our main results, and is therefore abstracted away in our model.

[12] The results would qualitatively hold under a more general assumption that high engagement reduces σ, but not necessarily to zero.

The expected purchase probability for a consumer with match value m, denoted $\Phi_m^{e_{on}}$, is the probability that the consumer proceeds down the sales funnel to offline engagement, times his expected purchase probability, given that he has moved down the funnel:

$$\Phi_m^{e_{on}} = \Pr\left[\tilde{t}_m^{e_{on}} > T\right] \cdot E_{\sigma,b}\left[\tilde{t}_m^{e_{on}} \middle| \, \tilde{t}_m^{e_{on}} > T\right]$$

And the expected mass of purchasers, $Q^{e_{on}}$, is given by:

$$Q^{e_{on}} = \tau\Phi_1^{e_{on}} + (1-\tau)\Phi_0^{e_{on}}$$

Since we consider consumers who buy one unit of the product at most, $Q^{e_{on}}$ is also the expected level of sales, in terms of number of products sold.

Analysis: When High Online Engagement Reduces Offline Sales

In the above online-to-offline model, high online engagement has two effects: it reduces uncertainty about consumers' match with the product and biases consumers toward the product. While the bias effect drives all consumers to the offline channel, the uncertainty reduction effect only drives offline engagement by consumers who match with the product. Bias and uncertainty-reduction thus exert opposing effects for non-matching consumers' offline engagement. The model and its main intuitions are summarized in the following Table S9.

Table S8: Model summary and intuitions**.**

Match value: $\boldsymbol{m}$	Share in population	Engagement: $\boldsymbol{e_{on}}$	Perceived match value: $\boldsymbol{\tilde{t}_m^{e_{on}}}$	Proceed Offline $w.p.$ $\mathbf{Pr}\left[\boldsymbol{\tilde{t}_m^{e_{on}}} \geq \boldsymbol{T}\right]$
$\boldsymbol{m = 0}$	$1 - \tau$	L	$\tilde{t}_0^L = \sigma$	Proceed if uncertainty is high
		H	$\tilde{t}_0^H = b$	Proceed if bias is high
$\boldsymbol{m = 1}$	τ	L	$\tilde{t}_1^L = 1 - \sigma$	Proceed if uncertainty is low
		H	$\tilde{t}_1^H = 1$	Always proceed

The result is that offline engagement levels and subsequent sales may be higher when online engagement is low. This is the case when the average uncertainty level is high, such that it creates more conversions to offline engagement than the introduction of a positive bias. High uncertainty is a strong driver of conversions when the share of non-matching consumers is relatively high. These results are formally derived and stated in the following propositions.

We begin by deriving the mass of consumers proceeding to offline engagement. This mass is denoted $q^{e_{on}}$ and given by:

$$q^{e_{on}} = \tau \Pr\left[\tilde{t}_1^{e_{on}} > T\right] + (1 - \tau) \Pr\left[\tilde{t}_0^{e_{on}} > T\right]$$

Comparing q^H and q^L we find the conditions for which low online engagement creates higher offline engagement levels. These are summarized in proposition 1.

Proposition 1: Offline engagement may be higher under $e_{on} = L$, when the average σ is relatively high, and higher than the average b_H, and when τ is sufficiently low. The conditions for $q^L > q^H$ are given by:

(a) $\overline{\sigma} > \overline{b} > T$ and $\tau < \frac{T(\overline{\sigma}-\overline{b})}{\overline{\sigma}T-\overline{b}(1-\overline{\sigma})}$.

(b) $\overline{\sigma} > T > \overline{b}$ and $\tau < \frac{\overline{\sigma}-T}{2\overline{\sigma}-1}$.

Proof: Using the definitions of $\tilde{t}_0^{e_{on}}$ and $\tilde{t}_1^{e_{on}}$, we substitute $\tilde{t}_0^H = b, \tilde{t}_1^H = 1$, $\tilde{t}_0^L = \sigma$ and $\tilde{t}_1^L = 1 - \sigma$ in the above equation. This yields $q^H = \tau + (1-\tau)\Pr[b > T]$ and $q^L = \tau \Pr[\sigma < 1 - T] + (1-\tau)\Pr[\sigma > T]$. Since $\sigma \sim U[0, \overline{\sigma}]$ and $b \sim U[0, \overline{b}]$:

$$q^H = \begin{cases} \tau & for\ \overline{b} \leq T \\ 1 - \dfrac{(1-\tau)T}{\overline{b}} & for\ \overline{b} > T \end{cases}$$

And

$$q^L = \begin{cases} \tau & for\ \overline{\sigma} \leq 1 - T \\ \dfrac{\tau(1-T)}{\overline{\sigma}} & for\ \overline{\sigma} \in (1-T, T] \\ (1-\tau) + \dfrac{\tau - T}{\overline{\sigma}} & for\ \overline{\sigma} > T \end{cases}$$

Comparing q^H and q^L in the different domains of $(\overline{b}, \overline{\sigma})$, we derive the conditions in (a) and (b).

■

Quite intuitively, when the proportion of matching types is low and uncertainty levels are high, consumer uncertainty is a more powerful tool for the brand than introducing a positive bias. This intuition carries over, when we consider the effect of online engagement on sales. Conditions for which expected sales are higher when online engagement is lower are stated in proposition 2.

Proposition 2: Expected sales may be higher under $e_{on} = L$ when consumers' average uncertainty σ is relatively high, and higher than the average bias b_H. Formally, $Q^L > Q^H$ when:

(a) $\overline{b} \leq T < \overline{\sigma}$

(b) $T < \overline{b} < \overline{\sigma}$ and $\tau < \frac{B+\frac{1-T^2}{\overline{\sigma}}}{B+2}$. [13]

Proof: Substituting $\tilde{t}_0^H = b, \tilde{t}_1^H = 1$, $\tilde{t}_0^L = \sigma$ and $\tilde{t}_1^L = 1 - \sigma$ in the equation for $\Phi_t^{e_{on}}$, we derive the following expected purchase probabilities, by consumer match value and online engagement level:

	$m = 1$	$m = 0$
$e_{on} = H$	$\Phi_1^H = 1$	$\Phi_0^H = \begin{cases} 0 & for\ \overline{b} \le T \\ \frac{\overline{b}^2 - T^2}{2\overline{b}} & for\ \overline{b} > T \end{cases}$
$e_{on} = L$	$\Phi_1^L = \begin{cases} 1 - 0.5\overline{\sigma} & for\ \overline{\sigma} \le 1 - T \\ \frac{1 - T^2}{2\overline{\sigma}} & for\ \overline{\sigma} > 1 - T \end{cases}$	$\Phi_0^L = \begin{cases} 0 & for\ \overline{\sigma} \le T \\ \frac{\overline{\sigma}^2 - T^2}{2\overline{\sigma}} & for\ \overline{\sigma} > T \end{cases}$

These are used to derive expected sales for $e_{on} \in \{H, L\}$:

$$Q^H = \begin{cases} \tau & for\ \overline{b} \le T \\ \tau + \frac{(1-\tau)\left(\overline{b}^2 - T^2\right)}{2\overline{b}} & for\ \overline{b} > T \end{cases}$$

$$Q^L = \begin{cases} \tau(1 - 0.5\overline{\sigma}) & for\ \overline{\sigma} \le 1 - T \\ \frac{\tau(1 - T^2)}{2\overline{\sigma}} & for\ \overline{\sigma} \in (1 - T, T] \\ \frac{\tau(1 - T^2) + (1-\tau)\left(\overline{\sigma}^2 - T^2\right)}{2\overline{\sigma}} & for\ \overline{\sigma} > T \end{cases}$$

Comparing Q^H and Q^L in the different domains of $\left(\overline{b}, \overline{\sigma}\right)$, we find that $Q^H > Q^L$ whenever $\overline{\sigma} \le T$. For $\overline{\sigma} > T$, we identify two cases for which $Q^L > Q^H$: (a) $\overline{b} \le T$; and (b) $\overline{b} > T$, when we

[13] Where $B \equiv \frac{\overline{\sigma}^2 - 1}{\overline{\sigma}} - \frac{\overline{b}^2 - T^2}{\overline{b}}$.

additionally have $\tau < \frac{B+\frac{1-T^2}{\overline{\sigma}}}{B+2}$, with $B \equiv \frac{\overline{\sigma}^2-1}{\overline{\sigma}} - \frac{\overline{b}^2-T^2}{\overline{b}}$. (Otherwise, if $\overline{b} > T$, and $\tau > \frac{B+\frac{1-T^2}{\overline{\sigma}}}{B+2}$ then $Q^H > Q^L$). ■