

Online Appendix to “Campaigns That Click: Unleashing the Power of Push Notifications on Mobile Apps”

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A. Variable Construction and Measurement Diagnostics

Table A1. Variable Definitions and Construction Details

Variables	Explanation	Construction Details
Panel A. Dependent Variables		
click_focal_senddate	Click on the advertised merchant on the send date	Binary indicator: 1 if user i clicks any content from campaign j 's focal (advertised) merchant on the campaign send date, 0 otherwise. Constructed from the platform's click log joined with campaign metadata.
click_focal_7day	Click on the advertised merchant within 7 days of the send date	Binary indicator: 1 if user i clicks the focal merchant on any of the seven days following the send date (day +1 through day +7, exclusive of the send date itself), 0 otherwise. Same data source as click_focal_senddate.
click_samecate_senddate	Click on a non-focal same-category merchant on the send date	Binary indicator: 1 if user i clicks any non-focal merchant whose category matches campaign j 's focal merchant on the send date, 0 otherwise. Same-category determined from the platform's merchant-category metadata.
click_samecate_7day	Same-category spillover within 7 days	Same as click_samecate_senddate but defined over the seven-day window following the send date (exclusive of the send date itself).
click_diffcate_senddate	Click on a different-category merchant on the send date	Binary indicator: 1 if user i clicks any merchant outside campaign j 's focal merchant's category on the send date, 0 otherwise. Determined from the platform's merchant-category metadata.
click_diffcate_7day	Cross-category spillover within 7 days	Same as click_diffcate_senddate but defined over the seven-day window following the send date (exclusive of the send date itself).
Panel B. Treatment Variable		
PushReceived	Whether the platform delivered campaign j 's push notification to user i	Binary indicator: 1 if the platform's delivery system recorded that the push notification for campaign j was sent to user i 's device, 0 otherwise. Interpreted as an intent-to-treat indicator—delivery confirmation does not imply that the user actually saw or interacted with the notification.
Panel C. Moderators		
(Heterogeneity Dimensions)		
DayofWeek	Indicators of day of week of the campaign: Monday-Sunday	Derived from the campaign send date. Create day-of-week dummy variables: for each weekday, code 1 if campaign j is sent on that weekday and 0 otherwise (one weekday is omitted as the reference category in regressions).
Morning	Indicator of whether the campaign is launched in the morning (1 if yes, 0 if no)	Derived from the campaign send timestamp. Code Morning_ j = 1 if the notification is sent at or before 13:00 (inclusive) (local time of the campaign timestamp), and 0 otherwise (Afternoon).
Category	Indicator of merchant category: Accessories_ j , DepartmentStore_ j , Electronics_ j , FoodDining_ j , HomeGarden_ j , Ecommerce_ j , Supermarket_ j	From the platform's merchant-category label for the advertised merchant in campaign j . Create category dummy variables: code 1 for the campaign's category and 0 otherwise (one category omitted as the reference category).
Sentiment	Sentiment of the message	Computed from the message text using VADER (Hutto and Gilbert 2014). We apply the VADER compound score, which ranges from -1 (most negative) to $+1$ (most

		positive).
Subjectivity	Tone of the message as measured by subjectivity (using TextBlob)	Computed from the message text using TextBlob subjectivity (Loria 2014). The resulting score ranges from 0 (objective) to 1 (subjective).
Holiday	Topic of the coupon is holiday (1 if yes, 0 if no)	Binary indicator based on message-topic detection from the message text. Code Holiday_j = 1 if the message contains holiday-related terms (e.g., Valentine's Day, Christmas), and 0 otherwise (classified using GPT-3.5-Turbo on the message text).
Clearance	Topic of the coupon is clearance (1 if yes, 0 if no)	Binary indicator based on message-topic detection from the message text. Code Clearance_j = 1 if the message contains clearance-related terms (e.g., clearance, final sale, end of season), and 0 otherwise (classified using GPT-3.5-Turbo on the message text).
Urgency	Whether the promotion is urgent	Binary indicator based on urgency cues in the message text. Code Urgency_j = 1 if the message includes explicit urgency/limited-time language (e.g., today only, ends tonight, last chance, limited time, hurry, act now), and 0 otherwise.
Emojis	Whether the message contains emojis	Binary indicator based on the message text. Code Emojis_j = 1 if the message contains at least one emoji character, and 0 otherwise.
Character	Number of characters contained in a message	Message length computed from the message text in Python. Character_j equals the number of characters in the message string (including spaces/punctuation as they appear in the stored text).
Percentoff	Indicator of whether the promotion features a percentage-off discount or can be converted into a percentage-off discount (1 if yes, 0 if no).	Binary indicator coded from the message text. Code Percentoff_j = 1 if the promotion states a percentage-off discount or contains a discount expression that can be converted to an equivalent percent-off value (e.g., "20% off," "\$10 off \$100," "Buy one get one"), and 0 otherwise. (Manually coded based on the message text.)
Percentdepth	The depth of the coupon if it can be converted to percent off type	Continuous discount depth for messages with Percentoff_j = 1; Percentdepth is set to zero when Percentoff = 0. Because Percentoff and Percentdepth jointly represent the extensive and intensive margins of percentage-off discount information, the Percentdepth coefficient should be interpreted conditional on the model also including Percentoff. We convert all eligible discount formats into an equivalent percent-off value: If the message states "X% off," set Percentdepth_j = X/100 (i.e., the decimal fraction). If the message states "\$A off \$B," set Percentdepth_j = A/B. If the message states a convertible deal (e.g., BOGO), convert to the implied fraction (e.g., "Buy one get one" → 0.50). (Manually standardized based on the message text.) For campaigns without a convertible percentage-off discount (Percentoff_j = 0), Percentdepth_j is coded as 0 in the regression specification.
Restriction	Whether the promotion has restrictions	Binary indicator based on restriction language in the message text. Code Restriction_j = 1 if the promotion includes explicit restrictions (e.g., minimum spend such as "\$50 off \$200," keywords like minimum purchase, min, exclusions apply, select items/styles, in-store only, with

		code), and 0 otherwise.
Lavgrank	Log of merchant rank (lower = more popular)	Log-transformed merchant rank from the platform's merchant ranking metadata (lower rank value = more popular merchant). Lavgrank _j is the natural-log-transformed rank of campaign j's focal merchant.
System (1 = iOS)	Indicator of operating system used by individual i	From the platform's user device/OS information. Create OS dummy variables: System_ios_i = 1 if user i uses iOS and 0 otherwise; System_android_i analogously (one OS omitted as the reference category).
Tenure	Number of months a user has had an account	Computed from platform account metadata. Tenure _{ij} equals the number of months between user i's account registration date and the campaign date of j (expressed in months).
Panel D. Auxiliary Controls		
Affinity	Affinity score of user i at campaign j	Provided directly by the platform as a continuous algorithm/targeting score. According to the platform, it is computed a few days prior to each campaign based on user i's past activity with the focal merchant and similar merchants (exact formula confidential).
click_focal_sdw	Whether user i checks content from the advertised merchant on the same day of the week over the past 8 weeks	Constructed from the user's historical activity logs. For each user–campaign pair, compute user i's average click-through activity on the focal advertised merchant on the same weekday as campaign j, over the prior 8 weeks (i.e., the prior eight occurrences of that weekday).
click_samecate_sdw	Whether user i checks content from merchant(s) of the same category on the same day of the week over the past 8 weeks	Analogous to click_focal_sdw, but computed using user i's click activity on non-focal merchants in the same category as the advertised merchant, on the same weekday as campaign j, over the prior 8 weeks (average over the relevant historical days).
click_diffcate_sdw	Whether user i checks content from merchant(s) of a different category on the same day of the week over the past 8 weeks	Analogous to click_focal_sdw, but computed using user i's click activity on merchants in different categories (relative to the advertised merchant), on the same weekday as campaign j, over the prior 8 weeks (average over the relevant historical days).

Notes: Holiday and Clearance are classified from message text using GPT-3.5-Turbo. For each message, the model received only the message text and was prompted to return binary labels for whether the message referred to a holiday or holiday-shopping occasion (Holiday) and whether it referred to clearance, end-of-season, or final-sale themes (Clearance). We manually validated a random subset of messages; the manual–GPT agreement was high for both indicators, and disagreements were rare and resolved by the authors.

Table A2. Pairwise Correlations of Message Characteristics

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Sentiment	1.000									
(2) Subjectivity	0.450*** (0.000)	1.000								
(3) Holiday	-0.023 (0.735)	-0.143** (0.038)	1.000							
(4) Clearance	-0.095 (0.171)	-0.161** (0.019)	-0.078 (0.258)	1.000						
(5) Urgency	0.111 (0.107)	0.278*** (0.000)	0.002 (0.982)	-0.082 (0.237)	1.000					
(6) Emojis	-0.011 (0.878)	-0.179*** (0.009)	0.063 (0.361)	0.092 (0.183)	-0.032 (0.642)	1.000				
(7) Character	0.357*** (0.000)	0.294*** (0.000)	0.062 (0.370)	-0.086 (0.215)	0.076 (0.274)	-0.031 (0.656)	1.000			

(8) Percentoff	-0.360*** (0.000)	-0.283*** (0.000)	-0.063 (0.366)	0.157** (0.023)	-0.206*** (0.003)	-0.088 (0.201)	-0.076 (0.272)	1.000		
(9) Percentdepth	-0.287*** (0.000)	-0.209*** (0.002)	0.029 (0.676)	0.319*** (0.000)	-0.059 (0.392)	0.085 (0.219)	0.025 (0.713)	0.635*** (0.000)	1.000	
(10) Restriction	0.141** (0.041)	0.143** (0.038)	-0.158** (0.022)	-0.188*** (0.006)	-0.112 (0.104)	-0.003 (0.965)	0.099 (0.153)	-0.050 (0.472)	-0.192*** (0.005)	1.000

Notes: Pairwise correlations of message-level characteristics across the 211 campaigns in the analytic sample. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B. Robustness Checks for the Baseline Model

Table B1. Robustness Check: Including Merchant and Campaign Fixed Effects

	1		2		3	
	Current Model		Merchant FE		Campaign FE	
PushReceived	1.961***	(0.004)	1.958***	(0.004)	1.989***	(0.004)
Affinity	93.029***	(1.144)	127.232***	(1.592)	129.263***	(1.636)
click_focal_sdown	1.315***	(0.007)	1.161***	(0.007)	1.144***	(0.007)
Lavgrank	-0.112***	(0.001)				
Accessories	1.002***	(0.011)				
DepartmentStore	0.928***	(0.011)				
Electronics	0.935***	(0.012)				
FoodDining	1.273***	(0.012)				
HomeGarden	0.579***	(0.012)				
Ecommerce	0.488***	(0.013)				
Supermarket	0.919***	(0.012)				
System_ios	-0.226***	(0.006)	-0.227***	(0.006)	-0.220***	(0.006)
Tenure	-0.005***	(5.06e-5)	-0.005***	(5.32e-5)	-0.005***	(6.85e-5)
Monday	-0.303***	(0.005)	-0.029***	(0.006)		
Tuesday	-0.113***	(0.005)	-0.178***	(0.007)		
Wednesday	0.052***	(0.005)	0.255***	(0.005)		
Thursday	0.173***	(0.005)	0.260***	(0.006)		
Friday	0.583***	(0.005)	0.773***	(0.006)		
Saturday	-0.188***	(0.005)	-0.142***	(0.006)		
Morning	0.467***	(0.003)	0.226***	(0.004)		
Constant	-4.585***	(0.013)	-4.478***	(0.017)	-4.252***	(0.015)
Merchant FE	X		√		X	
Campaign FE	X		X		√	
Observations	62,928,984		62,328,314		62,328,314	

Notes: Logistic regressions with high-dimensional fixed effects are subject to the incidental-parameters problem (Greene 2004; Wooldridge 2010); the merchant-FE and campaign-FE estimates therefore serve as descriptive robustness checks rather than bias-corrected maximum-likelihood estimates. Groups with no within-group outcome variation (e.g., singletons or strata in which the click outcome is constant) do not contribute to identification in the fixed-effects specifications and are dropped, accounting for the reduction in observations relative to Column 1. Standard errors clustered at the user level are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table B2. Alternative Specification: 4-Week Variables as Controls

	click_focal_senddate	
PushReceived	1.96***	(0.004)
Affinity	93.713***	(1.163)
click_focal_sdown	1.346***	(0.007)
Lavgrank	-0.104***	(0.001)
Accessories	1.002***	(0.011)
DepartmentStore	0.942***	(0.011)
Electronics	0.945***	(0.012)
FoodDining	1.363***	(0.012)
HomeGarden	0.576***	(0.012)
Ecommerce	0.608***	(0.013)
Supermarket	0.931***	(0.012)
System_ios	-0.23***	(0.006)
Tenure	-0.005***	(5.12e-5)
Monday	-0.315***	(0.005)
Tuesday	-0.14***	(0.005)
Wednesday	0.132***	(0.005)
Thursday	0.167***	(0.005)
Friday	0.555***	(0.005)
Saturday	-0.186***	(0.005)
Morning	0.492***	(0.003)
Constant	-4.651***	(0.013)
Observations	62,374,632	

Notes: Standard errors clustered at the user level are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table B3. Alternative Specification: Control for Seasonality

	click_focal_senddate	
PushReceived	1.96***	(0.004)
Affinity	95.492***	(1.156)
click_focal_sdown	1.304***	(0.007)
Lavgrank	-0.108***	(0.001)
Accessories	0.907***	(0.011)
DepartmentStore	0.89***	(0.011)
Electronics	0.845***	(0.012)

FoodDining	1.164***	(0.012)
HomeGarden	0.535***	(0.012)
Ecommerce	0.457***	(0.013)
Supermarket	1.002***	(0.012)
System_ios	-0.217***	(0.006)
Tenure	-0.005***	(6.49e-5)
Monday	-0.343***	(0.005)
Tuesday	-0.21***	(0.005)
Wednesday	-0.017***	(0.005)
Thursday	0.068***	(0.005)
Friday	0.567***	(0.005)
Saturday	-0.269***	(0.005)
Morning	0.473***	(0.003)
February	0.859***	(0.013)
March	1.1***	(0.014)
April	0.776***	(0.014)
May	0.78***	(0.015)
June	1.279***	(0.015)
Constant	-5.396***	(0.018)
Observations	62,928,984	

Notes: Standard errors clustered at the user level are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table B4. Alternative Specification: Probit Model

	click_focal_senddate	
PushReceived	0.856***	(0.002)
Affinity	48.134***	(0.439)
click_focal_sdown	0.624***	(0.003)
Lavgrank	-0.047***	(3.07e-4)
Accessories	0.412***	(0.004)
DepartmentStore	0.385***	(0.004)
Electronics	0.382***	(0.004)
FoodDining	0.515***	(0.004)
HomeGarden	0.244***	(0.004)
Ecommerce	0.203***	(0.005)
Supermarket	0.383***	(0.004)
System_ios	-0.08***	(0.002)
Tenure	-0.002***	(1.98e-5)

Monday	-0.141***	(0.002)
Tuesday	-0.057***	(0.002)
Wednesday	0.006***	(0.002)
Thursday	0.062***	(0.002)
Friday	0.236***	(0.002)
Saturday	-0.081***	(0.002)
Morning	0.193***	(0.001)
Constant	-2.327***	(0.005)
Observations	62,928,984	

Notes: Standard errors clustered at the user level are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table B5. Alternative Specification: Android Users Only

	click_focal_senddate	
PushReceived	2.278***	(0.006)
Affinity	135.76***	(2.635)
click_focal_sdown	1.107***	(0.010)
Lavgrank	-0.104***	(0.001)
Accessories	0.899***	(0.016)
DepartmentStore	0.835***	(0.017)
Electronics	0.749***	(0.017)
FoodDining	1.237***	(0.017)
HomeGarden	0.514***	(0.017)
Ecommerce	0.34***	(0.019)
Supermarket	0.772***	(0.017)
Tenure	-0.006***	(8.24e-5)
Monday	-0.223***	(0.008)
Tuesday	-0.096***	(0.008)
Wednesday	0.044***	(0.008)
Thursday	0.143***	(0.007)
Friday	0.378***	(0.007)
Saturday	-0.156***	(0.007)
Morning	0.357***	(0.004)
Constant	-4.506***	(0.019)
Observations	23,447,548	

Notes: Standard errors clustered at the user level are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table B6. Alternative Specification: Same-Day Notification Overlap

	click_focal_senddate	
PushReceived	1.959***	(0.004)
Same_Day_Overlap	-0.362***	(0.034)
Affinity	92.239***	(1.126)
click_focal_sdown	1.248***	(0.007)
Lavgrank	-0.129***	(0.001)
Accessories	0.983***	(0.011)
DepartmentStore	0.883***	(0.011)
Electronics	0.905***	(0.012)
FoodDining	1.085***	(0.012)
HomeGarden	0.532***	(0.012)
Ecommerce	0.358***	(0.013)
Supermarket	0.857***	(0.012)
System_ios	-0.22***	(0.006)
Tenure	-0.004***	(5.07e-5)
Monday	-0.252***	(0.005)
Tuesday	-0.058***	(0.005)
Wednesday	-0.098***	(0.005)
Thursday	0.198***	(0.005)
Friday	0.614***	(0.005)
Saturday	-0.171***	(0.005)
Morning	0.451***	(0.003)
Constant	-4.446***	(0.013)
Observations	62,287,658	

Notes: Same_Day_Overlap equals 1 if user i receives two notifications on the focal campaign's send date and 0 otherwise. Standard errors clustered at the user level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B7. Alternative Specification: Control for Overlapping Campaigns

	click_focal_senddate	
PushReceived	1.823***	(0.004)
Affinity	92.56***	(1.134)
click_focal_sdown	1.307***	(0.007)
Lavgrank	-0.114***	(0.001)
Accessories	1.004***	(0.011)
DepartmentStore	0.933***	(0.011)

Electronics	0.949***	(0.012)
FoodDining	1.265***	(0.012)
HomeGarden	0.580***	(0.012)
Ecommerce	0.504***	(0.013)
Supermarket	0.920***	(0.012)
System_ios	-0.229***	(0.006)
Tenure	-0.005***	(5.06e-5)
Monday	-0.298***	(0.005)
Tuesday	-0.109***	(0.005)
Wednesday	0.049***	(0.005)
Thursday	0.180***	(0.005)
Friday	0.591***	(0.005)
Saturday	-0.186***	(0.005)
Morning	0.471***	(0.003)
Msg_same_company	-0.033***	(0.008)
Msg_diff_company	0.112***	(0.002)
Constant	-4.580***	(0.013)
Observations	62,928,984	

Notes: Variable definitions. `Msg_same_company_ij` and `Msg_diff_company_ij` are integer counts (at the user–campaign level) of other push notifications received by user *i* within the seven days preceding campaign *j*'s send date—`Msg_same_company_ij` from the same merchant as the focal campaign, and `Msg_diff_company_ij` from any other merchant. The seven-day window matches the control described in Footnote 4 of the main paper. Standard errors clustered at the user level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C. Propensity Score Matching and Instrumental Variables

We estimate propensity scores using the logit specification in Table C2, Model 3, and implement 1-to-1 nearest-neighbor matching without replacement, common-support trimming, and a caliper of $0.25 \times \text{SD}(\text{propensity score}) \approx 0.017$. Table C1 reports post-matching balance diagnostics, and Table C3 reports the matched-sample treatment-effect estimate.

Table C1. Alternative Specification: Balance after Propensity Score Matching

VARIABLES	Mean			t-test		V(T)/V(C)
	Treated	Control	%bias	t	p> t	
Lavgrank	7.616	7.633	-0.8	-7.67	0.000	0.98*
click_focal_sdown	0.087	0.100	-5.0	-44.10	0.000	.
Accessories	0.393	0.402	-1.8	-17.63	0.000	.
DepartmentStore	0.160	0.161	-0.3	-2.95	0.003	.
Electronics	0.074	0.071	0.9	8.86	0.000	.
FoodDining	0.153	0.151	0.4	4.14	0.000	.
HomeGarden	0.093	0.092	0.4	3.57	0.000	.
Ecommerce	0.035	0.035	0.0	0.19	0.847	.
Supermarket	0.081	0.076	1.7	17.03	0.000	.
System_ios	0.549	0.555	-1.2	-11.09	0.000	.
Tenure	89.897	90.199	-0.7	-6.65	0.000	0.92*
Monday	0.135	0.134	0.3	2.85	0.004	.
Tuesday	0.137	0.137	0.0	-0.07	0.944	.
Wednesday	0.133	0.130	0.9	8.33	0.000	.
Thursday	0.155	0.154	0.4	3.89	0.000	.
Friday	0.144	0.147	-0.7	-7.05	0.000	.
Saturday	0.173	0.174	-0.3	-2.89	0.004	.
Morning	0.675	0.684	-1.9	-18.41	0.000	.
Log_Affinity	-8.519	-8.481	-2.7	-26.49	0.000	0.88*

Notes: With the matched sample size (millions of observations), conventional two-sample t-tests have extremely high power, so even economically trivial mean differences register as statistically significant. We therefore interpret balance through the magnitude of the standardized differences (V(T)/V(C) close to 1 and small relative mean gaps) rather than through significance stars; the post-matching gaps are substantially smaller than the corresponding differences in the unmatched sample, and we report this table as a sensitivity check rather than as a stand-alone identification claim. Balance diagnostics are based on the matched sample from the propensity-score specification in Table C2.

Table C2. Estimates, Fit Statistics, and Likelihood Ratio Tests for Propensity Score Models

Variables	M1		M2		M3	
	Coeffs	SE	Coeffs	SE	Coeffs	SE
Lavgrank			0.006***	(0.001)	-0.001*	(0.001)
click_focal_sdown			0.424***	(0.004)	0.392***	(0.004)
Accessories			0.101***	(0.007)	0.147***	(0.007)
DepartmentStore			-0.042***	(0.008)	0.075***	(0.008)
Electronics			0.201***	(0.009)	0.293***	(0.009)
FoodDining			0.151***	(0.008)	0.189***	(0.008)
HomeGarden			-0.119***	(0.008)	-0.058***	(0.008)
Ecommerce			-0.046***	(0.009)	0.041***	(0.009)
Supermarket			-0.047***	(0.008)	0.099***	(0.008)
System_ios			-0.375***	(0.004)	-0.377***	(0.004)
Tenure			0.002***	(2.90e-5)	0.004***	(3.49e-5)
Monday			0.02***	(0.003)	0.029***	(0.003)
Tuesday			0.119***	(0.003)	0.102***	(0.003)
Wednesday			-0.065***	(0.003)	-0.053***	(0.003)
Thursday			0.069***	(0.003)	0.077***	(0.003)
Friday			-0.071***	(0.003)	-0.059***	(0.003)
Saturday			-0.231***	(0.003)	-0.238***	(0.003)
Morning			0.014***	(0.002)	0.026***	(0.002)
Log_Affinity					0.109***	(0.001)
Constant	-0.757***	(0.002)	-0.844***	(0.009)	-0.066***	(0.01)
Observations	7,844,803		7,844,803		7,844,803	
Log Likelihood	-4914055		-4850152		-4835303	
Pseudo R2	0		0.013		0.016	
Degree of Freedom	1		19		20	
BIC	9,828,127		9,700,606		9,670,923	
LR χ^2			M2 vs. M1		M3 vs. M2	
			127806.02 (p<0.01)		29698.91 (p<0.01)	

Notes: The PSM specifications use $\text{Log_Affinity}_{ij} = \ln(\text{Affinity}_{ij})$ and are estimated on the subsample with strictly positive platform-computed affinity. Standard errors clustered at the user level are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table C3. Effects of PushReceived on click_focal_senddate Using Matched Data from PSM

	click_focal_senddate	
PushReceived	1.290***	(0.007)

Constant	-3.325***	(0.007)
Observations	3,971,901	

Notes: Standard errors clustered at the user level are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

We report the IV analysis as a supplementary sensitivity check for nonrandom push delivery. The specification uses a campaign-level instrument based on campaign recipient counts, adds temporal and merchant-level controls, and implements a control-function approach for the binary treatment. Table C4 reports the first-stage relevance diagnostics. Because the exclusion restriction cannot be conclusively verified in this observational setting, we interpret the IV results as complementary rather than primary identification evidence.

Identifying assumption. The instrument, campaign-level targeting intensity, is assumed to be driven primarily by merchant category and popularity rather than by campaign-specific offers or short-term demand conditions. For example, department stores tend to target larger user bases than local or niche merchants, such as restaurants or specialty retailers. To absorb category- and popularity-driven variation as well as seasonal demand fluctuations, the first-stage regression includes temporal and merchant-level controls. This type of higher-level variation is commonly used to instrument individual-level treatments and outcomes in empirical work (e.g., Angrist and Lavy 1999; Hoxby 2000; Goldsmith-Pinkham et al. 2020). In our setting, the instrument reflects platform-side allocation decisions made at the campaign level, while treatment receipt and user engagement are realized at the user level.

Table C4. Supplementary Sensitivity Check: Instrumental-Variable Specification

Panel A: First Stage

Panel A.1: Logit Specification

Variables	(1)		(2)	
	Coefficient	SE	Coefficient	SE
Campaign_count	1.76e-6***	(4.00e-7)	1.67e-6***	(4.69e-7)
Constant	-3.452***	(0.442)	-3.703***	(0.556)
Individual Characteristic	YES			
Control (tenure, operating system)			YES	

Merchant Characteristic Control (category, popularity)	YES	YES
Timing Control (day of week, time of day)	YES	YES
Seasonality Control (month)	NO	YES
N Campaigns	211	211
Wald chi-square	1162.63	1611.83
R square	0.017	0.018
Observations	62,928,984	62,928,984

Panel A.2: Linear Probability Specification

Variables	(1)		(2)	
	Coefficient	SE	Coefficient	SE
Campaign_count	1.22e-7***	(2.58e-8)	1.23e-7***	(2.71e-8)
Constant	0.017	(0.027)	-2.88e-4	(0.034)
Individual Characteristic Control (tenure, operating system)	YES		YES	
Merchant Characteristic Control (category, popularity)	YES		YES	
Timing Control (day of week, time of day)	YES		YES	
Seasonality Control (month)	NO		YES	
N Campaigns	211		211	
F-statistic	25.78		40.64	
R square	0.010		0.011	
Observations	62,928,984		62,928,984	

Panel B: Second Stage (Control Function)

Panel B.1: Logit Control Function

	(1)		(2)	
	Click_focal_senddate		Click_focal_senddate	
PushReceived	3.344***	(0.022)	3.105***	(0.015)
First-stage Residual	-1.361***	(0.021)	-1.126***	(0.015)
click_focal_sdown	-0.407***	(0.027)	-0.109***	(0.019)
Lavgrank	-0.145***	(0.001)	-0.138***	(0.001)
Accessories	0.656***	(0.012)	0.701***	(0.011)
DepartmentStore	0.247***	(0.015)	0.344***	(0.013)
Electronics	0.237***	(0.015)	0.345***	(0.014)
FoodDining	0.813***	(0.012)	0.882***	(0.012)
HomeGarden	0.266***	(0.012)	0.310***	(0.012)

Ecommerce	-0.415*** (0.018)	-0.271*** (0.016)
Supermarket	0.072*** (0.017)	0.211*** (0.014)
iOS	0.349*** (0.010)	0.250*** (0.008)
Tenure	-0.005*** (5.14e-5)	-0.005*** (5.10e-5)
Monday	-0.303*** (0.005)	-0.312*** (0.005)
Tuesday	-0.094*** (0.005)	-0.105*** (0.005)
Wednesday	0.274*** (0.006)	0.229*** (0.006)
Thursday	0.253*** (0.005)	0.235*** (0.005)
Friday	0.608*** (0.005)	0.594*** (0.005)
Saturday	0.067*** (0.006)	0.013** (0.005)
Morning	0.407*** (0.003)	0.418*** (0.003)
Constant	-0.510*** (0.063)	-1.196*** (0.045)
Observations	62,928,984	62,928,984

Panel B.2: Linear Probability 2SLS Control Function

	(1)	(2)
	Click_focal_senddate	Click_focal_senddate
PushReceived	0.547*** (0.010)	0.420*** (0.006)
First-stage Residual	-0.480*** (0.010)	-0.354*** (0.006)
click_focal_sdown	-0.008*** (0.001)	0.009*** (0.001)
Lavgrank	-0.002*** (1.53e-5)	-0.002*** (1.15e-5)
Accessories	0.006*** (1.33e-4)	0.008*** (1.02e-4)
DepartmentStore	-0.002*** (2.68e-4)	0.001*** (1.66e-4)
Electronics	-0.003*** (2.93e-4)	0.001*** (1.86e-4)
FoodDining	0.009*** (1.36e-4)	0.010*** (1.04e-4)
HomeGarden	0.002*** (1.27e-4)	0.003*** (1.03e-4)
Ecommerce	-0.012*** (3.67e-4)	-0.008*** (2.24e-4)
Supermarket	-0.005*** (3.45e-4)	-0.001*** (2.13e-4)
iOS	0.009*** (2.74e-4)	0.006*** (1.66e-4)
Tenure	-7.66e-5*** (6.51e-7)	-7.51e-5*** (6.48e-7)
Monday	-0.005*** (6.77e-5)	-0.005*** (6.75e-5)
Tuesday	-0.001*** (7.17e-5)	-0.001*** (7.18e-5)
Wednesday	0.005*** (1.50e-4)	0.004*** (1.10e-4)
Thursday	0.004*** (7.65e-5)	0.003*** (7.07e-5)
Friday	0.010*** (7.77e-5)	0.009*** (7.73e-5)
Saturday	0.002*** (1.26e-4)	0.001*** (8.59e-5)
Morning	0.006*** (4.38e-5)	0.006*** (4.08e-5)
Constant	-0.013*** (0.001)	-0.006*** (3.51e-4)
Observations	62,928,984	62,928,984

Notes: Control Function approach (Wooldridge 2015) for IV with a binary endogenous variable. Panel A reports first-stage estimates; Panel B reports second-stage estimates that include the actual PushReceived treatment along with the first-stage residual as an additional regressor. Logit specifications use the generalized residual; LPM 2SLS specifications use the standard residual. The first-stage F-statistic for the LPM specifications is 25.78 (no FE) and 40.64 (with month FE), and the squared campaign-clustered t-statistic of the excluded instrument (equivalent to the Kleibergen-Paap rk Wald F-statistic with a single instrument) is 22.5 and 20.5; both exceed the Stock-Yogo (2005) critical value for 10% maximal IV size bias; the significant first-stage residual suggests that the control-function term is empirically relevant in this supplementary specification. Standard errors clustered at the campaign level (Panel A, because the instrument varies at the campaign level) and at the user level (Panel B) are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D. Alternative Outcome Specifications

Table D1. Alternative Specification: Indirect Effect of Push Notification

	Indirect Click	
PushReceived	0.771***	(0.005)
Affinity	50.395***	(0.500)
click_focal_sdown	1.547***	(0.007)
Lavgrank	-0.119***	(0.001)
Accessories	1.176***	(0.013)
DepartmentStore	1.175***	(0.013)
Electronics	1.151***	(0.014)
FoodDining	1.439***	(0.014)
HomeGarden	0.720***	(0.014)
Ecommerce	0.656***	(0.015)
Supermarket	1.060***	(0.014)
System_ios	0.102***	(0.006)
Tenure	-0.005***	(5.63e-5)
Monday	-0.473***	(0.006)
Tuesday	-0.189***	(0.006)
Wednesday	0.048***	(0.006)
Thursday	0.157***	(0.006)
Friday	0.679***	(0.005)
Saturday	-0.233***	(0.005)
Morning	0.571***	(0.003)
Constant	-4.960***	(0.015)
Observations	62,928,984	

Notes: Standard errors clustered at the user level are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table D2. Broader Engagement Outcomes: Session Count and Active Usage Time

	Active Usage Time		Session Count	
PushReceived	1.138***	(0.004)	1.986***	(0.006)
Affinity	205.386***	(2.133)	106.487***	(1.407)
click_focal_sdown	1.387***	(0.011)	1.196***	(0.009)
Lavgrank	-0.001***	(3.49e-4)	-0.006***	(4.15e-4)
Accessories	-0.032***	(0.004)	-0.301***	(0.005)
DepartmentStore	-0.069***	(0.004)	-0.311***	(0.005)

Electronics	-0.121***	(0.004)	-0.35***	(0.005)
FoodDining	0.048***	(0.004)	-0.268***	(0.005)
HomeGarden	-0.024***	(0.004)	-0.324***	(0.005)
Ecommerce	-0.025***	(0.005)	-0.237***	(0.005)
Supermarket	-0.103***	(0.004)	-0.385***	(0.005)
System_ios	0.096***	(0.004)	-1.562***	(0.007)
Tenure	-0.002***	(3.16e-5)	0.001***	(5.08e-5)
Monday	-0.137***	(0.003)	-0.153***	(0.003)
Tuesday	-0.081***	(0.003)	-0.035***	(0.003)
Wednesday	-0.028***	(0.003)	-0.018***	(0.004)
Thursday	-0.044***	(0.003)	0.071***	(0.003)
Friday	0.038***	(0.003)	0.309***	(0.003)
Saturday	0.241***	(0.003)	0.307***	(0.003)
Morning	0.064***	(0.001)	0.14***	(0.002)
Constant	-10.442***	(0.006)	-7.808***	(0.008)
Observations	62,928,984		62,928,984	

Notes: Both Active Usage Time (in minutes) and Session Count are modeled as continuous outcomes in logarithmic form, $\log(y + 0.00001)$, using ordinary least squares (OLS) as a transparent and comparable robustness check; because session counts and active time are skewed, these estimates are interpreted as descriptive evidence rather than as primary causal estimates, with the same control vector as the baseline click-through specification (Equation 1). Standard errors clustered at the user level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

E. Heterogeneous Effects and Marginal Effect Analyses

Table E1. Model Estimates for Advertised Merchants on the Campaign Day with Heterogeneous Effects

	click_focal_senddate	
PushReceived	2.916***	(0.03)
Affinity	91.75***	(1.114)
Push×Accessories	-0.783***	(0.023)
Push×DepartmentStore	-1.037***	(0.024)
Push×Electronics	-1.083***	(0.026)
Push×FoodDining	-0.756***	(0.024)
Push×HomeGarden	-0.492***	(0.025)
Push×Ecommerce	-0.671***	(0.028)
Push×Supermarket	-0.719***	(0.025)
Push×Lavgrank	0.054***	(0.002)
Push×Sentiment_vader	0.068***	(0.009)
Push×Subjectivity_textblob	-0.019**	(0.008)
Push×Holiday	-0.038***	(0.008)
Push×Clearance	-0.015**	(0.007)
Push×Urgency	0.161***	(0.006)
Push×Character	-4.41e-5	(1.81e-4)
Push×Emojis	0.055***	(0.006)
Push×Percentoff	-0.482***	(0.007)
Push×Percentdepth	0.61***	(0.012)
Push×Restriction	-0.116***	(0.006)
Push×Morning	-0.368***	(0.006)
Push×Monday	0.437***	(0.01)
Push×Tuesday	0.132***	(0.01)
Push×Wednesday	-0.004	(0.010)
Push×Thursday	-0.01	(0.009)
Push×Friday	-0.642***	(0.010)
Push×Saturday	0.065***	(0.009)
Push×Tenure	0.003***	(7.52e-5)
Push×System_ios	-0.66***	(0.007)
Lavgrank	-0.127***	(0.001)
click_focal_sdown	1.323***	(0.007)
Accessories	1.264***	(0.014)
DepartmentStore	1.279***	(0.015)
Electronics	1.267***	(0.015)

FoodDining	1.454***	(0.015)
HomeGarden	0.79***	(0.015)
Ecommerce	0.733***	(0.017)
Supermarket	1.141***	(0.015)
Tenure	-0.006***	(5.77e-5)
System_ios	-0.009	(0.006)
Morning	0.599***	(0.004)
Monday	-0.484***	(0.007)
Tuesday	-0.171***	(0.007)
Wednesday	0.019***	(0.006)
Thursday	0.185***	(0.006)
Friday	0.745***	(0.006)
Saturday	-0.208***	(0.006)
Constant	-4.919***	(0.017)
Observations	62,928,984	

Notes: Standard errors clustered at the user level are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

To examine how push notification effectiveness varies with merchant characteristics (Danaher et al. 2020), we focus on the category and popularity of the advertised merchant. Because logistic regression coefficients reflect changes in log odds, they cannot be directly interpreted as impacts on the dependent variable. This challenge is further compounded in the case of heterogeneous effects, which are estimated through interaction terms and thus make translating coefficients into substantive effects even more difficult. To address this limitation, we evaluate the impact of push notifications by predicting click-through rates (CTR) under three scenarios: (1) Observed Assignment (S1): Notifications follow the empirical data. For each user–campaign pair, we use the estimated model to predict the click probability given the actual assignment, then average first within each campaign and then across campaigns (and by category). (2) Push set to 0 (C1): The push indicator is set to zero for all users, and predicted click probabilities are aggregated in the same way. (3) Push set to 1 (S2): The push indicator is set to one for all users, and predicted click probabilities are aggregated in the same way.

Table E2. Push Notification Effects on Click-Through Rate by Category

Current Scenario	Model-based Prediction	Ad Effect (%)
------------------	------------------------	---------------

	Observed Strategy (S1)		Push set to 0 (C1)		Push set to 1 (S2)		Observed Effect	Predicted Effect (Push = 1)
	CTR Mean	CTR S.D.	CTR Mean	CTR S.D.	CTR Mean	CTR S.D.	(S1-C1)/C1	(S2-C1)/C1
Overall	1.48%	0.65%	1.05%	0.56%	6.64%	1.77%	40.82%	532.27%
Accessories	1.40%	0.59%	1.02%	0.53%	6.47%	1.54%	37.01%	534.66%
Department Store	1.82%	0.83%	1.39%	0.72%	6.47%	1.89%	31.06%	364.44%
Ecommerce	1.31%	0.43%	0.81%	0.25%	5.74%	1.91%	60.86%	604.42%
Electronics	2.00%	0.57%	1.52%	0.58%	6.81%	1.17%	31.52%	346.45%
Entertainment	0.73%	0.17%	0.47%	0.16%	4.78%	0.74%	55.14%	915.44%
FoodDining	1.57%	0.57%	1.00%	0.40%	8.50%	1.61%	56.71%	745.97%
HomeGarden	0.92%	0.23%	0.64%	0.22%	5.01%	0.78%	44.18%	688.46%
Supermarket	1.90%	0.62%	1.22%	0.53%	7.82%	1.37%	55.26%	538.60%

Notes: Model-based predicted click-through rates by category under three scenarios — Observed Strategy (S1), Push set to 0 (C1), and Push set to 1 (S2) — and corresponding ad effects defined as percentage differences relative to the C1 baseline. Predictions are computed from the focal-merchant logistic regression in Online Appendix Table E1, holding all other covariates at their observed values.

The first six columns of Table E2 report the mean and standard deviation of predicted CTR under these three scenarios, both overall and by merchant category. The last two columns present the ad effect, defined as the percentage difference relative to the no-push baseline: Observed Effect = $(S1 - C1)/C1$ and Predicted Effect (Push = 1) = $(S2 - C1)/C1$.¹ Note that this analysis is intended to quantify the effects of push notifications in a comparative-statics sense rather than to simulate actual business operations, as the platform does not send notifications to all or none of its users.

We apply the same simulation procedure to additional heterogeneity dimensions. To examine merchant popularity, we vary merchant rank at selected percentiles (10th, 20th, 30th, 40th, and 50th) while holding all other covariates at their observed values. To examine user heterogeneity, we vary user tenure at the same percentiles and separately set the operating-system indicator to Android or iOS for all users. To examine timing heterogeneity, we vary the day-of-week and morning indicators while keeping other covariates fixed. In each case we recompute predicted click probabilities under the Push set to 0 (C1) and Push set to 1 (S2) scenarios and aggregate as in Table E2. The resulting predicted CTRs are visualized in Figure 2 of the main text.

¹As a robustness check, we also computed ad effects using an alternative aggregation method (calculating ad effects at the individual level and then averaging across users). The results are qualitatively similar and available upon request.

F. Spillover Effects

Table F1. Estimation Results for Spillover Effects

	click_samecate_senddate		click_diffcate_senddate	
PushReceived	2.007***	(0.025)	0.455***	(0.019)
Affinity	86.46***	(1.097)	65.47***	(0.903)
Push×Accessories	-0.904***	(0.02)	0.16***	(0.013)
Push×DepartmentStore	-0.809***	(0.021)	0.17***	(0.014)
Push×Electronics	-0.414***	(0.022)	0.329***	(0.015)
Push×FoodDining	-0.433***	(0.021)	0.296***	(0.014)
Push×HomeGarden	-0.403***	(0.021)	0.108***	(0.014)
Push×Ecommerce	-0.538***	(0.023)	0.243***	(0.016)
Push×Supermarket	-0.084***	(0.021)	0.257***	(0.014)
Push×Lavgrank	-0.005***	(0.001)	-0.001	(0.001)
Push×Sentiment_vader	-0.016**	(0.007)	-0.216***	(0.007)
Push×Subjectivity_textblob	0.054***	(0.006)	-0.03***	(0.006)
Push×Holiday	0.116***	(0.007)	-0.341***	(0.007)
Push×Clearance	0.09***	(0.006)	-0.037***	(0.006)
Push×Urgency	0.146***	(0.005)	-0.057***	(0.005)
Push×Character	-0.001***	(1.51e-4)	1.57e-5	(1.39e-4)
Push×Emojis	0.082***	(0.005)	-0.133***	(0.004)
Push×Percentoff	-0.297***	(0.006)	-0.187***	(0.006)
Push×Percentdepth	0.19***	(0.01)	0.404***	(0.01)
Push×Restriction	-0.11***	(0.005)	0.071***	(0.004)
Push×Morning	0.036***	(0.004)	0.024***	(0.004)
Push×Monday	0.231***	(0.007)	0.166***	(0.007)
Push×Tuesday	0.11***	(0.007)	-0.018***	(0.006)
Push×Wednesday	0.299***	(0.007)	-0.024***	(0.006)
Push×Thursday	0.278***	(0.007)	0.005	(0.006)
Push×Friday	-0.069***	(0.007)	-0.097***	(0.007)
Push×Saturday	-0.103***	(0.006)	-0.15***	(0.006)
Push×Tenure	0.001***	(5.43e-5)	0.002***	(4.90e-5)
Push×System_ios	-0.273***	(0.005)	0.136***	(0.005)
Lavgrank	-0.018***	(4.95e-4)	0.001***	(3.67e-4)
Accessories	1.586***	(0.01)	-0.453***	(0.003)
DepartmentStore	1.142***	(0.01)	-0.287***	(0.003)
Electronics	0.572***	(0.01)	-0.277***	(0.004)

FoodDining	1.014***	(0.01)	-0.238***	(0.004)
HomeGarden	0.701***	(0.01)	-0.14***	(0.003)
Ecommerce	1.019***	(0.011)	-0.202***	(0.004)
Supermarket	0.59***	(0.01)	-0.211***	(0.004)
Tenure	-0.003***	(3.56e-5)	-0.003***	(2.92e-5)
System_ios	0.064***	(0.004)	0.11***	(0.004)
Morning	0.117***	(0.002)	0.079***	(0.001)
Monday	-0.372***	(0.003)	0.061***	(0.003)
Tuesday	-0.282***	(0.003)	0.051***	(0.003)
Wednesday	-0.526***	(0.004)	0.157***	(0.003)
Thursday	-0.311***	(0.003)	0.001	(0.002)
Friday	-0.016***	(0.003)	-0.009***	(0.002)
Saturday	-0.03***	(0.003)	0.168***	(0.002)
click_samecate_sdown	1.062***	(0.003)		
click_diffcate_sdown			1.109***	(0.003)
Constant	-4.375***	(0.011)	-2.683***	(0.006)
Observations	62,928,984		62,928,984	

Notes: Standard errors clustered at the user level are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

G. Delayed Effects

Table G1. Estimation Results for Delayed Effects

	click_focal_7day		click_samecate_7day		click_diffcate_7day	
PushReceived	0.798***	(0.027)	0.3***	(0.017)	0.077***	(0.014)
Affinity	53.29***	(0.577)	129.3***	(1.882)	153.01***	(2.203)
Push×Accessories	0.323***	(0.02)	-0.089***	(0.013)	0.043***	(0.010)
Push×DepartmentStore	0.27***	(0.02)	0.078***	(0.014)	0.133***	(0.01)
Push×Electronics	0.168***	(0.021)	0.116***	(0.015)	0.089***	(0.011)
Push×FoodDining	0.698***	(0.021)	0.272***	(0.014)	0.149***	(0.01)
Push×HomeGarden	0.215***	(0.021)	-0.098***	(0.014)	-0.004	(0.01)
Push×Ecommerce	0.511***	(0.027)	0.184***	(0.016)	0.009	(0.012)
Push×Supermarket	0.459***	(0.021)	0.436***	(0.015)	0.127***	(0.01)
Push×Lavgrank	0.041***	(0.002)	0.014***	(0.001)	0.008***	(0.001)
Push×Sentiment_vader	-0.268***	(0.009)	-0.2***	(0.005)	-0.075***	(0.005)
Push×Subjectivity_textblob	0.013	(0.009)	0.098***	(0.005)	3.24e-5	(0.004)
Push×Holiday	-0.055***	(0.009)	0.065***	(0.005)	0.081***	(0.005)
Push×Clearance	-0.191***	(0.008)	0.072***	(0.005)	-0.046***	(0.004)
Push×Urgency	-0.263***	(0.006)	-0.098***	(0.004)	0.045***	(0.003)
Push×Character	-0.003***	(1.82e-4)	0.002***	(1.09e-4)	4.33e-5	(1.01e-4)
Push×Emojis	-0.19***	(0.006)	-0.042***	(0.004)	-0.01***	(0.003)
Push×Percentoff	-0.422***	(0.007)	-0.184***	(0.005)	-0.067***	(0.004)
Push×Percentdepth	0.68***	(0.013)	0.009	(0.008)	0.075***	(0.007)
Push×Restriction	0.061***	(0.006)	-0.067***	(0.004)	0.027***	(0.003)
Push×Morning	0.113***	(0.006)	0.03***	(0.003)	-0.02***	(0.003)
Push×Monday	-0.201***	(0.009)	0.051***	(0.005)	0.04***	(0.005)
Push×Tuesday	0.042***	(0.01)	-0.025***	(0.005)	-0.062***	(0.004)
Push×Wednesday	0.189***	(0.009)	-0.019***	(0.005)	-0.013***	(0.004)
Push×Thursday	0.074***	(0.009)	0.069***	(0.005)	0.054***	(0.004)
Push×Friday	-0.208***	(0.009)	-0.068***	(0.005)	-0.078***	(0.005)
Push×Saturday	-0.142***	(0.008)	-0.035***	(0.005)	-0.062***	(0.004)
Push×Tenure	0.002***	(6.24e-5)	0.001***	(4.06e-5)	0.002***	(3.79e-5)
Push×System_ios	-0.105***	(0.006)	0.127***	(0.004)	0.203***	(0.004)
Lavgrank	-0.259***	(0.001)	-0.019***	(2.66e-4)	-0.003***	(2.15e-4)
Accessories	-0.43***	(0.006)	1.018***	(0.004)	-0.233***	(0.002)
DepartmentStore	0.146***	(0.006)	0.509***	(0.004)	-0.06***	(0.002)
Electronics	0.096***	(0.006)	0.268***	(0.004)	-0.054***	(0.002)

FoodDining	-0.344***	(0.007)	0.237***	(0.004)	0.022***	(0.002)
HomeGarden	-0.231***	(0.006)	0.443***	(0.004)	-0.034***	(0.002)
Ecommerce	-1.816***	(0.010)	-0.301***	(0.005)	0.029***	(0.002)
Supermarket	-0.719***	(0.007)	-0.298***	(0.005)	-0.073***	(0.002)
Tenure	-0.003***	(4.26e-5)	-0.002***	(2.83e-5)	-0.002***	(2.62e-5)
System_ios	0.062***	(0.005)	0.072***	(0.004)	0.073***	(0.003)
Morning	0.176***	(0.002)	0.139***	(0.001)	0.05***	(0.001)
Monday	0.36***	(0.003)	0.004***	(0.001)	0.012***	(0.001)
Tuesday	-0.086***	(0.004)	-0.03***	(0.001)	0.089***	(0.001)
Wednesday	-0.174***	(0.003)	0.023***	(0.001)	0.085***	(0.001)
Thursday	0.03***	(0.004)	-0.105***	(0.001)	0.063***	(0.001)
Friday	0.167***	(0.003)	-0.066***	(0.001)	-0.023***	(0.001)
Saturday	0.106***	(0.003)	-0.152***	(0.001)	-0.027***	(0.001)
click_focal_sdown	1.43***	(0.005)				
click_samecate_sdown			1.009***	(0.003)		
click_diffcate_sdown					1.047***	(0.002)
Constant	-1.646***	(0.009)	-2.199***	(0.005)	-1.017***	(0.004)
Observations	62,928,984		62,928,984		62,928,984	

Notes: Standard errors clustered at the user level are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table G2. Delayed Effects by Category

	Focal	Same Category	Different Category
Overall	166.80%	46.27%	27.35%
Accessories	188.07%	33.77%	26.35%
Department Store	132.19%	56.35%	31.13%
Ecommerce	169.22%	73.05%	20.00%
Electronics	90.74%	57.48%	24.07%
Entertainment	113.01%	41.99%	20.01%
FoodDining	302.44%	101.66%	34.58%
HomeGarden	152.97%	36.12%	23.26%
Supermarket	222.65%	120.67%	28.22%

H. Other Auxiliary Diagnostic Tests

Table H1. Test of Difference in Affinity Scores Between Users Receiving a Push Notification and Those Not Receiving One

Group	Obs	Mean	Std. Err.	Std. Dev.	95% CI
Not Received (0)	58,848,578	0.0000482	8.39e-08	0.0006438	[0.0000480, 0.0000483]
Received (1)	4,080,406	0.0003405	8.35e-07	0.0016866	[0.0003388, 0.0003421]
Combined	62,928,984	0.0000671	9.58e-08	0.0007597	[0.0000669, 0.0000673]
<i>Difference (0 - 1)</i>	—	-0.000292 3	8.39e-07	—	[-0.0002940, -0.0002907]

Notes: Two-sample t-test with unequal variances on the user-campaign-level affinity score, pooled across the 211 campaigns and computed on the regression sample (N = 62,928,984). Group 0 = users not selected to receive the notification; Group 1 = recipients. $t \approx -348$ (Satterthwaite df $\approx 4.2e+06$). H_a : diff $\neq 0$ yields $p < 0.001$. Recipients have significantly higher affinity scores than non-recipients.

Table H2. Relationship Between Merchant Rank and Discount Level

Variable	Coefficient	Std. Error	t-value	p-value	95% CI Lower	95% CI Upper
Lavgrank	-0.015	0.00795	-1.89	0.061	-0.0307	0.0007
Intercept (_cons)	0.4778	0.06179	7.73	0	0.3558	0.5998
Model Summary	R ² = 0.0211	Adj R ² = 0.0152	F(1,165) = 3.55	p = 0.0612	N = 167	

Notes: OLS regression of percentage discount depth on merchant rank (Lavgrank) across N = 167 campaigns with non-zero discount depth. Standard errors are reported alongside coefficients.

Table H3. Relationship Between Merchant Rank and Day of Week

Group Summary	Count	Sum	Mean	Variance
weekday=0 (Sunday)	24	165.21	6.884	1.4907
weekday=1 (Monday)	25	181.81	7.2724	4.8441
weekday=2 (Tuesday)	30	241.29	8.0431	5.5788
weekday=3 (Wednesday)	29	217.36	7.4952	3.02
weekday=4 (Thursday)	33	255.47	7.7414	5.1773
weekday=5 (Friday)	28	225.83	8.0654	3.5952
weekday=6 (Saturday)	42	324.18	7.7185	3.5157

Source of Variation	SS	df	MS	F	p-value	F crit
Between Groups	28.2404	6	4.7067	1.1946	0.3105	2.1432

Within Groups	803.7776	204	3.9401
Total	832.018	210	

Notes: One-way ANOVA of merchant rank (Lavgrank) across the seven day-of-week categories ($k = 7$), based on campaign-level averages. $F = 1.19$, $p = 0.31$ indicates that merchant popularity does not vary systematically with the day of the week on which campaigns are sent.

Table H4. Difference Between Morning and Afternoon Sessions

Variable	Obs	Mean	Std. Dev.	Mean Difference	t-value	df	p-value (two-tailed)
Activity Count							
Morning Count	13,016,913	0.493	0.95	-0.715	-1600	13,016,912	< 0.001
Afternoon Count	13,016,913	1.208	1.298				
Average Duration							
Morning Average Duration	13,016,913	14.403	104.246	-13.721	-210	13,016,912	< 0.001
Afternoon Average Duration	13,016,913	28.124	207.756				

Notes: Mean difference calculated as morning value minus afternoon value. p-values are from two-tailed tests ($\Pr(|T| > |t|)$).

I. Mechanism Summary

Table I1. Heterogeneous Results and Mechanism Summary

Heterogeneity Factor	Effectiveness Summary	Mechanism Explanation (Attention / Information)
Advertised Merchant: FoodDining	More effective	Routine, low-effort decisions; notifications provide actionable information that can be processed and acted upon immediately
Advertised Merchant: Department Store / Electronics	Less effective	More deliberative, planned purchases; notifications generate smaller incremental gains as decisions require greater evaluation
Advertised Merchant: Less Popular Brand	More effective	Push increases visibility; less known → higher informational value
Timing: Thursday / Monday	Favorable timing response	Weekend-planning relevance and lower baseline engagement increase receptivity to reminders
Timing: Morning	Less effective	Low attention bandwidth in morning due to work distractions
App User: Short Tenure	More effective	More curious and exploratory users; higher marginal info value
App User: Android	More effective	Push visibility higher due to Android's permissive notification settings
Message: Stronger Sentiment / Emojis / Objective Tone / Urgency	More effective	Visual + emotional cues enhance salience and urgency perception
Message: High Discount Depth	More effective	Higher perceived value drives response (informational mechanism)
Message: Topic = Holiday / Clearance	Less effective	Overused themes, low salience and novelty
Message: No explicit or convertible percentage-off discount	More effective	More flexible and surprising offers → higher curiosity and attention

J. Experimental Materials and Supplementary Statistics

This section reproduces the survey instrument and supplementary statistical results used in the experimental analyses.

Experiment 1

A. Brand Comparison

Q1 How often do you use mobile apps for purposes other than making calls and sending messages?

- ☐ Every Day (1)
- ☐ Several times a week (2)
- ☐ Once a week (3)
- ☐ Less than once a week (4)

Q2 What is your favorite brand of jeans?

- ☐ Gap (1)
- ☐ Levi's (2)
- ☐ Wrangler (3)
- ☐ Calvin Klein (4)
- ☐ None of the above (5)

Q3 Imagine there is a mobile app that offers coupons for various brands. How interested are you in installing this app on your phone?

[7-point scale: Not at all interested (1) – Extremely interested (7)]

Condition 1 (Participants were randomly assigned to one of four between-subject conditions corresponding to Q4 through Q7; each participant answered only the click-likelihood item for their assigned condition.)

Q4 Imagine you have installed this mobile app on your phone. On a regular day, how likely are you to check the mobile app for Levi's coupons? Rate on a scale of 1 to 7 (1 = Extremely Unlikely, 7 = Extremely Likely).

[7-point scale: Extremely unlikely (1) – Extremely likely (7)]

Condition 2

Q5 Imagine you have installed this mobile app on your phone. Today, you have received a push message through the app, which says, 'Levi's coupons are now available for your savings!' How likely are you to check the mobile app for Levi's coupons? Rate on a scale of 1 to 7 (1 = Extremely Unlikely, 7 = Extremely Likely).

[7-point scale: Extremely unlikely (1) – Extremely likely (7)]

Condition 3

Q6 Imagine you have installed this mobile app on your phone. Today, you have received a push message through the app, which says, 'Extra **10%** off Levi's coupons are now available for your savings!' How likely are you to check the mobile app for Levi's coupons? Rate on a scale of 1 to 7 (1 = Extremely Unlikely, 7 = Extremely Likely).

[7-point scale: Extremely unlikely (1) – Extremely likely (7)]

Condition 4

Q7 Imagine you have installed this mobile app on your phone. Today, you have received a push message through the app, which says, 'Extra **30%** off Levi's coupons are now available for your savings!' How likely are you to check the mobile app for Levi's coupons? Rate on a scale of 1 to 7 (1 = Extremely Unlikely, 7 = Extremely Likely).

[7-point scale: Extremely unlikely (1) – Extremely likely (7)]

Chance of checking other brands/other categories

Q8 Would you like to check for other apparel coupons on the platform?

☐ No (21)

☐ Yes (22)

Q9 Would you like to check for coupons in other categories (e.g., electronics, food, home appliances) on the platform?

☐ No (21)

☐ Yes (22)

Block 10

Q10 Please explain briefly why you want to check for other apparel coupons on the platform

Block 11

Q11 Please explain briefly why you want to check for coupons in other categories on the platform

Experience with jeans

Q12 How often do you purchase jeans?

- ☐ Once a month or more (1)
- ☐ A few times a year (2)
- ☐ Once a year (3)
- ☐ Less than once a year (4)

Q13 Have you ever purchased jeans from Levi's?

- ☐ Yes (1)
- ☐ No (2)

Display This Question: If Have you ever purchased jeans from Levi's? = Yes

Q14 How would you rate your overall experience with Levi's jeans? Rate on a scale of 1 to 5 (1 = Very Poor and 5 = Excellent).

[5-point scale: Very poor (1) – Excellent (5)]

Experience with Coupon

Q15 How often do you use coupons for online purchases?

- ☐ Less than 10% of the time (1)
- ☐ 10-30% of the time (2)
- ☐ 31-50% of the time (3)
- ☐ 51-70% of the time (4)
- ☐ More than 70% of the time (5)

Q16 What percentage discount do you typically expect with a jeans coupon?

0 5 10 15 20 25 30 35 40 45 50

Demographic Information

Q17 What is your age?

- ☐ 18-24 (1)
- ☐ 25-34 (2)
- ☐ 35-44 (3)
- ☐ 45-54 (4)
- ☐ 55-64 (5)
- ☐ 65 and above (6)

Q18 What is your gender?

- ☐ Male (1)
- ☐ Female (2)
- ☐ Non-binary / third gender (3)
- ☐ Prefer not to say (4)

Q19 What is the operating system of your primary phone?

- ☐ iOS (1)
- ☐ Android (2)
- ☐ Others (3)

Table J1. Experiment 1 — Descriptive Statistics on Click Likelihood by Condition

Condition	N	Min	Max	Mean	SD
Condition 1: No push (Q4)	248	1	7	3.94	1.99
Condition 2: Push, no discount (Q5)	253	1	7	4.94	1.85
Condition 3: Push + 10% off (Q6)	249	1	7	4.30	2.04
Condition 4: Push + 30% off (Q7)	251	1	7	4.69	1.91

Notes: Likelihood to check the app for coupons is rated on a 1–7 scale (1 = Extremely Unlikely, 7 = Extremely Likely). Condition labels reference the corresponding survey questions in Experiment 1.

Table J2. Experiment 1 — Independent-Samples t-Tests on Click Likelihood

Comparison	Mean Diff.	t	df	p (two-tailed)	95% CI
No push (C1) vs. Push, no discount (C2)	–1.00	–5.83	499	< .001	[–1.34, –0.66]
Push + 10% off (C3) vs. Push + 30% off (C4)	–0.40	–2.24	498	.026	[–0.74, –0.05]

Notes: Independent-samples t-tests with equal variances assumed. Mean differences are reported as Group 1 – Group 2; negative values indicate that the second group has the higher mean. C# refers to conditions defined in Table J1.

Experiment 2

Consent Form

Q0 I hereby consent to participate in the captioned research conducted by the research team. I understand that information obtained from this research may be used in future research and published. However, my right to privacy will be retained, i.e., my personal details will not be revealed. The procedure as set out in the attached information sheet has been fully explained. I understand the benefits and risks involved. My participation in the project is voluntary. I acknowledge that I have the right to question any part of the procedure and can withdraw at any time without penalty of any kind.

☐ Yes to begin (1)

☐ No to exit (2)

A. Warm-up

Q1 How often do you use mobile apps for purposes other than making calls and sending messages?

☐ Every Day (1)

☐ Several times a week (2)

☐ Once a week (3)

☐ Less than once a week (4)

Q2 Please select all jeans brands that you have heard of:

☐ Gap (1)

☐ Levi's (2)

☐ Calvin Klein (3)

☐ None of the above (4)

Q3 Imagine there is a mobile app that offers coupons for various brands. How interested are you in installing this app on your phone? Rate on a scale of 1 to 7 (1 = Not at all interested, 7 = Extremely interested).

[7-point scale: Not at all interested (1) – Extremely interested (7)]

Without Push

Q4 Imagine you have installed this mobile app on your phone. On a regular day, how likely are you to check the mobile app for jeans coupons? Rate on a scale of 1 to 7 (1 = Extremely Unlikely, 7 = Extremely Likely).

[7-point scale: Extremely unlikely (1) – Extremely likely (7)]

Condition 1 (Participants were randomly assigned to one of six experimental conditions that varied the order in which they received three brand messages (Levi's, Gap, and Calvin Klein). To reduce redundancy, only one representative condition is shown below.)

Q5 Imagine you have installed this mobile app on your phone. Today, you have received a push message through the app, which says, 'Levi's coupons are now available for your savings!' How likely are you to check the mobile app for Levi's coupons? Rate on a scale of 1 to 7 (1 = Extremely Unlikely, 7 = Extremely Likely).

[7-point scale: Extremely unlikely (1) – Extremely likely (7)]

Q6 How annoying do you find the push notification you just received? Rate on a scale of 1 to 7 (1 = Not at all annoying, 7 = Extremely annoying).

[7-point scale: Not at all annoying (1) – Extremely annoying (7)]

Q7 Now, you receive another push notification from the app: 'Gap coupons are now available for your savings!' How likely are you to check the mobile app for Gap coupons? Rate on a scale of 1 to 7 (1 = Extremely Unlikely, 7 = Extremely Likely).

[7-point scale: Extremely unlikely (1) – Extremely likely (7)]

Q8 How annoying do you find the push notification you just received? Rate on a scale of 1 to 7 (1 = Not at all annoying, 7 = Extremely annoying).

[7-point scale: Not at all annoying (1) – Extremely annoying (7)]

Q9 A few hours later, you receive another push notification: 'Calvin Klein coupons are now available for your savings!' How likely are you to check the mobile app for Calvin Klein coupons? Rate on a scale of 1 to 7 (1 = Extremely Unlikely, 7 = Extremely Likely).

[7-point scale: Extremely unlikely (1) – Extremely likely (7)]

Q10 How annoying do you find the push notification you just received? Rate on a scale of 1 to 7 (1 = Not at all annoying, 7 = Extremely annoying).

[7-point scale: Not at all annoying (1) – Extremely annoying (7)]

Acceptable Number of Push Notifications per Day

Q11 In your opinion, how many push notifications from this app would be acceptable to receive in a single day? (Please enter a whole number, e.g., 0, 1, 2, ...)

Table J3. Experiment 2 — Paired t-Tests on Click Likelihood Across Repeated Push Notifications

Comparison	Mean (1st)	Mean (2nd)	Difference	t	df	p (two- tailed)	N
Push 1 vs. Push 2	4.41	4.23	0.18	1.80	199	.074	200
Push 2 vs. Push 3	4.23	3.80	0.43	3.38	199	< .001	200
Push 3 vs. Baseline (no push)	3.80	3.86	−0.06	−0.47	199	.639	200

Notes: Within-subject paired t-tests on click likelihood (1–7 scale) for the first, second, and third push notifications received in sequence (Push 1, Push 2, Push 3) and the no-push baseline (Q4). The pattern (Push 1 > Push 2 > Push 3 ≈ Baseline) indicates diminishing responsiveness under repeated exposure.

Table J4. Experiment 2 — Paired t-Tests on Perceived Annoyance Across Repeated Push Notifications

Comparison	Mean (1st)	Mean (2nd)	Difference	t	df	p (two- tailed)	N
Annoyance 1 vs. Annoyance 2	3.19	3.27	−0.08	−1.45	199	.148	200
Annoyance 2 vs. Annoyance 3	3.27	3.64	−0.37	−4.16	199	< .001	200

Notes: Within-subject paired t-tests on perceived annoyance (1–7 scale, 1 = Not at all annoying, 7 = Extremely annoying) measured after each push notification. Annoyance increases significantly between the second and third push.

Table J5. Experiment 2 — Distribution of Acceptable Number of Push Notifications per Day (Q11)

Statistic	Value
N	197
Mean	1.61
Standard error	0.12
Standard deviation	1.72
Median	1
Mode	1
Minimum	0
Maximum	15
Skewness	3.45
Kurtosis	20.56

Notes: Self-reported maximum acceptable number of push notifications per day. The distribution is heavily right-skewed (skewness = 3.45) with mode and median both equal to 1, indicating that most users prefer to receive at most one notification per day.

K. Back-of-Envelope Estimate of Campaign-Level Engagement Value

To translate the estimated push-notification effects into a rough dollar magnitude, we conduct a back-of-envelope calculation. For each engagement category (focal advertiser, same-category spillover, cross-category spillover), value is computed as:

$$\text{Engagement value} = N \times \Delta\text{CTR} \times \text{Conversion} \times \text{AOV}$$

where $N = 19,346$ is the average number of push recipients selected per campaign, as reported in Table 2 (we use this quantity as the reference population for the back-of-envelope per-campaign engagement-value calculation); ΔCTR is the difference between the predicted click-through rate when all selected users receive the push notification and the predicted click-through rate when no users receive the notification, computed from the prediction procedure applied to the models reported in Table E2 (focal advertiser, same day), Table F1 (same-category and cross-category spillovers, same day), and Tables G1–G2 (delayed effects over the seven days following the send date); Conversion is the assumed click-to-purchase rate (5%); and AOV is the assumed average order value (\$100; Opensend.com 2025).

Applying this formula to the empirical estimates yields the following per-campaign engagement values:

Table K1. Back-of-Envelope Engagement Value per Campaign

Component	Source	Predicted CTR (Push=0)	Predicted CTR (Push=1)	ΔCTR (pp)	Engagement Value
Same-day effects					
Focal advertiser	Table E2 estimates	1.05%	6.64%	5.59	~\$5,400
Same-category spillover	Table F1 estimates	3.64%	10.26%	6.62	~\$6,400
Cross-category spillover	Table F1 estimates	6.90%	12.20%	5.30	~\$5,100
Delayed effects (7-day)					
Focal advertiser	Table G1 estimates	2.30%	6.12%	3.83	~\$3,700
Same-category spillover	Table G2 estimates	17.29%	25.29%	8.00	~\$7,700
Cross-category spillover	Table G2 estimates	29.94%	38.13%	8.19	~\$7,900

Notes: Baseline and Push-set-to-1 CTRs are computed from the prediction procedure based on the indicated model estimates. ΔCTR = Predicted CTR (Push=1) – Predicted CTR (Push=0), expressed in percentage points. Engagement value is computed as $N \times \Delta\text{CTR} \times \text{Conversion} \times \text{AOV}$, with $N = 19,346$, Conversion = 0.05, and AOV = \$100. N denotes the average number of push recipients per campaign (Table 2) and serves as the reference population for the per-campaign "value of one push" prediction; this dollar figure should be interpreted as the average per-campaign engagement value rather than as a platform-wide aggregate. The calculation assumes a uniform conversion rate and order value across categories and engagement windows, applies average per-campaign lifts to overall (across-category) baseline rates, and does not net out campaign costs, user fatigue, opt-out behavior, or the possibility that repeated exposure erodes future responsiveness. The figures should therefore be read as rough order-of-magnitude benchmarks rather than precise revenue estimates.

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