Online Appendix to
Hide the Cookie Jar: Nudging Towards Healthy Eating

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Contents

A Data Details

This Appendix provides further details on our data.

For each day, there are six spreadsheets. Three correspond to the cookie section, and three to the pizza section. Within each section, there is one spreadsheet per service: breakfast, lunch and dinner. We discard all data on breakfast, because there is hardly any pizza served on breakfast.

In addition to these, it is common that the spreadsheets contain annotations. These annotations correct the original information, and range from the item number, to the forecast made. One by one, we correct for each of these annotations.

We eliminate datapoints with non-consistencies. The first non-consistency includes observations with negative consumption, that is, when the amount "forecasted" is less than the amount "left". These include 13 observations. The second one is an observation that includes 2,000 portions of cookies, which is prepared for a special event. This number is excessive, given a mean of 162 with a standard deviation of 110, and all other observations are below 1,000.[1]

A.1 Names of cookies

COOKIES, M & M*	BROWNIE, PLAIN*	CRISP, APPLE
COOKIE, VEGAN MERINGUE	BAR, CP CREAM CHEESE	CHEF'S CHOICE CAKE
COOKIE, SNICKERDOODLE*	COOKIE, OATMEAL RAISIN*	COOKIE, VEGAN LEMON*
COOKIE, DOUBLE CHOCOLATE*	CAKE, BOSTON CREAM PIE	COOKIE, VEGAN SUGAR*
HALL ASSORTED MUFINS*	BARS, ASSORTED HALL*	COOKIE, PEANUT BUTTER*
HALL ASSORTED DANISH*	COOKIE, CHOCO CRANBERRY OAT*	CAKE, CP CARROT
SMORGASBORD, ICE CREAM	COOKIE, VEGAN CRAN OATMEAL*	COOKIE, CHOCOLATE CHIP*
COOKIE, VEGAN GINGERSNAP*	CAKE, HALL DECADENCE CHOC	BAR, RICE KRISPIE*
CHEF'S WHOOPIE PIES	BAR, CONGO-CP*	CAKE, HOLL ANGEL FOOD W/ STRAW
CP GERMAN CHOCOLATE CAKE	BROWNIE, HOLL CHOC MINT*	COOKIE, SUGAR*
PUDDING, WARM BROWNIE	PICNIC WHOOPIE PIE	COOKIES AND CREAM BAR
HOLLOWAY SHORTCAKE, STRAWBERRY	BAR, CARAMEL APPLE CHEESECAKE	PIE, CHOCOLATE PEANUT BUTTER
CAKE, HALL TRES LECHE	BROWNIE, BLONDIE-CP*	COOKIE BUILDER BAR*
CAKE, CP TURTLE BAR	BAR, HOLL FRUITED RICE*	HOLLOWAY BLUEBERRY COBBLER
CAKE, HALL NUTELLA	COOKIE, VEGAN CH MERINGUE*	CANNOLI, HOLLOWAY MINI*
PIE, CHOCOLATE CREAM	CAKE, CP CONFETTI	STILLING CHEESE CAKE
BAR, CHOCOLATE MACAROON*	CAKE, CP RED VELVET	CAKE, HALL SALTED CARAMEL
CHEF CHOICE BREAD PUDDING	PIE, LEMON MERINGUE	COOKIE, VEGAN CHOC MERINGUE*
BAR, CPMAGIC COOKIE*	PIE, BLUEBERRY	CUPCAKE, DECORATING STILL*
CAKE, CARROT APPLE	CAKE ROLL, PUMPKIN	LH, APPLE CRISP
BAR, LEMON RASP CRUMB	CAKE, DIRT	BROWNIE, BLONIE-CP*
APPLE DIP BAR*	BAR, CP MAGIC COOKIE*	BROWNIE, BLONDE-CP*
PIE, STRAWBERRY	BAR, WHT CHOCOLATE NUT*	COOKIE, COCONUT MACAROON*
CHOC MINT WHOOPIE PIE	CAKE, TRES LECHE	CAHE, HOLL TURTLE BAR SHEET
CAKE, NUTELLA	BAR, HOLLOWAY PUMPKIN*	BROWNIE, BLONDE*
CAKE, HALL CHOC RASP CONFETTI	CAKE, HALL RED VELVET 96 CT	BAR, CHOC RASPBERRY*
CAKE, SALTED CARAMEL	BAR, MAGIC COOKIE HC*	CAKE, WHITE RUSSIAN
BAR, PEANUT SCOTCHEROO*	COFFEECAKE, SOUR CREAM	BAR, CRANBERRY ALMOND*
CAKE, HOLLOWAY CARROT	CAKE, HOLL TURTLE BAR SHEET	CANOLI, HOLLOWAY MINI*
PIE, BURBERRY	PIE, STRAWBERRY / RHUBARB	BAR, CONGO*
PIE CHOCOLATE CREAM	PIE, HI APPLE	CAKE, HALL OREO 96CT
COOKIE BUILDR BAR*	BAR, LEMON CHEESECAKE BAR*	CHEF'S CHOICE BREAD PUDDING
PIE, PUMPKIN	BAR, TWIX-CP*	COOKIE, HALL ASSORTED*
CAKE, HOLL ANGEL FOOD WITH STRAW*	BROWNIE, HOT CHOC MINT*	CUPCAKES, DECORATING STYLE*
BAR, CRANBERRY CRUNCH*	CHEF' CHOICE CAKE	STRAWBERRY CHEESECAKE
BARK, WHT CHOCOLATE NUT*	PUDDING, CLASSIC BREAD	WELLNESS FRUIT BAR DELI*
FF LEMON BLUEBERRY BREAD PUDDING		

Table A.1: Names of cookie types. * These cookies were considered easy to take away, that is, "take-awayables".

A.2 Names of pizzas

[1] Leaving the observations in the analysis yields very similar results.

IMPINGER VEGGIE PIZZA	IMPINGER BACON/TOMATO PIZZA	IMPINGER CHEESY BREAD
IMPINGER CHEESE PIZZA	IMPINGER PEPPERONI PIZZA	IMPINGER CHEESEBURGER PIZZA
IMPINGER BUFFALO CHICKEN PIZZA	IMPINGER MARGHERITA	IMPINGER CHEF'S CHOICE PIZZA
IMPINGER MARGHERITA PIZZA	STROMBOLI, CHICKEN BROCCOLI	CHEF'S CHOICE PIZZA
IMPINGER CINNAMON STICKS	IMPINGER BBQ CHICKEN PIZZA	IMPINGER STROMBOLI, STEAK & CH
IMPINGER CHICKEN PESTO PIZZA	IMPINGER HAWAIIAN PIZZA	CHEF'S CHOICE BREAD
IMPINGER MEATZA-MEATZA PIZZA	ITALIAN MEAT STROMBOLI	IMPINGER BBQ STROMBOLI
IMPINGER SAUSAGE PIZZA	MUSH-SPINACH STROMBOLI	IMPINGER CHICKEN BACON RANCH P
IMPINGER SHRIMP SCAMPIE PIZZA	IMPINGER TACO PIZZA	LH, BBQ VENISON PIZZA
PIZZA, HARVEST WHITE CLAM LH	HARVEST VEGETABLE PIZZA	LH, CHOCOLATE EXPLOSION
BREADS AND SPREADS	LH, FOUR CHEESE PIZZA	IMPINGER BBQ JALAPENO CHICKEN
WH CHOC DIPT PRETZELS	HOLLOWAY NICK'S WHITE	MEATBALL PIZZA
SOUTWEST VEGAN PIZZA	CHICKEN & BROC ALFREDO PIZZA	IMPINGER THANKSGIVING PIZZA
HOLLOWAY BACON/TOMATO PIZZA	BALSAMIC-BLUE FLATBREAD	CINNAMON STICKS
IMPINGER BREAD STICK	IMPINGER PIZZA	SAUSAGE RICOTTA STROMBOLI
FLORENTINE PIZZA	OVEREASY BRKFAST PIZZA	HOLL VEGGIE BREAKFAST PIZZA
IMPINGER OVEREASY PIZZA	IMPINGER BUFFALO PIZZA	IMPINGER MONKEY BREAD
IMPINGER BREAKFAST PIZA	FOCACCIA	IMPINGER HARVEST VEGETABLE PIZZA
CHOCOLATE ZUCCHINI BREAD	TEMPURA CHICKEN BITE	CORNBREAD
ROTISSERIE JERKED CHICKEN	IMPINGER MEAT STROMBOLI	SE, LOBSTER PIZZA
IMPINGER CINNAMON BREAD	IMPINGER CHIXPESTO/BUFFALO PIZZA	MONSTER LOADED PIZZA
BACON CHICKEN RANCH	PEPERRONI MOZARELLA	CHEF' CHOICE PIZZA
CHEESY BREAD	IMPINGER CHEESY PIZZA	IMPINGER SROMBOLI, STEAK
WILDCAT PIZZA	HOLLOWAY CHEESE PIZZA	IMPINGER PEPPERJACK CHEESY BREAD
HOLLOWAY BUFFALO CHICKEN PIZZA	PIZZA, STEAK AND CHEESE	CAFE RUSSIA
IMPINGRE CHHESE PIZZA	BAKED ZITI BOLOGNESE	BAKED ZITI RICOTTA & PESTO
BAKED SHELLS & CAULIFLOWER	BRUSCHETTA FLATBREAD	WELLNESS GRILLED CHICKE
WELLNESS STEAMED BROCCOLI FLOR	WELLNESS SALAD, TUSCAN CAESAR	WELLNESS BEEF STEW
WELLNESS GF STEAK CHILI	WELLNESS FRIED RICE	WELLNESS SALAD, CUCUMBER TOMATO
LH SUPER MUSHROOM PIZZA	ROASTED VEGETABLE STROBOLI	IMPINGER PIZZA WILDCAT LOADED
FOCACCIA EGG BREAD		

Table A.2: Names of pizza types.

B Additional Regression Estimates

This section reports additional regressions that we mention in the paper that are used as robustness.

Tables B.1 and B.2 show the results of the linear regression model and the negative binomial model. In all cases, the sign of our estimates are the same as in our baseline model. Also as in the baseline model, all these estimates are significant at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$d_{2018}d_{cookie}$	-23.2843	-28.0353	-28.2541	-28.8140	-27.7913	-27.9751	-27.7886	-27.8487	-26.2147	-28.5440
	(8.8174)	(7.1985)	(7.2757)	(7.2291)	(7.2222)	(7.1941)	(7.0907)	(7.1099)	(7.2208)	(7.0095)
Product FE	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fall FE	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓
Weekend	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗
Weekday FE	✗	✗	✗	✗	✓	✓	✓	✓	✓	✓
Service FE	✗	✗	✗	✗	✗	✓	✓	✓	✓	✓
Trend	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓
Finals Week	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓
Options	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗

Robust standard errors in parentheses.

Table B.1: Linear Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$d_{2018}d_{cookie}$	-0.1329	-0.1534	-0.1548	-0.1600	-0.1528	-0.1530	-0.1477	-0.1481	-0.1390	-0.1949
	(0.0481)	(0.0253)	(0.0253)	(0.0251)	(0.0249)	(0.0247)	(0.0248)	(0.0248)	(0.0248)	(0.0294)
Product FE	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fall FE	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓
Weekend	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗
Weekday FE	✗	✗	✗	✗	✓	✓	✓	✓	✓	✓
Service FE	✗	✗	✗	✗	✗	✓	✓	✓	✓	✓
Trend	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓
Finals Week	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓
Options	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗

Table B.2: Negative Binomial Regression Results

	Weekend Interaction	Dinner Interaction	Finals Interaction
$d_{2018}d_{cookie}$	-0.1575	-0.1972	-0.1701
	(0.0424)	(0.0396)	(0.0419)
$d_{2018}d_{cookie}Weekend$	-0.0362		
	(0.0346)		
$d_{2018}d_{cookie}Dinner$		0.0546	
		(0.0406)	
$d_{2018}d_{cookie}Finals$			0.0349
			(0.0438)
Product FE	✓	✓	✓
Fall FE	✓	✓	✓
Weekday FE	✗	✓	✓
Service FE	✓	✗	✓
Trend	✓	✓	✓
Finals Week	✓	✓	✗

Robust standard errors in parentheses.

Table B.3: Adding different interaction terms in our model. Column 1 introduces a weekend interaction with cookies, column 2 interacts dinner with cookies, and column 3 interacts finals with cookies.

Table B.3 introduces interaction terms in our baseline model to focus on the lack of significant results in some of our sub-samples. More precisely, when focusing on dinner services and finals, we found no significant effects of the re-location. One possible explanation for this is the low number of observations. In the baseline estimations, the number of observations is 3,573. This drops to 547 on weekends, 1,281 during dinner, and 418 in Finals.

As an alternative to identify potential effects during dinner and finals, we use all our sample and include an interaction term between the variable of interest and a dummy equal to 0 in Fall 2017 and 1 otherwise along with the dummy variable which is equal to 1 for cookies.

Column 1 introduces an interaction between a dummy variable that is equal to one for "weekend". Column 2 shows an interaction for dinner. Column 3 proceeds similarly with finals. The results are not significant. Thus, this provides evidence that the lack of significance in our earlier results is not related to the limited number of observations.

C Pre and post re-location trends during dinner

This section shows the analysis of the trend in cookie and pizza consumption before and after the re-location during dinner, complementing the lunch analysis in the paper. Notice that our main results conclude that there is no significant change in the consumption of cookies relative to pizza during dinner. This section shows that the pre- and post- trends during dinner behave very differently than those during lunch.

Figure C.1 shows that in the Fall of 2017 there was a relative reduction in the consumption of cookies during dinner relative to pizza. The lines show the behavior of the trend subtracting the mean, so it is centered around zero. Extending this behavior to semesters after the re-location would conclude that at least part of the decline in cookie consumption after Spring 2018 was for reasons other than the re-location.

Figure C.2 adds to the pre-trend the behavior following the relocation. The lines are the trend minus the mean before the re-location, so that only the lines before the re-location are

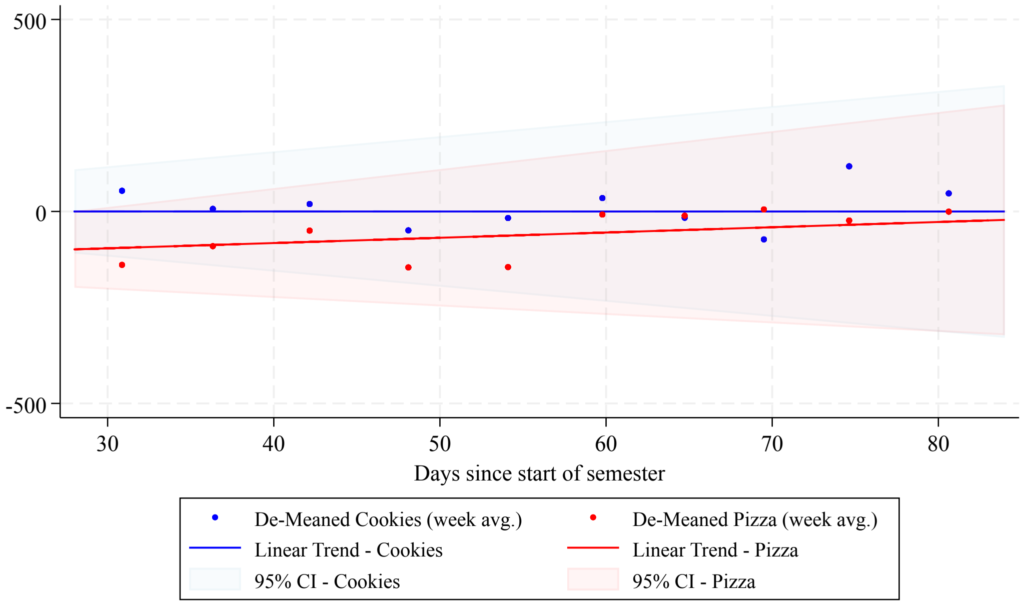

Figure C.1: De-meaned dinner trends and actual consumption of cookies and pizza before the re-location during dinner.

centered around zero. There is a drop in both cookie and pizza consumption, and the drop is larger in cookies, consistent with the nudging effects of the re-location. However, the post-trend in cookie consumption is increasing relative to the post-trend in pizza consumption, which may suggest that, during dinner, the nudge is short lived. We, unfortunately, can not analyze this finding further as we lack the necessary data.

Figure C.3 aggregates the behavior for lunch and dinner to study the pre-trend behavior. Once again, the pre-trends look very similar.

The aggregate behavior including lunch and dinner after the relocation is a combination of the behavior in lunch, where cookies drop more than pizza, with dinner, where the drop in pizza is gradual. Figure C.4 shows the change in trends around the re-location aggregating lunch and dinner.

D Verifying that the Consumption of Cookies Drops After Fall 2017

This section studies the behavior of cookies directly, to understand whether the consumption after the re-location drops. We start by estimating the following linear equation using all our sample:

$$y_{kt} = \beta_0 + \beta_1 * d_{2018_t} + \beta_2 * trend_t + \beta_3 * d_{2018_t} * trend_t + \beta_4 * Z_k + \alpha_k + \varepsilon_{kt} \tag{1}$$

where y_{kt} is the consumption of good k at time t, and k denotes types of cookies. d_{2018} is equal to one for observations after Fall 2017, and equal to 0 otherwise. Z_k contains our controls, and $trend$ is the time trend. Table D.4 shows that the estimate for β_1 is negative and significant, implying that the consumption of cookies drops by about 27 portions a day after the re-location.

Next we compare the consumption of cookies near the time of re-location. We interpret this similarly to a regression discontinuity design, albeit many problems that prevents us from formally doing so. In particular, there are two important problems with the interpretation of regression discontinuity. First and foremost, the end of the semester is followed by a break of

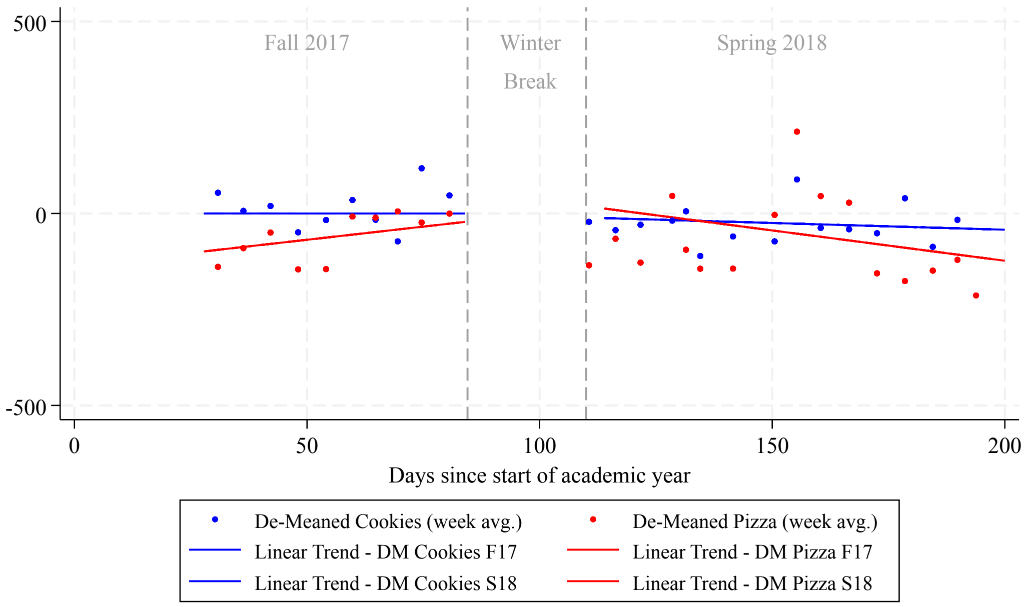

Figure C.2: Difference in de-meaned dinner trends before and after the re-location.

almost two months, time used by the dining hall to re-organize, and the next observations come from the following semester. Second, there are many differences across semesters that renders the analysis less informative, such as a change in the number of diners, which we cannot control for. As such, this exercise is illustrative, and is not interpreted as part of our main results.

Since global linear estimators maybe misleading as they may incorrectly perceive non-linearity as a break point, we follow the non-parametric estimation strategy presented by Hahn et al. (2001), which boils down to a weighted least squares regression local to the relocation date. As such, we estimate a linear regression via weighted least squares, using data points within $\pm$ 30, 60, and 75 days around the time of location change. We weight the observations via triangular kernel, putting less weights to observations closer to the bounds set above and more weights to the observations close to the change. As can be seen on Table D.4, in all of the set cut offs, we see a negative and significant estimate, i.e., a decrease in consumption of cookies.

We also estimate a log-linear model, to quantify the changes in percentages. We again find negative and significant effects, slightly higher in magnitude compared to the relative results we reported in comparison to pizza.

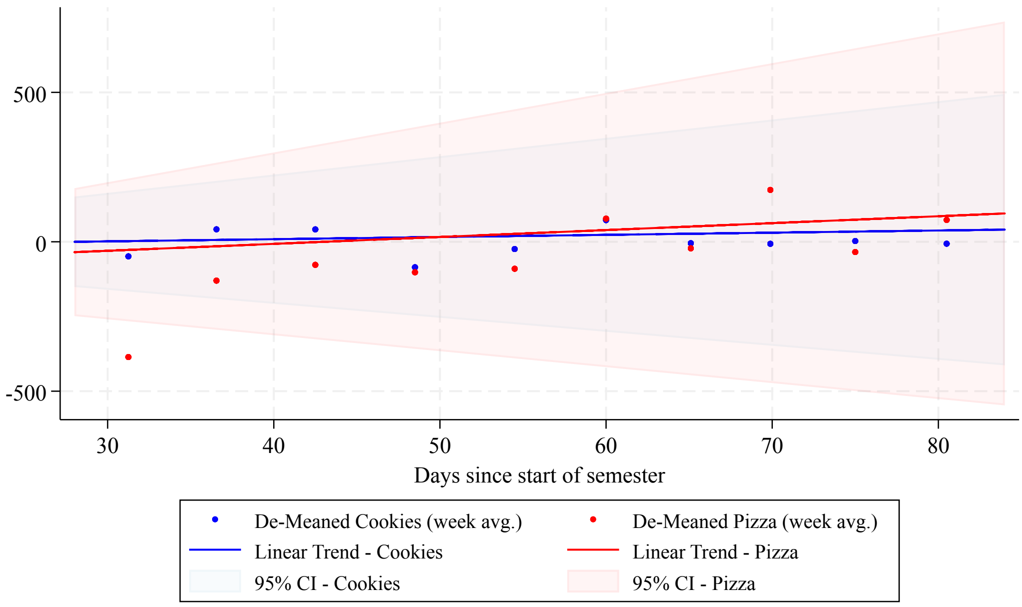

Figure C.3: De-meaned trends and actual consumption of cookies and pizza before the re-location during lunch and dinner.

E Complete Regression Output for the Baseline Model

Table E.5 reports the estimates for all the controls used in our main regression.

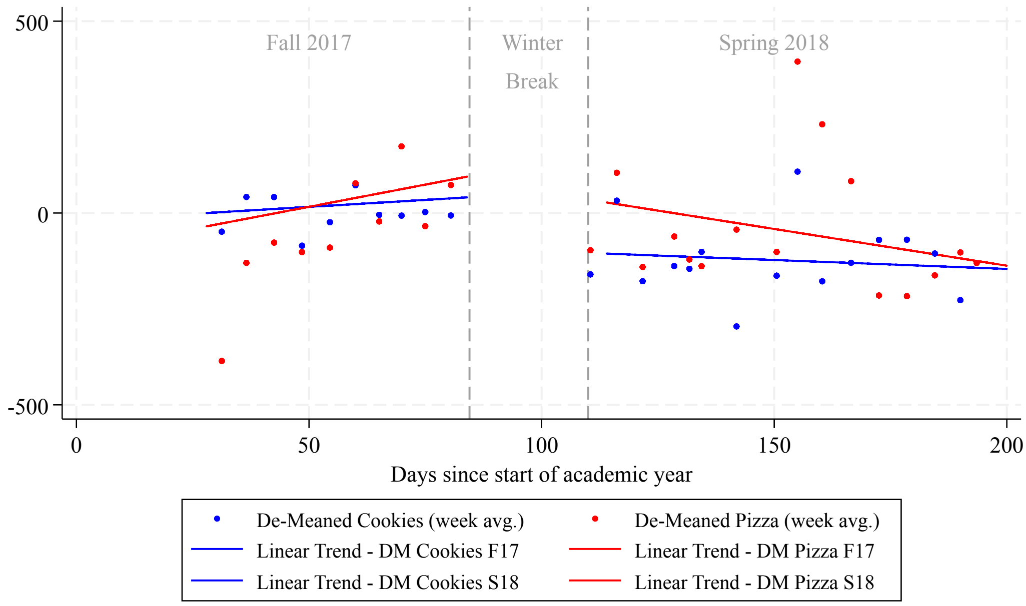

Figure C.4: Difference in de-meaned lunch and dinner trends before and after the re-location.

Cookies before and after the change		
	Cookie Consumption	log(Cookie Consumption)
Linear Regression	-27.3062	-0.1723
	(12.3274)	(0.0791)
Local - Linear Regression		
30 days around the cut-off	-54.3000	-0.2468
	(22.35)	(0.1329)
60 days around the cut-off	-51.2600	-0.2410
	(17.44)	(0.1122)
75 days around the cut-off	-47.9400	-0.2231
	(16.10)	(0.1020)

Robust standard errors are reported in parentheses. All models have product, semester, weekday, final week, and service fixed effects. Results are obtained via triangular kernel.

Table D.4: Comparing Cookies before and after the change

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
d_{2018}	0.0400	0.0526	0.0814	0.0783	0.0797	0.0789	0.0783	0.0789	0.0764	0.0812
	(0.0240)	(0.0300)	(0.0342)	(0.0357)	(0.0359)	(0.0364)	(0.0364)	(0.0364)	(0.0365)	(0.0395)
d_{cookie}	0.1828	-	-	-	-	-	-	-	-	-
	(0.0414)	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
$d_{2018}d_{cookie}$	-0.1329	-0.1564	-0.1578	-0.1602	-0.1542	-0.1551	-0.1540	-0.1543	-0.1435	-0.1587
	(0.0491)	(0.0364)	(0.0370)	(0.0369)	(0.0378)	(0.0378)	(0.0374)	(0.0375)	(0.0385)	(0.0435)
$Fall$			0.0484	0.0449	0.0506	0.0500	0.0480	0.0492	0.0593	0.0531
			(0.0187)	(0.0191)	(0.0184)	(0.0185)	(0.0186)	(0.0188)	(0.0202)	(0.0201)
$Tuesday$					0.0096	0.0204	0.0205	0.0200	0.0244	0.0200
					(0.0335)	(0.0345)	(0.0345)	(0.0344)	(0.0338)	(0.0344)
$Wednesday$					0.0041	0.0156	0.0155	0.0154	0.0177	0.0152
					(0.0282)	(0.0296)	(0.0297)	(0.0297)	(0.0295)	(0.0298)
$Thursday$					-0.0510	-0.0422	-0.0416	-0.0419	-0.0372	-0.0421
					(0.0441)	(0.0500)	(0.0501)	(0.0500)	(0.0498)	(0.0500)
$Friday$					-0.2377	-0.2020	-0.2021	-0.2022	-0.1844	-0.2022
					(0.0751)	(0.0727)	(0.0727)	(0.0726)	(0.0697)	(0.0726)
$sunday$					-0.2022	-0.1934	-0.1943	-0.1940	-0.2044	-0.1939
					(0.0743)	(0.0761)	(0.0764)	(0.0765)	(0.0752)	(0.0765)
$Dinner$						0.1360	0.1358	0.1358	0.1899	0.1358
						(0.0334)	(0.0334)	(0.0334)	(0.0473)	(0.0334)
$Trend$							0.0013	0.0009	0.0003	0.0009
							(0.0008)	(0.0010)	(0.0010)	(0.0010)
$Trend^2$							-0.0000	-0.0000	-0.0000	-0.0000
							(0.0000)	(0.0000)	(0.0000)	(0.0000)
$FinalWeek$								-0.0202	-0.0232	-0.0202
								(0.0246)	(0.0234)	(0.0246)
$Falld_{cookie}$										-0.0077
										(0.0360)
$Weekend$				-0.1527						
				(0.0580)						
$Products$									0.0211	
									(0.0088)	
Product FE	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗

Robust standard errors in parentheses.

Table E.5: Baseline Regression Estimates - Complete Results

F A Model of Temptation

This section develops a model of temptation to guide our empirical approach, based on Gul & Pesendorfer (2001). Consider an individual that makes decisions in two sub-periods. The first one takes place outside the restaurant, where she sets off to eat healthy. The second period is inside, where tempting unhealthy items change her preferences. This can be represented by the following maximization problem:

$$U(A) = \max_{x \in A} u(x) \quad s.t. \quad v(x) \geq \max_{y \in A} v(y) \tag{2}$$

The utility function $U(A)$ describes a decision maker who chooses to maximize v over a consumption set A but evaluates these choices according to u.

To apply this to our setting, assume there are three types of goods: fish (x_f, healthy), cookies (x_c, unhealthy), and pizza (x_p, unhealthy). In all cases, individuals choose whether to consume one unit or none. There are J_t individuals in period t. Let the utility functions for individual j be $u_j(\mathbf{x}) = x_f - (x_c + x_p)$, where $\mathbf{x} = (x_f, x_c, x_p)$.

The utility function v changes based on whether the cookies are in sight or not. Consider the decision process when cookies are in sight. Let $v_j(\mathbf{x}) = \beta_j(x_c + x_p)$. The parameter β_j represents how "tempting" food is for individual j: the higher the β_j, the larger the temptation. The solution to problem (2) is

$$\begin{aligned} x^*_{jf} &= x^*_{jc} = x^*_{jp} = 1 \text{ if } \beta_j > 0, \\ x^*_{jf} &= 1, x^*_{jc} = x^*_{jp} = 0 \text{ if } \beta_j \leq 0. \end{aligned}$$

When cookies are out of sight, $v(x) = \beta_j x_p + (\beta_j - I)x_c$. The solution to problem (2) now depends on the sign of $\beta_j - I$, where $I > 0$ represents the lower temptation introduced by the relocation:

$$\begin{aligned} x^*_{jf} &= x^*_{jp} = x^*_{jc} = 1 \text{ if } \beta_j > I, \\ x^*_{jf} &= x^*_{jp} = 1, x^*_{jc} = 0 \text{ if } 0 < \beta_j < I, \\ x^*_{jf} &= 1, x^*_{jp} = x^*_{jc} = 0 \text{ if } \beta_j < 0. \end{aligned}$$

We are interested in the proportion of people that stop eating cookies because of the relocation. Assuming that the parameters β_j are random draws of a cumulative distribution function $G(\beta)$, this proportion is $\frac{1-G(I)}{1-G(0)}$. We can measure this by comparing the consumption of cookies and pizza in two periods. Let C_t denote cookies consumption in period t and define P_t similarly for Pizza. The ratio of cookies in both periods is $\frac{C_2}{C_1} = \frac{(1-G(I))J_2}{(1-G(0))J_1}$. The same ratio for pizza is $\frac{P_2}{P_1} = \frac{(1-G(0))J_2}{(1-G(0))J_1} = \frac{J_2}{J_1}$. Thus $\frac{C_2/C_1}{P_2/P_1} = \frac{1-G(I)}{1-G(0)}$.

Consider the following estimation equation, where y_{it} is the logarithm of consumption of good $i = C, P$ at time $t = 0, 1$:

$$y_{it} = \gamma_0 d_{it} + \gamma_1 c_{it} + \gamma_2 d_{it} c_{it} + \varepsilon_{it}, \tag{3}$$

where d_{it} is a dummy that equals 1 after the relocation and 0 otherwise, and s_{it} is 1 if the good is a cookie, 0 otherwise. Then

$$\hat{\gamma}_2 = (y_{C1} - y_{C0}) - (y_{P1} - y_{P0}) = \log\left(\frac{C_1/C_0}{P_1/P_0}\right).$$

This is the basis for the empirical section.

References

Gul, F. & Pesendorfer, W. (2001), 'Temptation and self-control', *Econometrica* **69**(6), 1403–1435.

Hahn, J., Todd, P. & van der Klaauw, W. (2001), 'Identification and estimation of treatment effects with a regression-discontinuity design.', *Econometrica* **69**.