The perils of proactive churn prevention using plan recommendations: Evidence from a field experiment

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WEB APPENDIX

In this appendix, we present a detailed description of the analyses performed to obtain certain results discussed in the main manuscript.

WEB APPENDIX A: HETEROGENEITY IN THE EFFECT OF TREATMENT ON CUSTOMER REVENUE

To assess the statistical significance of heterogeneity in the treatment effects in customer revenue, we estimate a linear model using revenue difference as dependent variable. In particular, we model the revenue change as:

$$\Delta Revenue_i | \widetilde{\theta}, T_i, X_i^c = \theta_0 + \theta_T\, T_i + \theta_c X_i^c + \theta_{TC} T_i X_i^c + \zeta_i \qquad \text{(A1)}$$

Where T_i is a dummy variable that takes value 1 if the customer received the treatment, and 0 otherwise, X_i^c contains all the usage-based characteristics (i.e., *overage*, *variability*, and *trend*) as well as a tariff dummy to further control for idiosyncratic differences across customers allocated in different tariffs.[1] The vector $\tilde{\theta}$ includes the estimated parameters, including the constant (θ_0), main (θ_T , θ_c), and interactions effects (θ_{TC}) and ζ_i is normally distributed with mean 0 and unit variance.

Table W1 shows the results for the revenue model. In Column 1, we corroborate the null effect of treatment on the change in revenues (see Table 2) and show its robustness by adding multiple control variables (column 2). The results in Column 2 show that customers who have lower levels of usage in the first three months, lower variability and a positive trend tend to

[1] Here the tariff dummy indicates whether the customer's pre-campaign tariff was the closest to the featured plans. We also run the models including dummy variables for all 4 tariffs (all non-featured tariffs) but no differences were found in behavior across all lowest tariffs. Thus, we keep a single tariff dummy for model parsimony.

increase their future consumption. Most importantly, we find that there is substantial heterogeneity in the treatment effect (Column 3) since all the interaction terms are significant.

TABLE W1: HETEROGENEITY IN THE EFFECT OF ENCOURAGEMENT ON REVENUE

	Revenue difference (Main effect)	Revenue difference (Controls)	Revenue difference (Heterogeneity)
Treatment	–.0013	.377	-.972
	(.481)	(.454)	(.706)
Overage		–.231***	–.181***
		(.003)	(.008)
Variability		–24.06***	–3.72***
		(1.349)	(3.377)
Trend (% increase)		21.35***	16.13***
		(.924)	(2.315)
$39 plan dummy		.131	–1.647*
		(.335)	(.847)
Treatment*overage			–.057***
			(.009)
Treatment*variability			7.827**
			(3.684)
Treatment*trend			6.194**
			(2.524)
Treatment*$39 plan dummy			2.111**
			(.922)
Constant	–4.403***	–4.959***	–3.782***
	(.440)	(.461)	(.656)
Observations	60,218	60,213	60,213
R-square	.0%	11.1%	11.2%

Standard errors in parentheses. *** p<.01, ** p<.05, * p<.1
Results from a linear regression with (individual) revenue difference as dependent variable. For easier interpretation, overage, variability and trend have been mean-centered.

WEB APPENDIX B: ALLOWING FOR TEMPORAL DYNAMICS AND HETEROGENEITY IN CHURN

To test the robustness of the results presented in the empirical section of the main manuscript, we re-estimate the churn model using multiple observations per customer. This approach allows us to control for time effects and for unobserved customer heterogeneity. We estimate two nested specifications, both including a random effect to capture unobserved individual heterogeneity. In the parsimonious version we allow for time dynamics including month dummies. In the second specification we also allow for the effect of treatment to vary over time (i.e., we include the interactions between the time dummies and the treatment variable).

Both model specifications lead to statistically equivalent results (Columns 1 and 2 in Table W2). Importantly, we observe that all estimates are similar to those presented in Table 6 of the main manuscript. We then conclude that all the findings regarding the effect of the encouragement on churn are robust even when allowing for temporal dynamics and unobserved customer heterogeneity.

TABLE W2: HETEROGENEITY IN THE EFFECT OF ENCOURAGEMENT ON CHURN

	Churn (1)	Churn (2)
Treatment	.520***	.585***
	(.078)	(.082)
Overage/1000	.414	.408
	(.811)	(.795)
Variability	.537	.526
	(.343)	(.337)
Trend (% increase)	-.080	-.080
	(.235)	(.231)
$39 plan dummy	.238***	.231**
	(.092)	(.090)
Treatment*overage/1000	.448	.464
	(.854)	(.839)
Treatment*variability	.985***	1.016***
	(.367)	(.361)
Treatment*trend	–.609**	–.618**
	(.251)	(.247)
Treatment*$39 plan dummy	–.116	–.108
	(.098)	(.096)
Constant	–5.752***	–5.737***
	(.075)	(.078)
Ln(Sigma) of constant	2.784***	2.754***
	(.012)	(.012)
Time dummies	Yes	Yes
Interaction Treatment and time	No	Yes
Observations	183,392	183,392
Number of customers	64,141	64,141

Standard errors in parentheses. *** p<.01, ** p<.05, * p<.1
Results from a random effect probit model with churn as dependent variable. Overage, variability and slope have been mean-centered. Overage is rescaled to avoid standard errors of zero.

WEB APPENDIX C: MODELING CHURN AND PLAN SWITCHING SIMULTANEOUSLY

We test the robustness of the results presented in the empirical sectionof the main manuscript by modeling churn and plan switching jointly. Unlike the models presented in the main document, this approach allows the encouragement to alter both behaviors simultaneously. Results of the regression analysis are presented in Table W3.

We find that all estimates for churn (Column 1) are similar to those presented in Table 6 of the main manuscript. We therefore conclude that the findings about the effect of the encouragement on churn are not driven by unobserved factors related to customers' switching propensity.

TABLE W3: EFFECT OF THE ENCOURAGEMENT ON CHURN AND SWITCHING (JOINT) MODEL

	Churn	Switching
Treatment	.161***	.420***
	(.038)	(.047)
Overage/1000	.915*	.544
	(.507)	(.492)
Variability	-.447*	.333
	(.237)	(.211)
Trend (% increase)	.0507	–.082
	(.163)	(.145)
$39 plan dummy	–1.035***	.035
	(.059)	(.056)
Treatment*overage/1000	.102	.185
	(.535)	(.519)
Treatment*variability	.401	.602***
	(.253)	(.224)
Treatment*trend	.177	–.311**
	(.173)	(.154)
Treatment*$39 plan dummy	.298***	–.093
	.177	–.311**
Constant	–1.598***	–2.071***
	(.036)	(.044)
Observations	64,141	64,141

Standard errors in parentheses. *** p<.01, ** p<.05, * p<.1
Results from a multinomial probit regression with churn and plan switching as dependent variables. For easier interpretation, overage, variability and slope have been mean-centered. Variable overage is rescaled to avoid standard errors of zero.
For the purpose of this estimation, customers who switched and then churned are coded as churners. We estimated the same model coding those customers as switchers. Both models give convergent set of results.

WEB APPENDIX D: MODEL SPECIFICATIONS FOR THE PROPENSITY SCORE ANALYSIS

When analyzing tariff switching behavior we use propensity score analysis to control for possible self-selection due to acceptance/rejection of the campaign. We model several specifications (including transformations and interactions of the observed variables) in order to select the model that best fits the data. Here we present the results from all specifications (Table W3). We compare the specifications using the Likelihood Ratio (LR) test and select ModelW4 as the one that best fits the data.

TABLE W4: PARAMETERS ESTIMATES OF THE PROPENSITY MODELS

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Overage	.0011***	.0011***	.0023***	.0019***	.0017***	.0019***	.0019***	.0019***	.0019***
	(.0002)	(.0002)	(.0005)	**(.0005)**	(.0006)	(.0005)	(.0005)	(.0005)	(.0005)
Overage ^{2}			-3.19e-06***	-3.34e-06***	-3.38e-06***	-3.31e-06***	-3.33e-06***	-3.33e-06***	-3.33e-06***
			(1.23e-06)	**(1.22e-06)**	(1.24e-06)	(1.18e-06)	(1.21e-06)	(1.22e-06)	(1.21e-06)
$39 plan dummy	.188***	.187***	.188***	.186***	.144**	.186***	.186***	.160***	.188***
	(.0282)	(.0282)	(.0282)	**(.0283)**	(.0616)	(.0283)	(.0283)	(.0539)	(.0284)
Variability	-.349***	-.287**	-.313***	-.631***	-.628***	-.599***	-.647***	-.709***	-.632***
	(.111)	(.113)	(.114)	**(.225)**	(.225)	(.226)	(.224)	(.265)	(.225)
Trend		.252***	.236***	.227***	.225***	.358**	.338**	.226***	.0679
		(.0771)	(.0774)	**(.0774)**	(.0775)	(.157)	(.167)	(.0775)	(.125)
Overage*Variability				.0023*	.0023	.0021	.0023*	.0023	.0023
				(.00138)	(.00139)	-.00138	(.00137)	(.00138)	(.00138)
Overage*Plan					.000332				
					(.000439)				
Overage*Trend						-.000954			
						(.000992)			
Variability*Trend							-.300		
							(.397)		
Variability*Plan								.130	
								(.233)	
Trend*Plan									.254
									(.158)
Constant	-2.287***	-2.290***	-2.358***	-2.313***	-2.297***	-2.316***	-2.310***	-2.298***	-2.314***
	(.0341)	(.0342)	(.0409)	**(.0487)**	(.0529)	(.0479)	(.0486)	(.0559)	(.0486)
Log Likelihood	-4241.2815	-4235.8933	-4230.0639	**-4228.762**	-4228.4734	-4228.2967	-4228.4822	-4228.6042	-4227.4714
LR test w.r.t next simpler (df=1)	81.7384	1.7764	11.6588	**2.6038**	.5772	.9306	.5596	.3156	2.5812
Observations	54,089	54,083	54,083	**54,083**	54,083	54,083	54,083	54,083	54,083

Standard errors in parentheses. *** p<.01, ** p<.05, * p<.1. Logistic regression with accepting the promotion as dependent variable.

WEB APPENDIX D: TESTING FOR THE NON-LINEARITY OF THE INTERACTION EFFECT OF OVERAGE

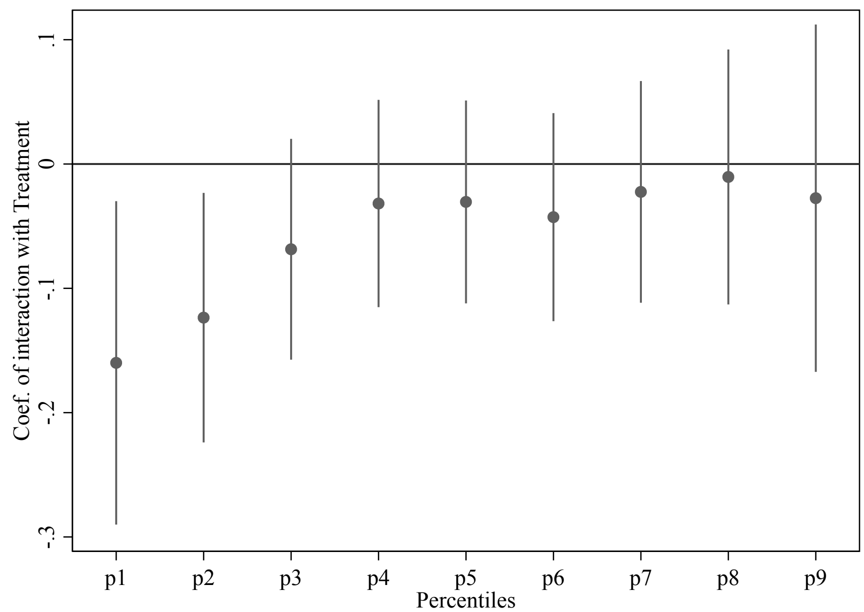
Table 6 shows that the interaction between overage and treatment is positive but not significant (as is also the case for the modified versions of the model presented in W1 and W3). We suspect that overage does moderate the effect of the treatment, but that such an interaction is not linear in the values of overage.

To test this claim we specify the overage variable as a dummy variable (instead of continuous). To find the appropriate threshold, we split the overage variable by its percentiles and look for the level of overage that shows differential effects of treatment. More specifically, we create 9 dummy variables representing whether overage is less than 10^{th} percentile, less than 20^{th} percentile, and so on. Then we estimate a binary probit model for churn including the treatment variable, the overage dummy and the interaction between the two. Note that we estimate a separate regression — 9 regressions in total — for each specification of the overage dummy variable.

Figure W3 shows the size of the interaction variable (between treatment and overage _dummy) for each model in which overage_dummy is being defined as "1 if usage < percentile (p1, p2, etc.), and 0 otherwise".

This analysis clearly shows that the interaction between treatment and overage is not linear (hence the lack of significance in the main model presented in Table 6 or the main manuscript). More specifically the interaction is *significantly negative* when we split customers by levels of overage *lower* than $40, which corresponds to the lower 25^{th} percentile of the overage distribution. That is, the treatment is more beneficial more for customers whose overage is below $40, as compared to those whose overage is above $4.

FIGURE W3: MODERATING EFFECT OF OVERAGE IN THE TREATMENT EFFECT



Interaction coefficients from estimating a probit model with 'churn' as dependent variable and 'treatment, overage dummy, and their interaction' as independent variables. The dots and lines correspond to the parameter estimate and confidence interval for the interaction variable in each of the estimated models.