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I'll Have the Ice Cream Soon and the Vegetables Later: Decreasing Impatience over Time in Online Grocery Orders

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Abstract:

How do decisions for the near future differ from decisions for the more distant future? Most economic models predict that they do not systematically differ. With online grocery data, we show that people are decreasingly impatient the further in the future their choices will take effect. In general, as the delay between order completion and delivery increases, customers spend less, order a higher percentage of "should" items (e.g., vegetables), and order a lower percentage of "want" items (e.g., ice cream). However, orders placed for delivery tomorrow versus two days in the future do not show this want/should pattern. A second study suggests that this arises because orders placed for delivery tomorrow include more items for planned meals (as opposed to items for general stocking) than orders placed for delivery in the more distant future, and that groceries for planned meals entail more should items than groceries for general stocking.

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Keywords: Decision-making; intertemporal choice; want/should conflict; multiple selves; dynamic inconsistency; hyperbolic discounting

Have you ever noticed that you are considerably more likely to believe you will go to the gym, eat salad for lunch, and avoid watching television next week than to believe you will exhibit these behaviors tomorrow? The further into the future your imagination wanders, the more virtuous you believe you will become. Forecasting several years out, you might even believe you will exercise daily, no longer smoke, and volunteer for charity on a regular basis. However, you are unlikely to harbor these illusions about yourself in the nearer-term. This may be due in part to the fact that the further into the future you forecast, the more uncertainty you face about your life, affording you an opportunity to make more creative projections. This explanation does not, however, account for our tendency to become increasingly optimistic about how we will behave in the future. An explanation that better accounts for this tendency describes individuals as living in a state of internal conflict between the desires of a *want* self and the ambitions of a *should* self (Bazerman, Tenbrunsel, and Wade-Benzoni, 1998), with circumstances cueing which self will dominate the other in decision making. Specifically, more immediate, visceral and concrete forecasts cue the *want* self, while more distant, cognitive and abstract forecasts cue the *should* self.

In this paper, we provide field evidence supporting the hypothesis that people believe they will be increasingly virtuous the further into the future they project. We use data provided by an online grocer to examine the effects of the time between an order's completion and its delivery on overall spending and on purchases of *should* groceries (e.g., healthy foods like vegetables) and *want* groceries (e.g., unhealthy foods like ice cream). Our data set allows us to examine differences in people's preferences over goods they will receive in the near future, beginning as early as tomorrow, versus the more distant future. We find that consumers spend less and order a higher percentage of *should* goods and a lower percentage of *want* goods the further in advance of delivery they place a grocery order. This is consistent with multiple-selves models of individual decision making (Bazerman, Tenbrunsel, and Wade-Benzoni, 1998; Thaler and Shefrin, 1988), with construal level theory (Trope and Liberman, 2003), and with economic models of consumers as decreasingly impatient (Loewenstein and Prelec, 1992), but at odds with mainstream economic models and the leading behavioral model of time discounting (Laibson, 1997), which suggest that people exhibit nearly constant time discounting between the utility they anticipate receiving in the near future versus the more distant future.

Time Inconsistent Preferences

Past research on intrapersonal conflict, also known as the multiple selves phenomenon (Schelling 1984), has documented a tension between the behaviors people feel they *should* exhibit (e.g., saving more next week, going to the gym next week, starting a diet next week) and the behaviors they find themselves hedonically *want*ing to exhibit and often choosing to exhibit (e.g., spending frivolously next week, watching television instead of going to the gym next week, and eating cake with lunch next week). Bazerman, et al. (1998) describe this tension as stemming from two selves - a *want* self and a *should* self - which have competing preferences.[1] The *want* self represents the desires people feel close to the time when a decision will take effect, while the *should* self represents the more deliberative feelings people have about what they ought to do

[1] Shefrin and Thaler (1988) also propose that people live in a state of internal conflict between multiple selves. They posit that people have two selves - a 'doer' self and a 'planner' self. The 'doer' self described by Shefrin and Thaler (1988) is consistent with the *want* self described by Bazerman et al. (1998), while Shefrin and Thaler's 'planner' self parallels Bazerman et al.'s *should* self.

given their long-term interests. Loewenstein (1996) argues that intrapersonal conflicts, which result in inconsistent preferences and behaviors, are not the result of competing internal selves but rather stem from changes in the conditions under which decisions are made. He proposes that when visceral factors (e.g., emotions and psychological cravings like hunger) are cued by the context in which a decision is made, people will make more hedonic choices. Loewenstein considers visceral factors to be the source of observed differences between the preferences people exhibit when making choices that will take effect in the short-run and choices that will take effect in the long-run.

Both Loewenstein's (1996) model and the multiple selves framework described by Bazerman et al. (1998) predict that in situations where visceral factors are more prominent, decision-makers will be more likely to make choices favoring their affective desires. This prediction suggests that money spent in situations that cue more visceral states will result in increased spending on goods that would be preferred by the *want* self, or "*want* goods", while money spent in situations that cue more deliberative states will result in increased spending on goods preferred by the *should* self, or "*should* goods". Loewenstein's (1996) model and the Bazerman et al. (1998) framework provide the theoretical basis for our predictions about the effects of delivery lead time on grocery purchasing behavior. If thinking about temporally closer outcomes induces affective reactions in recipients, people will purchase relatively more *want* items and fewer *should* items the sooner they anticipate receiving a grocery order.

Recent psychological research on construal level theory suggests an alternative mechanism that may lead people to purchase relatively more *should* items and fewer *want* items the further in advance of delivery they complete a grocery order. Construal level theory posits that people think differently about the near future and the distant future (for a review of this literature, see Trope and Liberman, 2003). When thinking about the near future, people construe actions, objects, and social events in more concrete, specific terms than when thinking about the more distant future. Thinking about the more distant future, in turn, leads people to construe actions, objects, and social events in more abstract, general terms than thinking about the near future (Liberman and Trope, 1998; Vallacher and Wegner, 1987; Fujita, Henderson, Eng, Trope and Liberman, 2006). This suggests that when ordering groceries for the near future, people are likely to construe foods more concretely than when ordering groceries for the more distant future. A more concrete construal of a food would focus on attributes like taste (or the short-term utility that is likely to be derived from the food), while a more abstract construal would focus on attributes like healthfulness (or the long-term utility that is likely to be derived from the food). Thus construal level theory predicts that *want* foods, which offer relatively more short-term utility and less long-term utility than *should* foods, will be more appealing to people in the near future when foods are construed more concretely. Meanwhile, *should* foods will be more appealing relative to *want* foods in the distant future when foods are construed more abstractly. This leads to the same prediction as the Loewenstein (1996) and Bazerman et al. (1998) theories described above: when ordering for the more distant future, people will spend relatively more on *should* goods and less on *want* goods. Consistent with this prediction, a recent study by Fujita, Trope, Liberman, and Levin-Sagi (2006) demonstrated that more concretely construed choices involving food cause people to experience more temptation and self-control problems.

Related research conducted by Kivetz and Tyler (2007), which has integrated construal level theory with a multiple-selves model, offers additional support for our predictions about the effects of delivery lead time on grocery purchasing behavior. Kivetz and Tyler propose that each individual possesses both an *idealistic* self and a *pragmatic* self. The *idealistic* self, which resembles what Bazerman et al. (1998) call the *should* self, is concerned with principles and values rather than practical considerations, while the *pragmatic* self, which resembles the Bazerman et al. *want* self, is concerned with practical matters. Kivetz and Tyler find that people tend to more closely identify with the attributes associated with their *idealistic* selves (e.g., values, principles) when primed with a distant future perspective as opposed to a near future perspective. On the other hand, when primed with a near future perspective, people tend to identify more with the attributes associated with their *pragmatic* selves (e.g., action oriented, practical) than when primed with a distant future perspective. These findings are consistent with our prediction that people will exhibit decreasing impatience over time to the extent that a stronger identification with the *pragmatic* self relative to the *idealistic* self leads people to prefer *want* items over *should* items, and visa versa.

Strotz's (1956) observation that people exhibit more impatience when making decisions that will take effect in the short-run than decisions that will take effect in the long-run spawned a considerable economics literature on the systematically inconsistent preferences people exhibit over time. Economists refer to this phenomenon as "dynamic inconsistency" (for partial reviews of this literature, see Loewenstein and Thaler, 1989; Ainslie, 1992; O'Donoghue and Rabin, 1999; and Frederick, Loewenstein, and O'Donoghue, 2001). A number of economists have used non-standard time discount functions to model the observation that people have great difficulty passing up a large reward in the present for a larger reward tomorrow, while they have considerably less difficulty passing up a large reward tomorrow for a larger reward in two days.[2] Laibson's (1996) quasi-hyperbolic time discount model, a discrete version of Ainslie's (1992) hyperbolic discount model, predicts that preference reversals will occur when people make repeated choices over the same set of options, some of which will take effect in the present and some of which will take effect in the future. Laibson's discrete-time discount function models the extreme short-run drop in valuation that has been observed in people's time preferences by adding a $\beta << 1$ discount rate to all but the first time period of a traditional discrete-time discount model. This leads to the following equation, which describes the way Laibson assumes individuals discount future utilities:

$$\boldsymbol{U}_{net}(\boldsymbol{x}) = \boldsymbol{u}_0(\boldsymbol{x}) + \sum_{i=1}^{\infty} \beta\delta^i \boldsymbol{u}_i(\boldsymbol{x}) \qquad \beta << \delta = 1 - \varepsilon$$

For decisions that will take effect immediately, this model discounts options with more long-run utility (e.g., vegetables) at a considerably higher rate than options with more short-run utility (e.g., ice cream), but for decisions that will take effect in the future, both options are discounted at an equivalent rate. The distinction between options that offer primarily short-run utility and those that offer primarily long-run utility may be mapped onto the *want* and *should* constructs described previously: an option that offers primarily short-run utility (e.g., ice cream) will be experienced as a *want* option relative to an option that offers primarily long-run utility (e.g., vegetables), which will be experienced as a *should* option.

[2] A time discount function is a function that specifies how utility should be weighted based on when in the future it will be realized.

Laboratory experiments have demonstrated that the quasi-hyperbolic time discount model accurately predicts preference reversals between now and later over choice sets composed of different amounts of money (McClure, Laibson, Loewenstein and Cohen, 2004; Thaler, 1981; Kirby and Herrnstein, 1995; Kirby and Marakovic, 1996; Kirby, 1997), various types of lottery tickets (Read, Loewenstein, and Kalyanaraman, 1999), highbrow and lowbrow films (Read et al., 1999; Khan, 2005), healthy and unhealthy foods (Wertenbroch, 1998; Khan, 2005), and a range of other consumables (Millar and Navarick, 1984; King and Logue, 1987; Kirby and Marakovic, 1995). Field studies have also been conducted to confirm various predictions of the quasi-hyperbolic time discount model in the domains of gym attendance (Della Vigna and Malmendier, 2006), magazine newsstand and subscription pricing (Oster and Scott Morton, 2005), savings behavior (Angeletos, Laibson, Repetto, Tobacman, and Weinberg, 2001; Ashraf, Karlan, and Yin, 2006), and supermarket purchases (Wertenbroch, 1998).

Almost all of the research on dynamic inconsistency to date has focused on confirming the existence of the steep discount rate people are predicted to place on future utility relative to present utility in Laibson's quasi-hyperbolic time discount model. Considerably less attention has been paid to the question of whether people exhibit dynamic inconsistency when making choices for the near future versus the more distant future - the question that is the focus of this paper. Laibson's model of hyperbolic discounting assumes that preference reversals should only be observed when choices made for the present are compared with choices made for a later date. At all moments in the future, Laibson's model assumes people have a discount rate that is extremely close to one (i.e. they barely discount future utility, and the rate at which they do so is relatively constant). However, Loewenstein and Prelec (1992) have proposed a model of consumers as "decreasingly impatient," which allows for the possibility that people exhibit inconsistent preferences when making decisions that will take effect in the near future versus the more distant future. Loewenstein and Prelec propose that the following equation describes the way individuals discount future utilities:

$$\boldsymbol{U}_{net}(\boldsymbol{x}) = \sum_{i=0}^{\infty} \boldsymbol{u}_i(\boldsymbol{x})(1+\boldsymbol{\alpha t}_i)^{-\beta/\alpha}, \qquad \boldsymbol{\alpha}, \boldsymbol{\beta} > 0$$

When α and β are chosen correctly,[3] this model predicts that individuals will exhibit dynamic inconsistency in their choices for tomorrow versus the more distant future. Specifically, the further in the future a decision will take effect, the relatively more weight a decision maker will give to its implications for her long-term utility relative to her short-term utility, a phenomenon Loewenstein and Prelec term "decreasing impatience."

Few empirical studies have approached the question of how people's preferences differ when the outcomes of their decisions will be realized in the near future versus the more distant future. One exception is a study by Benzion, Rapopport and Yagil (1989), which employed a survey design that allowed the authors to estimate participants' 6 month, 1 year, 2 year and 4 year discount rates over different hypothetical sums of money ($40, $200, $1,000 and $5,000). The authors found that participants' inferred discount rates decreased as the time they had to wait for a reward increased, meaning participants exhibited decreasing impatience. On average, participants exhibited implied yearly

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[3] In their paper, Loewenstein and Prelec suggest that setting $\alpha = 5$ and setting $(1+\alpha)^{-\beta/\alpha} = 0.3$ would yield a reasonable discount curve. This curve would lead to preference reversals between tomorrow and the more distant future.

discount rates of 0.32 over 6 months, 0.21 over 1 year, 0.17 over two years, and 0.15 over 4 years.

Overview of Studies

In this paper, we extend previous work on dynamic inconsistency by conducting a study of the way people's preferences differ when they make choices for the near future versus the more distant future. Our study relies on a large field data set, which allows us to identify off of within-person variation. We find evidence that people are decreasingly impatient over time. Study 1 presents our main results with regard to grocery purchasing, and Study 2 presents a survey we conducted to help explain an unexpected pattern in our Study 1 results. We conclude with a discussion of our findings and their implications for public policy, supply chain managers, and models of time discounting.

Study 1

In Study 1 we test the prediction that people become decreasingly impatient the further in the future their decisions will take effect. We begin by describing the details of the data set we obtained from a large, online grocer, which we use for our primary analyses. We then describe the methods we employ to classify the groceries in our data set as *should* items or *want* items so we can compare the types of purchases consumers make when the time between the completion and delivery of an order varies. Finally, we present the results of a series of panel regressions, which test the hypothesis that people are decreasingly impatient, or more virtuous the further in the future their choices will take effect.

Data

The online grocer we collaborated with on this study operates in North America and serves urban customers.[4] Its customers place orders by visiting a website where they may tour virtual supermarket aisles or search for specific products as they make decisions, one by one, about what items to add to their online shopping carts. Returning customers have easy access to the lists of items they purchased on their previous shopping trips to facilitate repeat purchases. Customers have the option to schedule a delivery during an available delivery slot for as early as tomorrow or for further in the future. During the period studied, the grocer charged a delivery fee for online orders. In addition, customers were required to spend a minimum dollar amount on each order.

We obtained a novel panel data set from the aforementioned online grocery retailer containing information about the orders placed by all of the company's customers between January 1, 2005 and December 31, 2005. The online grocery company provided a record of each item in each order placed during the 12-month period in question, as well as the price each customer paid for each item, the date of each order, the date of each order's delivery, and the customer who placed each order. If a customer modified his or her order, we were told how many times order modifications were made, as well as the first and last dates when the customer modified his or her shopping basket. All customer accounts in our data set are labeled by anonymous, unique ID numbers, and all customer ID's are accompanied by the date when a customer first and last placed an online grocery order. Our online grocery collaborator also provided us with detailed category and brand information about each item available for purchase through its website.

[4] To preserve business confidentiality, company-specific information has been withheld from this document.

We restrict our analysis in this paper to customers who ordered groceries for delivery between one and five days in advance sometime between January 1, 2005 and December 31, 2005. We exclude all orders involving the redemption of a coupon because discount coupons have been shown to affect online grocery spending as well as the distribution of goods in a customer's shopping basket (Milkman, Beshears, Rogers and Bazerman, 2007).

In total, between January 1, 2005 and December 31, 2005, tens of thousands of customers ordered groceries for delivery between one and five days in advance without redeeming a discount coupon.[5] We eliminate each customer's first order of the year,[6] spending outliers (top 1%), and outliers in the number of visits made to the grocer's website during an order (top 1%).[7] This leaves us with over a million grocery orders in 2005 (customers in our analyses ordered an average of 5 to 10 times). The average dollar size of an order in this sample is $154.71 and the average grocery order consists of 58 items. For additional summary statistics, see Table 1.

Table 1
SUMMARY STATISTICS

	Mean	Standard Deviation
Spending	$154.71	$65.83
Number of Groceries	58.38	25.95
Number of Web Visits for Order	3.27	2.59
Days btw First and Last Web Visits for Order	1.37	0.73
Days Since Last Delivery	21.84	29.48

[5] Details about the number of unique customers, total number of grocery orders, and average number of orders per customer in our data set are not provided in order to preserve the anonymity of our data provider.
[6] In our regression analyses, we control for the amount of time that has elapsed since a customer's previous order. We eliminate each customer's first order of the year because we are unable to calculate this variable for these observations.
[7] We eliminate spending outliers and orders involving an unusually large number of visits to the grocer's website so that these observations do not exert undue influence on the results of our regression analyses.

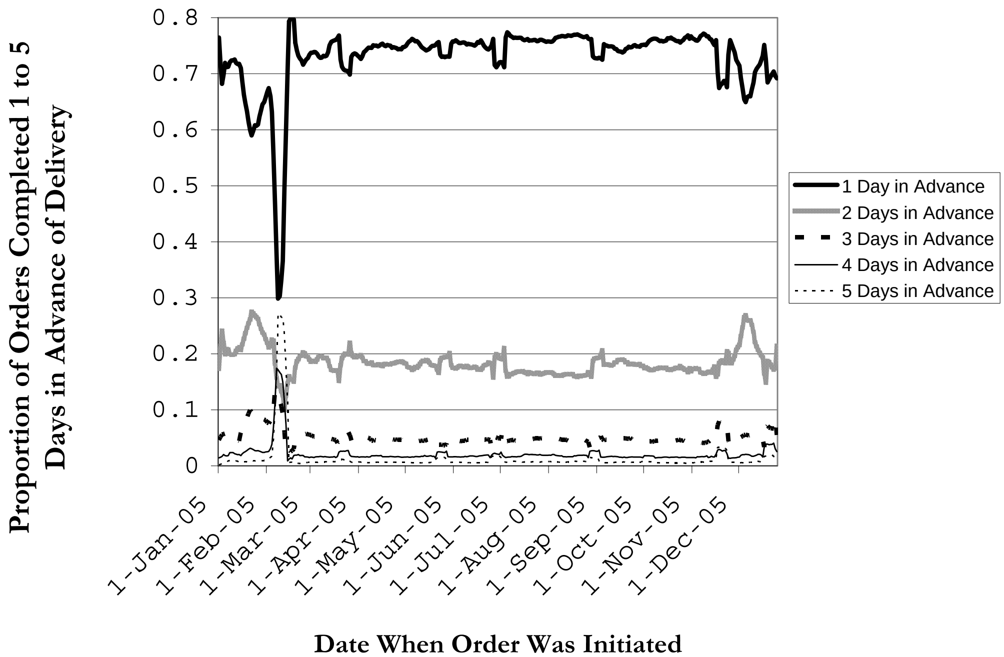
The majority of customers in our data set completed their grocery orders one day in advance of delivery. However, many customers completed orders in 2005 between two and five days in advance of their scheduled delivery date (see Table 2). We assume that variation in the time between a customer's last visit to the online grocer's website and the delivery of her order is relatively random and due to the fact that customers' busy schedules do not always allow them to schedule deliveries the same number of days after they have completed an order. Figure 1 demonstrates that there is limited seasonality in the rate at which customers' order lead times vary with the exception of an unusual week in February. In all of our analyses of this data, we include week fixed effects, and we also re-run each analysis without January and February data to ensure that these two somewhat unusual months, when snowstorms may have affected both order lead times and the types of items customers purchased, are not driving our results.

Table 2
DELIVERY LEAD TIME SUMMARY STATISTICS

% of Orders Completed 1 Day in Advance of Delivery	74.40%
% of Orders Completed 2 Days in Advance of Delivery	18.17%
% of Orders Completed 3 Days in Advance of Delivery	4.76%
% of Orders Completed 4 Days in Advance of Delivery	1.85%
% of Orders Completed 5 Days in Advance of Delivery	0.82%

Summary statistics describing the percentage of orders completed varying numbers of days in advance of delivery, excluding each customer's first order of 2005.

Figure 1. Illustration of the proportion of orders completed varying numbers of days in advance of delivery over time (smoothed over 7 day intervals).



Classifying Groceries

To classify the foods in our grocery data set based on their position along the spectrum from *should* to *want*, we conducted an online survey. We paid 154 subjects to participate in this survey, and we asked each subject questions about approximately 30 food categories from our database of groceries. Groceries in our data set have all been classified by our online grocer into one of 117 categories (e.g. Frozen Vegetables, Cream, Cosmetics, Cookies, etc.). We randomly partitioned the grocery categories into four groups of approximately 30 categories each, and every survey participant was randomly assigned to answer questions about one of these four groups. Subjects were only asked about 30 grocery categories to reduce the likelihood of boredom and mechanical responses.

Our survey respondents were anonymous volunteers from all over the United States who signed up over the Internet to participate in online paid polls administered by Harvard Business School's Computer Lab for Experimental Research (CLER). After being provided with concept definitions (see Appendix I), subjects were asked to rate grocery categories along a 1 – 7 Likert scale anchored on *not a "want" grocery category* and *a strong "want" grocery category*, and a 1 – 7 Likert scale anchored on *not a "should" grocery category* and *a strong "should" grocery category*. Subjects saw the name of a grocery category and the names of its associated subcategories when completing our survey (e.g., Candy & Gum: Candy Chocolate, Candy Non-Chocolate, Gum & Mints), and the order in which they were asked to rate grocery categories along *should* and *want* scales was randomized. No significant order effects were present in our survey data.[8]

We gave subjects an incentive to provide accurate ratings of grocery categories by paying them for performance. For each grocery category a survey participant classified within one point of the average rating across respondents, her "accuracy score" was increased by one. The 20% of participants who received the highest accuracy scores were paid a bonus of $5 on top of their $5 participation fee.

To generate a *should minus want* variable for each grocery category, we subtract each grocery category's *want* score from its *should* score. We average our raters' *should minus want* scores to create an overall *should minus want* index for each grocery category. If our survey ratings contain a meaningful signal, we should find that the *should minus want* scores assigned by different survey participants to the same grocery

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[8] Wilks' lambdas from multivariate analysis of variances (MANOVAs) run to examine potential ordering effects were all insignificant at the 5% level.

category are more tightly clustered than the *should minus want* scores assigned by different survey participants to different grocery categories. We run a one-way analysis of variance (ANOVA) to compare ratings variation between grocery categories to ratings variation within grocery categories (Shrout and Fleiss, 1979). An intraclass correlation of 0.34 and an estimated reliability of a grocery category mean of 0.95 confirms that our survey averages are reliable – survey ratings vary more between grocery categories than within grocery categories. For a catalog of the grocery categories in our sample and an ordered list of their associated average *should minus want* ratings, see Appendix II.

In addition to developing *should minus want* scores for each of the grocery categories in our data set, we created several other classification schemes to determine which groceries are *should* items and which are *want* items. We created these additional classification schemes because having multiple, imperfectly correlated measures of *should* and *want* groceries would allow us to test the robustness of our results. The grocery category designations used by the online grocery company allow us to classify a subset of foods as "perishable" and another subset as "alcohol and tobacco" products (see Table 3). Conceptually, perishable items may be interpreted as a class of *should* groceries, while alcohol and tobacco products may be interpreted as a category of *want* groceries.

Table 3
CLASSIFICATIONS OF GROCERIES

Perishable	Alcohol & Tobacco
BAKERY-FRESH	WINE/WINE COOLERS
DELI-FRESH	MIXERS/BAR NEEDS
PRODUCE-VEGETABLES	SPIRITS
MEAT-FRESH	PREPARED COCKTAILS
SEAFOOD-FRESH	BEER & CIDER
PRODUCE-FRUITS	CIGARS & TOBACCO
	CIGARETTES

In addition, we categorize groceries as “treats” following Heilman et al.’s (2002) definition of this class of goods. These authors created a list of treats based on the items that 57 grocery shoppers said they would buy if they “wanted to treat themselves or their families to something special” (Heilman et al., 2002, p. 246). Of the groceries that were listed, the 50% that were listed most often by these survey respondents were labeled “treats,” as were goods found in the checkout aisle of a grocery store. We match grocery categories in our database to the groceries in the Heilman et al. “treats” list, as shown in Table 4, and we define goods that fall into these categories as “treats.” Conceptually, this category may be interpreted as a class of extreme *want* groceries.

Table 4
CLASSIFICATION OF GROCERIES AS TREATS

Treats	**Corresponding Groceries in Our Data**	
According to Heilman et al. (2002)	**Category**	**Sub-category**
Ice Cream	ICE CREAM	
Bakery Goods	BAKERY-FRESH	
Steak		ALL OTHER FRESH MEAT
		MEAT
Wine		WINE/WINE COOLERS
Candy	CANDY & GUM	
Cheese	CHEESE	
Cookies	COOKIES	
Magazine		MAGS/NEWSPAPERS/BOOKS
Chocolate	CANDY & GUM	
		HOT CHOCOLATE MIX
Flowers	FLORAL	
Cake		CAKE MIXES
		CAKES (FRESH)
Seafood	SEAFOOD-FRESH	
	SEAFOOD-FROZEN	
Baby Toy	*NA*	*NA*
Chips		POTATO CHIPS
		TORTILLA CHIPS
		CORN CHIPS/SNACKS
Cosmetics	COSMETICS	
Movie Rental		MUSIC/MOVIES
Pie		PIES (FRESH)
Gum/Mints	CANDY & GUM	

Grocery categories classified as "treats" in our study based on the categories listed by Heilman et al. (2002).

We constructed a number of different outcome variables for our analyses using the grocery classifications discussed above. One of our outcome variables is conceptually designed to capture the overall makeup of a customer's grocery order. This variable is the average *should minus want* score of all of the groceries in a customer's basket. Three of our outcome variables are conceptually designed to capture groups of extreme *should* groceries. These outcome variables include the percentage of an order's dollar value composed of each of the following types of items: fresh foods, groceries receiving one of the five highest *should minus want* scores, and groceries receiving one of the ten highest *should minus want* scores. Six of our outcome variables are conceptually designed to capture groups of extreme *want* groceries. These outcome variables include the percentage of an order's dollar value composed of each of the following types of items: groceries receiving one of the five lowest *should minus want* scores, groceries receiving one of the ten lowest *should minus want* scores, alcohol and tobacco, groceries receiving one of the five lowest *should minus want* scores excluding alcohol and tobacco, groceries receiving one of the ten lowest *should minus want* scores excluding alcohol and tobacco, and treats. Table 5 presents the correlations between these different outcome variables as well as summary statistics about dollar spending per order on each category of groceries.

Table 5

CORRELATIONS BETWEEN OUTCOME MEASURES AND SUMMARIES OF SPENDING ON EACH CATEGORY OF GROCERIES

		% of Order's Dollar Value Compsosed of:								
	Basket's Average SMW Score	Fresh Foods	5 Highest SMW Scores	10 Highest SMW Scores	5 Lowest SMW Scores	10 Lowest SMW Scores	5 Lowest SMW Scores (No Alc/Tob)	10 Lowest SMW Scores (No Alc/Tob)	Alcohol & Tobacco	Treats
Fresh Foods	0.3722***									
5 Highest SMW Scores	0.4516***	0.4198***								
10 Highest SMW Scores	0.5524***	0.1865***	0.7093***							
5 Lowest SMW Scores	-0.4334***	-0.1592***	-0.0747***	-0.1212***						
10 Lowest SMW Scores	-0.4551***	-0.1860***	-0.0971***	-0.1510***	0.8578***					
5 Lowest SMW Scores (No Alc/Cigs)	-0.4206***	-0.2101***	-0.1189***	-0.1608***	0.6059***	0.6664***				
10 Lowest SMW Scores (No Alc/Cigs)	-0.6449***	-0.3407***	-0.2088***	-0.2668***	0.4015***	0.4317***	0.6301***			
Cigarettes & Alcohol	-0.0773***	-0.0857***	-0.0470***	-0.0734***	0.2973***	0.4311***	-0.0380***	-0.0345***		
Treats	-0.3098***	0.0006	-0.0655***	-0.1572***	0.6489***	0.5485***	0.3749***	0.2072***	0.1813***	
Average Spending/(Score) on Category	-0.0646	$39.00	$11.01	$21.84	$5.57	$7.21	$11.09	$18.83	$1.11	$14.91
Std of Spending/(Score) on Category	0.6678	$29.20	$10.90	$16.36	$9.37	$10.95	$11.78	$18.99	$7.65	$14.28

Correlation coefficients between outcome variables and summary statistics about spending on each category of groceries. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Results

We begin by evaluating the overall impact of the time between an order's completion and its delivery on customer spending. Table 6 presents the results of ordinary least squares (OLS) regressions estimating the relationship between the amount a customer spends on groceries and how far in advance of delivery she completes her grocery order. In these regressions and in subsequent regressions, the explanatory variables include the number of days in advance of delivery a customer completed her order, the number of times the customer visited the online grocer's website in the course of placing an order, the number of days between the first and last visit the customer made to the grocer's website in the course of placing an order, the number of days since the customer last received a grocery delivery, a dummy indicating if 60 or more days have passed since the customer's last grocery order, the number of orders placed by the customer year to date, dummies for the day of the week when the order was placed, dummies for the day of the week when the order was delivered, dummies for each week in 2005, and customer fixed effects. By including customer fixed effects, we are able to identify off of within customer variation our analyses of the effects of lead time on consumer behavior.

Consistent with the hypothesis that people behave more impulsively when planning for the more immediate future, we find that holding all else constant, the dollar size of a grocery order decreases by approximately 2.0 percent for each additional day that separates a customer's last visit to the online grocer's website and the date when her groceries are delivered (see Table 6, Regression (2)). Regression (1) in Table 6 indicates that this effect corresponds to approximately \$2.70 less in spending on groceries per day of additional order lead time. While this result is consistent with our hypothesis that people become decreasingly impatient the further into the future their decisions will take effect, assuming that the mere act of spending is impulsive, there are plausible alternative explanations for the observed decrease in spending associated with orders placed for the more distant future. For example, this result may be driven by the fact that people know more about exactly what their needs will be when ordering groceries for the more immediate future and thus purchase more groceries the sooner their groceries will be delivered.

Table 6
THE EFFECTS OF ORDER LEAD TIME ON SPENDING: BASIC RESULTS

	Spending (1)	Log(1+Spending) (2)
Days btw Order Completion and Delivery	-2.6994***	-0.0195***
	(0.0805)	(0.0005)
Number of Web Visits for Order	3.1705***	0.0209***
	(0.0295)	(0.0002)
Days btw First and Last Web Visits for Order	-0.1359***	-0.0009***
	(0.0047)	(0.0000)
Days Since Last Delivery	0.2517***	0.0016***
	(0.0046)	(0.0000)
60 or More Days Since Last Order	-11.8873***	-0.0762***
	(0.3774)	(0.0023)
Days Since First Order with Grocer	0.0707***	0.0005***
	(0.0072)	(0.0000)
Orders Year to Date	-0.0186	-0.0002
	(0.0189)	(0.0001)
Day of the Week Order Placed Fixed Effects	Yes	Yes
Day of the Week Order Delivered Fixed Effects	Yes	Yes
Week of the Year Fixed Effects	Yes	Yes
Customer Fixed Effects	Yes	Yes
Observations	1 million +	1 million +
Customers	100,000 +	100,000 +
Overall R^2	0.0192	0.0218

Columns (1) and (2) report OLS coefficients from regressions of customer spending on a continuous variable indicating how far in advance of delivery an order was completed controlling for the other variables listed. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

In order to test our prediction that people become decreasingly impatient the further into the future their decisions will take effect without worrying about potential alternative explanations for our spending results, we shift our focus to the impact of delivery lead time on the percentage of a customer's spending that is concentrated on different types of goods and the average *should minus want* score of goods in a customer's basket. By looking at the percentage composition and average *should minus want* score of customers' baskets, we control for the overall decrease in spending across categories of goods that is associated with orders placed for the more distant future.

In the regression that follow, rather than simply including a linear effect for the number of days in advance of delivery a customer places an order, we also include a dummy variable indicating whether an order was completed one day in advance of delivery. We include this dummy variable because exploratory data analyses revealed that this regression specification was most appropriate given the patterns in our data.[9] In order to calculate the predicted effect of completing a grocery order one day in advance of delivery in the regressions that follow, the coefficient on the variable "One Day btw Order Completion and Delivery" should be added to the coefficient on the variable "Days btw Order Completion and Delivery". The predicted effect of completing an order two or more days in advance of delivery may be obtained by multiplying the coefficient on the variable "Days btw Order Completion and Delivery" by two (to calculate the two day effect), three (to calculate the three day effect), and so on.

[9] In order to determine the appropriate specification for our regressions, we began by running each analysis with dummy variables indicating the number of days in advance of delivery an order had been completed. These regressions demonstrated a consistent pattern – a linear trend was apparent in the *should* and *want* contents of orders completed between two and five days in advance of delivery, and orders completed one day in advance of delivery did not follow this monotonic pattern. The results of these analyses are available upon request.

In Table 7 and 8, we present the results of a series of OLS regressions estimating the relationship between the percentage of a customer's grocery spending concentrated on different types of *should* and *want* groceries, the average should minus want score of items in a customer's basket, and how many days in advance of delivery a customer completes her order. The results presented in Table 7 and 8 indicate that for orders completed between two and five days in advance of delivery, the further in advance of delivery a customer completes an order, the relatively more *should* goods and fewer *want* goods she will purchase, consistent with the hypothesis that people are decreasingly impatient. However, contrary to our prediction, orders completed one day in advance of delivery contain a higher percentage of *should* goods and a lower percentage of *want* goods than orders completed two days in advance of delivery (see Figures 2 and 3 on page 29). This apparent nonlinearity in customers' discount rates is persistent across different measures of *should* and *want* goods, although the nonlinearity lies within one standard error of the linear trend of decreasing impatience detected across our analyses. In Study 2, we will discuss this surprise in our data in more detail and offer a potential explanation for it. The remainder of this section, however, will focus on our findings with respect to the differences between orders completed between two and five days in advance of delivery.

Regression (3) in Table 7 demonstrates the effect of an increase in the time between an order's completion and its delivery on the average *should minus want* score of a grocery basket. It shows that for orders placed between two and five days in advance of delivery, for each additional day in advance of delivery an order is completed, the average *should minus want* score of an entire grocery basket increases by 0.0053 (or approximately 0.008 standard deviations). Regressions (4), (5) and (6) in Table 7 provide information about the change in the percentage of an order composed of *should* items that is associated with a change in how far in advance of delivery the order is completed. These regressions show that for orders placed between two and five days in advance of delivery, for each additional day in advance of delivery an order is completed, the percent of the order composed of fresh foods increases by 0.24 (or an average of $0.37), the percent composed of groceries with the 5 highest *should minus want* scores increases by 0.07 (or an average of $0.11), and the percent composed of groceries with the 10 highest *should minus want* scores increases by 0.12 (or an average of $0.19). Regressions (7) through (12) in Table 7 focus on the change in the percentage of an order composed of *want* items that is associated with a change in how far in advance of delivery an order is completed. They show that for orders placed between two and five days in advance of delivery, for each additional day in advance of delivery an order is completed, the percent of the order composed of groceries with the five lowest *should minus want* scores decreases by 0.05 (or an average of $0.08) and the percent composed of groceries with the 10 lowest *should minus want* scores decreases by 0.06 (or an average of $0.09). In addition, the percent of an order composed of groceries with the five lowest *should minus want* scores excluding alcohol and tobacco decreases by .06 (or an average of $0.09), the percent composed of groceries with the 10 lowest *should minus want* scores excluding alcohol and tobacco decreases by 0.06 (or an average of $0.09), the percent composed of *treats* decreases by 0.04 (or an average of $0.07), and the percent composed of alcohol and tobacco decreases insignificantly by 0.005 (or an average of $0.01). Each of these results is consistent with a model of individuals as decreasingly impatient. Each of these regressions also contains a nonlinearity at day one, however, which is inconsistent with this pattern of decreasing impatience over time.

Table 7
THE EFFECTS OF ORDER LEAD TIME ON SHOULD AND WANT SPENDING

		% of Order's Dollar Value Compsosed of								
	Basket's Average SMW Score (3)	**Fresh Foods (4)**	**5 Highest SMW Scores (5)**	**10 Highest SMW Scores (6)**	**5 Lowest SMW Scores (7)**	**10 Lowest SMW Scores (8)**	**5 Lowest SMW Scores (No Alc/Tob) (9)**	**10 Lowest SMW Scores (No Alc/Tob) (10)**	**Treats (11)**	**Alcohol and Tobacco (12)**
One Day btw Order Completion and Delivery	0.0070***	0.2838***	0.06481*	0.0914**	-0.0907***	-0.1002***	-0.0871***	-0.1196***	-0.0470	-0.0328**
	(0.0025)	(0.0511)	(0.0338)	(0.0397)	(0.0203)	(0.0231)	(0.0260)	(0.0340)	(0.0347)	(0.0131)
Days btw Order Completion and Delivery	0.0053***	0.2381***	0.0702***	0.12168***	-0.0491***	-0.0562***	-0.0595***	-0.0606***	-0.0427*	-0.0050
	(0.0018)	(0.0336)	(0.0258)	(0.0282)	(0.0135)	(0.0151)	(0.0169)	(0.0227)	(0.0242)	(0.0084)
Number of Web Visits for Order	-0.0023***	-0.1545***	-0.0214***	-0.0211***	0.0127***	0.0039	0.0079**	-0.0104**	0.0245***	0.0053***
	(0.0003)	(0.0064)	(0.0030)	(0.0041)	(0.0026)	(0.0030)	(0.0032)	(0.0041)	(0.0039)	(0.0020)
Days btw First and Last Web Visits for Order	0.0000	0.0067***	0.0010**	0.0001	0.0007*	0.0010**	0.0006	-0.0003	0.0010*	0.0006
	(0.0000)	(0.0011)	(0.0004)	(0.0006)	(0.0004)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0004)
Days Since Last Delivery	0.0004***	-0.0160***	-0.0061**	-0.00289***	-0.0043***	-0.0045***	-0.0029***	0.0002	-0.0081***	-0.00193**
	(0.0000)	(0.0010)	(0.0005)	(0.0006)	(0.0004)	(0.0000)	(0.0005)	(0.0006)	(0.0006)	(0.0003)
60 or More Days Since Last Order	-0.0046	0.5527***	0.2318***	0.2144***	0.0705**	0.0637*	0.0078	-0.1687***	0.1934***	0.0840***
	(0.0036)	(0.0856)	(0.0393)	(0.0563)	(0.0321)	(0.0387)	(0.0430)	(0.0566)	(0.0510)	(0.0245)
Days Since First Order with Grocer	0.0000	-0.0028	-0.0013	-0.0015	-0.0026**	-0.0014	0.0020**	0.0038***	-0.0030**	-0.0011
	(0.0001)	(0.0018)	(0.0009)	(0.0014)	(0.0009)	(0.0010)	(0.0009)	(0.0012)	(0.0012)	(0.0008)
Orders Year to Date	0.0007***	-0.0082*	0.0015	0.0064**	0.0011	0.0033*	0.0045**	0.0024	-0.0058**	-0.0019
	(0.0002)	(0.0043)	(0.0023)	(0.0028)	(0.0018)	(0.0020)	(0.0022)	(0.0028)	(0.0025)	(0.0013)
Day of the Week Order Placed Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of the Week Order Delivered Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week of the Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Customer Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1 million +	1 million +	1 million +	1 million +	1 million +	1 million +	1 million +	1 million +	1 million +	1 million +
Customers	100,000 +	100,000 +	100,000 +	100,000 +	100,000 +	100,000 +	100,000 +	100,000 +	100,000 +	100,000 +
Overall R^2	0.0017	0.0098	0.0007	0.0001	0.0004	0.0002	0.0001	0.0007	0.0001	0.0014

Columns (3) through (12) report OLS coefficients from regressions of customer spending on categories of groceries on a dummy indicating whether an order was completed one day in advance of delivery and a continuous variable indicating how far in advance of delivery an order was completed, controlling for the other variables listed. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Table 8 presents two OLS regressions in which the various different, somewhat overlapping categories of *should* groceries are merged into a single group and the various different, somewhat overlapping categories of *want* groceries are merged into a single group. The average spending per order on groceries classified as *should* items is \$49.76, and the average spending per order on groceries classified as *want* items is \$26.34. For orders placed between two and five days in advance of delivery, for each additional day in advance of delivery an order is completed, Regression (13) indicates that the percent of an order composed of *want* groceries decreases by 0.07 (or an average of \$0.11), and Regression (14) indicates that the percent of an order composed of *should* groceries increases by 0.27 (or an average of \$0.42). The results presented in Table 8 are, on the whole, consistent with a story of decreasing impatience. Like the regressions presented in Table 7, however, both of the regressions in Table 8 contain a nonlinearity at day one, a feature of our results that is inconsistent with the overall pattern of decreasing impatience we detect, and which will be addressed by Study 2.

Table 8
THE EFFECTS OF ORDER LEAD TIME ON EXCLUSIVE SHOULD AND WANT SPENDING

	% of Order's Dollar Value Compsosed of:	
	Groceries in One or More Want Categories (13)	Groceries in One or More Should Categories (14)
One Day btw Order Completion and Delivery	-0.1298***	0.3163***
	(0.0389)	(0.0549)
Days btw Order Completion and Delivery	-0.0749***	0.2697***
	(0.0257)	(0.0372)
Number of Web Visits for Order	0.0055	-0.1285***
	(0.0049)	(0.0065)
Days btw First and Last Web Visits for Order	-0.0002	0.0046***
	(0.0007)	(0.0010)
Days Since Last Delivery	-0.0026***	-0.0104***
	(0.0008)	(0.0010)
60 or More Days Since Last Order	-0.0921	0.4764***
	(0.0662)	(0.0872)
Days Since First Order with Grocer	0.0020	-0.0037*
	(0.0016)	(0.0019)
Orders Year to Date	-0.0021	-0.0031
	(0.0032)	(0.0041)
Day of the Week Order Placed Fixed Effects	Yes	Yes
Day of the Week Order Delivered Fixed Effects	Yes	Yes
Week of the Year Fixed Effects	Yes	Yes
Customer Fixed Effects	Yes	Yes
Observations	1 million +	1 million +
Customers	100,000 +	100,000 +
Overall R^2	0.0017	0.0052

Columns (13) and (14) report OLS coefficients from regressions of customer spending on categories of groceries on a dummy indicating whether an order was completed one day in advance of delivery and a continuous variable indicating how far in advance of delivery an order was completed, controlling for the other variables listed. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

In order to control for an alternative explanation for our findings, we run one more series of regressions. It is plausible that our observation that people spend proportionally more on *should* goods and less on *want* goods the further in advance of delivery they complete an order is driven by the following story: people spend less on orders placed for delivery in the more distant future because their needs are more uncertain, and when people spend less on groceries, their orders contain a higher percentage of goods that are basic necessities, which are more likely to be *should* goods than *want* goods. In order to control for this possible explanation for our findings, we run a series of regressions in which we examine the types of goods purchased by customers above and beyond what they purchased during their last online grocery order. We assume that goods purchased on two consecutive orders constitute "staples" or basic necessities, while goods purchased during one order that were not purchased during the previous order do not fall into this category.

In Table 9, Regression (15) presents the results of an OLS regression estimating the relationship between the percentage of an order's dollar value spent on groceries that were not purchased during a customer's previous order and the number of days in advance of delivery a customer completes her order. We find that for orders placed between two and five days in advance of delivery, for each additional day in advance of delivery an order is completed, the percent of the order composed of goods that were not purchased during a customer's previous order decreases by 0.20 (or an average of $0.31). This suggests that people buy a higher proportion of "staples" and a lower proportion of frivolous goods, or "non-staples," the further in advance of delivery they complete an order – a result that is consistent both with the idea that people are decreasingly impatient and with the alternative "uncertainty" explanation for our findings proposed above.

Models (16) and (17) in Table 9 present two OLS regressions estimating the relationship between the length of delay between an order's completion and delivery and the percentage of a customer's grocery spending on non-staple goods that are classified as *should* and *want* groceries. The average amount a customer spends on non-staple goods is $98.90. For orders placed between two and five days in advance of delivery, for each additional day in advance of delivery an order is completed, Regression (16) indicates that the percent of non-staple spending that is composed of *want* groceries decreases insignificantly by 0.02 (or an average of \$0.02), and Regression (17) indicates that the percent of non-staple spending that is composed of *should* groceries increases by 0.20 (or an average of \$0.20). These findings are consistent with a model of customers as decreasingly impatient. In addition, these results suggest that this observed pattern of decreasing impatience may be driven more by increased *should* spending when decisions are made for the more distant future than by decreased *want* spending. It should again be noted that the day one nonlinearity in *should* and *want* spending patterns is again present in Regressions (16) and (17).

Table 9
THE EFFECTS OF ORDER LEAD TIME ON SPENDING ON NON-STAPLE GOODS

	% of Order's Dollar Value Spent on Goods Not Purchased During Previous Order	% of Spending on Goods Not Purchased During Previous Order Compsosed of:	
		Groceries in One or More Want Categories	Groceries in One or More Should Categories
	(15)	(16)	(17)
One Day btw Order Completion and Delivery	0.0409	-0.0726**	0.0990***
	(0.0738)	(0.0289)	(0.0384)
Days btw Order Completion and Delivery	-0.1957***	-0.0188	0.1994***
	(0.0480)	(0.0200)	(0.0250)
Number of Web Visits for Order	0.7188***	-0.1294***	-0.2538***
	(0.0095)	(0.0034)	(0.0048)
Days btw First and Last Web Visits for Order	-0.0339***	0.0051***	0.0131***
	(0.0020)	(0.0007)	(0.0010)
Days Since Last Delivery	0.0343***	-0.0014**	-0.0221***
	(0.0016)	(0.0006)	(0.0008)
60 or More Days Since Last Order	2.6201***	-0.7104***	-0.2487***
	(0.1282)	(0.0477)	(0.0605)
Days Since First Order with Grocer	0.0025	0.0012	-0.0047***
	(0.0034)	(0.0011)	(0.0015)
Orders Year to Date	-0.0019	-0.0011	-0.0026
	(0.0061)	(0.0024)	(0.0035)
Day of the Week Order Placed Fixed Effects	Yes	Yes	Yes
Day of the Week Order Delivered Fixed Effects	Yes	Yes	Yes
Week of the Year Fixed Effects	Yes	Yes	Yes
Customer Fixed Effects	Yes	Yes	Yes
Observations	1 million +	1 million +	1 million +
Customers	100,000 +	100,000 +	100,000 +
Overall R^2	0.0169	0.0059	0.0014

Columns (15) through (17) report OLS coefficients from regressions of customer spending on categories of groceries on a dummy indicating whether an order was completed one day in advance of delivery and a continuous variable indicating how far in advance of delivery an order was completed, controlling for the other variables listed. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Finally, we re-run all of the above analyses without including orders placed in January or February to ensure that our results are not driven by any unusual events in these months that may have caused a number of orders to be completed further in advance of delivery than usual (see Figure 1). The results of our regressions remain meaningfully and statistically unchanged when orders placed in these months are eliminated.

Discussion

The results we presented in Study 1 demonstrate systematic differences in the choices customers make when they complete grocery orders between two and five days in advance of delivery, which are consistent with a model of consumers as decreasingly impatient. First, we find that customers spend less, suggesting they behave less impulsively, the further in advance of delivery they complete an online grocery order. Second, we find that for orders placed between two and five days in advance of delivery, for each additional day in advance of delivery an order is completed, the percent of an order composed of *want* groceries decreases and the percent composed of *should* groceries increases. This effect is robust across our various definitions of *should* and *want* goods. We also find that orders completed further in advance of delivery contain a higher percentage of staple items (and thus, we infer, a lower percentage of frivolous items) than orders completed closer to the time of delivery. Finally, we find that for orders placed between two and five days in advance of delivery, as the time between an order's completion and its delivery increases, the percent of non-staple spending composed of *should* groceries increases significantly, while the percent of non-staple spending composed of *want* groceries declines insignificantly.

In addition to supporting the hypothesis that people exhibit decreasing impatience, the regression analyses discussed above also expose one surprising and persistent feature of our data. The results of our analyses indicate that orders completed one day in advance of delivery include a lower proportion of *want* goods and a higher proportion of *should* goods than orders placed two days in advance of delivery. This finding is inconsistent with a model of consumers as decreasingly impatient and with previously discussed trends in the composition of orders completed between two and five days in advance of delivery. The unexpected pattern in our data, which is present in Regressions (3) through (14), (16) and (17), or all analyses of *should* and *want* spending, is illustrated in Figures 2a and 2b. Each of these figures contains a nonlinearity in its overall trend line resulting from the higher percentage of *should* goods and lower percentage of *want* goods in orders placed for delivery tomorrow relative to orders placed for delivery two days in advance. In order to gain an understanding of what might account for this unexpected nonlinearity in consumers' decreasing impatience, we designed a second study, which is discussed below.

Figure 2. How percentage of order composed of *want* and *should* groceries varies by delay until delivery.

*Figure 2a***.** Illustration of change in the proportion of spending concentrated on *want* groceries when orders are completed different lengths of time in advance of delivery for the average order

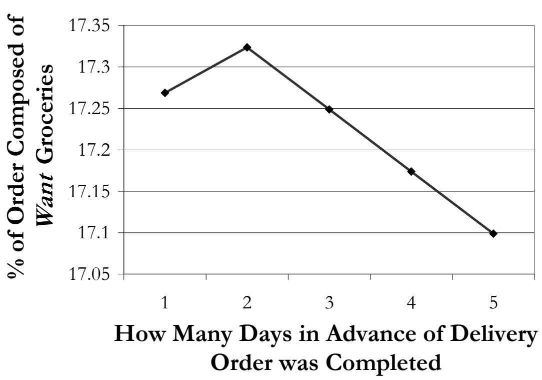
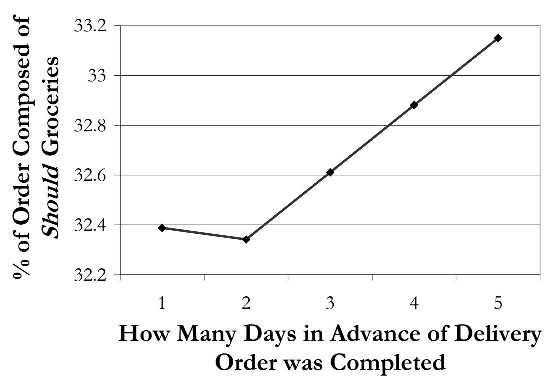


*Figure 2b***.** Illustration of change in the proportion of spending concentrated on *should* groceries when orders are completed different lengths of time in advance of delivery for the average order



Study 2

Study 2 was designed to explain the puzzle that emerged in Study 1. We originally predicted that orders placed for delivery tomorrow would be composed of a higher proportion of *want* goods and a lower proportion of *should* goods than orders placed for delivery in the more distant future. Yet, we consistently observed that this pattern did not hold. We found that a higher percentage of *should* groceries and a lower percentage of *want* groceries were ordered when delivery was slotted for tomorrow than for two days in the future. The results from Study 1 led us to hypothesize that this unexpected pattern was due to differences in the specificity of customers' intended uses for groceries ordered for delivery tomorrow as opposed to the more distant future. Construal level theory (Trope and Liberman, 2003), which was discussed previously, provides the theoretical basis for this conjecture. If groceries ordered for tomorrow are construed at a lower-level (i.e., thought about in more concrete, specific terms) than groceries ordered for the more distant future, then customers should have more specific intended uses for groceries ordered for tomorrow than for groceries ordered for delivery in the more distant future. This leads to the following hypotheses:

H1a: Food ordered for tomorrow is intended for more specific, planned meals than food ordered for delivery in the more distant future.

H1b: Food ordered for delivery later than tomorrow is intended more for general pantry stocking than food ordered for tomorrow.

Simply confirming H1a and H1b would not explain the anomaly found in Study 1. However, the anomaly might be explained if these hypotheses are confirmed and if it is determined that foods ordered for specific, planned meals are more likely to be classified as *should* groceries and less likely to be classified as *want* groceries than foods ordered for more general uses, such as pantry stocking. The hypotheses we test to confirm the second part of this explanation for the Study 1 anomaly are as follows:

H2a: Foods ordered for specific, planned meals are classified as should foods more often than foods ordered for general pantry stocking.

H2b: Foods ordered for general pantry stocking are classified as want foods more often than foods ordered for specific, planned meals.

To complement the analyses of field data in Study 1, we designed a survey that allowed us to test the above hypotheses and to manipulate which delivery lead time condition participants were assigned to.

Method

In order to test the above hypotheses, we conducted an online survey. We collected 230 responses to this survey in two phases. In the first phase we surveyed participants in a lab session in the Computer Lab for Experimental Research (CLER) at Harvard Business School (N = 85), and in the second phase we collected survey responses from participants recruited for an online CLER study (N = 145).

Participants were assigned to one of three conditions based on the month when they were born. Participants in each condition were asked to imagine ordering items from an online grocer for delivery either tomorrow, in two days, or in five days. To make this task more realistic, we asked each participant to list ten items she would include in her order and to briefly explain, in writing, why she chose to order these items. To test hypotheses H1a and H1b, participants were then asked a series of questions about the extent to which the items they listed were intended for specific, planned meals as opposed to being intended for general pantry and refrigerator stocking (see Appendix III for precise wording).

Next, participants in all three conditions were introduced to the concepts of *want* and *should* (see Appendix III). To test H2a and H2b, all participants were then asked if they purchase more *want* or *should* groceries when shopping for specific, planned meals, when shopping for general food for their pantry and refrigerator, or if there is no difference (see Appendix III for precise wording).

Results

We begin by examining the responses to survey questions intended to address whether people order more foods for specific, planned meals and fewer general, pantry-stocking foods when they order for delivery tomorrow versus the more distant future. Table 10 shows that participants in the *ordering for delivery tomorrow* condition report that they would purchase significantly more food intended for specific, planned meals than participants in the other two, more distant delivery conditions, $t\ (227) = -3.49$, $p = .001$. This provides strong support for hypothesis H1a. The analyses presented in Table 10 also provide marginally significant support for hypothesis H1b. They show that participants in the *ordering for delivery tomorrow* condition report that they would purchase marginally significantly less food intended for general pantry stocking than participants in the other two, more distant delivery conditions, $t(227) = -1.92$, $p = .056$.

Table 10
THE EFFECTS OF ORDER LEAD TIMES ON SPENDING INTENTIONS

Experimental Condition	N	Items purchased were more for specific planned meals	Items purchased were more for general pantry stocking
Groceries Will Be Delivered Tomorrow	71	3.85***	4.65*
		(2.01)	(1.77)
Groceries Will Be Delivered in 2 Days	71	2.89	5.08
		(1.86)	(1.61)
Groceries Will Be Delivered in 5 Days	88	2.93	5.16
		(1.76)	(1.77)

Comparison of purposes described for items survey participants listed when asked to imagine what groceries they would order in different experimental conditions. Standard errors are in parentheses. *** This cell is significantly greater than the two cells below it in a planned comparison (-2, 1, 1) at the level of p = .001. * This cell is marginally significantly less than the two cells below it in a planned comparison (-2, 1, 1) at the level of p = .056.

Next we examine the responses given to survey questions that were intended to establish whether food ordered for specific, planned meals tends to be *should* food (H2a), and if food ordered for general pantry stocking tends to be *want* food (H2b). Table 11 displays the data collected to address this. To examine H2a, we first test the null hypothesis that when asked what shopping goal results in more purchases of *should* foods, participants are equally likely to answer “specific, planned meals”, “general pantry stocking”, and “no difference”. Consistent with H2a, we are able to reject this null hypothesis X^2 (2, N = 228) = 9.50, p = .009 – participants are not equally likely to give each of these three answers. Also consistent with H2a, we find that marginally significantly more survey participants report that they order more *should* groceries when ordering for specific, planned meals (N = 97) than when ordering for general pantry stocking (N = 71) (binomial test of proportions, N = 168, p = .053). Next, to examine H2b, we test the null hypothesis that when asked what shopping goal results in more purchases of *want* foods, participants are equally likely to answer “specific, planned meals”, “general pantry stocking”, and “no difference”. Consistent with H2b, we are able to reject this null hypothesis X^2 (2, N = 228) = 59.87, p < .001 – participants are not equally likely to give each of these three answers. Finally, consistent with H2b, we find that significantly more survey participants report that they order more *want* groceries when ordering for general pantry stocking (N = 131) than when ordering for specific planned meals (N = 51) (binomial test of proportions, N = 182, $p < .001$).

Table 11
TYPES OF GROCERIES AND WHEN THEY ARE PURCHASED

	Specific Planned Meal	General Pantry Stocking	No Difference
Purpose for Which More Should Groceries Would be Purchased*	43% (N = 97)	31% (N = 71)	26% (N = 60)
Purpose for Which More Want Groceries Would be Purchased**	22% (N = 51)	57% (N = 131)	20% (N = 46)

Comparison of types of food associated with different spending purposes. * Binomial test of proportions p =.053; ** Binomial test of proportions p < .001.

Discussion

In Study 2 we present evidence supporting all four of our hypotheses, which together offer a potential explanation for why it may be the case that people order a higher proportion of *should* foods and a lower proportion of *want* foods when placing an order for delivery tomorrow versus two days in the future. We find that when people imagine ordering groceries for tomorrow, they report ordering more foods for specific, planned meals and fewer foods for general pantry stocking than when ordering groceries for the more distant future. In addition, we find that *should* groceries are more strongly associated with foods ordered for specific, planned meals than foods ordered for pantry stocking, while *want* groceries are more strongly associated with foods ordered for pantry stocking than foods ordered for specific, planned meals.

General Discussion

In this paper we provide evidence supporting the hypothesis that people are decreasingly impatient over time. Study 1 shows that the further in advance of delivery a grocery order is completed, the more heavily customers weigh their long-term interests relative to their short-term interests. Our two primary results support this claim. First, we find that customers spend less (suggesting they behave less impulsively) the further in advance of delivery they complete an order. Second, we find that, in general, customers order a higher percentage of *should* items (e.g., vegetables and toothpaste) and a lower percentage of *want* items (e.g., ice cream and cookies) the further in advance of delivery they complete an order. Consistent with this, we also find that, for orders to be delivered two to five days after an order is completed, the average *should minus want* score for the grocery basket increases with the delay between delivery and order completion.

In conducting our analyses for Study 1, we also discovered an unexpected pattern in our data, which was inconsistent with our hypothesis that people are decreasingly impatient. We found that grocery orders completed one day in advance of delivery contain a higher percentage of *should* items and a lower percentage of *want* items than grocery orders completed two days in advance of delivery. To investigate a potential explanation for this surprising finding, we conducted a second study. Study 2 confirmed our conjecture that orders placed for delivery tomorrow are more likely to include groceries intended for use in preparing specific meals than orders placed for delivery in the more distant future, and that items ordered for specific meals are more likely to contain *should* foods. Meanwhile, orders placed for delivery two or more days in the future are more likely to include groceries intended for general pantry-stocking than orders placed for delivery tomorrow, and items ordered for general pantry-stocking are more likely to contain *want* foods.

Together, Studies 1 and 2 suggest that increasing lead times between a grocery order's completion and its delivery give rise to two separate psychological effects. First, people exhibit decreasing impatience over time. Second, people construe the way they will use groceries they order for delivery tomorrow more concretely than the way they will use groceries ordered for delivery in the more distant future. We argue that these two effects combine to produce the kinked purchasing patterns we observe in our online grocery data.

One important caveat to point out about our findings in Study 1 is that their validity hinges on the assumption that variation in the delay between when a customer completes an order and when that order is delivered is relatively random. It is possible that people choose to order further in advance of delivery when shopping for different types of occasions and that these differences drive our results. However, it is unclear why the types of events people might order for further in advance would be associated with reduced overall spending or increased spending on *should* items relative to *want* items. It seems more plausible that the types of people who choose to pay a fee to avoid the time-consuming act of grocery shopping are extremely busy and face many scheduling constraints when they search for an available delivery slot at a time when they can be home to receive their groceries.[10] Such customers would likely schedule some orders for delivery two days in advance and others for delivery three days in advance due to scheduling constraints rather than fundamental differences in their shopping goals.

Another caveat should be noted with regard to our Study 1 findings. Customers may choose when their groceries will be delivered at any point in the order process. If some customers do not decide when to have their groceries delivered until after they have selected all of their groceries, these customers will not exhibit any differences in the

[10] Delivery slots can fill up if demand exceeds capacity in a given time slot. This may prevent customers from always choosing to have their orders delivered the same number of days in the future.

types of foods they purchase as a function of how far in advance of delivery they complete an order. Assuming some customers follow this pattern of behavior, our findings underestimate the effects of the delay between an order's completion and its delivery on purchasing behavior.

It is worth discussing a possible alternative explanation for our primary results, which is that people are not decreasingly impatient over time, they are increasingly uncertain. This competing story would predict that people exhibit different purchasing patterns when ordering for delivery in the near future versus the more distant future. However, an increasing uncertainty story does not explain why people would choose to purchase a higher percentage of *should* goods and a lower percentage of *want* goods the further in the future their order will be delivered. The theory that people experience a tension between the competing preferences of a *want* self and a *should* self, with different conditions cueing which self dominates the other in decision making, parsimoniously explains our finding that grocery orders placed for the more distant future involve a higher percentage of *should* goods and a lower percentage of *want* goods than orders placed for the near future.

The findings we present in this paper have a number of different implications for researchers, managers, consumers, and policy-makers. First, they have implications for economic models of time discounting. Our findings suggest that Loewenstein and Prelec's (1992) model of individuals as decreasingly impatient better predicts human behavior than alternative time discounting models, which assume either relatively constant discounting over all periods or relatively constant discounting over all periods beyond the present. Future research should continue to investigate the way people discount utility they anticipate receiving in the near future versus the more distant future.

Our study of dynamic inconsistency also has implications for online and catalog retailers that offer a range of goods for sale and also offer different delivery options. Such companies might be able to improve their demand forecasting by taking into account the fact that their customers may be decreasingly impatient and thus likely to order a higher percentage of *want* goods and a lower percentage of *should* goods for delivery in the near future relative to the more distant future.

Our finding that people select healthier foods for themselves the further in the future their groceries will be delivered also has policy implications.[11] Motivated by research on hyperbolic discounting, Rogers and Bazerman (2007) conducted a series of studies demonstrating that people are more likely to select *should* policies (e.g., increased taxes on fossil fuels, increased charitable spending, etc.) when they will be implemented in the distant future rather than immediately. Offering people *should* choices that will take effect in the future is a strategy that they termed "future lock-in." It takes advantage of the fact that people will heavily discount the negative short-run consequences (e.g., higher gas prices) of *should* policies relative to their positive long-run consequences (e.g., a cleaner environment) when they think about those policies taking effect in the present rather than in future. Our finding that people are more likely to prefer *should* items to *want* items the further in advance of delivery they order groceries suggests that "future lock-in" may be more effective the further in advance of implementation people are asked to vote on *should* policies.

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[11] *Should* foods are generally healthier than *want* foods (see Appendix II).

Finally, combining the specific domain in which our research was conducted with past work on future lock-in, our findings have implications for nutrition policy. Encouraging healthier eating has been an important public policy challenge in recent years (Lueck and Severson, 2006). Our findings suggest that encouraging people to order their groceries up to five days in advance of consumption could influence the healthfulness of the foods people consume.[12] Similarly, asking students in schools to select their lunches up to a week in advance could considerably increase the healthfulness of the foods they elect to eat. An attractive aspect of policies like these is that they preserve the decision-maker's choice set and autonomy by changing only the context in which decisions are made. By changing the decision context, policy-makers can increase the likelihood that people will make 'better' choices without infringing upon their freedom (Sunstein and Thaler, 2003).

[12] Although it is possible that people only buy a healthier bundle of groceries when they order further in the future and do not actually eat healthier groceries, it seems likely that purchases are highly correlated with consumption.

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APPENDIX I: STUDY 1: ONLINE SURVEY

Research Participation Consent Form

Grocery Categorization

Names and emails of authors were listed here

The purpose of this study is to obtain ratings of a sample of grocery categories along two different dimensions. In the study, you will be introduced to two conceptual categories of groceries - "want" and "should." You will then be provided with information about the contents of a sample of grocery categories and asked to rate each grocery category's conformity to the "want" and "should" categories described at the outset of the study. Your participation in this study will take fifteen to twenty minutes. If you have any questions about the study, please e-mail us, and we will respond promptly.

For your participation in the study, you will receive $5.

You will be rating grocery categories along "should" and "want" scales that range from one to seven. You will be given an "accuracy" score based on your grocery ratings. For each grocery category you classify within one point of the average rating across survey participants who also rated that grocery category, your accuracy score will be increased by one. The 20% of participants (32 people out of 160) who receive the highest accuracy scores will be paid a bonus of $5.

Your participation in this study is purely voluntary, and you may withdraw your participation or your data at any time without any penalty to you.

Your data will be kept completely confidential by the researchers involved, who will not store any of your personal identifiers with the answers you provide on their survey. When the research is completed, the data collected will be stored in a safe place by the researchers involved. In the future, the individuals conducting this study may use the data they collect to write research papers and present at conferences.

If you have read the description of this study, your questions have been answered, and you give your consent to participate, please click on the link below and you will be redirected to the online study.

Study Link: Grocery Survey

Harvard University has a Standing Committee on the Use of Human Subjects in Research (CUHS) to which complaints or problems concerning any research project may, and should, be reported if they arise. If you have concerns about this project, please contact (name of research coordinator)

Grocery Survey - Instructions

Dear Survey Participant,

Thank you in advance for taking the time to participate in this research project. Before beginning the survey, you will be introduced to two concepts. You will then be briefly quizzed on these concepts (to insure that you understand them) before you are asked to complete the survey.

<u>Concept Introduction</u>

"Want" Groceries: As part of this survey, you will be asked to score a number of grocery categories on a scale from 1 (not a "want" grocery category) to 7 (a strong "want" grocery category). A "want" grocery is one that someone would choose to consume for the pure enjoyment of it. There may be additional reasons for consuming the grocery - e.g.,, it may be healthy, but such reasons are ***not*** to be taken into account when determining the "want" score of the grocery. The "want" score is intended to reflect the extent to which someone's decision to consume this type of grocery would be indulgent and pleasure-based. *Example of a strong "want" grocery: A tasty snack that most people would enjoy consuming.*

"Should" Groceries: You will also be asked to rate a number of grocery categories on a scale from 1 (not a "should" grocery category) to 7 (a strong "should" grocery category). A "should" grocery is one that someone would feel compelled to consume. This might be because the grocery is expected to improve the consumer in some way - health-wise or otherwise. The "should" score ought to reflect the extent to which someone's choice to consume the grocery would be made for virtuous, self-improving reasons, regardless of other potential factors. *Example of a strong "should" grocery: A grocery that consumers feel compelled to consume for the long-term benefits - in other words, for reasons besides sheer pleasure.*

IMPORTANT: When rating the grocery categories in this survey, you should imagine that someone is standing in a grocery store and has just chosen to purchase an item from the grocery category in question. Give the grocery category "should" and "want" scores based on the feelings you imagine the consumer has toward the grocery that he or she is buying. You should ***not*** give the grocery categories in this survey "want" and "should" scores based on how much you ***personally*** want to consume them or feel that you should consume them.

Please note that "want" and "should" groceries are not mutually exclusive - a grocery category may receive both a high "want" score and a high "should" score.

<u>Comprehension Check</u>

Please enter your unique three-digit participant number, which you received when you agreed to take part in this study. Your participant number will be used to ensure that you are paid for participating in this study and to determine your eligibility for the ten dollar bonus described at the outset of this survey.

Participant Number:

1. A "want" grocery:
    a. is a grocery that someone would only consume because of its outstanding long-term health benefits: True False
    b. is a grocery that someone would choose to consume for the sheer pleasure of doing so: True False
2. A "should" grocery:
    a. cannot also receive a high "want" score: True False
    b. is a grocery that someone would feel compelled to consume in order to improve him or herself: True False
3. When answering the questions in this survey you should:
    a. imagine that someone has elected to purchase an item from the grocery category in question, and give the category a "should" score and a "want" score based on the motivations you imagine that person must have for choosing to consume a grocery in this category: True False
    b. simply call upon your **own** feelings about how much you "want" to consume items in a grocery category or think you "should" consume items in a grocery category: True False

Submit Comprehension Check

If you experience any problems with this program, please e-mail: email address of one of the authors.

APPENDIX II: AVERAGE SHOULD MINUS WANT SCORES FOR GROCERY CATEGORIES IN OUR DATA SET

Grocery Category	Average *Should Minus Want* Score
COOKIES	-5.098
WINE/WINE COOLERS	-4.976
ICE CREAM	-4.976
CANDY & GUM	-4.420
CIGARS & TOBACCO	-4.300
MIXERS/BAR NEEDS	-4.140
FROZEN PIZZA	-4.073
CIGARETTES	-4.000
SPIRITS	-4.000
PREPARED COCKTAILS	-3.963
COSMETICS	-3.951
FLORAL	-3.927
BAKING MIXES	-3.659
FROZEN SNACKS/APPETIZERS	-3.600
BEVERAGES-SODA	-3.600
CREAM	-3.439
FRZN POTATOES/ONION RINGS	-3.360
TOYS/CARDS	-3.185
BAKERY-COMMERCIAL	-3.049
PARTY FAVORS/BALLOONS	-3.000
BAKERY-FRESH	-2.951
BAKING SUPPLIES/INGREDNTS	-2.902
SPREADS	-2.854
BEVERAGES-CREAMERS	-2.640
DIPS (RFG)	-2.481
SYRUP FLAVORNG (NON-BKFST)	-2.407
BEVERAGES-COFFEE	-2.320
PREPARED FOOD	-2.260
BEVERAGES-JUICE/DRNKS	-2.244
FRUIT SNACKS	-2.220
GRAVY/MARINADE/SAUCES	-2.140
SAUCES (RFG)	-2.049
FROZEN DINNERS/ENTREES	-1.926
SOUR CREAM	-1.880
SEASONAL	-1.880
BREAKFAST (FROZEN)	-1.778
SALAD DRESSING/TOPPINGS	-1.732
BEVERAGES-ISOTONICS	-1.560
DELI-PACKAGED	-1.520
BUTTER/MARGARINE/SPREADS	-1.512
SALTY SNACKS	-1.455
BEER & CIDER	-1.303
DOUGH (RFG)	-1.259
BREAD/DOUGH (FROZEN)	-1.222
ALL OTHER GENERAL MERC	-1.200
ICE CREAM TOPPINGS/CONES	-1.182
FRZN DESSERT/PIE/PASTRIES	-1.182
GELATN/PUDDNG SNCKS (RFG)	-1.152
NON-ALCOHOLIC BEER/WINE	-1.148
OLIVE/PICKLE/PEPPERS (RFG)	-1.000
ENTERTAINMENT	-0.909
SPICES/EXTRACTS	-0.900
BEVERAGES-HOT CHOCOLATE	-0.848
GELATIN/PUDDING	-0.788
CRACKERS	-0.727
PASTA (RFG)	-0.704
SOFT GOODS	-0.606
BEVERAGES (FROZEN)	-0.576
FRUITS (FROZEN)	-0.545

Grocery Category	Average *Should Minus Want* Score
BREAKFAST	-0.481
DRIED BREAD	-0.481
CONDIMENTS	-0.455
ICE	-0.444
BEVERAGES (RFG)	-0.364
DIET CARE	-0.280
FRUITS	-0.242
FILM/BATTERIES	-0.212
BEVERAGES-TEA	-0.185
AIR CARE	-0.182
SEAFOOD-FROZEN	-0.148
SOAP	-0.061
CHEESE	0.024
SEPTIC SYSTEM/SOFTNR SALT	0.030
BABY HEALTH	0.061
DELI-FRESH	0.061
AUTOMOTIVE	0.122
MEAT-FROZEN	0.140
PESTICIDES/BUG REPELLANTS	0.240
HOUSEWARES	0.364
MEAT/SEAFOOD	0.364
PASTA/GRAINS	0.488
MEDICATIONS	0.515
OFFICE/SCHOOL SUPPLIES	0.545
SKIN CARE	0.556
BABY FOOD	0.576
OIL/VINEGAR/COOKING WINE	0.593
BEVERAGES-WATER	0.606
SOUP	0.704
ALL OTHER DAIRY	0.732
BAGS/WRAPS/DISP CONTNRS	0.758
PET CARE	0.780
HAIR CARE	0.815
PRODUCE-VEGETABLES	0.939
MEAT-FRESH	0.940
YOGURT	0.980
SEAFOOD-FRESH	1.000
FAMILY PLANNING	1.200
PET CARE-CAT FOOD	1.300
INCONTINENCE	1.370
SHAVING NEEDS	1.407
PAPER	1.740
DISH CARE	1.880
PET CARE-DOG FOOD	1.976
DEODORANTS/ANTI-PERSP	2.037
EGGS/EGG SUBSTITUTES	2.146
EYE/EAR/FOOT CARE	2.268
BEVERAGES-SOY/RICE	2.296
LAUNDRY CARE	2.512
HOUSEHOLD CLEANERS	2.556
MILK	2.593
FEMININE CARE	2.700
VEGETABLES	2.704
PRODUCE-FRUITS	2.732
VEGETABLES (FROZEN)	2.829
VITAMINS	2.852
FIRST AID	2.900
ORAL HYGIENE	3.390

APPENDIX III: STUDY 2: ONLINE SURVEY

eGroceries is an online grocery delivery service. They offer all of the same grocery items that are offered in a normal grocery store. eGroceries users do their grocery shopping online, then choose a delivery date and time when a driver will deliver the groceries to their door.

Please imagine that you have decided to do your grocery shopping with eGroceries online site today. Imagine that you will have your food delivered to you **[tomorrow/in two days/in five days]**. This means that tomorrow your groceries will arrive at your house without you having to go to an actual grocery store.

In the following lines please list at least 10 items that you would order for delivery **[tomorrow/in two days/in five days]**:

…

Why would you order the items you listed above?

…

[NEW PAGE]

To what extent are the items you would order for delivery **[tomorrow/in two days/in five days]**intended for specific, planned meals (as opposed to being intended generally for having food around the pantry and refrigerator)?

1 - not at all for specific, planned meals

7 - entirely for specific, planned meals

To what extent are the items you would order for delivery **[tomorrow/in two days/in five days]** intended generally for having food around the pantry and refrigerator (as opposed to being intended for specific, planned meals)?

1 - not at all for generally having food around pantry and refrigerator

7 - entirely for generally having food around pantry and refrigerator

[NEW PAGE]

At eGroceries you can choose to have groceries delivered to you as soon as tomorrow, or as far into the future as several days.

We are interested in how the time until your groceries are delivered affects the extent to which you would order groceries for specific, planned meals.

Consider the following delivery schedules: delivery tomorrow, delivery in 2 Days, delivery in 5 Days.

For which delivery schedule would you purchase the MOST groceries for SPECIFIC, PLANNED MEALS?

Tomorrow

2 Days

5 Days

No Difference

[NEW PAGE]
Now, we are interested in how the time until your groceries are delivered affects the extent to which you would order groceries for generally having food around the pantry and refrigerator.

For which delivery schedule would you purchase the MOST groceries for GENERALLY HAVING FOOD AROUND THE PANTRY AND REFRIGERATOR?

Tomorrow
2 Days
5 Days
No Difference

[NEW PAGE]
We would now like to introduce you to two concepts. Please read the following carefully:

"Want" Groceries: A "want" grocery is one that someone would choose to consume for the pure enjoyment of it. There may be additional reasons for consuming the grocery - e.g., it may be healthy, but such reasons were not taken into account when determining the "want" score of the grocery. The "want" score is intended to reflect the extent to which someone's decision to consume this type of grocery would be indulgent and pleasure-based. Example of a strong "want" grocery: A tasty snack that most people would enjoy consuming.

"Should" Groceries: A "should" grocery is one that someone would feel compelled to consume. This might be because the grocery is expected to improve the consumer in some way - health-wise or otherwise. The "should" score reflects the extent to which someone's choice to consume the grocery would be made for virtuous, self-improving reasons, regardless of other potential factors. Example of a strong "should" grocery: A grocery that consumers feel compelled to consume for the long-term benefits - in other words, for reasons besides sheer pleasure.

Note that "want" and "should" groceries are not mutually exclusive - a grocery may receive both a high "want" score and a high "should" score

Now, we are interested in how the time until your groceries are delivered affects the extent to which you would order 'WANT' groceries.

When would you purchase MORE "WANT" groceries?

When purchasing groceries for generally having food around the pantry and refrigerator
When purchasing groceries for specific, planned meals
No Difference

When would you purchase MORE "SHOULD" groceries?

When purchasing groceries for generally having food around the pantry and refrigerator
When purchasing groceries for specific, planned meals
No Difference