FRACTIONING CHOICE UNDER TEMPTATION: CAN "ATTRIBUTE DISTORTION" BE THE MISSING LINK IN THE TEMPTATION-CHOICE TANDEM?

A Dissertation

by

SAMIR HUSEYNOV

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Chair of Committee,	Marco A. Palma
Committee Members,	Dmitry Vedenov
	Desmond Ng
	Alex L. Brown
Head of Department,	Mark Waller

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ABSTRACT

This dissertation work scrutinizes economic-decision making process when visceral feelings are present in the decision environment. I carefully model and study the role of attribute distortion, salience, self-control cost and attention in choosing high-quality and low-calorie food products. The first chapter of this dissertation shows that high price salience reduces the likelihood of purchasing high-quality, low-calorie food items at a price premium. I also find that income is an important factor that moderates this effect. The low-income group demonstrates similar purchasing behaviors regardless of the existence or the absence of price salience. However, in the absence of price salience (and distortion) in the decision environment, the high-income group is more likely to choose more expensive low-calorie foods. This effect vanishes when high-income consumers are exposed to environments with high price salience. In the second chapter of my dissertation, I document that the magnitude of the calorie distance between food items can explain the contradictory findings in previous literature regarding the impact of calorie labeling laws. The developed theoretical model suggests that the relative calorie difference between alternatives in food menus is a missing link important for understanding the impact of calorie labeling information on calorie intake and reconciling inconsistencies in previous findings. I implement laboratory and lab-in-the-field restaurant experiments where participants make incentivized food choices in binary menus. I exogenously manipulate the magnitude and saliency of the calorie distance between food alternatives. I find that providing accurate calorie information increases the likelihood of low-calorie choices by 3% and 10% in the lab and restaurant experiments, respectively. However, the menu-dependent calorie distance discounts the effect of information-provision. My findings suggest that a 100-calorie increase in the calorie distance between the food

alternatives reduces the probability of choosing the low-calorie alternative by 3%. My dissertation also demonstrates the importance of visual attention in attribute distortion and food choices. Findings suggest that equal salience of the calorie information of food alternatives does not alter the effect of the menu-dependent self-control cost. However, over-attention to any calorie information neutralizes the effect of the calorie distance or the menu-dependent self-control cost. This is important evidence to show that when a decision-maker experiences a trade-off and compares the calorie content of food products by spending the same fixation time on both alternatives, s/he is vulnerable to the menu-dependent self-control cost. In the case of disproportional attention to any product information, the decision-maker does not face the trade-off, and the effect of the menu-dependent self-control cost vanishes.

DEDICATION

To Mete and Atilla.

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CHAPTER I

INTRODUCTION

The Conventional Economics considers attention, attribute salience, temptation, self-control issues, and other decision process factors as peripheral elements of economic decision-making, hence these factors are not explicitly modeled vis-à-vis established economic concepts. Core models of economic choice (e.g., Expected Utility) and fundamental concepts (e.g., Weak Axiom of Revealed Preferences) are exclusively tuned to work with outcome data without any reference to the choice process itself. For instance, traditional models assume that economic agents possess "stocked" preferences, and economic decision-making is an instantaneous mapping from the preference space to the outcome space. Thus, under fundamental economic assumptions, decision outcomes are satisfactory for understanding preferences, and the decision process has been predominantly less relevant to economic research.

However, the economic decision-making process includes rich information that can provide more insights about "true" preferences. The recent advancement of biometric technology further enables researchers to map every millisecond of the economic decision-making process and incorporate seemingly"ephemeral" but actually relevant elements into core models of Economics. For instance, assume that an agent chooses an apple from the choice set C1=[apple, banana]. She also chooses the apple from the choice set C2=[apple, orange]. Now, the question is, "What will she choose if she faces choice set C3=[orange, banana]?"[1] This question cannot be answered if the researcher only has access to choice-outcome data. Suppose that in addition to choice outcomes, we also observe the time the agent spends making her decisions.Suppose that the consumer spent 10 seconds when facing C1, and she spent 2 seconds to choose the apple in C2. We can easily infer that the choice in C1 was harder compared to the trade-off in C2, and therefore the agent spent more time in C1. Thus, we

[1](see Krajbich et al.,2014 for a more detailed discussion)

can conclude that for the decision-maker, the decision value of the apple is closer to the value of the banana. Since she repeatedly chose the apple in both cases, we can use response times to infer decision values and predict that she will choose the banana from C3. This simple example shows how explicitly modeling "process data" can bring completely new insights into economic research. Understanding the decision process helps to identify decision biases and the circumstances in which they arise to improve the prediction of decision outcomes.

My dissertation explicitly accounts for choice-process specific variables and models those factors to better understand economic decisions, specifically food choices. **The second chapter** of my dissertation and its findings demonstrate that attribute distortion and salience have a significant impact on the quality of food choices. For example, I show that high price salience reduces the likelihood of purchasing high-quality, low-calorie food items at a price premium. I also find that income is an important factor that moderates this effect. The low-income group demonstrates similar purchasing behaviors regardless of the existence or the absence of price salience. However, in the absence of price salience (and distortion) in the decision environment, the high-income group is more likely to choose more expensive low-calorie foods. This effect vanishes when high-income consumers are exposed to environments with high price salience. Therefore, my findings present a new behavioral insight about income elasticity, which is important in projecting the effects of different market shocks (e.g., commodity price changes, tax hikes, subsidies, etc.) on consumer food choices.

The third chapter of my dissertation showcases that the magnitude of the calorie distance between food items can explain the contradictory findings in previous literature regarding the impact of calorie labeling laws. My theoretical model suggests that the relative calorie difference between alternatives in food menus is a missing link important for understanding the impact of calorie labeling information on calorie intake and reconciling inconsistencies in previous findings. I implement laboratory and lab-in-the-field restaurant experiments where participants make incentivized food choices in binary menus. I exogenously manipulate the magnitude and saliency of the calorie distance between food alternatives. I find that providing accurate calorie information increases the likelihood of low-calorie choices by 3% and 10% in the lab and restaurant experiments, respectively. However, the menu-dependent calorie distance discounts the effect of information-provision. My findings suggest that a 100-calorie increase in the calorie distance between the food alternatives reduces the probability of choosing the low-calorie alternative by 3%.

The third chapter of my dissertation also identifies the role of visual attention in attribute distortion and food choices. My findings suggest that equal salience of the calorie information of food alternatives does not alter the effect of the menu-dependent self-control cost. However, over-attention to any calorie information neutralizes the effect of the calorie distance or the menu-dependent self-control cost. This is important evidence to show that when a decision-maker experiences a trade-off and compares the calorie content of food products by spending the same fixation time on both alternatives, s/he is vulnerable to the menu-dependent self-control cost. In the case of disproportional attention to any product information, the decision-maker does not face the trade-off, and the effect of the menu-dependent self-control cost vanishes.

The last chapter concludes my dissertation and points to possible future research directions.

Overall, my dissertation enriches the attribute salience literature with insights based on process data from food choices. I successfully incorporate menu-dependent preferences into attribute salience models and show that this combined approach is more suitable in explaining self-control issues in food decision-making. Moreover, with the help of eye-tracking technology I quantify they role of visual attention, hence salience in food choices. Therefore, this work makes both theoretical and empirical contributions to the food choice literature.

CHAPTER II

DISTRIBUTIONAL EFFECTS OF PRICE SALIENCE ON RESERVATION WAGES AND FOOD CHOICES

The word Economics originates from the Greek term *oikonomia*, which means frugal use of household resources (Leshem, 2016). The representative agent of conventional economic models optimizes consumption decisions by carefully considering binding budget constraints. A plethora of empirical studies predominantly focus on the economic decision-making of poor households. See for example, Mani et al. (2013); Shafir and Mullainathan (2012); Shah et al. (2015, 2012). The extant literature documents that low income individuals engage in suboptimal and costly behavior. For example, low income individuals are less likely to save (Duflo et al., 2006), more likely to take on excessive and high interest debt (Amar et al., 2011), fail to enroll on welfare assistance programs (Currie, 2004), and have lower quality diets (Kuhn, 2018a,b). The current state of the relevant literature implicitly conjectures that relatively well-off households are less affected by financial concerns. However, even materially better provisioned households may face paycheck to paycheck scarcity and struggle to meet financial responsibilities and pay their bills (Rivlin, 2007). Living paycheck to paycheck can generate consumption cycles within a month triggering different economic choices at the beginning of the month (i.e. payday) compared to the end of the month. Crucially, previous literature documents changes in the economic behavior of low income individuals under *perceptional* scarcity environments (i.e. without shifts in income). We present compelling evidence that perceptional scarcity can have more general effects on the economic behavior of individuals across the income spectrum than previously considered.

We study the factors in the decision environment that trigger price conscious behavior and affect the demand for high-quality and discretionary goods. We build our work on a rapidly growing strain of literature which documents how the decision environment can change the relative weights decision-makers place on product attributes inducing changes in economic behavior.[2] For example, Bordalo et al. (2013) show that choice set specificities change the salience of the price attribute, and consequently can alter choice outcomes. The results of this emerging literature also suggest that salience of product attributes can be an important consideration for understanding consumer willingness to pay a price premium for low-calorie healthy food products. In this article, with the help of a controlled laboratory experiment involving real food purchases, we scrutinize the triad of salience, relative price changes, and low-calorie food choices. The United States has one of the lowest expenditures on food as a proportion of income, making food in general, and more specifically low-calorie healthy food expenditures very discretionary.[3] Our research question is relevant not only to the United States, but also to many low and middle income countries around the world experiencing an emerging growth in middle class households with increased purchase capacity and expected improvements in diet quality. Even though we study the effects of perceptional scarcity on food choices, our results have important implications for other goods beyond food. For example, perceptional abundance at the beginning of the month, when most households receive their paychecks, may result in higher likelihood of purchasing highly discretionary goods, such as restaurant visits, vacations and tourism, charitable donations, durable goods, etc.

We develop a theoretical framework for dichotomous choice situations by explicitly modeling induced price salience, the moderation effect of income, and the role of relative price changes in low-calorie food choices. In our model, we show that there exists a range of values for the weight consumers place on the price attribute, which induces individuals to choose a low-calorie more expensive product instead of a high-calorie and less expensive alternative,

[2]See for example, Thaler (1985); Tversky and Kahneman (1981); Thaler (1999); Bordalo et al. (2013, 2015, 2017); Chetty et al. (2009); Kőszegi and Szeidl (2012); Gabaix (2014); Hastings and Shapiro (2013); Chetty et al. (2009); Goldin and Homonoff (2013); Bushong et al. (2015); Gabaix (2017); Herweg et al. (2018); Kıbrıs et al. (2018); Finkelstein (2009); Ellis and Masatlioglu (2019); Dertwinkel-Kalt and Köster (2017); Dertwinkel-Kalt et al. (2017).

[3]See https://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=76967

and this behavior is highly correlated with income. Our theoretical model also predicts that when prices are highly salient, decision-makers are more likely to choose the high-calorie and less expensive alternative. Although secondary data sources can be used to study food consumption cycles, food carries strong homegrown preferences that are highly correlated with income. An experimental approach has the distinctive advantage of enabling the random assignment of different levels of price salience while controlling all other factors that drive food choices, including relative prices. Our experimental design enables us to capture the causal relationship between induced price salience, relative prices and food choices.

We conduct a between subject laboratory experiment where participants are randomly assigned to one of three experimental conditions: *No Price-Salience*, *Low Price-Salience* (where financial resource abundance is induced), and *High Price-Salience* (where financial resource scarcity is induced). Our research design enables us to differentiate four consumption behaviors: *health-seeking*, when consumers are willing to pay a price premium to buy more expensive low-calorie food products (as it is the case for most products in treatments); *health-conscious*, when consumers are willing to buy the low-calorie food item only when it has the same price as the high-calorie alternative; *cost-minimizing*, when consumers always prefer the least expensive alternative; and *pleasure-seeking*, when consumers are willing to pay a premium price to buy high-calorie (tasty) food products.[4] For each experimental condition, participants go through two Multiple-Price-List (MPL) tasks with 11 food choice sets in each. In each MPL, the relative prices of food products are exogenously changed across choice sets by decreasing (increasing) the price of the low calorie food item in \$0.50 increments. Participants are informed that one of the 22 food choice sets will be randomly selected as binding at the end of the study. For the binding decision, participants have to pay the price of their chosen product.

[4]We are not claiming that high-calorie food items are always tasty. However, in this article, we carefully selected food items that were used in previous experimental studies as hedonic products (see, for example, Shiv and Fedorikhin (1999)). The high-calorie food products in our study are associated with high temptation and with low diet quality. Therefore, throughout the paper, we use the terms low-calorie (high-calorie) and high-quality (low-quality) interchangeably.

After completing the incentivized food choices, and before randomly determining the binding MPL decision, subjects participate in a real effort task, which allows them to potentially offset their food expenses. In this task, subjects go through 11 questions in a MPL and reveal their reservation wage for supplying their labor for a real effort task to offset their food expenses using the strategy method of recording their preferences for every possible binding price. Since, the MPL technique for the real effort task is completed before the determination of the binding food price, our design is incentive compatible, and it enables us to elicit each participant's true reservation wage for their labor supply for different price salience levels.[5]

We find that inducing high price salience decreases the probability of exhibiting a health-seeking behavior compared to the control. This result means that when participants are reminded about financial hardship constraints, they are less likely to pay a premium to buy low-calorie healthy items. Additionally, the high-income group has a higher likelihood of exhibiting health-seeking and health-conscious behavior. However, the analysis of the decisions of high-income participants across the experimental conditions reveals that the difference between the No Price-Salience and High-Price Salience conditions is mainly driven by the high-income group. High-income subjects align their consumption decisions with low-income participants when they are induced with a financial hardship condition. Interestingly, after being exposed to the financial constraints in the Low Price-Salience condition, high-income subjects display the same behavior and reduce their willingness to pay a price premium to buy low-calorie food items. Individuals in the low-income group do not change their behavior in response to the exogenous manipulation of price salience. These results suggest that price may always be salient for low-income participants, and they have little room to make adjustments in response to price salience environments (Darmon and Drewnowski, 2008).[6] However, the fact that the high-income group is very responsive to price salience

[5]The details of the design are presented in the experimental section.

[6]A similar ceiling effect has also been documented in the SNAP benefits take-up rates (Finkelstein and Notowidigdo, 2019).

and eventually mimics the low income group suggests that future studies should also focus on the food decisions of middle and upper-middle income households. Our findings show that medium and upper middle income groups are highly susceptible to changes in the decision environment and switch to high-calorie low-quality food products. Recent reports show that the obesity rate among middle-income households is similar or higher than low-income households in the United States (Ogden et al., 2017). Being ineligible for most social welfare programs may leave middle-income households vulnerable to changes in the economic environment than can significantly affect their diet quality. Our results suggest that this group can be highly responsive to behavioral nudges that change the decision environment to improve diet quality.

As expected, participants react to changes in the relative prices of low- and high-calorie food products. In the current market conditions, low-calorie food is more expensive than high-calorie food (De Quervain et al., 2004). In our experiment, when the price was the same, almost 80% of the selections were low-calorie healthy options. Price discounts of around 20% resulted in over 95% low-calorie food choices. This result provides useful information for the design of nutrition assistance programs and tax or subsidy policies.

We also document that high-income participants have a higher reservation wage to perform a real effort task to compensate their food expenses compared to low-income participants in the No Price-Salience condition. When induced with price salience, high-income participants reduce their reservation wage to the same level as the low-income group. Overall, our findings show that only the high-income group reacts to induced price salience by reducing their willingness to pay for low-calorie products and their reservation wage for labor supply to cover their food expenses. This finding presents a new perspective to the well-developed labor economics literature which predominantly focuses on labor supply decisions of welfare program participants (Finkelstein and Notowidigdo, 2019; Hoynes and Schanzenbach, 2012; Fernandez and Saldarriaga, 2013; Deshpande, 2016a) and our results suggest that inducing financial hardship constraints can also affect labor supply decisions of the labor force with relatively higher incomes.

One of our main contributions to the literature is that we develop a new protocol based on Mani et al. (2013) to induce price salience before economic agents make real food purchases. Haushofer and Fehr (2014) and Mani et al. (2013) argue that in addition to changes in prices and income, salience of financial hardship can change the relative importance of key decision attributes. This aspect of our research design helps us to introduce a new angle on price salience, which has been predominantly explored via price changes in previous economics literature (Bordalo et al., 2013). In addition, by exogenously changing relative price differences between the low- and high calorie products, we capture the interaction effects of induced price salience with food expenditures. In this regard, our study speaks to empirical economic studies, which show that modifications to the Supplemental Nutrition Assistance Program (SNAP) disbursement schedules may generate consumption cycles within a benefit month and change the salience of food prices (see for example, (Kuhn, 2018a; Cotti et al., 2018; Kuhn, 2018b; Beatty et al., 2019)). It is conceivable to think that food expenditures at the beginning of the month, when most people receive their paychecks, may differ from expenditures at the end of the month when income constraints are more pronounced (Stephens Jr, 2003; Carvalho et al., 2016). In fact, Kuhn (2018b) shows that toward the end of a benefit month, presumably because of higher financial constraints, SNAP users become more price-sensitive and primarily buy low-quality, unhealthy, and less expensive food products. Using food products with salient hedonic attributes helps us to bring insights from the consumer psychology literature, which documents that food choices are mainly driven by hedonic attributes when decision-makers are mentally preoccupied (Shiv and Fedorikhin, 1999, 2002). Finally, previous studies provide insights about the effects of affective states on food choices (Argyle, 1989; Amabile et al., 2005; Graham et al., 2004; Lyubomirsky et al., 2005), participation in welfare programs (e.g., Yelowitz (1995); Hoynes et al. (1996); Eissa and Liebman (1996); Moffitt (2002); Blundell et al. (2016)), and influence of the decision environment (Imas et al., 2016; Lakdawalla and Philipson, 2007; De Quidt, 2017; Angrist and Evans, 1998; Field, 2007) in contract choices, effort level and labor supply. Moreover, some studies find that welfare programs affect the number of hours worked (Deshpande, 2016b; Gelber et al., 2017; Deshpande, 2016a; Finkelstein and Notowidigdo, 2019; Hoynes and Schanzenbach, 2012; Fernandez and Saldarriaga, 2013; Goodman-Bacon, 2016). Surprisingly, little is known about how induced price salience influences labor supply. We offer a compelling research design to scrutinize this link via an incentivized real effort task after inducing price consciousness and real food purchases.

2.1 Related Literature

Scarcity of resources and budget constraints constitute the central building block of economic modeling. Conventional economic models predominantly focus on monetary constraints and the consequences of income shocks (Wales and Woodland, 1983; Wilcox, 1989; Hayashi, 1985; Shapiro and Slemrod, 2003; Bernanke, 1985). However, recent findings suggest that not only real monetary constraints, but also inducing thoughts of scarcity of financial resources can change the economic behavior of agents (Haushofer and Fehr, 2014; Mani et al., 2013).

Monetary concerns force agents to pay more attention to every detail of daily financial transactions. For example, Spears (2011) shows that the poor face more difficult trade-offs in their purchasing decisions compared to the rich. Limited monetary resources make basic utility payments challenging, bring opportunity costs into the decision-making process, and consequently magnify the mental resources needed even for small financial transactions (Shah et al., 2012, 2015; Spiller, 2011). Significant mental costs of scarcity burden poor people with a higher cognitive workload and consequently affect economic decisions (Shah et al., 2015; Adamkovič and Martončik, 2017; Vohs, 2013; Deck and Jahedi, 2015; Dalton et al., 2017).

Decision constraints may also direct the attention of decision-makers to more salient information (Haushofer and Fehr, 2014). Recent studies show that the decision environment may divert the focus of consumers to a small subset of choice attributes and consequently change economic decisions (see, e.g., Gabaix et al. (2006); Bordalo et al. (2013); Kőszegi and Szeidl (2012); Taubinsky and Rees-Jones (2017); Allcott and Kessler (2019); Palma (2017); Königsheim et al. (2019); Huseynov et al. (2019b)). We expect that monetary concerns affect economic choices by making price the salient attribute and consequently increasing the attentional focus to it (Shah et al., 2012). If price is salient, then decision-makers will focus more on the price attribute, and will try to minimize their expenditures.

2.2 Paycheck to Paycheck Consumption

Monetary concerns can nullify the expected positive effects of welfare assistance programs. Recent studies have increasingly documented the impact of consumption cycles generated by payment schedules on the economic behavior of low-income households. On this regard, the Supplemental Nutrition Assistance Program (SNAP) disbursement schedules have been extensively scrutinized (see, e.g., Carr and Packham (2019); Kuhn (2018a); Cotti et al. (2018); Kuhn (2018b); Lovett (2018); Beatty et al. (2019); Todd and Gregory (2018)). Monthly SNAP benefits are usually transferred to program participants during the first half of the month (Carr and Packham, 2019). Previous literature shows that SNAP users have difficulties smoothing consumption, and they often use most of the program benefits during the first half of the month (Todd, 2014). Consequently, overspending in the first half of the month leaves limited funds remaining for the rest of the consumption period (Smith et al., 2016; Hamrick and Andrews, 2016). Notice that high and low consumption periods of SNAP users do not change the total amount of available funds for the benefit month. We argue that, the perceptional abundance of monetary resources during the first half of the month and consequential perceptional scarcity of material resources experienced during the rest of the benefit period may influence the economic behavior of program participants. Kuhn (2018b)'s findings empirically confirm this proposition and show that SNAP cycles can generate food insecurity and overconsumption of high-calorie and unhealthy foods toward the end of the benefit month. With the help of a field study, Mani et al. (2013) explore similar consumption cycles generated by sugarcane harvests in rural India, and the authors find that villagers demonstrate a higher cognitive performance right after the harvest (i.e., when they face abundance of financial resources) compared to before the harvest (i.e., when they experience material scarcity).

Over the last decade, the relationship between scarcity of financial resources and cognitive performance has attracted a great deal of attention (see, e.g., Shah et al. (2012); Mani et al. (2013); Haushofer and Fehr (2014); Shah et al. (2015); Carvalho et al. (2016)). This literature reports that monetary concerns induce negative feelings which impede the cognitive performance, and consequently affect economic decisions (Mani et al., 2013; Haushofer and Fehr, 2014). In consumer research, cognitive function has been extensively modeled as a crucial mechanism that transmits or moderates the effect of visceral feelings, such as mood, affect and emotions (see, e.g., Bettman et al. (1998); Shiv and Fedorikhin (1999); Drolet and Frances Luce (2004)). In their seminal paper, Shiv and Fedorikhin (1999) show that when cognitive resources are constrained, hedonic food alternatives are chosen more frequently. Hedonic consumption has also been linked to negative emotions, credit card overspending, and other suboptimal behaviors (Dubé et al., 2005; Thomas et al., 2010; Shiv and Nowlis, 2004; Kemp et al., 2013).

2.3 Abundance of Financial Resources

Contrary to financial concerns, abundance of material resources has been understudied. The literature reports a limited number of findings on the effect of abundance of financial resources on decision-making. Shah et al. (2012) suggest that the state of abundance is also important and it needs to be studied. Roux et al. (2015) urge researchers to explicitly model and analyze how consumers change their decisions in response to abundance-related situations. There is evidence that abundance can trigger different *neural* mechanisms compared to scarcity. Huijsmans et al. (2019) find that abundance is associated with more activation in the dorsolateral prefrontal cortex region of the brain - which is associated with a goaldirected choice. Some studies link abundance to unethical behavior (Gino and Pierce, 2009), violence (Koren, 2018), attention to central attributes of products (Hansen et al., 2012), being less helpful to others (Vohs et al., 2008), cheating for others (Aksoy and Palma, 2019), and showing increased persistence (Vohs et al., 2006). There is also evidence that scarcity induces too much engagement with certain attributes, therefore, it is reasonable to expect that abundance may induce less engagement with the same attributes (Shah et al., 2012, 2015). For instance, if economic agents are more preoccupied with money when they face scarcity, they should be less preoccupied with financial issues in a state of abundance (Mullainathan and Shafir, 2014; Gennetian and Shafir, 2015). Perceptional abundance can also affect food choices. For instance, showing a picture of a stack of money results in less enjoyment of eating a chocolate (Quoidbach et al., 2010). Similarly, Laran and Salerno (2013) find that inducing people with thoughts of abundance makes them more likely to choose a garden salad more frequently than cupcakes. Zhu and Ratner (2015) show that when induced with abundance, subjects chose a lesser amount of their most preferred yogurt and vegetables compared to a scarcity condition.

2.4 Price Salience

One of the important mechanisms studied in related studies is that when prices increase, the quality attribute becomes more salient and some consumers frequently choose high-quality and expensive products compared to the state before the price hike. Hastings and Shapiro (2013) study parallel price increases in the U.S. gasoline market and provide evidence that the income effect cannot explain this behavior.[7]

[7]The change of the relative salience of choice attributes has also been explained by the "range effect". Kőszegi and Szeidl (2012) model the source of salience as the attribute dimension that places the alternatives on the edges of a large range of values. Bushong et al. (2015) predict that in large ranges of attribute values, fixed differences might seem unimportant. On the other hand, Bordalo et al. (2013) show that the salience of an attribute arises in comparison with the "average attribute" level of the choice set. Bondi et al. (2017) offer a good example to portray predictions of Kőszegi and Szeidl (2012) and Bushong et al. (2015). When choosing between living in Los Angeles and Chicago, decision-makers may over-focus on the weather attribute in which Los Angeles stands out, but they forget other dimensions such as cost of living and job prospects (Kőszegi and Szeidl, 2012). Since in this decision context, the weather attribute has a large range of values, the difference between Chicago and New York along this dimension might seem negligible (Bushong et al.,

Some experimental studies have also analyzed the salience of attributes in consumer choices by exogenously varying price levels.[8] This emerging line of research mostly employs parallel price changes (i.e., proportionally changing relative prices in the same direction) and/or vertically differentiated products (e.g., Internet services with low- and high-speed, smartphones from different brands). In reality, relative prices also change, such as retail store sales on high-quality products (Ortmeyer et al., 1991), or surcharges (or sin taxes) on unhealthy food items (Shah et al., 2014). Moreover, in the consumer psychology literature, some studies have established a link between salience and hedonic food choices, where the choice alternatives are not close substitutes and consumers may have strong preferences for one of the alternatives (Elder and Mohr, 2016; Huang and Wyer Jr, 2015). Therefore, the relationship between exogenously manipulated price salience, relative prices changes, and hedonic food choices is an under-addressed research inquiry in economics.

We conclude the literature review by highlighting that the aforementioned studies provide support to the notion that real and induced mental monetary concerns and feelings of scarcity or abundance of material resources can affect economic decision making.

2.5 The Price Salience Theoretical Model

We develop our theoretical model building from the salience model developed by Bordalo et al. (2013). We focus on a case where agent i chooses one of two available alternatives in $X \equiv \{a, b\}$ and each product has two decision attributes, quality and price, $X \equiv \{(q_a, p_a), (q_b, p_b)\}$, respectively. We also assume that $\mathscr{X} = \{X_1, X_2, ..., X_n\}$ is a set of binary choice sets.

In this model, q and p denote the quality and price of the product, respectively. The

2015). Hence, when the choice set includes Los Angeles, Chicago, and New York, the decision-maker may prefer New York, even when it is not the optimal choice.

[8] See for example, Azar (2011); Dertwinkel-Kalt et al. (2017); Somerville (2019). Most of the empirical studies in this literature, explore salience in financial decisions (See Beshears et al. (2018) for a review of the relevant studies).

following weighted linear utility function represents the net utility, that agent i derives from consuming product k:

$$V_k = (1 - w_p)q_k - w_p p_k \tag{1}$$

where, decision weights are non-negative and we normalize the sum of the weights to one. We assume that the weights agents assign to each product attribute is a function of individual characteristics, and they do not change across decisions in $\mathscr{X}$.

Definition 1: 1.1 When attribute salience is not present in the decision environment, the agent assigns equal weights ($w_p = 0.5$) to the price and quality attributes of product k.

1.2 If the quality or price is salient in the decision environment, the utility function will have unequal decision weights with the following relative magnitudes, $w_p < 0.5$ (low price salience), and $w_p > 0.5$ (high price salience), respectively.

1.3 If the agent has a lexicographic preference, then she has either $w_p = 0$, or $w_p = 1$. When $w_p = 1$ ($w_p = 0$), the agent makes her decisions solely considering the price (quality) attribute of product k.

Definition 2: The weight of price is a symmetric and continuous function $w_p(\cdot)$, with ordering property. Let $\gamma \in \{0, 1\}$, and $\gamma = 1$ if the agent has a low income level, and $\gamma = 0$ if the agent has a high income level. Then by using the ordering property we can get $w_p(\gamma = 0) < w_p(\gamma = 1)$ for any price weight.

For any $X \in \mathscr{X}$, we can formulate the choice correspondence induced by (1) as $C(X) = argmax_{a \in X}[(1 - w_p)q_a - w_p p_a]$. Then $C(X) = \{a\}$ if $(1 - w_p)q_a - w_p p_a > (1 - w_p)q_b - w_p p_b$.

Assume $\varepsilon \sim F$ is symmetric with zero mean. We also assume that F is an increasing function. Then, because of the symmetry of F around zero:

$$Pr[C(X) = \{a\}] = Pr[((1 - w_p)q_a - w_p p_a) - ((1 - w_p)q_b - w_p p_b) + \varepsilon > 0]$$

$$= F((1 - w_p)q_a - w_p p_a) - ((1 - w_p)q_b - w_p p_b)) \quad (2)$$

Remark 1: 1.1 If there is no salience and the decision maker assigns equal weights to each attribute ($w_p = 0.5$), then according to our choice correspondence, $C(X) = \{a\}$ if $q_a - p_a > q_b - p_b$. This relationship shows that the agent prefers a if the unweighted relative gain from quality is higher for a compared to b.

1.2 If the agent has a lexicographic preference and $w_p = 1$ (or $w_p = 0$), then $C(X) = \{a\}$ if $p_a < p_b$ (or $q_a > q_b$). Thus, lexicographic preferences can be captured as a special case of our general model.

1.3 If attribute salience is present in the decision environment, then the relative magnitudes of weights affect which product will be chosen by agent i.

$$(1 - w_p)(q_a - q_b) - w_p(p_a - p_b) > 0 \quad (3)$$

The main difference between our model and the salience model of Bordalo et al. (2013) is that we do not explicitly model which choice alternative has a higher quality. Thus, we do not rely on the comparison of quality/price ratios of the alternatives. We assume that q is valued based on idiosyncratic individual preferences and we fix the decision alternatives in $\mathscr{X}$. This is a reasonable assumption for food products, in which consumers have strong homegrown preferences. We infer the relative quality difference of alternatives by exogenously changing the relative price difference across choice sets. Moreover, we assume that when the agent makes choices in the multiple price list schedule, she already has pre-determined (homegrown) weights for the choice attributes. Therefore, in our model, attribute weights are modified before the choice task.

Suppose, the agent prefers alternative a in X. Then according to our linear utility function we define, ***Lemma 1***:

1.1 If $p_a = p_b$, then from the agent's perspective, product a is qualitatively superior to product b. Intuitively, if the price of product a and product b is the same, the agent's choice reveals which of the products has a superior quality to the agent.

1.2 a) If $p_a < p_b$, then the term $-w_p(p_a - p_b)$ increases the magnitude of the utility of choosing product a. If price has high salience ($w_p > 0.5$), then the term $-w_p(p_a - p_b)$ contributes more to the magnitude of the net utility. b) Conversely, this contribution is discounted if $w_p < 0.5$. c) Moreover, as the magnitude of $p_a - p_b$ shrinks, the agent bases her decision predominantly on the magnitude of the term $(1 - w_p)(q_a - q_b)$.

1.3 If $p_a > p_b$, then the magnitude of $(1-w_p)(q_a-q_b)$ should be high enough to compensate for the negative effect of the price difference. In other words the agent is willing to pay a price premium to obtain the product with her revealed higher quality.

Remark 2: 2.1: One important conclusion from Lemma 1 is that when the price of a is equal to the price of b, the agent exhibits her true preference.

2.2: Another conclusion is that if we fix the relative quality difference in $\mathscr{X}$, then by exogenously changing the relative price difference between product a and product b, we can infer the relative quality difference the agent assigns to each choice alternative.

Definition 3: (*Constant-Relative-Quality*) If $X, X' \in \mathscr{X}$, with $X \equiv \{(q_a, p_a), (q_b, p_b)\}$ and $X' \equiv \{(q_a, p'_a), (q_b, p'_b)\}$, then these choice sets have *constant-relative-quality.* Notice that in the *constant-relative-quality* choice sets, choice decisions are driven by relative price changes.

Proposition 1: Assume that $p_a - p_b < p'_a - p'_b < 0$ in *constant-relative-quality* choice sets, where $q_a < q_b$ is also true. Notice that when $q_a < q_b$ and $p_a > p_b$, the decision outcome is trivial. When the low-quality alternative a is more expensive or the high quality alternative b is less expensive, then the agent will choose b. Then for every $\triangle_q = q_a - q_b$ there exists at least one non-zero value of w_p that will induce the agent who preferred a in X to prefer b in X'.

Proof: See the proof of Proposition 1 in Appendix A.

Proposition 1 shows that when we fix the choice alternatives across choice sets in $\mathscr{X}$ and we only exogenously change the relative price differences between product a and product b, for each quality difference level, there exists a range of the decision weight for the price attribute that will cause an agent to switch from one of the alternatives to the other without experiencing a sign change for the relative price difference. This conclusion means that for certain values of the price weight and relative price changes, the decision maker will switch from the low-quality and lower price product to the high-quality and higher priced product.

By following the steps in the proof, it can be easily shown that for $q_a > q_b$ and $p'_a - p'_b > p_a - p_b > 0$ and for *constant-relative-quality* choice sets, there exists a certain range of w_p that induces the agent who chose a in X to choose b in X'.

Remark 3: In *constant-relative-quality* choice sets, if an agent chooses the low-quality and lower price (high-quality and higher price) alternative a in X, then for every relative price decrease (increase) there exists a price salience weight that will induce switching from a to b in X'.

Proposition 2: For *constant-relative-quality* choice sets $X, X' \in \mathscr{X}$, with $X \equiv \{(q_a, p_a), (q_b, p_b)\}$ and $X' \equiv \{(q_a, p'_a), (q_b, p'_b)\}$, among the agents who choose a in X, high-income agents will be more likely to choose b in X' compared to low-income subjects.

Proof: See the proof of Proposition 2 in Appendix A.

Proposition 2 shows that high-income agents are more likely to choose a in X and b in X' compared to low-income agents.

Let's introduce $\psi(\cdot,\cdot) > 0$, which is a strictly increasing continuous function. The function $\psi(\cdot,\cdot)$ illustrates how the salience of attributes increases depending on the economic decision environment. We assume that in some decision contexts the agent experiences high price salience without experiencing price and/or income changes. For example, in Mani et al. (2013) inducing thoughts of financial constraints significantly affected the behavior of participants without any changes to price or income.

Definition 4: Let $\lambda \in \{0,1\}$, and $\lambda = 1$ if the agent is in a *high price salience* state, and $\lambda = 0$ otherwise. Then:

$$\psi(\lambda = 1, w_p) > \psi(\lambda = 0, w_p) \tag{10}$$

Let $C(x)$ be the choice correspondence introduced in (1), without loss of generality, will obtain this form $C(X,\lambda) = argmax_{a\in X}[(1-\psi(\lambda,w_p))q_a - \psi(\lambda,w_p)p_a]$. Then $C(X,\lambda) = \{a\}$ if $(1-\psi(\lambda,w_p))(q_a - q_b) > \psi(\lambda,w_p)(p_a - p_b)$. Since F is an increasing function and it is symmetric around zero, then:

$$Pr[C(X,\lambda) = \{a\}] = Pr[(1-\psi(\lambda,w_p))(q_a - q_b) - \psi(\lambda,w_p)(p_a - p_b) + \varepsilon > 0]$$

$$= F((1-\psi(\lambda,w_p)(q_a - q_b) - \psi(\lambda,w_p)(p_a - p_b)) \tag{11}$$

Proposition 3: For the same choice sets (where $q_a < q_b$ and $p_a - p_b < 0$ are true), if the agent is in a *high price salience* state, then she will have a higher probability of choosing a compared to the agent who is not in *high price salience* state.

Proof: See the proof of Proposition 3 in Appendix A.

Remark 4: Based on Proposition 3, one can easily show that, for the same choice sets (where

$q_a < q_b$ and $p_a - p_b < 0$), if the agent is in a *low price salience* state, then she will have a higher probability of choosing b compared to the agent who is not in a *low price salience* state.

2.6 Experiment

2.6.1 Subjects

A total of 170 subjects (non students) from the Southwestern United States were recruited to participate in the experiment in January of 2018. The recruitment was done through advertisements in local newspapers. Bulk recruitment emails were also sent to community members in our subject database. To qualify for the study, participants had to be at least 18 years old and not have a history of any eating disorder and/or dietary restrictions. Nine sessions were conducted through the course of three consecutive days. Participants received a $25 compensation fee minus the cost of any food purchases they made during the experiment.

2.6.2 Video Stimuli and Price Salience

The experiment consisted of a between-subjects design, in which participants were randomly assigned to one of three experimental conditions: 1) No Price-Salience, 2) Low Price-Salience, and 3) High Price-Salience. We conducted three sessions per day. Sessions started at 9 am, 12 pm, and 3 pm, and each session was only dedicated to one of the experimental conditions. We randomized the order of the experimental conditions across sessions. Figure 2.1 displays the procedures and the timeline of the experiment.

In the Low Price-Salience condition (n = 50), subjects watched a 5-minute video showcasing financial resource abundance. The video depicted a shopping frenzy, where participants had to fill their shopping carts with products within a specified time limit and without paying attention to price tags. Subjects in the High Price-Salience condition (n = 63) were induced to think about everyday financial demands by watching a 5-minute video about financial

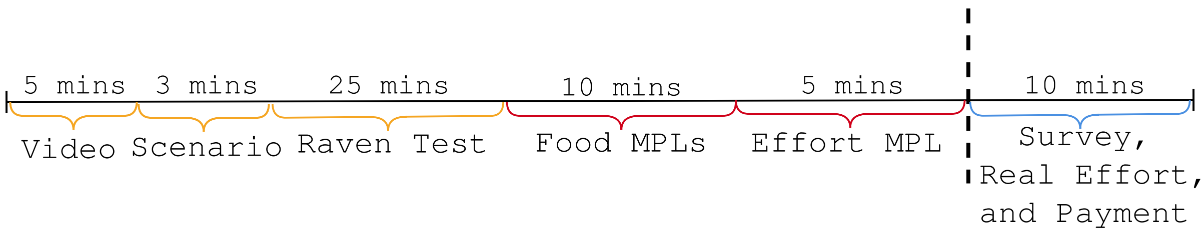


Figure 2.1: Procedures and timeline of the experiment.

Notes: a) The allocated time for the Raven test was 25 minutes and it was strictly enforced, b) The other tasks were not time-restricted, and this figure showcases the average amount of time subjects spent on those tasks, c) The dashed line represents the random determination of the binding choice set.

problems of poor households in the United States. The video part of our design resembles the video stimuli employed by Dalton et al. (2017). Finally, in the No Price-Salience condition (n = 57), subjects were exposed to a 5-minute neutral video at the beginning of the session. The neutral video resembled a computer screen-saver. The purpose of the neutral video was to expose subjects to a visual stimulus with the same amount of time as in the other conditions, but without any meaningful content, and by this way aligning the control condition with the treatments.

After watching their assigned videos, subjects in the High and Low Price-Salience conditions went through price-salience hypothetical scenarios of financial hardships. We used the hypothetical scenarios from Mani et al. (2013) with some minor modifications. In the High Price-Salience condition, we used the scenario of the Hard condition in Mani et al. (2013) without any changes. Mani et al. (2013) report that the scenario of the Hard condition induced monetary concerns and this effect was severe for relatively poor subjects in their study compared to relatively rich subjects (separated by median income). We expected that the video stimulus and the financial hardship scenario in the High Price-Salience would increase the salience of the price attribute. However, we replaced the words associated with financial hardships in the scenario of the High Price-Salience treatment with their antonyms to use in the Low Price-Salience condition. For instance, to induce feeling of abundance of financial resources, we replaced "an unforeseen event requires of you an immediate $2,000 expense" with "an unforeseen lottery win gives you a $2,000 gain" in the scenario of the Low Price-Salience condition. The scripts are available in the Appendix A. We expect that the video stimulus and the scenario of the Low Price-Salience treatment will make the price (quality) less (more) salient.

The session monitor read the scenarios out loud following the scripts in the Low and High Price-Salience conditions, and then asked subjects to reflect on the scenarios for three minutes. In the No Price-Salience control condition, the session monitor waited three minutes to time-wise align this condition with the treatments.

2.6.3 Experimental Design and Procedures

After watching their assigned video (and also going through the scenarios in the Low and High Price-Salience conditions), subjects completed a cognitive performance task that included 24 problems from the Raven's Progressive Matrices test (Raven, 2000; Segovia et al., 2019). This test is commonly used to measure fluid intelligence independent of acquired knowledge. Each problem consisted of a 3x3 matrix with the bottom right figure missing. Subjects were asked to choose from a set of 8 alternatives, which figure fitted the overall pattern of the matrix. This task had a time limit and subjects were allowed to spend 25 minutes to complete it. Before starting the test, the session monitor went through several examples to make sure participants had a clear understanding of the instructions.

The Raven's test task enabled us to control the possible cognitive impairments due to our induced price salience treatments, which has been documented by Mani et al. (2013). After solving the Raven's test, participants completed two Multiple-Price-Lists (MPL) tasks, one with food items and the other one with beverage products.[9] In one of the food MPL tasks, we followed Shiv and Fedorikhin (1999) and asked subjects to choose either a chocolate cake or a salad. In the other food MPL task, the choice trade-off was between a 16.9 ounces bottle of Fiji water and a 20.0 ounces Coca Cola bottle.

Each food MPL task consisted of 11 binary choices. In each choice question, participants had to choose between two food products with varying prices. Each choice decision was presented separately. A recent study by Brown and Healy (2018) shows that separately presenting MPL choices may enhance the incentive compatibility of MPL designs. Before the MPL task, subjects were informed that the food choices were real, and one of their choices would be randomly implemented and participants would pay for their selected product and receive it at the end of the experiment. Thus, the food MPLs were incentivized.

In Appendix A, Figure A1 panels (a) and (b) depict the first questions from the food MPLs. Table 2.1 shows how the relative prices of the products change across the food MPL rows. In the first choice question of the food MPLs, product A was free (i.e., $0) and product B was $5.0.[10] If a decision-maker switches from product A to product B in the first choice question of the MPLs, it indicates that the agent is willing to pay $5.0 to buy a bottle of Fiji water or a salad instead of getting a coca-cola or a chocolate cake for free. It also shows that the decision-maker is willing to incur an additional $5.0 expense to buy a low-calorie food product. Similarly, if the decision-maker switches from product A to product B in the second question, he is willing to pay a $4.0 premium to buy a low-calorie food item. Accordingly, switching in the sixth choice question, where the price of product a and product b is identical ($2.50), indicates that the decision-maker only prefers to buy a bottle of Fiji water or a salad when the price of the low-calorie and high-calorie products are the same. Notice that the choice in the sixth choice question of the MPLs reveals the agent's true preference when the

[9] We refer to these MPLs as food MPLs in Figure 2.1 and the rest of the article.

[10] In the food MPLs, the product in the left always started with a price of $0, it was the same ($ 2.50) in decision 6, and it reached the price of $5.0 in the final choice question. However, we randomized the place of the low-calorie (a salad and a bottle of Fiji water) and high-calorie (a chocolate cake and a bottle of Coca Cola) products. For half of the subjects the low-calorie item was on the left and vice versa for the other half.

Table 2.1: Choice questions of Multiple Price Lists.

1)	Produt A ($0)	Product B($5.0)
2)	Produt A ($0.5)	Product B($4.5)
3)	Produt A ($1.0)	Product B($4.0)
4)	Produt A ($1.5)	Product B($3.5)
5)	Produt A ($2.0)	Product B($3.0)
6)	Produt A ($2.5)	Product B($2.5)
7)	Produt A ($3.0)	Product B($2.0)
8)	Produt A ($3.5)	Product B($1.5)
9)	Produt A ($4.0)	Product B($1.0)
10)	Produt A ($4.5)	Product B($0.5)
11)	Produt A ($5.0)	Product B($0)

price attribute does not play a role in the purchasing decision. Switching at the seventh choice indicates the consumer minimizes the expenditures (Lemma 1). Switching after the seventh choice question suggests that the decision-maker is willing to pay a price premium to buy the high-calorie food item, perhaps because of an implied difference in perceived flavor.

One of the food MPLs and one choice decision were randomly selected to be the binding food MPL and choice question at the end of the experiment. Subjects had to purchase the product they chose in the binding decision. Notice that, the binding price was individual-specific. For instance, if the second choice question was selected as binding, then the binding price was $0.5 for subjects who selected product A, and $4.5 for subjects who selected product B. Note that the binding round was not selected until the end of the experiment. This is an important design feature for the next part of of our experimental design.

Once the two food MPLs were completed, subjects were given the opportunity to offset the cost of their purchases by performing a real effort task. The real effort task consisted of copying one paragraph from Charles Dickens's popular novel "A Christmas Carol".[11] This

[11]Five minutes was enough to accomplish this task. The expected earning was $2.50 for completing a 5-minute task. This translates into a $30-payment for an hour - which significantly exceeds minimum-wage levels across the United States.

part of the experiment, was only revealed to subjects after they completed their decisions in both food MPL tasks, and before the randomization to reveal the binding food MPL and the choice question. Figure A1 panel (c) depicts the effort MPL that was used to elicit subject's willingness-to-work to offset the cost of their purchases at all possible price points. For instance, if a decision-maker switches from "No" to "Yes" in the fourth choice question, it indicates that the agent is willing to pay up to $1.0 for the chosen product and not perform the real effort task to offset the purchasing cost. The switching point in the real effort task represents a reservation wage for the participant's labor supply. Switching in the fourth question indicates that in the ($0, $1.0) range, they are not willing to supply their labor (effort) or equivalently that their reservation wage for the real effort task is $1.0. This part of the design enables us to investigate one of the central topics in the labor economics literature in a controlled environment, which includes analyzing labor supply decisions to cover food purchases, reminiscent of welfare program participants (Finkelstein and Notowidigdo, 2019; Hoynes and Schanzenbach, 2012; Fernandez and Saldarriaga, 2013).

After the determining the binding task, if the randomly selected binding price is above the subject's reservation wage for exerting the effort, then the participant is required to perform the real effort task. For instance, if a subject switched from "No" to "Yes" in the sixth choice question, and the binding price was $3.0, the subject was invited to perform the real effort task and receive $3.0 in exchange, which would essentially offset the food purchase. However, if the randomly selected choice question revealed that the binding price for the subject was $1.0, then the subject had to pay the cost of the product out of her participation fee. Subjects who completed the effort task received a compensation of $25 and their chosen food product. Otherwise, subjects had to pay the price of the product and receive the food product they selected and the remaining amount from their $25 participation fee. Finally, subjects filled a demographic survey.

Table 2.2 lays out the predictions for the values of the weight of the price attribute, quality perceptions, price salience levels, and consumption types based on our theoretical model and our research design. In our theoretical model, we showed that there exists a range of values for the price attribute weights that creates low price salience and consequently induces consumers to switch from the low-quality and low price food item to the high-quality and high price alternative. In our experiment, we employ an MPL format which enables us to identify consumers who have price attribute weight values that lead to *low price-salience* behavior and they consequently prefer low-calorie food alternatives. More specifically, if the consumer switches from the high-calorie food item to the low-calorie alternative in the first five choices of the food MPLs, our model shows that she is willing-to-pay a premium to obtain the low-calorie option. In this case, the values of her weights for the price attribute is in the range of $[0, 0.5)$, and we label this kind of consumption behavior as *Health-seeking consumption.*

In the sixth choice of the food MPLs, both food items have the same price ($2.50) and the price attribute is not part of the decision process. This choice task helps us to elicit the true food preferences of consumers when the price is identical. Potentially, there might be two consumer types based on the outcome of the sixth choice question of the food MPLs: a) agents who switch from the high-calorie to the low-calorie alternative, or b) still prefers the high-calorie option. If the consumer switches from the high- to the low-calorie alternative, then she truly prefers the low-calorie option. However, the consumer is not willing to pay a premium to buy the product. This means that the agent puts a higher weight on price compared to quality when she is in the high price-salience state. We label this type of behavior as *Health-conscious consumption*, meaning that this type of consumers prefer low-calorie choices, but are not willing to pay a premium to buy low-calorie food products.

If the consumer switches from the high- to the low-calorie alternative in the seventh choice

Table 2.2: Model predictions about the range of the values of the price attribute weight and consumer type.

Switching Point	Prediction	Salience Level and Food Preference	Type
1-5	$w_p \in [0, 0.5)$, $q_a < q_b$	Low price-salience, prefers low-calorie food	Health-seeking consumption
6	$w_p \in (0.5, 1)$, $q_a < q_b$	High price-salience, prefers low-calorie food	Health-conscious consumption
7	$w_p = 1$, $q_a \gtreqless q_b$	High price-salience, quality of food does not matter	Cost-minimizing consumption
8-11	$w_p \in [0, 0.5)$ and $q_a > q_b$	Low price-salience, prefers high-calorie food	Pleasure-seeking consumption

task, it means that she tries to minimize her food consumption expenditures. This behavior indicates that the agent has lexicographic preferences and her price weight is 1 ($p_w = 1$) and we categorize this behavior as *Cost-minimizing consumption*. However, if she switches after the seventh choice task, it shows that she is willing-to-pay a premium to buy the high-calorie alternative, presumably because of strong homegrown preferences for flavor. Accordingly, she is in the low price-salience state and she exhibits *Pleasure-seeking consumption*.

In our model, Proposition 2 shows that high-income individuals are more likely to have lower values for the weight of the price attribute and be in the low price-salience state compared to low-income individuals. Proposition 2 predicts that high-income subjects will switch earlier in the food MPLs compared to low-income participants. Therefore, we predict that the percentage of health-seeking subjects will be higher in the high-income group compared to low-income participants.

Since low-income individuals are more likely to be affected by budget constraints and less likely to choose low-calorie and higher priced alternatives, we can also expect that being in the low-income group will increase the probability of exhibiting health-conscious consumption. Accordingly, we expect that being in the low-income group will increase the likelihood of demonstrating cost-minimizing behavior.

Hypothesis 1a: High-income subjects will be more likely to be in the health-seeking category compared to low-income participants.

Hypothesis 1b: High-income subjects will be less likely to be in the health-conscious category compared to low-income participants.

Hypothesis 1c: High-income subjects will be less likely to be in the cost-minimizing category compared to low-income participants.

Hypothesis 1d: On average, high-income subjects will switch from the high- to the low-calorie alternative in earlier choices of the food MPLs compared to the low-income group.

In our model, Proposition 3 shows that the values of the attribute weights can change depending on the price-salience state. We employ two states (i.e., treatments) in our experiment. We expect that in the High (Low) Price-Salience condition, subjects will have higher (lower) values for the price attribute weight. Thus, we expect that the low and high price-salience states will change the likelihood of subjects to be in the health-seeking, health-conscious, and cost-minimizing categories.

Hypothesis 2a: Subjects in the Low (High) Price-Salience condition will be more (less) likely to be in the health-seeking category compared to the No Price-Salience condition.

Hypothesis 2b: Subjects in the Low (High) Price-Salience condition will be less (more) likely to be in the health-conscious category compared to the No Price-Salience condition.

Hypothesis 2c: Subjects in the Low (High) Price-Salience condition will be less (more) likely to be in the cost-minimizing category compared to the No Price-Salience condition.

2.7.1 Price Salience Effects on Reservation Wages

Previous literature shows a strong relationship between labor supply and participation in welfare programs, and how poor households modify their labor supply depending on program structures and eligibility criteria (e.g., Yelowitz (1995); Hoynes et al. (1996); Eissa and Liebman (1996); Moffitt (2002); Blundell et al. (2016)). Recent findings suggest that factors in the decision environment affect contract choices and labor effort (Imas et al., 2016; De Quidt, 2017). Our study offers a unique insight in this discussion using an experimental approach. Our design enables us to explore a causal link between induced price salience and labor supply effort. Since subjects make 11 choice decisions in the real effort MPL and they reveal their reservation wages for performing a real effort task to compensate the costs of their food expenditures. This aspect of our design helps us to document the causal link between induced price salience and labor supply. We expect that low-income subjects will have a lower-reservation wage for their labor supply compared to high-income subjects. Moreover, we expect that being in the High (Low) price-salience condition will decrease (increase) the reservation wage. The results of this section have important policy implications for food assistance welfare programs.

Hypothesis 3a: Subjects in the Low Price-Salience condition will have a higher reservation wage for labor supply compared to the No Price-Salience condition.

Hypothesis 3b: Subjects in the High Price-Salience condition will have a lower reservation wage for labor supply compared to the No Price-Salience condition.

Hypothesis 3c: Subjects in the high-income group will have a higher reservation wage compared to low-income participants.

2.8 Results

Before testing our research hypotheses, we conduct a balance check of the demographic profiles of subjects across the experimental conditions and also test whether our results are affected by the impairment of cognitive function as previously found by Mani et al. (2013) and follow-up studies. We also discuss the observed frequencies of the predicted consumer types when there is no price salience in the decision environment.

In Appendix A, Table A1 shows the pairwise comparison of income, gender, race, education levels, Body Mass Index (BMI), marital status and household size for all participants. The randomization of participants across experimental conditions is successful, as demographic measures are balanced, except for gender. There is a weakly significant difference between the High Price-Salience and Low Price-Salience conditions in terms of the proportion of males. The percentage of male subjects is almost 16% higher in the High Price-Salience condition compared to the Low Price-Salience condition. Therefore, the gender (Male) variable is controlled for in our analyses. In this article, the food MPLs provide a crucial measure of economic decisions. The consistency of choices in each MPL is of great importance for our findings. If subjects switch columns multiple times in the MPL, it indicates that they either have inconsistent preferences or they misunderstood the experimental protocols. Charness et al. (2013) suggest that dropping observations with multiple switching points assures that the analysis only includes subjects who understand the experimental protocols and reveal their true preferences. Therefore, in our analyses, we only keep observations with a single switching point in the MPLs.

Table A1 shows that there are 50, 56, 45 subjects with consistent preferences in the No Price-Salience, Low Price-Salience and High Price-Salience conditions, respectively. We ended up having observations from 95 subjects with consistent choices for the High Price-Salience and No Price-Salience conditions combined, 101 subjects with consistent choices for the High Price-Salience and Low Price-Salience conditions combined, and 106 subjects for the

Low Price-Salience and No Price-Salience conditions combined. In this regard, our sample sizes are very similar to Mani et al. (2013). In the major analysis of their study, Mani et al. (2013) report their findings from three lab experiments with 101, 100, 96 subjects, respectively.

In Appendix A, Table A2 reports the results of regression analyses to test whether induced price salience affects the cognitive performance of low-income subjects compared to high-income subjects.[12] Since we measure the cognitive performance by Raven scores, if price salience impedes cognitive function then we expect to observe a significantly lower number of correct answers for low-income subjects compared to the high-income group in the High Price-Salience condition. Table A2 panel (a) reports OLS regression results when the High Income variable is 1 for subjects with effective income above the median. There is no reduction in the cognitive capacity overall or for low-income individuals in our experiment. To check the robustness of our results to the median split procedure, we also conduct the same analysis specifying income as a continuous variable. The results of this robustness check are presented in Table A2 panel (b). Our results are consistent; neither the experimental conditions, nor their interactions with the continuous income variable have a significant impact on cognitive performance. Although, we observe that the variable for income is independently correlated with performance in the Raven's test, the effect is only marginally significant. Thus, we do not replicate the effect of price salience on cognitive performance found in Mani et al. (2013). In this regard, our results align with Wicherts and Scholten (2013) and Carvalho et al. (2016) who fail to replicate the main findings of Mani et al. (2013) that monetary concerns impair cognitive performance. We conclude that the impairment of cognitive function is not contaminating our results, and our findings can only be attributed

[12] We follow Mani et al. (2013) in constructing our income variable. In line with their study, we compute effective income by dividing household income by the square root of household size. Across all experimental conditions, the distribution of the effective income variable has the following parameters: 1% percentile=$7,559.29, 50% percentile=$31,819.81, mean=$41,648.73, 99% percentile=$ 106,066.00. Moreover, in line with Mani et al. (2013), we define our "poor" and "rich" subsamples based on the median split of the effective income variable.

to the exogenously manipulated price salience. Thus, our results suggest *attribute salience* as an alternative channel that transmits the effect of price inducement of food choices.

Table 2.3 shows the frequencies of the predicted consumer types across experimental conditions. Since food preferences are idiosyncratic and we do not have a prior knowledge about the distribution of each type in the population, we initially assume that the above mentioned consumer types are equally likely to be observed in our experiment. We start our primary analysis by evaluating the observed frequencies in the No Price-Salience condition and statistically compare observed frequencies to expected benchmarks under the assumption that each consumer type is equally likely to be represented in the population.[13] The observed frequency of health-seeking subjects in the No Price-Salience condition is not significantly different ($p = 0.84$) than the random benchmark. The rest of the categories are significantly different compared to their random benchmarks. Since in the No Price-Salience condition, we do not introduce salience, we can argue that the observed frequencies constitute a raw distribution of modeled categories in the population. Interestingly, the observed proportion of health-conscious and cost-minimizing consumption behaviors are higher than the random benchmark. Contrarily, the frequency of pleasure-seeking participants is lower than the predicted random level. Table 2.3 also shows that 73% of subjects are in either the health-seeking or health conscious category. Therefore, it is not surprising that we observe relatively less frequent pleasure-seeking behavior. We conclude that almost three-quarters of our subjects prefer low-calorie food items and 43% of the total subject sample are willing to pay a premium to buy low-calorie food items. It is noteworthy that across all the experimental conditions, the frequency of pleasure-seeking consumers are significantly lower than the random benchmark and it remains around 10%. This group represents the segment of consumers who exhibit strong preferences for high-calorie food products and are willing-to-pay up to $5.00 to buy hedonic flavor. Across experimental conditions, cost-minimizing behavior is also observed more frequently than the random benchmark. Our analysis indicates that

[13] See Toussaert (2018) for a similar approach.

Table 2.3: The observed frequencies of modeled consumer types

Experimental Condition	Consumer Type	% of Subjects	Number of Choices	Random Benchmark	*p-value*
No Price-Salience			100		
	Health-seeking consumption	43%	43	42%	p=0.84
	Health-conscious consumption	30%	30	8%	p<0.01
	Cost-minimizing consumption	16%	16	8%	p<0.01
	Pleasure-seeking consumption	11%	11	42%	p<0.01
High Price-Salience			90		
	Health-seeking consumption	39%	35	42%	p=0.46
	Health-conscious consumption	38%	34	8%	p<0.01
	Cost-minimizing consumption	14%	13	8%	p<0.01
	Pleasure-seeking consumption	9%	8	42%	p<0.01
Low Price-Salience			112		
	Health-seeking consumption	34%	38	42%	p=0.06
	Health-conscious consumption	31%	35	8%	p<0.01
	Cost-minimizing consumption	24%	27	8%	p<0.01
	Pleasure-seeking consumption	11%	12	42%	p<0.01
Total	All Types and All Conditions		302		

The *p-values* are the result of a two-sided binomial test whether the observed percentages are equal to the benchmark percentages, when subjects choosing their preferred food products in both MPLs. Three subjects never switched from the low- to high-calorie alternative in our experiment. Therefore, the switching point variable is a positive integer values in the range of [1,12]. Random benchmarks are calculated as 1/12*(number of choices in each category). For instance, for the Health-seeking category it is 1/12*(5)=0.42.

when there is no price salience in the decision environment, 73% of consumers exhibit strong preferences for low-calorie food items and 16% of the total consumer population is primarily motivated by monetary concerns.

2.8.1 Result 1

Hypothesis 1a states that high-income subjects will be more likely to be in the health-seeking category compared to low-income participants. Figure 2.2 showcases the effect of income levels on the likelihood of being in each modeled consumption category in the pooled sample for all experimental conditions. Indeed, being in the high-income group increases the probability of being in the health-seeking category ($two-sided\ Wilcoxon\ test: Z = -10.78,\ p < 0.01$).

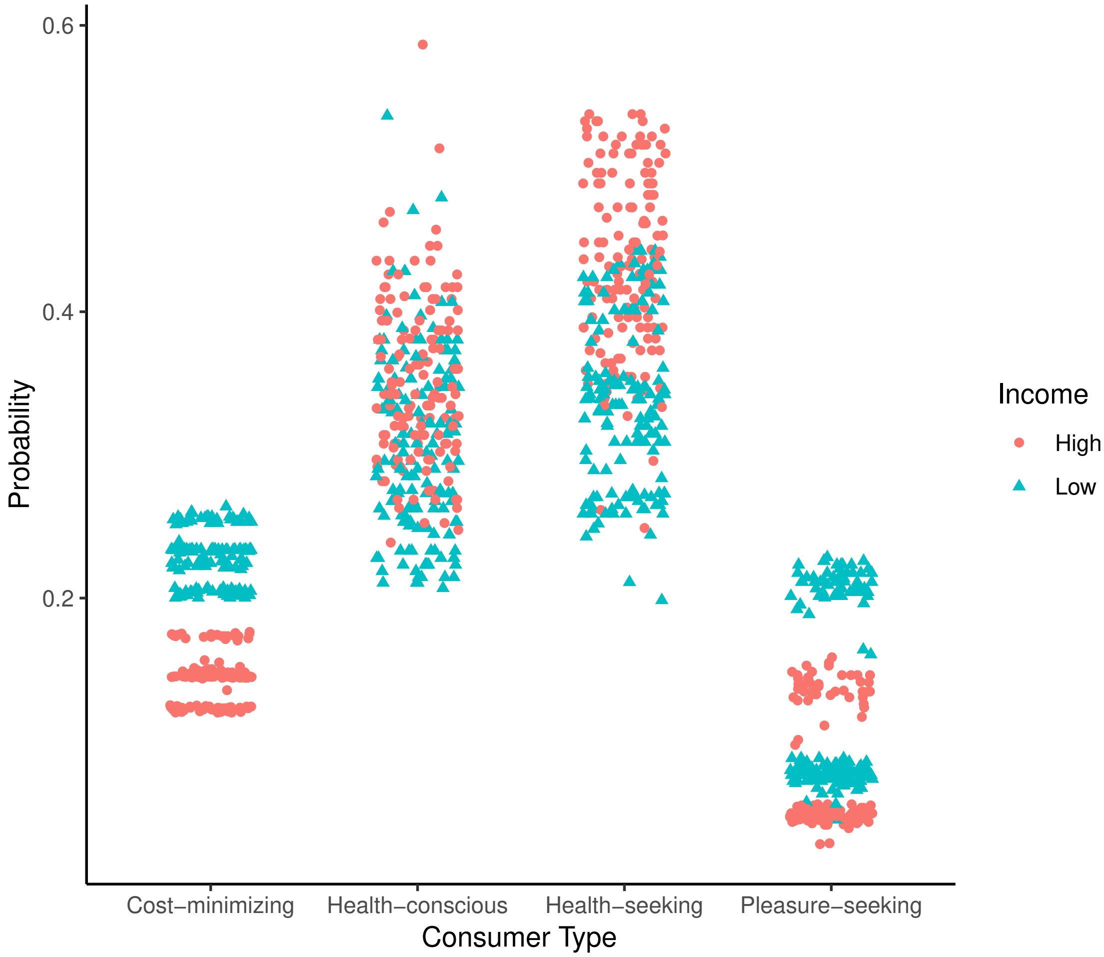


Figure 2.2: The role of income levels in predicting consumer types.

The probability estimations correspond to multinomial logit regression results where food type, gender, logged values of Raven scores and income are independent predictors. The estimation results are from the pooled sample, when experimental conditions are not controlled. This approach helps us to capture the direct effect of the income across all experimental condition.

Since high-income subjects can afford to be in the health-seeking category, according to Hypothesis 1b and 1c, we expect to observe the percentage of high-income participants to be lower in the health-conscious and cost-minimizing conditions compared to the low-income group. Figure 2.2 displays that the fitted probability of the high-income group to be in the health-conscious category is higher ($two - sided\ Wilcoxon\ test : Z = -6.24,\ p < 0.01$), and for the cost-minimizing conditions is lower ($two - sided\ Wilcoxon\ test : Z = -14.97,\ p < 0.01$) compared to the low-income group. Thus, we fail to reject Hypothesis 1a and 1c, and reject Hypothesis 1b. Interestingly, we observe that being in the low-income group increases the likelihood of being in the pleasure-seeking category ($two - sided\ Wilcoxon\ test : Z = -9.40,\ p < 0.01$).

Figure A2 presents the results of the consumer types, by separately fitting the likelihood of each consumption category for each experimental condition. We observe that in the No Price-Salience condition, being in the high-income group significantly increases the likelihood of demonstrating health-seeking behavior. Moreover, as observed in the pooled analysis, high-income subjects are less likely to be in the cost-minimizing and pleasure-seeking conditions. However, this effect vanishes in the other conditions. Namely, decreasing or increasing the salience of the price attribute decreases the probability of the high-income group to be in the health-seeking category. It should be noted that the significant gap between high- and low-income groups in terms of health-seeking behavior in the No Price-Salience conditions is closed because of changes in the behavior of the high-income group in the other experimental conditions. Figure A2 shows that the high income group aligns its behavior with the low-income subjects in the Low and High Price-Salience conditions. Thus, we conclude that high-income participants behave similarly to low-income participants when exposed to both Low and High Price-Salience conditions.

Hypothesis 1d makes a more general statement and focuses on average switching points. This hypothesis predicts that on average high-income subjects will switch earlier compared to low-income participants. Table 2.4 panel (a) and (b) show that, on average, high-income subjects switch from the high- to the low-calorie alternative in earlier food choice tasks of the MPLs compared to low-income participants. Thus, we confirm Hypothesis 1d.

Overall, Result 1 shows that being in the high-income group is correlated with earlier switching in early choice tasks of the food MPLs. However, when we analyze the association of income levels with modeled consumption categories, we can only confirm the predicted outcomes for the No Price-Salience condition. In the Low and High Price-Salience conditions, high-income subjects converge to the behavior of low-income subjects.

2.8.2 Result 2

In general, Hypothesis 2 predicts a causal relationship between price salience and switching from high- to low-calorie food items. Hypothesis 2a states that subjects in the Low (High) Price-Salience will be more (less) likely to be in the health-seeking category. However, according to Figure 2.3, being in the Low Price-Salience condition reduces the probability of health-seeking behavior compared to the No Price-Salience condition ($two-sided\ Wilcoxon\ test: Z = -5.89,\ p < 0.01$). We also observe that the High Price-Salience condition lowers the probability of being in the health-seeking category compared to the No price-Salience condition ($two-sided\ Wilcoxon\ test: Z = -2.01,\ p = 0.02$). Thus, we partially confirm Hypothesis 2a. Moreover, we observe that being exposed to the High Price-Salience condition increases the likelihood of being in the health-conscious condition compared to the No Price-Salience condition ($two-sided\ Wilcoxon\ test: Z = -6.79, p < 0.01$). So, we reject the predictions of Hypothesis 2b with our analysis.

Contrary to the prediction of Hypothesis 2c, being in the Low Price-Salience condition marginally increases the likelihood of demonstrating a cost-minimizing behavior. Overall, we cannot confirm Hypothesis 2b, and 2c, while partially substantiating the prediction of Hypothesis 2a. We also observe the reverse effect compared to what was predicted in hypothesis 2a and 2c.

The results of Table 2.4 are aligned with Result 2. We observe that the Low and High Price-Salience conditions do not affect the average switching points. However, their interactions with income significantly change the average switching points. Income is endogenous,

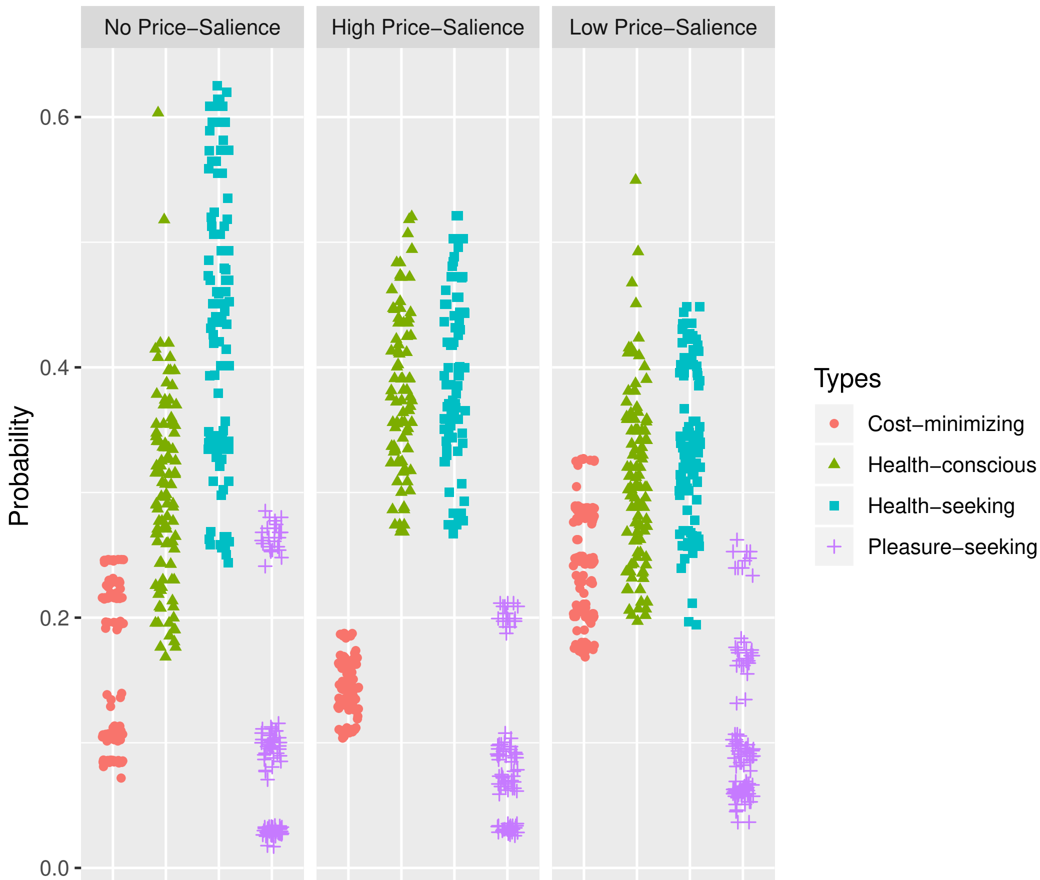


Figure 2.3: The role of experimental conditions in predicting consumer types.

The probability estimations correspond to multinomial logit regression results where food type, gender, logged values of Raven scores, income and experimental conditions are independent predictors.

but our experimental conditions are exogenously assigned, thus our results bear causality nature. Interestingly, in both Low and High Price-Salience conditions, high-income subjects switch later. As mentioned before, Figure A2 panel (a) shows that when there is no salience in the decision environment, high-income subjects are more likely to exhibit health-seeking behavior, but this effect vanishes in the Low and high Price-Salience conditions.

We conclude that Low and High Price-Salience conditions do not affect average switching directly, but they influence the behavior of high-income subjects and cause the income effect

Table 2.4: Switching point analysis in food choices

(a) Censored Poisson Regression Results

	(1) Switching Point	(2) Switching Point	(3) Switching Point
High Price-Salience	0.0325	0.0362	−0.193
	(0.34)	(0.38)	(−1.56)
Low Price-Salience	0.161*	0.157*	−0.00980
	(1.68)	(1.70)	(−0.09)
log (Raven Score)	0.0469	0.0450	0.0147
	(0.34)	(0.36)	(0.14)
Male	0.145**	0.123	0.112
	(1.97)	(1.53)	(1.53)
Food Choice (dummy)	−0.0252	−0.0380	−0.00342
	(−0.32)	(−0.48)	(−0.05)
High Income (dummy)		−0.0628	−0.312**
		(−0.78)	(−2.52)
High Price-Salience * High Income			0.427**
			(2.48)
Low Price-Salience * High Income			0.322**
			(1.96)
Constant	1.517***	1.563***	1.783***
	(3.66)	(4.05)	(5.05)
N	302	302	302

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) OLS regression results

	(1) Switching Point
High Price-Salience	−0.349
	(−0.73)
Low Price-Salience	0.0814
	(0.20)
log(Raven Score)	0.375
	(0.94)
Male	0.814***
	(3.25)
Food Choice (dummy)	−0.298
	(−1.23)
High Income (dummy)	−0.943**
	(−2.14)
High Price-Salience * High Income	0.768
	(1.24)
Low Price-Salience * High Income	1.063*
	(1.79)
Constant	4.455***
	(3.65)
N	302

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

to vanish by reverting the consumption behavior of high-income subjects to the behavior of low-income subjects. Contrary to predictions of Hypothesis 2a, the Low Price-Salience condition decreases the probability of being in the health-seeking condition.

Figure 2.4 presents the empirical Cumulative Distribution Functions of switching points across experimental condition. As was mentioned earlier, product prices are the same at switching point 6. The real market prices of products used in the experiment are close to \$2.50. Therefore, if a subject switches from the high- to low-calorie alternative in the first choice set of the food MPLs, s/he is willing to pay \$5.0 to buy the product. This also means that the subject is willing pay a 100% premium (compared to the real market value of \$2.50) to buy the high-quality food product. Switching points to the left of the vertical red dashed lines in Figure 2.4 indicate willingness to pay a non-zero premium for low-calorie food products. Another important point about Figure 2.4 is that, in the current market conditions, most low-calorie and healthy food products are relatively more expensive than high-calorie food alternatives. This essentially means that the real market prices of low-calorie and high-quality food products are on the left side of the vertical red dashed lines.

Figure 2.4 panel (a) shows that in almost 50% of the choices, the high-income group switches to low-calorie food products in the first five choice sets in the No Price-Salience condition. The low-income group is willing to pay a non-zero premium only in 30% of the choices. However, in the High and Low Price-Salience conditions, the difference between the low- and high-income group disappears. Overall, when prices of low- and high-calorie products are the same, two-thirds of the participants choose the low-calorie options. When the price of the low-calorie alternative is discounted by 20%, over 95% of the food choices are healthy across all experimental conditions.

It is worthwhile to mention that at a 40% discount (when a low-calorie alternative is 40% cheaper compared to its average real market value of $2.50) both the low- and high-income group completely switch to low-calorie alternatives. Notice that, when the price is highly salient the high-income group mimics the low-income group and substantially reduces its willingness to pay a premium. Interestingly, we observe that the high-income group acts similarly to the low-income group in the Low Price-Salience condition as well. These results align with the results depicted in Table 2.4.

2.8.3 Result 3

Hypothesis 3a (3b) states that being in the Low (High) Price-Salience state increases (decreases) the reservation wage for performing a real effort task to cover the food expenses. Figure 2.5 presents the comparison of average switching points in the real effort MPL across experimental conditions. We confirm Hypothesis 3b and show that being in the High Price-Salience condition decreases the reservation wage. However, we observe that being in the Low Price-Salience state also decreases the reservation wage, contrary to the prediction of

Hypothesis 3a.

Hypothesis 3c predicts a positive relationship between a high-income status and the reservation wage. We confirm that being in the high-income status is positively correlated with the reservation wage for labor supply in the No Price-Salience condition. In the other conditions, we observe that in the presence of low and high price salience, high-income subjects mimic the behavior of low-income subjects and reduce their reservation wages. The observed behavior of high-income agents in labor supply decision is closely aligned with Result 1 and 2. Thus, we confirm Hypothesis 3c only for the No Price-Salience condition.

Subjects revealed their reservation wages for exerting a real effort task in the effort-MPL after making their food choices in the food MPLs. If a subject switches earlier indicating she is willing-to-pay a premium to buy the low-calorie alternative; then in the effort MPL she has a higher incentive to reduce her reservation wage for performing a real effort task to compensate her food purchase expenses. Thus, their labor supply decisions can also be related to their previous food choices. Table 2.5 presents regression analyses where we explicitly control for the switching points in the food MPLs and other demographic variables. The results show that decisions in the food MPLs do not affect the labor supply decisions of subjects across all experimental conditions.

The results presented in Table 2.5 also confirm our results in Figure 2.5 and show that high-income subjects switch later in the effort MPL in the No Price-Salience condition. This result means they have a higher reservation wage for supplying their labor. However, high-income subjects switch earlier in the High and Low Price-Salience conditions and this result confirms our findings in figure 2.5 panel (b). Interestingly, when we control the interactions of the experimental conditions with income, the direct effects of the Low and High Price-Salience conditions on reservation wages disappears. This effect is documented in Figure 2.5 panel (a).

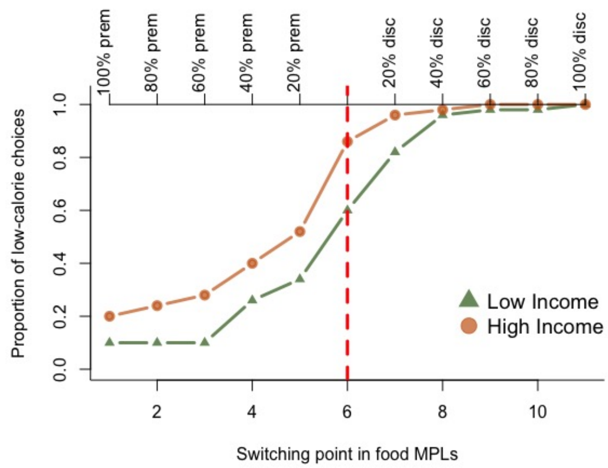
We conclude that food expenses do not affect the reservation wage for labor supply in

Table 2.5: Censored Poisson regression for switching point analysis in real effort task

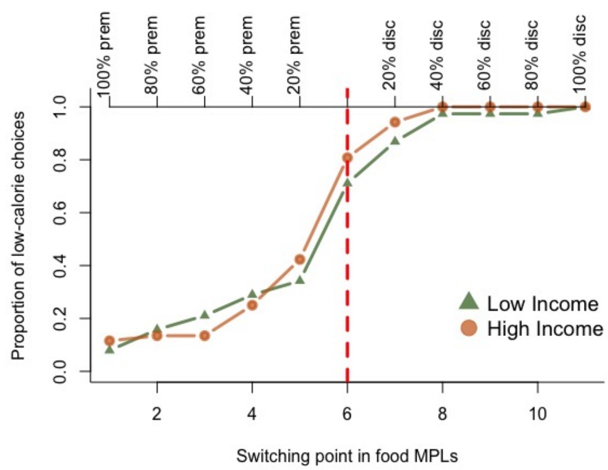
	(1) Switching Point	(2) Switching Point	(3) Switching Point
High Price-Salience	-0.250^{*}	0.0120	0.0120
	(-1.83)	(0.06)	(0.06)
Low Price-Salience	-0.376^{***}	-0.0597	-0.0597
	(-2.73)	(-0.31)	(-0.31)
High Income (dummy)	0.143	0.477^{**}	0.477^{**}
	(1.23)	(2.56)	(2.56)
log(Raven Score)	0.350	0.350	0.350
	(1.43)	(1.44)	(1.44)
Male	0.166	0.196	0.196
	(1.35)	(1.54)	(1.54)
Switching Point (Beverage)	0.0263	0.0304	0.0304
	(0.78)	(0.90)	(0.90)
Switching Point (Food)	-0.0282	-0.0248	-0.0248
	(-1.04)	(-0.90)	(-0.90)
High Price-Salience * High Income		-0.473^{*}	-0.473^{*}
		(-1.70)	(-1.70)
Low Price-Salience * High Income		-0.668^{**}	-0.668^{**}
		(-2.31)	(-2.31)
Constant	0.0484	-0.191	-0.191
	(0.07)	(-0.27)	(-0.27)
N	138	138	138

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

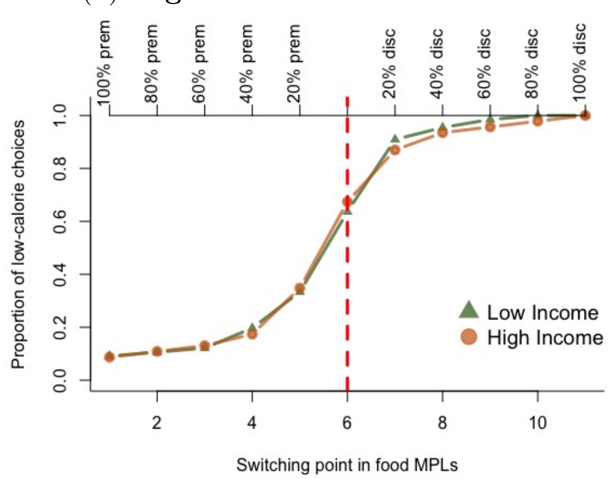
our experiment. Moreover, inducing price salience affects the reservation wage only for high-income subjects. When exposed to Low and High Price-Salience, participants in the high-income group reduce their reservation wage for exerting a real effort to compensate their food expenses. Our results partially confirm Hypothesis 3b and 3c, and we cannot support Hypothesis 3a with our findings.



(a) **No Price-Salience Condition**

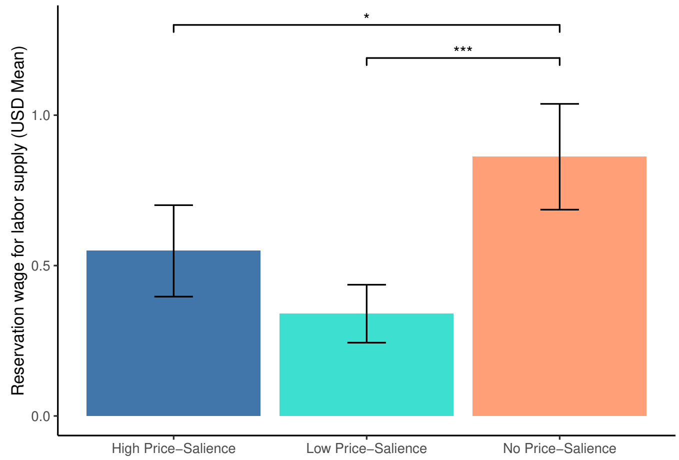


(b) **High Price-Salience Condition**

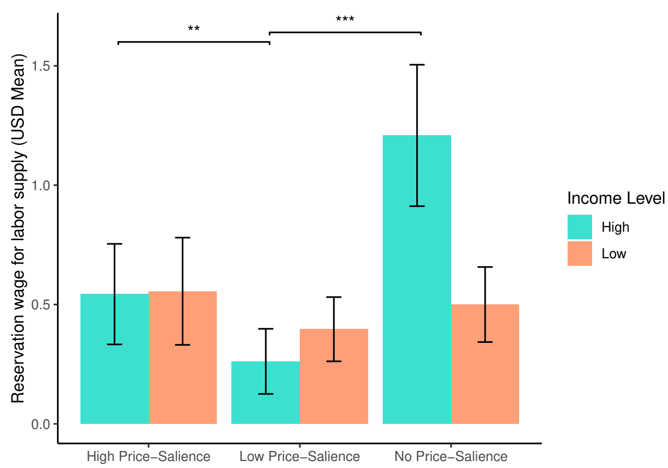


(c) **Low Price-Salience Condition**

Figure 2.4: The empirical Cumulative Distribution Function (CDF) of switching points across experimental conditions.



(a) This graph shows the willingness of subjects to do the real effort task across the experimental conditions. The y-axis shows the average possible binding price until which subjects did not want to complete the real effort task. For instance, the subjects in the No Price-Salience condition did not want to complete the real effort task if the binding price was around 80 cents or less.



(b) This graph shows the willingness of subjects to do the real effort task across the experimental conditions and income groups.

Figure 2.5: Reservation wage for labor supply across the experimental conditions

2.9 Conclusion

The importance of salience in choice attribute evaluation stands out as one of the central tendencies in recent consumer choice modeling (Bordalo et al., 2013, 2015, 2017; Chetty et al., 2009; Kőszegi and Szeidl, 2012; Gabaix, 2014; Hastings and Shapiro, 2013; Bushong et al., 2015; Gabaix, 2017; Dertwinkel-Kalt and Köster, 2017; Towal et al., 2013). We develop a theoretical model and show that there exists a strong relationship between price salience and product purchases. We conduct a lab experiment where price salience is exogenously manipulated by inducing price salience following the protocol developed by Mani et al. (2013). Our outcome measures are incentivized food purchases and we employ a Multiple-Price-List (MPL) framework to identify consumer types and test our hypotheses. Our study contributes to the attribute salience literature in economics by demonstrating that induced price salience also has an impact on the food choices of individuals across the income spectrum.

We find that high-income consumers are more likely to exhibit health-seeking (willing to pay a premium to buy low-calorie food products) and health-conscious (willing to buy the low-calorie food item when it has the same price as the high-calorie alternative) consumption behaviors compared to the low-income group. Our results also suggest that being in the low-income group increases the likelihood of following the cost-minimizing (always prefer the lower priced alternative) and pleasure-seeking (willing to pay a premium to buy high-calorie food products) behaviors. However, when induced with low or high price salience, high-income subjects align their consumption decisions with the low-income group and reduce their willingness-to-pay to buy low-calorie products. We conclude that the variation of our outcome measures across experimental conditions are mainly driven by high-income subjects. Low-income subjects show the same behavior whether or not the salience is present in the decision environment. This may explain why some studies documented null effect for labor-intensive public programs in poor countries (e.g., see Beegle et al. (2015)). However, high-income participants are very sensitive to the salience of price and react to it by mimicking the low-income group. Thus, our experimental framework also provides a useful information for designing nutritional assistance programs. First, it highlights potential effects of price-salience levels for the middle and upper-middle income groups. Second and most importantly, it provides a measure of the size of the discounts needed to incentivize agents to switch to low-calorie food alternatives.

We also find that being exposed to high price salience decreases the likelihood of being in the health-seeking category and increases the likelihood of health-conscious consumption. Based on our analysis on the behavior of the high-income group across experimental conditions, we conclude that the observed variations are mainly driven by high-income participants. We interpret this finding as a decreasing willingness-to-pay of high-income participants to buy low-calorie food items when induced with price salience. Subjects with a higher income move from health-seeking to health-conscious category when reminded about monetary costs or gains.

The existing literature primarily studies the effects of transitory and permanent income shocks on consumer spending (Jappelli and Pistaferri, 2010). However, an emerging literature also documents the effect of reference-point, memory and attention to consumer expenditures (Bordalo et al., 2019, 2017; Simonsohn and Loewenstein, 2006). Our results align with this new line of research and show that induced price-salience can also significantly change consumer spending.

Finally, we explore the relationship between food expenditures, price salience and labor supply by eliciting our subjects' reservation wage to perform a real effort task to cover their food expenditures. Some studies have already scrutinized the role of salience in this context (Imas et al., 2016; De Quidt, 2017). To our knowledge, our study is the first study to analyze the labor supply decisions via eliciting real reservation wages of economic agents with varied price salience levels. As our theoretical model predicts, we find that when there is no price salience, high-income subjects indicate a higher reservation wage to perform a real effort task to compensate their food expenditures. However, being exposed to low or high price salience changes the behavior of the high income group and they reduce their reservation wages to the same level of low-income participants. Our results also overlap with recent experimental findings documenting the positive impact of income shocks on reservation wages (Nebioğlu and Giritligil, 2018).

Overall, our findings show that price is always salient for low-income individuals. Therefore, the low-income group does not react to our experimental price salience conditions. The unidirectional reaction of the high-income group to both low and high price salience suggests that individuals with a higher income exhibit price salient behavior only when they are exposed to factors in the decision environment reminiscent of monetary transactions. Thus, our study presents a new behavioral insight about income elasticity which is important in projecting the effects of different market shocks (e.g., commodity price changes, tax hikes, subsidies, etc.) on consumer spending and labor supply.

Our results may be specific to the products studied in our experiment and the magnitude of the discount needed to induce consumers to switch to low-calorie food alternatives may differ depending on the type of food. However, in general, our findings show that consumers are differentially responsive to price changes under price-salience environments. From this standpoint, the use of MPL settings as an instrument to study the trade-offs between healthy and unhealthy food options in an incentivized framework has a great potential for policy analysis.

CHAPTER III

DOES THE MAGNITUDE OF RELATIVE CALORIE DISTANCE AFFECT FOOD CONSUMPTIONS?

Overconsumption of unhealthy and high-calorie food has become a public health crisis.[14] In response, food manufacturers and retailers are now legally required to add calorie information to their labels so that consumers can make informed choices regarding calorie intake. Since then, however, the relevant literature has reported mixed results.[15] Some empirical studies show that calorie labeling decreases calorie intake (Bollinger et al., 2011), and others find no significant changes (Finkelstein et al., 2011; Bleich et al., 2017). Dumanovsky et al. (2011) even report an increase in calorie consumption by customers of the Subway fast-food sandwich chain after the implementation of the calorie labeling law. Previous experimental studies also yield mixed results. Pang and Hammond (2013) and Cawley et al. (2018) find that listing calorie information reduces the number of ordered calories, while Ellison et al. (2014a) do not. Thus, studies using both secondary data and experimental framework offer mixed results on the effect of calorie information on consumed calories (Fernandes et al., 2016). The impact of calorie information on calorie intake and any potentially moderating factors, therefore, remain an unsolved research question.

Recent economic models offer insight into the factors that could potentially alter the impact of calorie information on food consumption. According to Gul and Pesendorfer (2001), a decision-maker derives two kinds of utilities from a choice alternative: *normative* utility

[14]For instance, in the United States, and many other countries, obesity has become a national health pandemic. According to recent empirical findings, the obesity rate has already surpassed 35% in seven U.S. states (Kuehn, 2018). This rate is very alarming, mainly because it was around 20% across all states in 1995 (Ellison et al., 2014b). One of the primary reasons for the high obesity rates is the prevalence of an unhealthy diet (Cecchini et al., 2010). An unhealthy diet and consequently obesity are associated with high rates of several chronic diseases, such as cardiovascular issues (35%), hypertension (29%), high cholesterol (16%), and diabetes (12%) (USDA, 2015).

[15]See for example Tangari et al. (2019); Dallas et al. (2019); Ellison et al. (2014b,a). We provide a comprehensive review of secondary data and experimental studies on this topic in the Literature Review section.

and *temptation* utility. Gul and Pesendorfer (2001) model self-control cost as the temptation utility difference between the most- and least-tempting alternatives on a menu. Noor and Takeoka (2010) show that as this difference increases, the decision-maker becomes more vulnerable to choosing the high-calorie and more tempting option. Consider, for example, an individual choosing a drink from two different menus. Facing a menu with a bottle of water and a zero calorie soft-drink induces a relatively lower temptation tradeoff compared to a menu with a bottle of water and a regular soft-drink bottle. The latter imposes a higher self-control cost on the decision-maker, since a bottle of regular-soft-drink is more tempting to the average consumer than a zero-calorie soft-drink bottle. Generally, commitments that require greater deviations from the tempting option are more difficult to accomplish. For example, overly ambitious new year's resolutions typically end in noncompliance because small deviations from the tempting option are easily manageable compared to huge leaps (Noor and Takeoka, 2010). Similarly, radical diet changes can burden the decision-maker with unbearable self-control costs, which in turn can lead to more frequent self-control failure. Noor and Takeoka (2015) argue that the outcomes of self-control efforts mainly depend on the choice-context. In that vein, we propose the hypothesis that the likelihood of choosing a low-calorie alternative declines as the "temptational distance," or the difference in the number of calories between alternatives in the menu, increases.

Much like the expression "distance makes the heart grow fonder," could the relative distance between the calories of food products make high calorie options more attractive? Additionally, could the saliency of the calorie distance between food products change food choices? In this article, we focus on food intake in binary menus by exogenously manipulating the *magnitude* and *saliency* of calorie distance between food alternatives. We study menu-dependent temptation in an experimental setting where relative temptation differences between choice alternatives are exogenously manipulated by varying calorie difference. Our theoretical model suggests that the concept of uphill self-control cost developed by Noor and Takeoka (2010) and Fudenberg and Levine (2006) is an important, previously missing link for understanding the impact of calorie information on calorie intake. We test our hypotheses in two separate experiments: a lab experiment and a lab-in-the-field experiment conducted in a national restaurant chain.

In the lab experiment, decision-makers are given 40 binary-choice incentivized menus and they select their preferred snack to eat at the end of the study. In the binary menus, the serving size of both alternatives is the same, so that the only difference is the calorie content of the products. Each menu has the same probability of being selected as the binding decision at the end of the experiment. In order to incentivize the experiments, participants had to consume their selected product in the binding decision in order to receive a payment. The main motivation for using binary menus is to identify the hypothesized causal relationship between the temptation distance (or calorie distance) and the probability of choosing low-calorie snacks.[16] We also apply a 2-alternative forced choice (2AFC) paradigm. Subjects have to chose one of the alternatives. In real life, most choice problems shrink to such 2AFC decisions (Vul et al., 2014), and this framework has been frequently used to study food choices (See for example, Clithero (2018); Krajbich (2018)).

The primary causal relationship of interest is also examined in the presence of the saliency of the food's calorie content. The calorie distance between snack products is made salient in an *accurate* calorie information treatment and also in a *homegrown* calorie knowledge treatment compared to a control condition with no calorie information. The effect of being in a more or less tempted state of hunger is also tested by randomly assigning subjects to drink a protein shake to reduce hunger before the real food choices are offered. Thus, a 3x2 design is employed, and the temptation distance is varied in each experimental design cell. Our design allows us to study menu-dependent self-control issues in the presence of varying temptation and calorie information.

[16]To study the effect of relative calorie differences on choices in menus with three or more food items, one needs to consider a more complex model that focuses on the properties of the calorie distribution (See for example, Choplin and Wedell (2014)).

We employ a similar design for the restaurant experiment. We conduct the second experiment in a local restaurant from a national chain using full meals from the restaurant's menu. In this experiment, subjects are randomly assigned to the *No Information* control group, which receives meal descriptions but no calorie information, or the *Accurate Information* group, which receives both meal descriptions and calorie information. Subjects make food choices in 86 independent, binary menus, and similar to the lab experiment, one of the menus is randomly selected at the end of the experiment as the binding menu. Subjects are only allowed to eat the meals inside the restaurant and are not allowed to share food with anyone. The restaurant experiment enables us to test our hypotheses with actual meals in a restaurant setting, and with greater relative calorie distances compared to the snacks in the lab experiment. An important aspect of our designs is that we do not introduce the price attribute in menus. In the lab experiment, we use alternatives from the same snack type and brand which also have the same market price. In the lab-in-the-field experiment, the price of the meals are identical, and we manipulate calorie the difference by changing side items.

The main result of the lab experiment is that food choice outcomes depend significantly on the calorie distance between food alternatives. We develop a theoretical model where we formulate self-control cost building from the work of Gul and Pesendorfer (2001) and Noor and Takeoka (2010, 2015). Our analyses suggest that the calorie difference variable is a good proxy for the incurred self-control cost. Specifically, we show that there is a significant and positive relationship between the number of calories in snacks and the degree of temptation the snacks generate.

We show that the effect of calorie information depends on the incurred self-control cost. In the lab experiment, subjects are more likely to exhibit self-control and choose low-calorie snacks when they know (the Accurate Information Condition) or believe (the Homegrown Information Condition) that a higher calorie distance exists between the snacks. This effect, however, is small and mostly offset by the self-control cost. This result offers a plausible explanation for why calorie labeling laws have not generated the desired outcome of reducing calorie intake (Bollinger et al., 2011; Dumanovsky et al., 2011). We show that the experienced menu-dependent self-control cost discounts the effect of calorie information. We also show that when subjects incur higher self-control costs, they tend to overestimate the calorie content of low-calorie snacks to a greater extent, which in turn significantly decreases the likelihood of choosing the low-calorie snacks.

We also confirm our primary hypothesis in the restaurant experiment. An increase in the calorie distance reduces the probability of choosing the low-calorie alternative, and providing calorie information increases the number of low-calorie choices. Visual attention to meal descriptions, measured using an eye tracking device, moderates the effect of calorie information.

3.1 Related Literature

3.1.1 Models on Temptation and Self-Control

Self-control and time-inconsistent preferences have become one of the central apparatuses of economic research since Strotz (1955) modeled an economic agent's multi-period consumption decision. Strotz (1955) showed that the agent would not follow the optimal future consumption plan determined at the present moment because he has a steeply decreasing discount factor. This line of research was later improved by modeling different discount functions (Laibson, 1997; Angeletos et al., 2001; O'Donoghue and Rabin, 1999), recency bias (O'Donoghue and Rabin, 1999), and strategic interaction of short-run and long-run selves (Levine and Fudenberg, 2006). In Strotz's model, the decision-maker does not have any willpower and quickly succumbs to temptation (Masatlioglu et al., 2016). Notice that, under the neoclassical economic modeling framework, a rational economic agent has infinite willpower, and therefore, never experiences self-control issues. Reality falls somewhere in between, where agents have limited willpower (Muraven and Baumeister, 2000) and may or may not succumb to temptation. It has been shown that willpower can be choice-context specific (Fudenberg and Levine, 2012).

The seminal paper of Gul and Pesendorfer (2001) was the first attempt to show that Strotz's model can be formulated with dynamically consistent and complete preferences (Ericson and Laibson, 2018). Their work led to the development of menu-dependent preferences (Gul and Pesendorfer, 2004; Dekel et al., 2001, 2009; Noor, 2007, 2011; Toussaert, 2018) where the decision outcome depends on menu-dependent self-control (Noor and Takeoka, 2010, 2015). The major distinctive idea of this literature is that temptation is not only an intrinsic feature of a choice alternative, but it can also become more severe or less "damaging" depending on the availability of other alternatives in the choice set. A decision-maker incurs different self-control costs depending on the menu he faces. The recent replication crises in ego-depletion research and its vague domain-generality assumption motivate modeling menu-dependent preferences and self-control costs instead of universal self-control resources (Lurquin and Miyake, 2017; Hagger et al., 2016). Our study makes an important contribution to this literature by modeling and quantifying menu-dependent self-control and linking the incurred cost to incentivized food choices.

3.1.2 Public Policy and Calorie Labeling Laws

Our study aims to scrutinize the effectiveness of the provision of calorie information when the choice object can induce visceral feelings of temptation. Conventional economic models predict that agents optimize their choices by attending to all relevant information. One of the main predictions of the existing Information Economics literature is that consumers decide with the help of product-related information, and they will seek information until the search cost exceeds the benefit (Stigler, 1961; Nelson, 1970, 1974). However, recent studies show that consumers can exhibit myopia; they can fail to pay complete attention to product attributes, and their focus can be altered depending on the choice-context (Gabaix et al., 2006; Kőszegi and Szeidl, 2012; Bordalo et al., 2013; Masatlioglu et al., 2016; Huseynov et al., 2019a). Consumers are subject to visceral feelings that can further exacerbate the quality of choice outcomes (Gul and Pesendorfer, 2001; Muraven and Baumeister, 2000; Noor and Takeoka, 2010; Levine and Fudenberg, 2006; Noor and Takeoka, 2015; Alós-Ferrer et al., 2015). From this perspective, our study joins a critical conversation on the effect of Calorie Labeling Laws on food choices.

It has been argued that food availability issues can depreciate the quality of daily nutritional intake. "Food desert" —areas with limited access to healthy and affordable food— have been shown to deteriorate public health (Morland et al., 2006; Beaulac et al., 2009). The main part of the existing literature mainly focuses on the availability of healthy food to overcome diet-related chronic diseases. Recent studies also explain the poor-diet and poor-health relationship through distracting cues that appear in food decision-making environments. Cooksey-Stowers et al. (2017) show that "food swamp" neighborhoods, with overwhelming access to junk and fast-food restaurants, predict obesity better than "food deserts." Perhaps the consumption of unhealthy food is not only driven by limited accessibility to healthy food but also by preferences for "tastier" high-calorie food products. Apart from the price incentive of consuming affordable cheap food (Ghosh-Dastidar et al., 2014), unhealthy diets have also been explained by succumbing to temptation and lack of self-control (Gul and Pesendorfer, 2001; Noor and Takeoka, 2010; Palma et al., 2018). Public health advocates might find it hard to propagate completely switching to fruit, fiber, and vegetable-intensive food diets because of budget and food culture restrictions. However, encouraging less calorie intake seems a plausible strategy in combating the obesity epidemic. Menus in many fast-food restaurants include high and relatively low-calorie food items, and thus, choosing low-calorie alternatives can be an initial step towards a healthy diet, and it can eventually lead to improving public health. It is not controversial to expect that habitual food preferences are inelastic in the short-run (Camerer, 2013). Therefore, finding appropriate behavioral mechanisms to encourage the consumption of relatively low-calorie food items can be a feasible and more effective policy alternative.

In 2008, New York City became the first jurisdiction in the United States to require restaurant chains to visibly post calorie information in their regular menus (Elbel et al., 2009). This policy initiative was later adopted by several states, including California, Massachusetts, and Oregon, and eventually became a nationwide law, effective May 2018 (Cawley et al., 2018). The law is binding for retailers including bakeries, coffee shops, movie theaters, and restaurant chains with 20 or more locations (Cawley et al., 2018). Follow-up studies report mixed results regarding the outcomes of the NYC calorie labeling law.

The existing literature offers a limited explanation of why the numeric calorie information is not effective in terms of encouraging low-calorie choices (Bollinger et al., 2011). Ellison et al. (2014a) find that numeric calorie information does not yield the expected policy outcome in calorie-labeling laws. Tangari et al. (2019) find that when the actual amount of calories of food items is less than the expected level, subjects tend to over-consume. Tangari et al. (2019) report that this "backfire effect" is observed when a snack product on the menu is perceived as "unhealthy." Their research suggests that temptation to food products may impact the effectiveness of numerical calorie information. Of course, each consumer's belief about the number of calories in a product is endogenous. Individual biases and heterogeneity define the way economic agents perceive and process calorie information. Tangari et al. (2019) suggest that by increasing the serving size, food manufacturers can also increase calories per serving, and nudge consumers towards less calorie intake. It has also been found that even the location of the calorie information on food labels matters in terms of healthy eating behavior. Dallas et al. (2019) find that since the United States population reads from left-to-right, presenting calories on the left side of food labels can help to reduce calorie intake by 16.31%. The distribution of calories within the menu can also affect the accuracy of recalled calories during food choices. Suppose an agent faces a menu consisting of multiple food items. If the agent is careful about what he eats, he will spend some amount of time examining each food item. He will try to memorize the properties of each examined item as he moves through different food products on the menu. The agent may revisit all (or some) of the food items on the menu before choosing his preferred item. Nevertheless, at the decision time, he will mostly rely on his recall of the calories he just (un)consciously tried to memorize. Choplin and Wedell (2014) tested how the recall process is impaired when the calorie distribution of the menu was positively and negatively skewed by introducing lower and higher calorie products, respectively. They report that the largest and smallest calorie values were recalled less in positively skewed distributions compared to negatively skewed distributions. Choplin and Wedell (2014)'s work implies that by adding a food item with an extremely large number of calories into the menu, the recalled or perceived calories of the other food products will be smaller compared to the case when the item is missing from the menu. Ellison et al. (2014b) find that compared to numeric calorie information, symbolic traffic light food labels are more effective in reducing calorie consumption. The parallel food labeling literature suggests that perceived and processed calorie information might be very different from the actual calorie amount shown on food labels. This information distortion can be very sensitive to the cues in the decision context. Our study follows this line of research and strives to disclose the behavioral underpinnings of the acquisition and processing of food calorie information. We hypothesize that when a consumer chooses from a food menu, the calorie distance between the food products affects his decision. Even when an economic agent faces a menu with multiple food products, his choice problem shrinks to the trade-off among a few alternatives. To keep it simple and identifiable, we use binary menus to study the impact of the calorie distance on healthy (low-calorie) food choices.

An important consideration in food choice and calorie intake is the behavior of food suppliers. Unfortunately, the reaction of restaurants to the calorie labeling laws is not clear (Bleich et al., 2017). Some initial studies report no significant changes in the nutritional and calorie content of menu items across targeted restaurants after the adoption of the law in 2008 (Namba et al., 2013; Deierlein et al., 2015). Namba et al. (2013) find that although the proportion of healthier food products has increased since 2008, the average calories of the studied menus stayed the same. This raises additional concerns about the "healthiness" of new food products considering the fact that average offered calories has not changed. Thus, based on initial findings, we can conclude that the calorie distance between new healthy items and conventional high-calorie food products have not changed significantly. Which according to our theoretical model and the results of our two experiments, may explain why calorie labeling laws have not been very effective.

3.2 Experiments

3.2.1 Lab experiment

We conducted two experiments to study the impact of calorie information and calorie distance on low-calorie food choices. The first experiment was a lab experiment conducted in the Summer of 2018. We employed a 3x2 between-subject design.[17] Subjects were recruited by a bulk email sent to all undergraduate students enrolled at a university located in the Southwestern United States. The email contained a sign-up link, and the main requirement was to abstain from eating and drinking for three hours before arriving to the lab.[18] The only exclusion criterion was having any known allergy and/or food and dietary restrictions. Upon arriving to the lab, subjects were randomly assigned to one of two experimental sessions: More Tempted and Less Tempted states. In the Less Tempted condition, subjects had to drink a protein shake (160 calories) before starting the experiment. In the More Tempted condition, subjects started the experiment without any food/beverage intake. Our assumption is that subjects who drink the protein shake are less hungry and hence less tempted compared to subjects who start the experiment without any calorie intake. In fact, our analyses show that in the More Tempted condition, on average, subjects reported more temptation to both high*(z=-1.32, p=0.09)* and low-calorie *(z=-2.14, p=0.02)* snacks com-

[17]See Appendix B for details.

[18]We did not have any available non-intrusive method to test whether subjects complied to the fasting requirement or not. However, random assignment of subjects to the experimental conditions can mitigate uncontrolled and unmeasured differences in pre-experimental fasting. Previous studies also used random assignment to deal with uncontrolled fasting (e.g., Brown et al. (2009); Bushong et al. (2010)).

pared to the Less Tempted condition.[19] This dimension helped us to understand the role of temptation in processing the calorie information and also to observe the moderation effect of visceral feelings in low-calorie food choices.

The experiment consisted of two treatments and one control. Subjects were randomly assigned to the treatments or to the control in the More and Less Tempted sessions. Subjects had to complete 40 food choices across 40 binary menus/trials. Before the experiment, subjects were informed that at the end of the study one of the trials would be randomly chosen, and they would have to consume their chosen product from the selected trial.[20] Since food choices were incentivized, meaning subjects had to eat their chosen product, it was in the best interest of subjects to choose the snack they actually wanted to eat. This procedure enables us to elicit subjects' true preferences by making possible deviations from their true preferences costly.

To control for brand effects and preferences for particular snack products, in each binary menu (i.e., in each trial), subjects were presented with a *regular* and a *reduced-calorie* version of the same snack. For example, in one of the choice menus, subjects had to choose either a regular Oreo or a reduced-fat Oreo. The serving sizes of alternatives were kept the same in order not to introduce a quantity difference between food snacks. Subjects were not shown nutritional contents of alternatives. Therefore, the calorie difference was the only dimension to compare snacks. Overall, each trial consisted of a binary-forced food choice problem.

In 16 (13) binary menus, the trade-off was along regular versus reduced-fat (reduced-sugar) products. The rest of the trials tested choice behavior without an explicit reference to either the sugar or fat dimension (for instance, regular vs. light yogurt). This aspect of the experiment helped us to observe differential behavioral approaches towards fat-intensive, sugar-intensive, and products where the source of the calorie reduction was undisclosed. Overall, in 20 trials, the relative calorie distance between products was less than or equal to

[19] Errors are clustered at the subject level.
[20] Subjects were required to eat only one serving size of the chosen product.

40 calories. In the rest of the trials, the calorie distance was over 40 calories.[21]

In the No Information condition, subjects were shown the food options in the original product packages without the table of nutrition details and any calorie information. Then, they had to choose one of the food snack alternatives. In the No Information condition, subjects were neither provided with the calorie information nor the calorie aspect of the food choice problems was salient. This helped us to capture the "raw human nature" before the introduction of calorie information. In the Accurate Information treatment, subjects were provided the calorie information of products, and they had to type the displayed calories into a box before indicating their choices. This feature was an important aspect of our design to make sure that subjects attended to and processed the accurate calorie information. Subjects had to choose their preferred products after typing the calorie information. This treatment allows us to study the effect of calorie information provided that consumers paid attention to the calorie product attribute. In the Homegrown Information treatment, subjects were asked to provide their *beliefs* about the calorie content of each product and type their beliefs into a box prior to making their food choice.[22] This part of the experiment helped us to observe the knowledge of consumers about the calorie content of food products in the absence of an external accurate information source.

The experimental sessions were scheduled from morning to evening hours. To minimize the effect of the time of the day, we randomized and balanced the number of More and Less Tempted sessions across all time slots. In each time slot, subjects were randomly assigned to the experimental conditions: No Information, Accurate Information, and Homegrown Information.[23]

[21] The distribution of the calorie distance across menus had the mean of 46.7 calories (Min=6, Max=190, st. dev.=45.48).

[22] We did not incentivize the elicitation of calorie beliefs on purpose. Monetary incentives would have pushed subjects to eliminate their biases and provide more accurate calorie estimates. However, that would not serve our research goals, as we wanted to observe whether consumers held systematic biases about the calorie contents of food products, and more importantly, whether they acted in line with their biases. Moreover, not incentivizing calorie guesses also helps us to align our design to a real-life situation where subjects have biases in their calorie beliefs, and they (mostly) act with those biases.

[23] Table B1 in Appendix B shows the demographic profile of subjects in each experimental condition. The

After the food-choice part of the experiment, subjects were presented with each snack product on a separate screen and were asked to indicate how much temptation they experienced towards the product.[24] This stage was followed by a demographic survey. To check subjects' compliance with the fasting requirement and also to test the effect of consuming the protein shake on the hunger level, we asked subjects to report their level of hunger prior to the experiment and at the time of answering the final survey questions. According to Table B1 in Appendix B, we do not detect statistically significant differences in "entry hunger" (the hunger level before consuming the protein shake in the Less Tempted condition) levels across the experimental conditions. We see the opposite case in "exit hunger" levels which hints that subjects were indeed less hungry if they had to drink the protein shake before the experiment.[25] We observe that when subjects did not consume the protein shake, they report a higher level of hunger at the end of the study. Although these results are based on self-reported measures, they suggest that consuming the protein shake helped to reduce the hunger level of subjects. An OLS regression analysis in Appendix B shows that there is a significant and positive correlation between the level of hunger and the reported temptation to snack products. Therefore, we can conclude that consuming the shake indeed changed the hunger level and consequently affected the temptation towards products.

3.2.2 Lab in the Field Experiment

Our lab experiment was designed to reveal the effect of the calorie distance when consumers were explicitly directed to notice and process the calorie information (Accurate Information) or when they were asked to submit their beliefs about the calorie content of food products without any external help (Homegrown Information). Both in the Accurate and Homegrown Information conditions, subjects had to mentally engage with calorie information (in the

comparison of conditions across different aspects of demographic profile reveals that the randomization was successful.

[24] Subjects used a 9-point Likert scale to report their temptation level (1 - "Not at all; 9 - "Extremely".)

[25] Unpaired Wilcoxon tests also support the findings in Table B1. In the Less Tempted condition, the exit and entry hunger levels were not statistically different (z=-0.90, p=0.18). However, in the More Tempted Condition, the exit and entry hunger levels were statistically different (z=-5.58,p<0.01).

form of processing the provided information or submit their beliefs) and type the provided or believed calorie amounts into a box before choosing their preferred snacks. The control condition did not engage subjects with any mental or typing activities. The distribution of the calorie distance across menus had a mean of 46.7 calories, and it raised the question of the sensitivity of our results to higher magnitudes of calorie differences as it is usually the case in full meals.

We conducted a lab-in-the-field experiment at a local restaurant from a national chain to address the above-mentioned concerns and to test the robustness of our findings in a more realistic environment. Our restaurant experiment took place in late January, 2019. Subjects were recruited from the student body of the University and the local community. Subjects were required to abstain from eating and drinking three hours before arriving to the restaurant and have no known allergies or food restrictions. Prior to the experiment, subjects were informed that they would choose their preferred food from especially designed menus and would have to eat their randomly selected choices before leaving the restaurant. Thus, they were neither allowed to take their selected food products out of the restaurant nor were they permitted to share their food with others. No participation reward was promised besides covering the food expenses. Thus, subjects had incentives to arrive hungry to enjoy their selected food items in the diner at the expense of the experimenters.[26]

We ran sessions from 12:00 pm until 8:00 pm on two consecutive Fridays, Saturdays, and Sundays. We installed two computer stations with eye-trackers in the backroom of the diner. We could only accommodate two subjects per half-an-hour slot. After arriving at the diner, subjects were briefed about the rules that were explicitly spelled out in the recruitment email, and they were provided with informed consent forms. After reading and signing the consent forms, subjects were randomly assigned either to the No Information or Accurate Information conditions. In both conditions, subjects went through 86 binary menus and selected their preferred meal in each menu. In the No Information condition, subjects

[26] All subjects complied with the rules.

were presented only with the descriptions of meals. However, in the Accurate Information condition they were also provided with calorie information below the food descriptions.

Similar to the lab experiment, to control for food preferences, subjects were offered the same or similar meals in each binary menu. We customized the ingredients and the side dishes of meals to exogeneously manipulate the magnitude of the calorie distance between the food products.[27]

Once subjects chose their meals in each menu and completed all 86 trials, we randomly selected one trial as the binding menu.[28] Subjects were informed about the randomly selected menu and shown their choice in that particular menu. In the No Information condition, subjects only saw the description of their selected meal (it was exactly the same description they had seen while indicating their choices in 86 trials). However, in the Accurate Information condition, subjects saw the descriptions and the calorie information of their chosen meal (similar to the previous 86 trials in that condition).

Then, subjects were provided with a beverage menu without the calorie information in the No Information, and with the calorie information in the Accurate Information condition. After choosing their preferred beverage, subjects were also provided with a dessert menu with and without the calorie information in the Accurate and No Information conditions, respectively. This part of the experiment was designed to observe whether subjects engage in any "calorie budgeting." We also used eye-tracking technology in our experiments. Appendix C presents the details regarding the eye-tracking data-collection process.

[27]The distribution of the calorie distance across menus had the mean of 435.87 calories (Min=30, Max=1320, st. dev.=322.71). The list of food items and their calories are reported in Appendix B.

[28]Since the number of trials is high it can trigger a fatigue effect. Note the presentation order of stimuli (binary menus) was randomized for each subject. In Appendix B, we control the presentation order of each menu and show that although the fatigue effect is marginally significant, it has a very negligible negative effect on the probability of choosing low-calorie choices. More importantly, controlling the possible fatigue effect does not change our main results.

3.3 Theoretical Model

3.3.1 Temptation, Self-Control Cost and Saliency of Information

Let $A = \{a_1, a_2, \cdots, a_n\}$ be a set of food items. Since agents choose from a menu with exactly two items, define $X = [A]^2$ i.e. X is the set of subsets of A with exactly two elements. The agent receives utility from consuming any $a \in A$. We denote this as $u(a)$ and refer to it as the normative utility of the item a. We want to assess an agent's decision when facing a menu with a low and a high-calorie alternative. Then, if $x = \{a, b\}$ and a has lower number of calories compared to b, $u(a) > u(b)$. In other words, we use normative utility to depict preferences of the agent from an objective perspective. Additionally, food choices generate temptation and, therefore, economic agents incur self-control costs in trying to resist temptation. Thus, we do not expect agents to always choose the low-calorie item in a real-world setting. As such, we argue that the agent can be tempted into choosing the high-calorie alternative (Gul and Pesendorfer, 2001; Noor and Takeoka, 2010, 2015). For any $a \in A$, we use $v(a)$ to depict item a's temptational utility. Then, following Noor and Takeoka (2015, 2010), for any $x \in X$, the agent's decision problem can be represented as:

$$W(x) = \max_{a \in x} \left[u(a) - \psi\left(\max_{b \in x} v(b)\right)\left(\max_{b \in x} v(b) - v(a)\right)\right] \tag{1}$$

where $\psi(\cdot) > 0$ is a weakly increasing continuous function. The second term in (1) is the self-control cost the agent faces by resisting the temptation of choosing the high-calorie item. This formulation shows that the agent has to choose the high-calorie item to lower the cost of resisting temptation. The function $\psi(\cdot)$ depicts the importance an agent places on his self-control cost and can be considered as its salience. For any $x \in X$, let $C(x)$ be the choice correspondence induced by (1) i.e. $C(x) = \text{argmax}_{a \in x}\left[u(a) + \psi\left(\max_{b \in x} v(b)\right) v(a)\right]$. Consider any $x \in X$ with $x = \{a, b\}$ such that $u(a) > u(b)$ and $v(a) < v(b)$. Then,

$C(x) = \{a\}$ if $u(a) - u(b) > \psi(v(b))[v(b) - v(a)]$. So, we have:

$$\begin{aligned} \Pr[C(x) = \{a\}] &= \Pr[u(a) - u(b) - \psi(v(b))[v(b) - v(a)] + \varepsilon > 0] \\ &= F[u(a) - u(b) - \psi(v(b))[v(b) - v(a)]] \end{aligned} \tag{2}$$

where we assume that $\varepsilon \sim F$ is symmetric around zero. Additionally, we assume that F is an increasing function. Since ε is symmetric around zero, $E(\varepsilon) = 0$. The introduction of the random variable ε allows some deviations from the decision problem of (1) owing to each agent's preferences but suggests that, on average, observed choices should be in accordance with (1).

Definition 1. (*Normatively identical menus*) Any $x, x' \in X$, with $x = \{a, b\}$ and $x' = \{a', b'\}$ such that $u(a) > u(b)$, $v(a) < v(b)$, $u(a') > u(b')$ and $v(a') < v(b')$, are said to be *normatively identical* if $u(a) = u(a')$ and $u(b) = u(b')$.

Definition 2. (*Higher temptation difference*) For any $x, x' \in X$, with $x = \{a, b\}$ and $x' = \{a', b'\}$ such that $u(a) > u(b)$, $v(a) < v(b)$, $u(a') > u(b')$ and $v(a') < v(b')$, x is said to have *higher temptation difference* than x' if $v(b) \geq v(b')$ and $v(b) - v(a) > v(b') - v(a')$.

The next proposition shows that, under certain circumstances, an increase in temptation utility distance increases the probability with which the high-calorie alternative is chosen over the low-calorie alternative.

Proposition 1. For *normatively identical menus*, the menu with *higher temptation difference* has lower probability of the low-calorie item chosen.

Proof: See Appendix D1

Quantifying temptation utility is quite challenging. Moreover, temptation utility is also essential in validating our model. In Appendix B, we show that there is positive correlation between the self-reported temptation difference and the calorie distance. Therefore, we employ the calorie distance between snacks in menus as a proxy for temptation difference. Establishing this empirical relationship enables us to state the first hypothesis of the model:

Hypothesis 1: Subjects will be less likely to choose low-calorie snacks as the calorie distance between the alternatives becomes greater.

The utility representation in equation (1) does not consider that temptation utilities and salience might vary across different states in a real-world setting. It is possible that certain circumstances make agents more concerned with their health and, as such, they might become less concerned with their self-control costs. Let $\tau \in \{0,1\}$. We say that the calorie content of snacks is *salient* if $\tau = 1$ and *not-salient* if $\tau = 0$. We would expect the agent to give less importance to his self-control costs when the calorie content of food alternatives is *salient*. This can be depicted as $\psi(\cdot;\tau=0) > \psi(\cdot;\tau=1)$.

On the other hand, circumstances can arise in which the agent is more susceptible to temptation. For instance, if a person is hungry, we would expect him to be more easily influenced into consuming a high-calorie item. Let $\lambda \in \{0,1\}$. We say an agent is *hungry* if $\lambda = 1$ and *non-hungry* if $\lambda = 0$. We would expect a *hungry* or *non-satiated* agent to receive more temptation utility from each item i.e. $v(\cdot;\lambda=1) > v(\cdot;\lambda=0)$. Additionally, we assume that a *non-satiated* agent faces at least as much self-control cost compared to a *satiated* agent which makes it harder for the former to exercise self-control. This suggests that for any $x \in X$, we have the following:

$$\max_{b\in x} v(b;\lambda=1) - v(a;\lambda=1) \geq \max_{b\in x} v(b;\lambda=0) - v(a;\lambda=0) \ \ \forall a \in x$$

Considering these particular states, the representation of (1) can be rewritten as follows:

$$W(x;\tau,\lambda) = \max_{a\in x}\left[u(a) - \psi\left(\max_{b\in x} v(b;\lambda);\tau\right)\left(\max_{b\in x} v(b;\lambda) - v(a;\lambda)\right)\right] \tag{3}$$

The choice correspondence associated with the problem presented in (3) can be given as:

$$C(x;\tau,\lambda) = \text{argmax}_{a\in x}\left[u(a) + \psi\left(\max_{b\in x} v(b;\lambda);\tau\right)v(a;\lambda)\right]$$

Then, we have:

$$\begin{aligned}\Pr\left[C(x;\tau,\lambda) = \{a\}\right] &= \Pr\left[u(a) - u(b) - \psi(v(b;\lambda);\tau)\left[v(b;\lambda) - v(a;\lambda)\right] + \varepsilon > 0\right] \\ &= F\left[u(a) - u(b) - \psi(v(b;\lambda);\tau)\left\{v(b;\lambda) - v(a;\lambda)\right\}\right] \qquad (4)\end{aligned}$$

Proposition 2. For the same menus, if the calorie content of products is *salient*, agents will choose the low-calorie menu item with a higher probability than agents who are in the choice-context where the salience of food information is missing.

Proof: See Appendix D2

In the experiment, in the Homegrown and Accurate Information conditions, the number of calories in food alternatives was salient for subjects. The only difference was that in the Homegrown condition, subjects had to rely on their own calorie estimates. However, in the Accurate Information condition subjects were provided with the accurate calorie information. Proposition 2 enables us to state the following hypothesis:

Hypothesis 2: Subjects in the Homegrown and Accurate Information conditions will be more likely to choose low-calorie snacks.

Proposition 3. For the same menus, *satiated* agents choose the healthy item with at least as much probability as *non-satiated* agents.

Proof: See Appendix D3

Recall that, in the Less Tempted condition, subjects drank a protein shake (160 Calories) before making food decisions. The average number of calories in low and high-calorie snacks was 85.88 and 132.6, respectively. Therefore, we assume that subjects who drank the protein shake were feeling less hungry compared to the subjects who started the study without any beverage intake. Table C1 also shows that at the end of the experiment, subjects who drank the protein shake were on average less hungry compared to subjects who started the study without any calorie intake. Based on Proposition 3, we can state the following hypothesis:

Hypothesis 3: Subjects in the Less Tempted condition will be more likely to choose low-calorie snacks.

3.3.2 Information Estimation

Consider any $x \in X$ such that $x = \{a, b\}$ where $u(a) > u(b)$ and $v(a;\lambda) < v(b;\lambda)$ for $\lambda \in \{0,1\}$. If normative utility difference is sufficiently high, the agent chooses menu item a otherwise he chooses menu item b. However, in certain situations, an agent may not actually have accurate information regarding his temptation utilities. In such circumstances, the agent might base his decisions on his estimated values of temptation utilities. Let estimated temptation utilities for an agent with incomplete information, for menu items a and b, be represented as $\tilde{v}(a;\lambda)$ and $\tilde{v}(b;\lambda)$, respectively. Additionally, assume that $\tilde{v}(a;\lambda)$ and $\tilde{v}(b;\lambda)$ are independently distributed according to cumulative distribution functions $F_a\left[\underline{v}(a;\lambda), \bar{v}(a;\lambda)\right]$ and $F_b\left[\underline{v}(b;\lambda), \bar{v}(b;\lambda)\right]$, respectively, such that $\bar{v}(a;\lambda) < \underline{v}(b;\lambda)$ and $\underline{v}(a;\lambda) \geq 0$.[29] Intuitively, this condition suggests that, even with incomplete information, agents can differentiate between (low-calorie) healthy and unhealthy items.

Definition 3. We define the following:

1. (*Unbiased temptation difference*) $E\left[\tilde{v}(b;\lambda) - \tilde{v}(a;\lambda)\right] = v(b;\lambda) - v(a;\lambda)$,[30]

2. (*Over-estimated temptation difference*) $E\left[\tilde{v}(b;\lambda) - \tilde{v}(a;\lambda)\right] > v(b;\lambda) - v(a;\lambda)$,[31] and

[29] These conditions ensure that estimated temptation utilities are positive and estimated temptation utility of healthy menu item is always greater than that of unhealthy menu item.

[30] Estimated temptation utilities of healthy and unhealthy items are equally biased (if at all).

[31] Estimated temptation utility of unhealthy item is upward biased relative to that of healthy item.

3. (*Under-estimated temptation difference*) $E\left[\tilde{v}\left(b;\lambda\right)-\tilde{v}\left(a;\lambda\right)\right]<v\left(b;\lambda\right)-v\left(a;\lambda\right)$.[32]

Consider any $x\in X$ with $x=\{a,b\}$ such that a and b are low-calorie and high-calorie menu items, respectively. For agents with incomplete information, define expected choice correspondence as:

$$
\begin{aligned}
EC\left(x;\tau,\lambda\right) &= \operatorname{argmax}_{a\in x}\left[u\left(a\right)-E\left\{\psi\left(\tilde{v}\left(b;\lambda\right);\tau\right)\left[\tilde{v}\left(b;\lambda\right)-\tilde{v}\left(a;\lambda\right)\right]\right\}\right] \\
&= \operatorname{argmax}_{a\in x}\left[u\left(a\right)+E\left\{\psi\left(\tilde{v}\left(b;\lambda\right);\tau\right)\tilde{v}\left(a;\lambda\right)\right\}\right]
\end{aligned}
$$

That is, $EC\left(x;\tau,\lambda\right)$ represents the choice made, on average, by an agent with incomplete information. Then, we have the following:

$$
\begin{aligned}
\Pr\left[EC\left(x;\tau,\lambda\right)=\{a\}\right] &= \Pr\left[u\left(a\right)-u\left(b\right)-E\left\{\psi\left(\tilde{v}\left(b;\lambda\right);\tau\right)\left[\tilde{v}\left(b;\lambda\right)-\tilde{v}\left(a;\lambda\right)\right]\right\}+\varepsilon>0\right] \\
&= F\left(u\left(a\right)-u\left(b\right)-E\left\{\psi\left(\tilde{v}\left(b;\lambda\right);\tau\right)\left[\tilde{v}\left(b;\lambda\right)-\tilde{v}\left(a;\lambda\right)\right]\right\}\right) \qquad (5)
\end{aligned}
$$

Proposition 4. If $\psi\left(\cdot;\tau\right)$ is constant, we have the following:

1. For *unbiased temptation difference*, an agent with incomplete information, on average, chooses the low-calorie item with the same probability as an agent with complete information,

2. For *over-estimated temptation difference*, an agent with incomplete information, on average, chooses the low-calorie menu item with lower probability as compared to an agent with complete information, and

3. For *under-estimated temptation difference*, an agent with incomplete information, on average, chooses the low-calorie menu item with higher probability than an agent with complete information.

[32] Estimated temptation utility of unhealthy item is downward biased relative to that of healthy item.

Proof: See Appendix D4

Hypothesis 4: (Placed in the same order as the parts of Proposition 4).

4.1. When the estimated and the true calorie distances are the same, there should be no difference in choices of the Homegrown and Accurate Information conditions,

4.2. When the estimated calorie distances is greater than the true calorie distance, agents in the Homegrown Information condition choose low calorie item with lower probability compared to agents in the Accurate Information condition, and

4.3. When the estimated calorie distances is less than the true calorie distance, agents in the Homegrown Information condition choose low calorie item with higher probability compared to agents in the Accurate Information condition.

To sum up, our model predicts that when an agent overestimates (underestimates) the calorie distance between the alternatives, he will be less (more) likely to choose the low-calorie alternative. However, when he estimates the calorie distance without an error, the probability of choosing low-calorie snacks will be the same as in the Accurate Information condition.

In Appendix D5, we also show that for an increasing and convex $\psi(\cdot;\tau)$ and *unbiased* temptation utilities, an agent with incomplete information chooses the low-calorie menu item with at least as much probability as an agent with complete information.

3.4 Results

3.4.1 The Effect of the Calorie Distance on Low-Calorie Choices (Result 1)

In our theoretical model, we show that food choices are mainly driven by the relative temptation utilities of the menu alternatives. Our first proposition states that subjects will incur in higher self-control costs as the temptation distance (or temptational utility difference) between the two alternatives increases. Table 3.1 shows that indeed, an increase in the temptational utility distance is associated with a lower likelihood of choosing the low calorie alternative. According to Table 3.1, a one-point increase in the temptational utility ranking difference reduces the probability of choosing the low-calorie snacks by 5 percentage points (p.p.).

Table 3.1: Low-calorie choice tendency and the temptation distance (lab experiment)

	(1)	(2)	(Sugar-subsample)	(Fat-subsample)	(Undisclosed-subsample)
(Intercept)	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Temptational distance	-0.05^{***}	-0.05^{***}	-0.05^{***}	-0.08^{***}	-0.04^{***}
	(0.01)	(0.01)	(-0.05)	(-0.08)	(-0.04)
Male		-0.12^{***}	-0.09^{**}	-0.14^{***}	-0.11^{***}
		(0.03)	(-0.09)	(-0.14)	(-0.11)
BMI		0.01^{*}	0.01	0.01^{**}	0.00
		(0.00)	(0.01)	(0.01)	(0.00)
High Income dummy (>60,000 USD)		-0.02	0.01	-0.06	0.00
		(0.03)	(0.01)	(-0.06)	(0.00)
AIC	11616.35	10773.57	3465.54	4231.66	3024.46
BIC	11630.48	10808.58	3494.93	4262.09	3053.02
Log Likelihood	-5806.18	-5381.78	-1727.77	-2110.83	-1507.23
Deviance	11612.35	10763.57	3455.54	4221.66	3014.46
Num. obs.	8640	8120	2639	3248	2233

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: The table shows the results of the Logit regression analysis across all experimental conditions with clustering at the subject level. The dependent variable is a binary measure, and it is "1" when the subject chooses the low-calorie alternative in the binary menu. The temptational distance variable is the temptation ranking difference between the alternatives. The clustering helps to account the possible serial correlation among repeated measures.

Moreover, Appendix B presents evidence that there is a significant positive relationship between calorie distance and temptation distance, and even after controlling for observables this relationship still holds. Thus, it justifies using the calorie distance variable as a proxy measure for the temptational utility difference.

One can argue that subjects might choose high-calorie snacks to obtain more nutritional content. Thus, choosing the high-calorie alternative does not necessarily mean succumbing to temptation. As mentioned in the *Experiment* section, subjects did not have access to the nutritional panel information. They only knew that in some choices the calorie trade-off was along the sugar dimension (e.g., Jellow Strawberry vs Jellow Strawberry Sugar free) or fat dimension (e.g., Colby Jack vs Colby Jack reduced fat). Moreover, in some choice sets, the trade-off dimension was not disclosed (e.g., Yoplait cherry vs Yoplait cherry light). Table 3.1 shows that a one point increase in the temptational utility difference is associated with 5 p.p. and 8 p.p. reduction in the probability of choosing low-calorie snacks in the Sugar-subsample (where the trade-off was along the sugar dimension) and Fat-subsample (where the trade-off was along the fat dimension), respectively. However, when the trade-off dimension was undisclosed, a one-point increase in the temptational utility difference reduced the likelihood of low-calorie choices by 4 p.p. These results suggest that the alternative explanation that subjects could have chosen high-calorie alternatives because of the nutritional content is not substantiated by our data. Furthermore, the fact that the negative effect of the temptational distance on low-calorie choices is more pronounced for sugar- and fat-intensive products, validates our assumption that a larger calorie difference because of more sugar or fat content is related to increased self-control costs. Therefore, our data is well-suited to study the role of the self-control cost (i.e., temptational utility difference) with the help of exogenously manipulated calorie differences in food choices.

Based on our model, we predict that the calorie distance between the alternatives will be a strong factor in explaining low-calorie choices. *Hypothesis 1* states that the probability of low-calorie choices depends on the calorie distance between the snacks, and an increase in the distance decreases the probability of choosing low-calorie alternatives.

We start our analysis focusing on the lab experiment results. Table 3.2 validates *Hypothesis 1* and shows that an increase in the calorie distance between the choice alternatives reduces the probability of choosing the low-calorie snack in the lab experiment. Table 3.2 column 5 displays that after controlling for demographic variables, a 100-calorie increase in the calorie distance decreases the probability of choosing the low-calorie snack by 3 p.p. This effect becomes larger and reaches 10 p.p. as we control for the experimental conditions and their interactions with the calorie distance in Table 3.2 column 6. Table 3.2 column 7 shows that when we include the interaction of the experimental conditions with the More Tempted state, the results are robust and do not change. The Akaike Information Criterion (AIC) has its lowest value in Table 3.2 column 7. Therefore, it shows that the model analyzed in the last column better fits our data compared to the model specifications in other columns of Table 3.2 The documented effect of the calorie distance on the low-calorie choice probability is a causal relationship, as we exogenously varied the relative difference between the calorie contents of the alternatives.

The results of the restaurant experiment also confirm *Hypothesis 1.* Table 3.3 column 5 shows that a 100-calorie increase in the calorie distance reduces the probability of choosing low-calorie foods by 2 p.p. This effect is robust across different model specifications in Table 3.3.

Our first set of results from both the lab and the restaurant experiments confirms *Hypothesis 1* and shows that the success of self-control acts mainly depends on the choice context or the menus in food decision-making. This result also provides strong evidence that models on menu-dependent preferences are very promising in explaining the empirical irregularities in previous research.

The analysis of the interaction terms in Table 3.2 column 7 shows that the effect of the calorie distance on the probability of low-calorie choices can be reversed if the calorie content of the food products is salient. A 100-calorie increase in the calorie distance increases the probability of choosing the low-calorie snack by 12 p.p and 9 p.p in the Accurate and Homegrown Conditions, respectively. It is also interesting that the Accurate and Homegrown Information conditions do not affect low-calorie choices directly, but only through the calorie distance variable. A 100-calorie increase in the distance reduces the probability of low-calorie choices because of incurred self-control costs, but it also increases the same probability due to the salience of the calorie content. However, we do not detect a significant interaction effect

Table 3.2: Low-calorie choice tendency and calorie distance (lab experiment)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male	-0.11^{***}	-0.11^{***}	-0.11^{***}	-0.10^{***}	-0.11^{***}	-0.11^{***}	-0.10^{***}
	(0.01)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
BMI	0.01^{***}	0.01^{*}	0.01	0.01^{*}	0.01^{*}	0.01^{*}	0.01^{*}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
High Income dummy (>60,000 USD)	-0.02^{**}	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Accurate Information		0.03		-0.00		-0.03	-0.05
		(0.04)		(0.06)		(0.04)	(0.06)
Homegrown Information		-0.01		0.02		-0.05	-0.02
		(0.04)		(0.06)		(0.05)	(0.06)
More Tempted			-0.01	-0.01		-0.01	-0.01
			(0.03)	(0.05)		(0.04)	(0.06)
More Tempted*Accurate Information				0.06			0.06
				(0.08)			(0.08)
More Tempted*Homegrown Information				-0.06			-0.06
				(0.08)			(0.08)
Calorie distance					-0.03^{*}	-0.10^{***}	-0.10^{***}
					(0.02)	(0.03)	(0.03)
Calorie distance*More Tempted						-0.01	-0.01
						(0.04)	(0.04)
Calorie distance*Accurate Information						0.12^{***}	0.12^{***}
						(0.04)	(0.04)
Calorie distance*Homegrown Information						0.09^{**}	0.09^{**}
						(0.04)	(0.04)
AIC	11020.64	11017.70	11021.42	11003.38	10998.42	10986.35	10971.40
BIC	11048.64	11059.71	11056.43	11066.40	11033.42	11063.36	11062.41
Log Likelihood	-5506.32	-5502.85	-5505.71	-5492.69	-5494.21	-5482.17	-5472.70
Deviance	11012.64	11005.70	11011.42	10985.38	10988.42	10964.35	10945.40
Num. obs.	8120	8120	8120	8120	8110	8110	8110

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: The table shows the results of the Logit regression analysis across all experimental conditions with clustering at the subject level. The dependent variable is a binary measure, and it is "1" when the subject chooses the low-calorie alternative in the binary menu. The clustering helps to account the possible serial correlation among repeated measures. The calorie distance variable is the actual calorie distance between the alternatives in the Accurate Information and No Information conditions. However, the calorie distance variable includes estimated calories by subjects in the Homegrown Information condition, since subjects acted on their believes in this condition. The calorie distance variable is normalized by 100 calories. Thus, the marginal effect shown in the table indicates the probability change due to a 100 calorie increase in the calorie distance variable.

of the calorie distance and the Accurate Information condition in the restaurant experiment.

The interaction effects necessitate average marginal effect analysis to reveal the "net effect" of the calorie distance on the probability of choosing the low-calorie food. Figure 3.1 panels (a) and (b) show the average marginal effect of the calorie distance variable on the

Table 3.3: Low-calorie choice tendency and calorie distance (lab-in-the-field experiment)

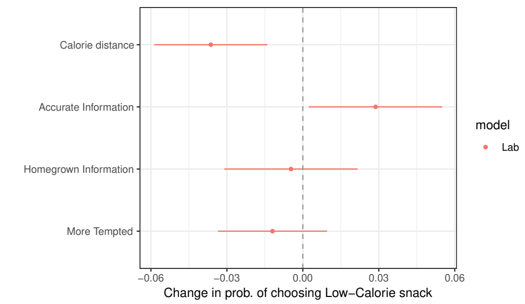
	(1)	(2)	(3)	(4)	(5)
(Intercept)	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male	-0.04^{***}	-0.04	-0.04	-0.04	-0.04
	(0.01)	(0.04)	(0.03)	(0.03)	(0.03)
BMI	-0.00^{***}	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
High Income dummy (>60,000 USD)	0.07^{***}	0.07^{*}	0.06	0.06	0.06
	(0.01)	(0.04)	(0.04)	(0.04)	(0.04)
Calorie distance		-0.02^{***}		-0.02^{***}	-0.02^{***}
		(0.00)		(0.00)	(0.00)
Accurate Information			0.11^{***}	0.11^{***}	0.09^{***}
			(0.03)	(0.03)	(0.03)
Calorie distance*Accurate Information					0.00
					(0.01)
AIC	13221.41	13131.86	13116.26	13025.68	13026.21
BIC	13250.10	13167.72	13152.13	13068.72	13076.42
Log Likelihood	−6606.71	−6560.93	−6553.13	−6506.84	−6506.10
Deviance	13213.41	13121.86	13106.26	13013.68	13012.21
Num. obs.	9632	9632	9632	9632	9632

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

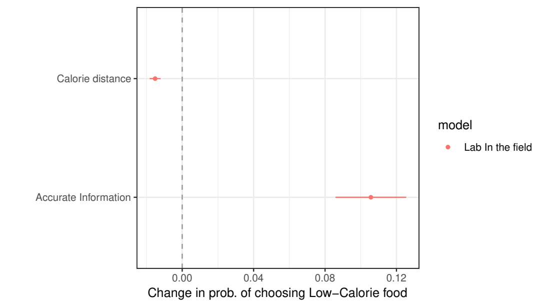
Note: This table displays the analysis of choices in the restaurant setting. The table shows the results of the Logit regression analysis across all experimental conditions with clustering at the subject level. The dependent variable is a binary measure, and it is "1" when the subject chooses the low-calorie alternative in the binary menu. The clustering helps to account the possible serial correlation among repeated measures. Calorie distance variable is the actual calorie distance between the alternatives and normalized by 100 calories. Thus, the marginal effect shown in the table indicates the probability change due to a 100 calorie increase in Calorie distance variable.

probability of low-calorie choices in the lab and restaurant experiments, respectively. Figure 3.1 panel (a) shows that the average marginal effect of the calorie distance is around 3 p.p in the lab experiment. Similarly, Figure 3.1, panel (b) reports that the average marginal effect of the distance is around 2 p.p. in the restaurant experiment. Both experiments confirm *Hypothesis 1* and demonstrate that an increase in the calorie distance burdens agents with self-control cost and eventually decreases the probability of choosing low-calorie foods.

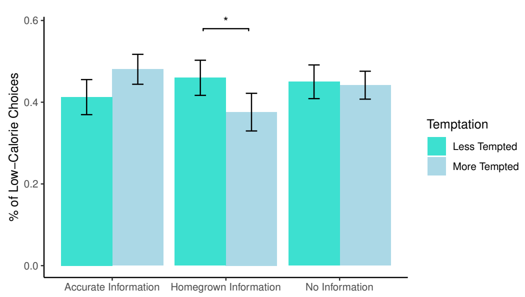
We observe that the demographic profile of subjects is a non-trivial determinant of their food choices in the lab experiment. According to Table 3.2 column 7, being a male on



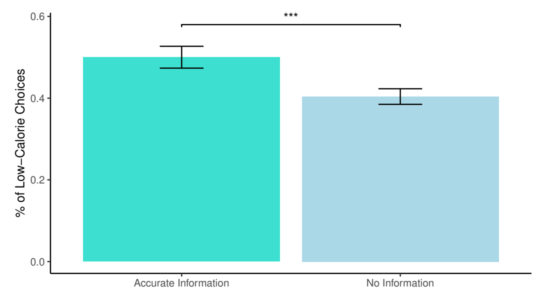
(a) The analysis of the average marginal effect of the calorie distance on low-calorie choices (lab experiment)



(b) The analysis of the average marginal effect of calorie distance on low-calorie choices (lab in the field experiment)



(c) Low-calorie choices across all experimental conditions (lab experiment)



(d) Low-calorie choices across all experimental conditions (lab in the field experiment)

Figure 3.1: Low-calorie choices across experimental conditions.

average reduces the probability of choosing the low-calorie food item by 10 p.p compared to females, and this result is robust across all considered models. Interestingly, higher BMI is associated with more frequent low-calorie choices. However, the marginal effect of BMI is 1 p.p. Table 3.2 demonstrates that income does not explain food choices in our sample. Table 3.3 reports that there is no significant relationship between demographic control variables and the probability of choosing low-calorie foods in the restaurant experiment. Overall, the relationship of demographic control variables with the outcome variable should be interpreted as correlation, since these variables are endogenous.

3.4.2 The Effect of the Saliency of the Calorie Content of Food Products on Low-Calorie Choices (Result 2)

Proposition 2 shows that consumers will be more likely to choose low-calorie snacks if the calorie content of food products is salient. In our model, we show that saliency of the calorie content reduces the severity of the experienced menu dependent self-control costs. Therefore, our model predicts that subjects will be willing to incur the self-control cost and still will be more likely to choose low-calorie foods in the Homegrown and Accurate Information conditions of the lab experiment and in the Accurate Information condition of the restaurant experiment. *Hypothesis 2* states that subjects will be more inclined to choose low-calorie alternatives if the calorie content of food products is salient.

Table 3.2 column 2 reports the results of logit regression analyses with dummies for experimental conditions and with demographic controls. We observe that the effect of the saliency of the calorie content of food products is not significant in the lab experiment. Our model with dummies for the Homegrown Information and Accurate Information conditions and with demographic control variables in column 2 robustly show that the effect of the saliency of the calorie content of snacks on low-calorie choices is null in the lab experiment. However, as discussed above, Table 3.2 column 7 shows that when the calorie information is salient, an increase in the calorie distance also increases the probability of low-calorie choices. It seems the saliency of calorie information affects choice outcomes mainly through the calorie distance in the lab experiment. Therefore, we have to consider the average marginal effect of saliency in the lab experiment. Figure 3.1 panel (a) shows that the Accurate Information condition has around 3 p.p average marginal effect on the probability of choosing low-calorie foods. The Homegrown Information condition has a null effect on low-calorie choices. Thus, we partially confirm *Hypothesis 2* in the lab experiment and show that only the Accurate information condition has an average marginal effect on low-calorie choices.

Following a similar line of analyses for the restaurant experiment in Table 3.3 reveals that the Accurate Information condition increases the probability of choosing low-calorie foods by 9 p.p. Figure 3.1 panels (c) and (d) show that the effect of the Accurate Calorie Information is much stronger in the restaurant experiment than in the lab experiment. Figure 3.1 panel (b) shows that the saliency of the calorie information increases the probability of choosing low-calorie foods by 11 p.p in the restaurant experiment.

Overall, we confirm that the saliency or the existence of the accurate calorie information *causally* increases low-calorie choices, and this effect is in the range of 3-11 p.p., depending on the food types and environment. It should be noted that the prediction of *Hypothesis 2* is the primary motivation behind Calorie Labeling Laws. As discussed in the Literature Review section, the effect of calorie information treatments is inconclusive in previous related studies (Fernandes et al., 2016). In this article, we also show that the saliency of the calorie content in decision environment has a non-uniform effect on food choices. We find a marginally significant and positive effect of calorie saliency on low-calorie choices in the lab experiment and this effect is mediated by the calorie distance. Our restaurant experiment shows that the effect of information saliency is around 11 p.p Our results are close to what Cawley et al. (2018) report in a recent study. Cawley et al. (2018) also find that showing consumers calorie information reduces the amount of ordered calories by 3 p.p. In this study, we show that the effect of the saliency of the calorie content of food products might be very small in some environments, and this effect can be observed only by explicitly modeling menu-dependent self-control costs. This finding further supports the importance of modeling menu-dependent self-control costs in understanding the effect of calorie information on food choices.

3.4.3 The Effect of temptation on Low-Calorie Choices (Result 3)

Proposition 3 shows that being in the hungry state reduces the probability of low-calorie choices. Our model shows that being hungry increases the effect of the temptation distance between food products and consequently imposes more self-control costs on decision-makers. *Hypothesis 3* states that subjects will be less likely to choose low-calorie snacks if they feel more hungry.

Figure 3.1 panel (c) shows the percentage of low-calorie snack choices across experimental conditions in the lab experiment. It can be observed that being more and less tempted has a marginal impact on the percentage of low-calorie choices only in the *Homegrown Information* condition *(z=-1.35, p=0.09)*. In other experimental conditions, if we compare more and less tempted states, we do not detect any significant differences in food choices. The regression analysis depicted in Table 3.2 column 3 shows that we do not detect any significant differential impact of the More Tempted state on low-calorie choices compared to the Less Tempted state. The analysis of the average marginal effects in Figure 3.1 panel (a) also confirms our previous results. Thus, we show that being in the Less and More Tempted states turns out to be ineffective in reducing calorie intake. In fact, it has recently been shown that the relationship between sugar intake and self-control resources is inconclusive (Vadillo et al., 2016). We confirm this finding by demonstrating that drinking a protein shake does not have a significant impact on food choices.

3.4.4 The Impact of the Bias in Calorie Estimates on Low-Calorie Choices (Result 4)

Until this point, we have shown that the calorie information itself does impact low-calorie choices, but specificities of menus mediate this effect in the lab experiment. We also have shown that the calorie distance between the alternatives is important in food choices and can mediate the effect of calorie information.

The Homegrown Information condition in the lab experiment helps us to identify one of the plausible channels through which the effect of the calorie distance can be transmitted to food choice outcomes. If the calorie distance is very closely related to temptation (which is shown in Appendix B), then its effect on the bias in calorie estimates can help us to understand the source of behavioral anomalies in food choices. In our model, and consequently in *Hypothesis 4*, we predict that upward biases in the belief estimates of the calorie distance between the alternatives will reduce the probability of low-calorie choices. The rationale of this prediction is that if subjects overestimate the distance, they also overrate the foregone temptational utility difference in case they choose the low-calorie product. In case of an overestimation of the distance, subjects become more vulnerable to choosing the high-calorie food items compared to the case with no bias in the calorie estimates (i.e., agents with the accurate calorie information). For the underestimated calorie distance, the logic works in the opposite direction. If an individual underestimates the calorie distance, then he thinks that the temptational utility sacrificed when choosing the low-calorie food is low. Thus, downward biases in the calorie estimates increase the probability of choosing low-calorie food items. When an individual precisely estimates the calorie distance, he has the same probability of choosing the low-calorie food product compared to an agent who has accurate calorie information. In our model, we show that the overestimated (underestimated) distance burdens the agent with greater (lower) self-control costs compared to the no-bias case, and eventually leads to less (more) frequent self-control failures.

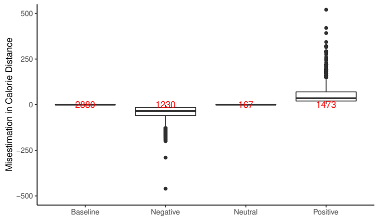
To test our hypothesis, we calculate the difference in estimated and true calorie distances, and we use choices in the Accurate Information as our baseline.[33] We label the choices in the Accurate information condition as "Baseline." Overestimated and underestimated calorie distances are labeled as "Positive" and "Negative, " respectively. Finally, the calorie distance estimates without an error are labeled as "Neutral."

Figure 3.2 panel (a) shows the distribution of biases in estimations of calorie distances and the number of choices in each category. We observe that the number of Neutral choices is very small. We also observe a small number of outliers both in Negative and Positive observations. In Figure 3.2, panel (b) we focus on the observations where the absolute magnitude of the biases is equal or less than 100 calories. It should be noted that this kind of observations constitute around 94% of the data.

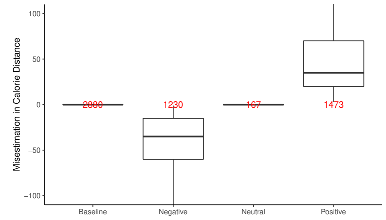
[33] The magnitude of the bias or misestimation is calculated as: Estimated Belief Calorie Distance — True Calorie Distance.

Figure 3.2 panel (b) shows that the average size of the misestimations is around -50 (50) calories for Negative (Positive) observations. When we analyze the percentage of the low-calorie choices across Baseline, Negative, Neutral, and Positive choices in Figure 3.2 panel (c), we do not detect any statistically significant difference. Comparing Neutral and Baseline observations is inconclusive because of the low sample size in Neutral observations. However, both Negative and Positive choices have a sufficient number of observations, but still, we do not detect a significant difference between them and the Baseline choices. Based on Figure 3.2 panel (c) we cannot confirm *Hypothesis 4*.

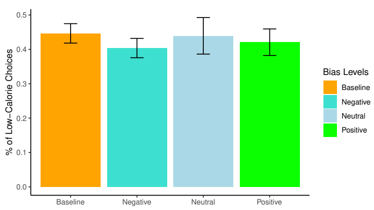
Table 3.4 shows regression analyses with categories that describe biases in the calorie distance estimation, where the effect of Negative, Positive, and Neutral dummies are compared to the dummy for Baseline choices. The models considered in Table 3.4 cannot confirm *Hypothesis 4*. We observe that there is no difference between Neutral and Baseline choices, which is in line with *Hypothesis 4*, but because of the small sample size of Neutral observations, we cannot rely on this outcome. Similar to Figure 3.2 panel (c), we also do not find any differential effect of Positive and Negative choices contrary to the predictions of *Hypothesis 4*. We find that only in the More Tempted state, the effect of overestimation in the calorie distance has the hypothesized effect. This means, when subjects started the experiment without drinking the protein shake, they were more vulnerable to choose high-calorie snacks if they overestimated the calorie distance. Notice that the accuracy of estimation is endogenous and might be related to individual characteristics. However, being in the More Tempted state is exogenous and allows us to reveal a causal relationship. This result suggests that More Tempted subjects were less likely to choose the low-calorie snacks when they overestimated the calorie distance compared to subjects in the Less Tempted state. The separate effect of the More Tempted state is null, and it is in line with our results from the previous sections. Accordingly, we can conclude that temptation mainly affects choice outcomes through individual beliefs about the relative calorie distance. In our model, in the More Tempted state, an agent experiences a greater self-control cost because temptation



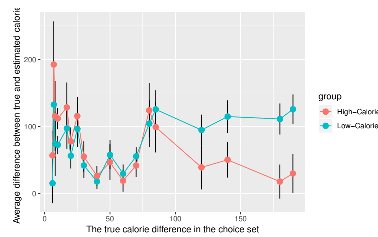
(a) "Average misestimation of calorie distance". This is the combination of the observations in Accurate and the Homegrown Information conditions. In the panel (b) we focus on the observations missestimations in the range of (-100,100).



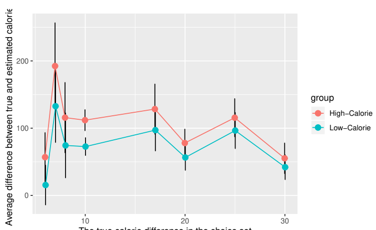
(b) "Average misestimation of calorie distance. This is the same figure depicted in panel (a). In this graph, to give e better sense about the means of the distributions, we focus on (-100, 100) range of misestimations, which represent 94% of the data."



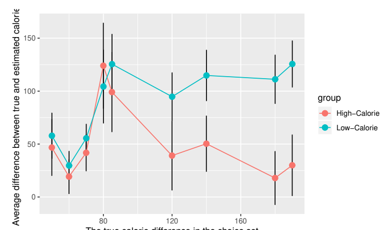
(c) "categories of misestimation of calorie distance and low-calorie choices"



(d) "Average misestimation of individual product calories"



(e) "Average misestimation of individual product calories in small (less than 40) calorie distance menus



(f) "Average misestimation of individual product calories in large (more than 40) calorie distance menus

Figure 3.2: Calorie estimation

increases the magnitude of the temptation utility distance. Observing a significant negative impact of Positive choices compared to Baseline choices in the More Tempted state aligns with our theoretical model.

Table 3.4: Low-calorie choice tendency and the estimated calorie distance

	(1)	(2)	(3)	(4)
(Intercept)	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Negative	−0.02	−0.03	−0.03	0.02
	(0.04)	(0.05)	(0.05)	(0.06)
Neutral	−0.00	−0.02	−0.02	0.02
	(0.06)	(0.06)	(0.06)	(0.08)
Positive	−0.04	−0.04	−0.04	0.04
	(0.05)	(0.05)	(0.05)	(0.07)
Male		−0.10**	−0.10**	−0.09**
		(0.04)	(0.04)	(0.04)
BMI		0.00	0.00	0.00
		(0.01)	(0.01)	(0.01)
High Income dummy (>60,000 USD)		−0.04	−0.04	−0.04
		(0.04)	(0.04)	(0.04)
More Tempted			−0.01	0.05
			(0.04)	(0.06)
Negative*More Tempted				−0.10
				(0.08)
Neutral*More Tempted				−0.09
				(0.12)
Positive*More Tempted				−0.14*
				(0.09)
AIC	7865.50	7260.08	7261.50	7245.11
BIC	7892.13	7306.17	7314.18	7317.55
Log Likelihood	−3928.75	−3623.04	−3622.75	−3611.56
Deviance	7857.50	7246.08	7245.50	7223.11
Num. obs.	5750	5350	5350	5350

stars

Note: This table displays the analysis of the relationship between the categories of misestimation in calorie distances and low-calorie choices. The dependent variable is a binary measure, and it is "1" when the subject chooses the low-calorie alternative in the binary menu. Neutral dummy means subjects precisely estimated the calories distance. Positive (Negative) dummy means subjects overestimated(underestimated) the calorie distance. The effect of Neutral, Positive and Negative dummies are estimated relative to Baseline dummy. All choices in the Accurate Information condition are represented with Baseline dummy in the regressions.

3.4.5 The Impact of the Bias in Calorie Estimates of Individual Products on Food Choices

In our theoretical model, we only focused on the calorie distance; that is why *Hypothesis 4* exclusively focuses on misestimations in the calorie distance and their effects on low-calorie choices. However, an individual can overestimate the distance by overestimating the number of calories in high-calorie foods and/or by underestimating the number of calories in the low-calorie foods. The individual can also underestimate the calorie distance by underestimating the number of calories in the high-calorie food and/or by overestimating the calorie content of the low-calorie foods. Since subjects estimated the calorie distance by separately estimating the calorie content of the products, we have an opportunity to scrutinize the effect of misestimations of the number of calories for each product on low-calorie choices.

Figure 3.2 panel (d) portrays the relationship between the true calorie difference and the magnitude of misestimations in product calories. The misestimation/bias variable is calculated as the difference between the estimated calorie content and the actual number of calories in the snack. We can observe that an increase in the calorie distance generates more errors in calorie estimations. Another interesting result is that when the distance becomes greater subjects overestimate calories in low-calorie alternatives more compared to high-calorie snacks. A part of this error can be related to the lack of proper knowledge about the nutritional content of products. However, another part of these systematic "mistakes" can be the product of visceral factors that are abundant in food choice environments. Especially, observing that the magnitude of mistakes is larger for low-calorie snacks compared to high-calorie alternatives raises the suspicion that perhaps subjects were trying to justify the consumption of high-calorie snacks by (deliberately) underestimating their calories. Indeed, the post-study survey reveals that on average subjects feel more temptation toward high-calorie snacks, which in turn can explain their more pronounced biased behavior in estimating the calories of low-calorie products.

Figure 3.2 panels (e) and (f) support our observations from panel (c). In the low-calorie distance menus, subjects demonstrate almost the same amount of misestimation in calories. However, as we move to high-calorie distance menus, we observe that subjects overestimate calories in low-calorie products more compared to their high-calorie alternatives.

The next logical question is "Does the bias in individual calorie estimates affect choice outcomes?" Appendix E presents several analyses to disentangle the effect of biases in the calorie estimates of products on low-calories choices. The results show that an increase in the true calorie distance increases (decreases) the magnitude of the bias in estimated calories of low-calorie (high-calorie) products. This suggests that, as the temptational trade-off between choice alternatives increases, subjects tend to show more biases regarding the calorie content of low-calorie snacks compared to high-calorie alternatives. Our follow-up analyses also show that only the bias in calorie estimates of low-calorie products has an impact on decision outcomes. Specifically, a 100-calorie upward misestimation of the number of calories in low-calorie snacks reduces the probability of choosing the low-calorie alternative by around 7 p.p.

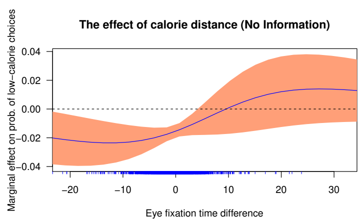
3.4.6 The Impact of Visual Attention on Food Choices

This section showcases the role of visual attention and hence salience in food choices. I employ eye-tracking data collected during the experiments described in Chapter III and demonstrate the importance of choice-relevant process data in understanding choice outcomes.

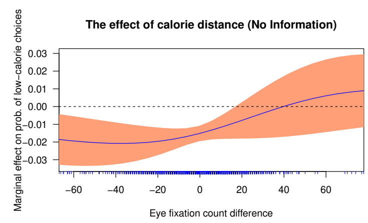
Here I present my analyses and findings starting from the lab-in-the-field experiment. Before starting our discussion, I have to acknowledge that the eye-tracking data is endogenous. The fixation time each subject spends on product descriptions, calorie information, and product pictures depends on personal characteristics. However, we have a number of treatment variables in our experiment, and our focus is on the moderation effect of visual attention on the probability of choosing low-calorie meals in the restaurant experiment. I focus on eye-fixation time and fixation counts in our discussion.

Figure 3.3 portrays the moderation effect of visual attention for the calorie distance. Eye fixation time and fixation counts measure the time subjects spent reading the description of meals in binary menus. In all plots, the X-axis shows the difference between the fixation time and fixation counts on the low-calorie and high-calorie alternatives. Positive (negative) values on the X-axis indicate that subjects spent more fixation time and fixation counts on the low-calorie (high-calorie) meals. Figure 3.3 panels (a) and (b) show that in the No Information condition, the negative effect of the calorie distance is prevalent if subjects spend more fixation time and counts on the high-calorie product. When the time subjects fixate on alternatives is balanced across low-calorie, and high-calorie alternatives in the No Information condition, a 100-calorie increase in the distance reduces the probability of choosing the low-calorie alternatives by 2 p.p. However, more fixation time and fixation counts on the low-calorie alternative neutralize the effect of the calorie distance. When subjects spent more than 5 seconds of fixation time (or more than 20 fixation counts) on the high-calorie alternative, we do not observe the negative effect of the calorie difference. Since subjects were not provided with the calorie information in the No Information condition, they could infer the calorie distance only by reading the ingredients of the meals. Therefore, it seems more attention to the product descriptions of the low-calorie alternatives helps to reduce the severity of the calorie distance/self-control costs. However, in the Accurate Information condition, if subjects over-fixate on any alternative, the effect of calorie distance vanishes (See Figure 3.3 panels (c) and (d)). The calorie distance reduces the probability of low-calorie choices only when subjects spend a similar amount of fixation time and fixation counts on alternatives.

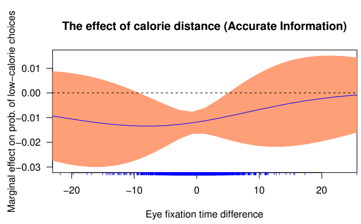
Contrary to the No Information condition, subjects were provided with the calorie information in the Accurate Calorie Information condition. Therefore, we have an opportunity to analyze a potential moderation effect of fixation time and fixation counts on the calorie information part of the screen for the calorie distance. This measure enables the identification of the role of attention to numeric calorie information in altering the effect of self-control cost/calorie distance. The novelty of this analysis is that previous studies mainly focused on the intent-to-treat effects when they disclosed the numeric calorie information to subjects in calorie information conditions. Indeed, there is evidence that relative visual salience differ-



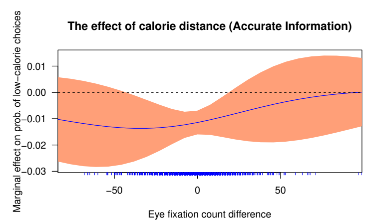
(a) Eye fixation time (in seconds) difference between low and high food products. If positive (negative) a subject spent more time fixating on the description of low-calorie (high-calorie) alternative.



(b) Eye fixation count difference between low and high food products. If positive (negative) a subject had more fixation count on the description of low-calorie (high-calorie) alternative.



(c) Eye fixation time (in seconds) difference between low and high food products. If positive (negative) a subject spent more time fixating on the description of low-calorie (high-calorie) alternative.



(d) Eye fixation count difference between low and high food products. If positive (negative) a subject had more fixation count on the description of low-calorie (high-calorie) alternative.

Figure 3.3: Moderation effect of attention on food descriptions.

ences can significantly change decision outcomes in food choices (Mormann et al., 2012). This analysis helps us to have a continuous measure of the information treatment and understand the differential impact of visual saliency on food choices.

Figure 3.5 panels (a) and (b) show that when subjects spend a similar amount of fixation time and fixation counts on the calorie information of both alternatives, the effect of calorie distance is significant. However, if they fixate more on any alternative's calorie information, the effect of the calorie distance vanishes. This result suggests that equal salience of the calorie information of food alternatives does not alter the effect of the menu-dependent self-control cost. Over-attention to any calorie information neutralizes the effect of the calorie distance or the menu-dependent self-control cost. This is important evidence to show that when a decision-maker experiences a trade-off and compares the calorie content of food products by spending the same fixation time on both alternatives, he is vulnerable to the menu-dependent self-control cost. In the case of disproportional attention to any product information, the decision-maker does not face the trade-off, and the effect of the menu-dependent self-control cost vanishes.

Figure 3.5 displays the moderation effect of the visual attention to product descriptions for the Accurate Information condition. Unlike Figure 3.4, the analysis in Figure 3.5 intends to show the effect of intent-to-treat (dummy for the Accurate Information condition) and how attention to product descriptions moderates its effects. The Y-axes in both plots show the difference between the Accurate Information and No Information conditions in terms of low-calorie choices. Figure 3.5 panels (a) and (b) portray that if we compare observations where subjects spend the same amount of fixation time and fixation counts on product descriptions in both experimental conditions, on average, we see around 10 p.p. more low-calorie choices in the Accurate Information condition. However, we do not see the effect of the Calorie Information condition for observations where subjects exhibit unbalanced fixation time and fixation counts on one of the alternatives. The analysis depicted in Figure 3.5 confirms our results from Figure 3.4. As in Figure 3.4, the effect of the information treatment is prevalent when decision-makers make trade-offs by focusing on alternatives and spend similar fixation times and fixation counts on meal descriptions. The effect of the information condition reduces, when they over-fixate on any alternative.

X-axes in Figure 3.6 represent the fixation time difference between low and high-calorie snacks in the lab experiment. We can observe that across all experimental conditions, subjects tend to choose low-calorie snacks more frequently if they spend more time fixating on the pictures of low-calorie snacks. It is important to note that the fixation time variable

(a) Eye fixation time (in seconds) difference between low and high food products. If positive (negative) a subject spent more time fixating on the calorie information of low-calorie (high-calorie) alternative.

(b) Eye fixation count difference between low and high food products. If positive (negative) a subject had more fixation counts on the calorie information of low-calorie (high-calorie) alternative.

Figure 3.4: Moderation effect of attention on calorie information.

(a) Eye fixation time (in seconds) difference between low and high food products. If positive (negative) a subject spent more time fixating on the description of low-calorie (high-calorie) alternative.

(b) Eye fixation count difference between low and high food products. If positive (negative) a subject had more fixation count on the description of low-calorie (high-calorie) alternative.

Figure 3.5: Compared moderation effect of attention to food descriptions.

for the Homegrown and Accurate Information conditions was measured after subjects were exposed to numerical calorie information (or provided their beliefs about the number of calories in the Homegrown condition). Therefore, these results points to the importance of non-numeric and visual information in food choices (Bordalo et al., 2013).

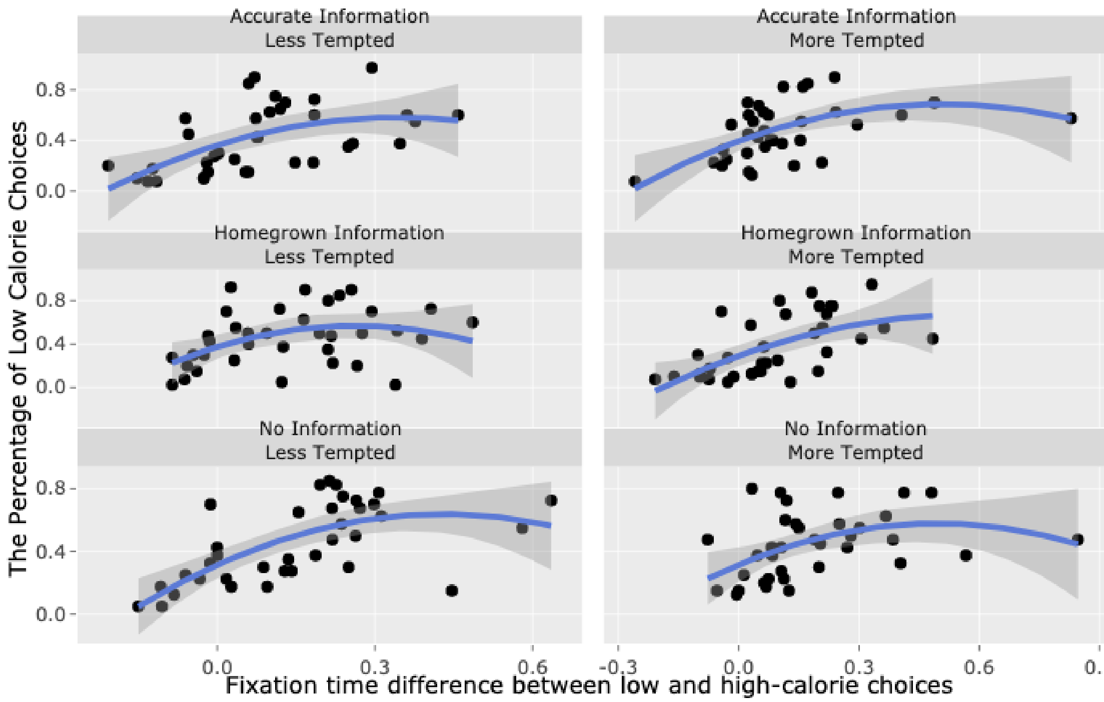


Figure 3.6: Analysis of fixation time.

Appendix F presents several results about the impact of the product types on biases in calorie estimates in the lab experiment. We show that when the calorie trade-off is across the *sugar* dimension, subjects tend to overestimate the number of calories in low-calorie products compared to high-calorie products. When the calorie trade-off is across the *fat* dimension or when the source of the calorie reduction is *undisclosed*, subjects demonstrate the same level of biases for low and high-calorie snacks in their calorie estimations. We also show that when the estimated calorie distance between products increases by 100 calories, the probability of choosing low calorie-snacks decreases around 9 p.p. in the *sugar* dimension, but we do not detect an effect for the other dimensions. Overall, our analyses show that biases in calorie estimates are also strongly related to product types.

Appendix G presents our analysis on whether subjects are calorie budgeting when they are provided with the accurate calorie information in the restaurant experiment. We show that when subjects have the accurate information and they know which meal they are going to eat, they consume more beverage calories compared to the No Information condition. In the same situation, they tend to consume fewer dessert calories compared to the No Information condition. This finding suggests that the calorie budgeting phenomenon is prevalent only in dessert choices and not in beverage choices.

CHAPTER IV

CONCLUSIONS

Menu-dependent preferences have gained a great deal of attention (Gul and Pesendorfer, 2001; Noor and Takeoka, 2015; Olszewski, 2011; Frick, 2016; Gómez-Miñambres and Schniter, 2014). The primary promise of this emerging literature is that choice outcomes depend greatly on the saliency of "competing" cues in the choice environment (Bordalo et al., 2013; Gabaix et al., 2006; Mormann et al., 2012). The seminal paper of Gul and Pesendorfer (2001) was the very first attempt to model menu-dependent preferences within the axiomatic choice framework. Noor and Takeoka (2015) made one of the first attempts to pin down the self-control costs of menus. This dissertation continues this effort, and through lab and restaurant experiments, shows the importance of menu-dependent self-control costs in food choices. I show that the relative calorie distance between food choice alternatives affects temptational utility differences. I also provide strong evidence that an increase in the relative calorie distance reduces the probability of choosing low-calorie choices both in the lab experiment when the trade-off is between snacks, and in the restaurant experiment when food choices are made in a real restaurant environment with full meals.

My dissertation also ties menu-dependent preferences and subsequent menu-dependent self-control costs to the effectiveness of calorie information when provided with food choices. As noted, both secondary data and experimental studies report mixed results in this regard. I show that while providing calorie information increases the probability of choosing low-calorie choices, this effect is counterbalanced by menu-dependent self-control costs. Thus, the projected effect of the calorie labeling laws is discounted by menu specifics. The policy relevance of this result is that calorie labeling laws exclusively focus on the demand and intend to nudge consumers. The supply side, however, is also important. Menus or choice environments can play a crucial role in moderating the expected impact of calorie information. Bringing food retailers on board in terms of nudging consumers to reduce calorie intake might be more effective in improving public health. Future studies should also focus on the reaction of food retailers to calorie labeling laws in order to provide a more detailed picture of the consequences of listing calorie information.

My dissertation also speaks to an emerging literature on the importance of motivated biases (Coutts, 2019; Bénabou and Tirole, 2016; Mayraz, 2011). I show that individual beliefs about calories are subject to systematic biases, and that these biases depend on menu-dependent self-control costs. The Homegrown Information condition of the lab experiment shows that consumers are more vulnerable to food-related temptation, especially when they do not have accurate calorie information and consequently are forced to rely on their personal beliefs. I find that as the true calorie distance between products increases, subjects overestimate the calorie content of the low-calorie alternative to a greater extent than that of the high-calorie alternative. I also show that only the bias in the estimation of the number of calories in the low-calorie products has a non-zero effect and significantly reduces the probability of choosing the low-calorie alternatives. Additionally, these results are prevalent only when the calorie trade-off is made because of the amount of sugar present. My findings could stem from the understanding that the Homegrown knowledge of calories also relates to individual characteristics, which in turn may also relate to individual preferences for healthy food. In fact, Wisdom et al. (2010) find a strong relationship between errors in the perceived calorie content of food products and demographic variables. For instance, females are less likely to misestimate the number of calories in meals compared to males. Temptation may also impair the cognitive function responsible for retrieving existing knowledge from the brain. Previous studies already establish a convincing link between cognitive load and temptation (Shiv and Fedorikhin, 1999; Levine and Fudenberg, 2006). My findings suggest that consumers may be less precise in estimating calories when food cues induce temptation. Overall, my results demonstrate the importance of biases in calorie estimates in food choices and their connection to menu-dependent self-control costs.

Finally, eye-tracking technology enables us to go beyond an intent-to-treat type of analysis and allows us to explore the moderation effect of the continuous measure of visual attention on food choices. I show that low-calorie choices are positively correlated with the attention given to images of low-calorie alternatives in the lab experiment. Menu-dependent self-control costs are also sensitive to the saliency of the food descriptions in the restaurant experiment. I also show that the positive effect of the calorie information on the probability of choosing the low-calorie alternative is significant when subjects pay similar amounts of visual attention to food alternatives. Thus, I show that the bias in visual attention can significantly alter the effect of information-provision on food choices.

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APPENDIX A

Proof of Proposition 1:

Part I: Since the agent prefers a in X:

$$(1-w_p^*)(q_a-q_b)-w_p^*(p_a-p_b)>0 \tag{4}$$

To find the cut-off value of w_p^* we can write this equality as:

$$(1-w_p^*)\triangle_q-w_p^*(p_a-p_b)=0$$

$$\triangle_q=w_p^*(\triangle_q+p_a-p_b)$$

$$\underline{w}_p=\frac{\triangle_q}{\triangle_q+p_a-p_b} \tag{5}$$

Then, for $1>w_p^*>\underline{w}_p$ the agent will choose a in X.

Part II: In order for the agent to choose b in X' the following should hold:

$$(1-w_p^*)(q_a-q_b)-w_p^*(p'_a-p'_b)<0$$

$$(1-w_p^*)\triangle_q-w_p^*(p'_a-p'_b)<0$$

Again, to find the cut-off value of w_p^* we can write this equality as:

$$(1 - w_p^*)\triangle_q - w_p^*(p'_a - p'_b) = 0$$

$$\triangle_q = w_p^*(\triangle_q + p'_a - p'_b)$$

$$\overline{w}_p = \frac{\triangle_q}{(\triangle_q + p'_a - p'_b)} \tag{6}$$

then the agent will choose b in X' if $0 < w_p^* < \overline{w}_p$

Part III:

Since $\overline{w}_p > \underline{w}_p$

Then the agent will always choose a in X and b in X' if $w_p^* \in (\underline{w}_p, \overline{w}_p)$. $\square$

Proof of Proposition 2:

Let's denote the price weight of agents who choose a in X as $w_p^* \sim U$, which follows a continuous uniform distribution. According to Definition 2, $w_p^*(\gamma = 0) < w_p^*(\gamma = 1)$. Then, w_p^* is a composite of two non-intersecting distributions: $w_p^* = w_p^*(\gamma = 0) \bigcup w_p^*(\gamma = 1)$. Then it is safe to assume that $w_p^*(\gamma = 0)$ and $w_p^*(\gamma = 1)$ are uniform distributions with support $(\underline{w}_p, m)$ and $(m, 1)$ for $m \in (0, 1)$, respectively. We also know that only the weights in $(\underline{w}_p, \overline{w}_p)$ cause switching from a to b in X'. Thus, all we need to show is that a random value $\tilde{w_p^*}(\gamma = 0)$ from the distribution of $w_p^*(\gamma = 0)$ is more likely to be in the interval of $(\underline{w}_p, \overline{w}_p)$ compared to a random value $\tilde{w_p^*}(\gamma = 1)$ from the distribution of $w_p^*(\gamma = 1)$.

Case I: Consider the case when $(\underline{w}_p < m < \overline{w}_p < 1)$, then for $Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 0) < \overline{w}_p)$ we can obtain the following:

$$Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 0) < \overline{w}_p) = \int_{\underline{w}_p}^{\overline{w}_p} \frac{1}{m - \underline{w}_p} dx$$

$$Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 0) < \overline{w}_p) = \frac{\overline{w}_p - \underline{w}_p}{m - \underline{w}_p} \tag{7}$$

since $m - \underline{w}_p < \overline{w}_p - \underline{w}_p$, then $Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 0) < \overline{w}_p) = 1$

and for $Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 1) < \overline{w}_p)$ we can obtain the following:

$$Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 1) < \overline{w}_p) = \int_{\underline{w}_p}^{\overline{w}_p} \frac{1}{1 - m} dx$$

$$Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 1) < \overline{w}_p) = \frac{\overline{w}_p - \underline{w}_p}{1 - m} \tag{8}$$

since $1-m$ can be lower, equal or greater than $\overline{w}_p - \underline{w}_p$, $Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 1) < \overline{w}_p) \in (1, 0)$. Therefore, in this case we obtain $Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 0) < \overline{w}_p) > Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 1) < \overline{w}_p)$.

Case II: Consider the case when $(\underline{w}_p < \overline{w}_p < m < 1)$, then for $Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 0) < \overline{w}_p)$ we still obtain the same previous relationship:

$$Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 0) < \overline{w}_p) = \frac{\overline{w}_p - \underline{w}_p}{m - \underline{w}_p} \tag{9}$$

Since $m - \underline{w}_p > \overline{w}_p - \underline{w}_p$, then $Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 0) < \overline{w}_p) \in (1, 0)$.

For $Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 1) < \overline{w}_p)$, since $(m, 1) \cap (\underline{w}_p, \overline{w}_p) = \emptyset$, then $Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 1) < \overline{w}_p) = 0$

Therefore, in this case we obtain $Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 0) < \overline{w}_p) > Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 1) < \overline{w}_p)$.

The results of Case I and II yield that $Pr(\underline{w}_p < \tilde{w_p^*}(\gamma = 0) < \overline{w}_p) \geq Pr(\underline{w}_p < \tilde{w_p^*}(\gamma =$

$1) < \overline{w}_p$). $\square$

Proof of Proposition 3:

Proof: Consider any $X \in \mathscr{X}$, $X = \{a, b\}$, such that $q_a < q_b$ and $p_a - p_b < 0$. Moreover, $\lambda \in \{0, 1\}$ and by Definition 4:

$$\psi(\lambda = 1, w_p) > \psi(\lambda = 0, w_p)$$

We can use this relationship to obtain:

$$(1 - \psi(\lambda, w_p)(q_a - q_b) - \psi(\lambda = 1, w_p)(p_a - p_b) > (1 - \psi(\lambda, w_p)(q_a - q_b) - \psi(\lambda = 0, w_p)(p_a - p_b) \tag{12}$$

Then based on (3), we obtain:

$$Pr[C(X, \lambda = 1) = \{a\}] > Pr[C(X, \lambda = 0) = \{a\}] \tag{13}$$

$\square$

Scenario (High Price-Salience): Imagine that an unforeseen event requires of you an immediate $2,000 expense. Are there ways in which you may be able to come up with that amount of money on a very short notice? How would you go about it? Would it cause you long-lasting financial hardship? Would it require you to make sacrifices that have long-term consequences? If so, what kind of sacrifices?

Scenario (Low Price-Salience): Imagine that an unforeseen lottery win gives you a $2,000 gain. Can you come up with a spending plan budget with that amount of money on a very short notice? How would you spend this money? Would it cause you long-lasting financial relief? Would gaining the extra money help you to have benefits that have long-term advantages? If so, what kind of benefits?

Table A1: Balance table for the experimental conditions

Variable	(1) No Price-Salience	(2) High Price-Salience	(3) Low Price-Salience	(4) High- vs No Price-Salience	(5) Low- vs No Price-Salience	(6) High- vs Low Price-Salience
Income	39,230.500	46,278.078	40,087.840	7,047.581	857.343	6,190.238
	(25,941.646)	(29,507.125)	(30,130.980)	(5,688.897)	(5,493.602)	(5,976.985)
Male	0.340	0.444	0.286	0.104	-0.054	0.159*
	(0.479)	(0.503)	(0.456)	(0.101)	(0.091)	(0.096)
White	0.640	0.711	0.679	0.071	0.039	0.033
	(0.485)	(0.458)	(0.471)	(0.097)	(0.093)	(0.093)
High School Education	0.080	0.044	0.071	-0.036	-0.009	-0.027
	(0.274)	(0.208)	(0.260)	(0.050)	(0.052)	(0.048)
College Education	0.560	0.489	0.518	-0.071	-0.042	-0.029
	(0.501)	(0.506)	(0.504)	(0.103)	(0.098)	(0.101)
Graduate School Education	0.360	0.467	0.411	0.107	0.051	0.056
	(0.485)	(0.505)	(0.496)	(0.102)	(0.096)	(0.100)
BMI	25.290	24.625	26.155	-0.664	0.865	-1.529
	(5.595)	(4.403)	(6.138)	(1.041)	(1.146)	(1.088)
Married (dummy)	0.460	0.378	0.429	-0.082	-0.031	-0.051
	(0.503)	(0.490)	(0.499)	(0.102)	(0.098)	(0.099)
Household Size	2.820	2.644	2.893	-0.176	0.073	-0.248
	(1.304)	(1.351)	(1.448)	(0.273)	(0.269)	(0.281)
Observations	50	45	56	95	106	101

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BMI is calculated based on self-reported measures of height and weight.

Table A2: The performance of subjects in the Raven test across experimental conditions (OLS results)

(a) With a dummy for high income subjects

	(1) log(Raven Score)	(2) log(Raven Score)	(3) log(Raven Score)	(4) log(Raven Score)
High Price-Salience	0.0615	0.0667	0.0565	0.0640
	(1.23)	(1.33)	(0.98)	(1.07)
Low Price-Salience	−0.0611	−0.0670	−0.135*	−0.118
	(−0.99)	(−1.11)	(−1.81)	(−1.59)
High Income (dummy)		−0.0662	−0.130	−0.108
		(−1.43)	(−1.60)	(−1.30)
High Price-Salience *High Income			0.0262	0.0105
			(0.26)	(0.11)
Low Price-Salience * High Income			0.153	0.120
			(1.26)	(1.00)
Male				0.0595
				(1.23)
Education	No	No	No	Yes
Constant	2.825***	2.858***	2.890***	2.826***
	(68.50)	(72.89)	(78.21)	(38.16)
N	151	151	151	151

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) With a continuous variable of income

	(1) log(Raven Score)	(2) log(Raven Score)	(3) log(Raven Score)	(4) log(Raven Score)
High Price-Salience	0.0615	0.0684	−0.0103	0.00544
	(1.23)	(1.34)	(−0.15)	(0.07)
Low Price-Salience	−0.0611	−0.0603	−0.161*	−0.135
	(−0.99)	(−0.98)	(−1.81)	(−1.49)
Income (continuous)		−0.00969	−0.0264**	−0.0219*
		(−1.25)	(−2.03)	(−1.71)
High Price-Salience * Income			0.0195	0.0154
			(1.20)	(0.91)
Low Price-Salience * Income			0.0256	0.0192
			(1.28)	(0.97)
Male				0.0545
				(1.11)
Education	No	No	No	Yes
Constant	2.825***	2.863***	2.929***	2.846***
	(68.50)	(64.27)	(68.61)	(35.42)
N	151	151	151	151

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Question 1.

Product A	Product B
	
Price is $0	Price is $5.0

(a) The first question of the MPL for beverage choices

Question 1.

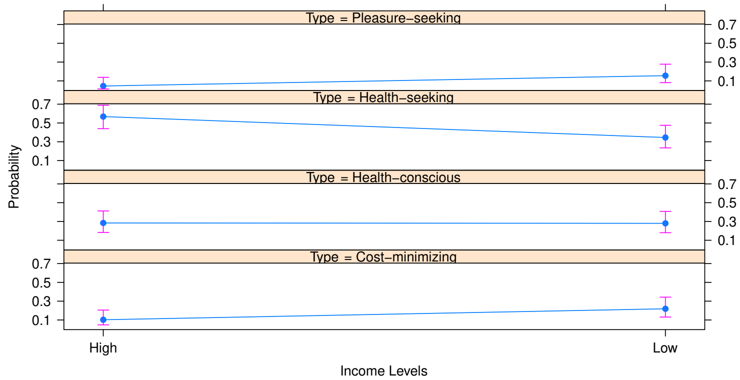
Product A	Product B
	
Price is $0	Price is $5.0

(b) The first question of the MPL for food choices

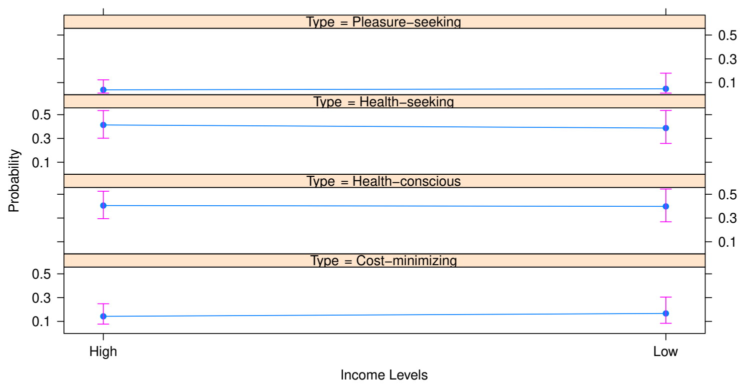
	Question: Would you like to complete the extra task to cover your purchase	**Your answer (Yes/No)**
1)	if the price of the selected food item is $0	Yes: _____ No: _____
2)	if the price of the selected food item is $0.5	Yes: _____ No: _____
3)	if the price of the selected food item is $1	Yes: _____ No: _____
4)	if the price of the selected food item is $1.5	Yes: _____ No: _____
5)	if the price of the selected food item is $2.0	Yes: _____ No: _____
6)	if the price of the selected food item is $2.5	Yes: _____ No: _____
7)	if the price of the selected food item is $3.0	Yes: _____ No: _____
8)	if the price of the selected food item is $3.5	Yes: _____ No: _____
9)	if the price of the selected food item is $4.0	Yes: _____ No: _____
10)	if the price of the selected food item is $4.5	Yes: _____ No: _____
11)	if the price of the selected food item is $5.0	Yes: _____ No: _____

(c) The MPL for the real effort task

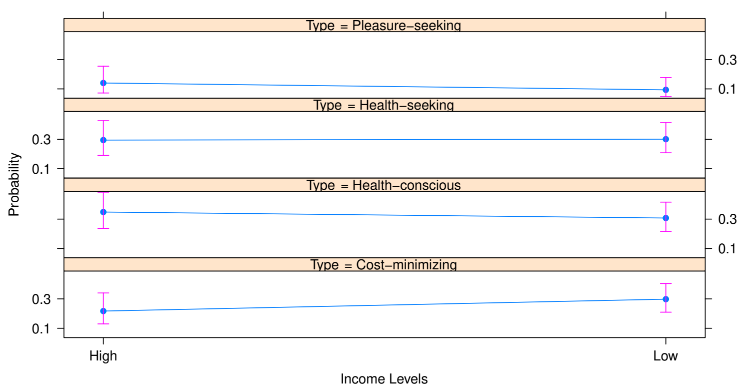
Figure A1: MPLs for food products and for the real effort task.



(a) No Price-Salience Condition



(b) High Price-Salience Condition



(c) Low Price-Salience Condition

Figure A2: The role of income levels in predicting consumer types. The probability estimations correspond to multinomial logit regression results where food type, gender, logged values of Raven scores and income are independent predictors. The estimation results are from the sub-samples based on experimental conditions. This approach helps us to capture the effect of the income in each experimental condition.

APPENDIX B

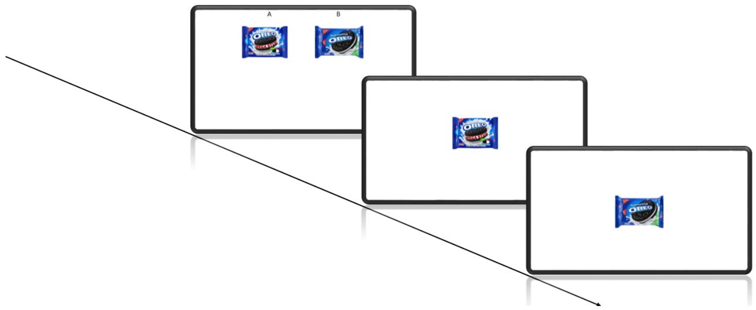
Here, we provide detailed information about experimental materials. Subjects were recruited by bulk emails sent to the entire undergraduate student body of a university in the Southwestern United States (IRB2017-0011D). The bulk email contained a link from www.signupgenius.com which listed all experimental sessions. We ran experimental sessions from 8 am until 5 pm in June and July of 2018. Each session lasted approximately 30 minutes, and we recruited five subjects per session. In the recruitment email, subjects were asked to fast for three hours (refrain from eating and drinking) before the study. Unfortunately, we were not able to test the compliance to the fasting requirement. We followed Brown et al. (2009) and randomly assigned subjects to the experimental conditions. Table A1 shows that initial hunger levels of subjects across experimental treatments were not statistically different.

Table B1: Balance test of the randomization of subjects across the experimental conditions (Lab experiment)

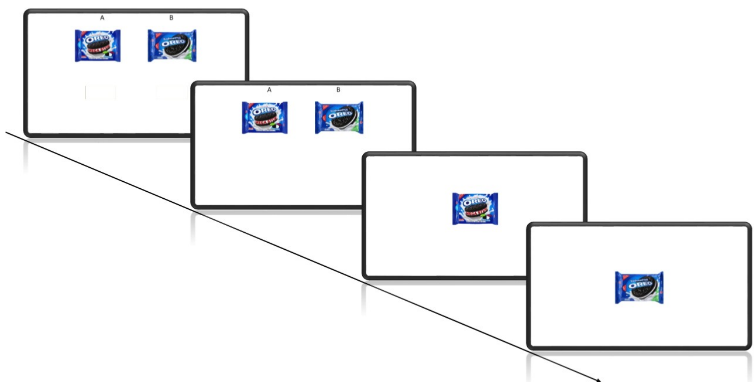
	(1) No Information(More Tempted)	(2) Homegrown Information(More Tempted)	(3) Accurate Information(More Tempted)	(4) No Information(Less Tempted)	(5) Homegrown Information(Less Tempted)	(6) Accurate Information(Less Tempted)	(7) p-value from joint orthogonality test of experimental conditions
Male	0.324	0.531	0.485	0.314	0.324	0.514	0.178
White	0.361	0.333	0.389	0.500	0.583	0.583	0.101
High Income (dummy)(>60,000 USD)	0.389	0.500	0.500	0.444	0.500	0.444	0.915
BMI	24.629	25.157	24.850	24.612	24.445	23.582	0.777
Hunger level (Entry)	5.971	5.312	6.788	5.600	5.943	5.200	0.369
Hunger level (Exit)	7.457	6.656	7.030	5.200	5.543	4.914	0.000
N	36	36	36	36	36	36	

The recruitment email also stated that subjects would be rewarded with $20 participation fee and they would have to make food decisions and be required to eat snacks. Therefore, only subjects with no known food allergy and restrictions were eligible to participate in the study. After arriving at the lab, subjects were given a detailed consent form, and they were informed that they would have to eat their preferred food product to receive the complete amount of the participation fee.

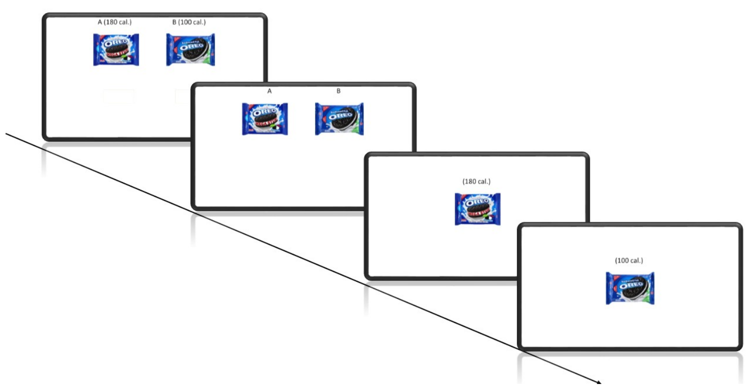
We randomly assigned sessions to Less Tempted (subjects drank a protein shake) or More Tempted (subjects did not drink a protein shake) conditions. All subjects in Less Tempted condition were given Ensure Protein shake with vanilla flavor. Subjects drank the shakes in the waiting room while signing consent forms. After signing consent forms (and drinking shakes in the Less Tempted condition) subjects were invited into the lab and were randomly assigned to the No Information, Homegrown Information and Accurate Information conditions. After completing food decisions on computers (and also with the presence of Tobii eye-tracking spectrums,) each subject was invited to another room and individually rolled a bingo cage to determine the binding decision. After the determination of the binding choice problem, subjects were given their preferred snack and were required to eat the snack in order to be entitled to the complete amount of the participation fee. Subjects had a right to stop participating in the study whenever they wanted. Subjects were entitled to prorated amount of the participation fee in the case of not completing all experimental protocols. All subjects completed the entire experimental protocols.



[a] No Information



[b] Homegrown Information



[c] Accurate Information

The figure depicts the sequence of stimuli across experimental stages in the lab experiment.

Figure B1: Stimuli in the lab experiment.

Figure B1 depicts the sequence of stimuli across experimental stages. In all experimental conditions, subjects made 40 food decisions in the first stage. In the No Information condition, subjects first saw snacks and on the same screen they selected their preferred food. No other information including the calorie content of snacks was provided or primed. In the Homegrown Information condition, on the first screen of each food choice, subjects saw snacks and had to provide their beliefs about the number of calories in each food product. They were also required to enter their beliefs below the pictures of snacks on the same screen. They moved to the next screen, where they saw the same products and had to indicate their preferred snack. In the Accurate Information condition, in each choice trial, subjects saw alternatives and the accurate calorie content of snacks and had to type shown numbers below the pictures of products. After typing the numerical calorie information, subjects immediately moved to the next screen and selected their preferred food.

After completing 40 choice decisions, subjects were shown each snack individually and were asked to indicate how much temptation they were feeling for each snack. After revealing their temptation level to all products, subjects completed a demographic survey and were invited to another room for the realization of randomization.[34]

We kept all 80 snack products in the lab and never ran out of any product that was randomly determined (see Table A2 for the complete list of snacks).

Table A3 shows the relationship between the calorie distance and the temptation distance. The results validate our assumptions of using the calorie distance as a proxy of the temptation distance.

Table B4 shows the demographic profile of subjects, and Table B5 and Figure B2 demonstrate the employed stimuli in the restaurant experiment.

[34]Subjects reported their gender, height, weight, income and also their entry and exit hunger levels.

Table B2: The list of snack products in each choice trial in the lab experiment.

Choice Trial	Product A	Product B	Calorie A	Calorie B
p1	Lays Kettle	Lays Kettle Less fat	160	140
p2	Lays Barbecue less fat	Lays Kettle Barbecue	120	180
p3	Sargento string	Sargento string light	60	50
p4	Farms cherry nonfat	Farms cherry	80	150
p5	Yoplait cherry light	Yoplait cherry	90	150
p6	Yoplait lime pie original	Yoplait lime pie light	150	90
p7	Quaker lightly salted rice cakes	Quaker caramel rice cake	33	50
p8	Pringles reduced fat	Pringles	140	150
p9	Cheezit	Cheezit reduced fat	150	130
p10	Nature Valley Sweet and Saulty Nut	Nature Valley Fruit and Nut	160	140
p11	Ritz reduced fat	Rizt	70	80
p12	Quaker	Quaker oatmeal	100	90
p13	Little debie oatmeal	Little debie honey	222	230
p14	Apple sauce	Apple sauce unsweetened	90	50
p15	Farms strawberry light	Farms strawberry	80	120
p16	Colby jack	Colby jack reduced fat	110	80
p17	Oreo	Oreo reduced fat	180	100
p18	Ahoy reduced fat	Ahoy	100	107
p19	Nilla reduced fat	Nilla	120	140
p20	Herr's	Herr's reduced fat	150	140
p21	Cod chips	Cod chip reduced fat	140	130
p22	Voortman vanila no sugar	Voortman vanila	130	140
p23	Werthers caramel	Werthers caramel no sugar	170	120
p24	Fig fat free	Fig	90	100
p25	Tates oatmil	Tates	130	140
p26	Del Monte Cherry Mixed Fruid	Del Monte Cherry Mixed Fruid (No sugar)	70	45
p27	Snack Pack Juicy Gels	Snack Pack Juicy Gels Sugar-Free	90	5
p28	Snack Pack pudding vanilla sugar free	Snack Pack pudding vanilla	60	100
p29	lance nekot peanut butter cookies	lance whole grain peanut butter cookies	240	200
p30	Gold Peak Sweet Tea	Gold Peak unsweetened Tea	190	0
p31	Diet lemon snapple green and black tea	Lemon snapple green and black tea	10	150
p32	Vitaminwater Power-C	Vitaminwater Power-C Zero	80	0
p33	Diet Ocean Spray juice	Ocean Spray juice	10	130
p34	Powerrade	Powerrade Zero	80	0
p35	Jello Strawberry	Jello Strawberry Sugar Free	80	10
p36	Honey Made Honey Lof Fat	Honey Made Honey	140	146
p37	Capri Sun® Roarin' Waters Fruit Punch Reduced Sugar	Capri Sun® Roarin' Waters Fruit Punch	30	80
p38	Russell Stover Sugar Free Coconut	Russell Stover Coconut	160	200
p39	Snapple Sweet Straightup' Tea	Snapple Sweet Straightup' Tea Unsweetened	180	0
p40	Ocean Spray Craisins Original Dried Cranberries Reduced Sugar	Ocean Spray Craisins Original Dried Cranberries	100	130

Note: We randomized the order (left (A) or right(B)) of low and high-calorie snacks in each trial. This randomization was fixed across subjects. However, the order of trials was randomized for each subject.

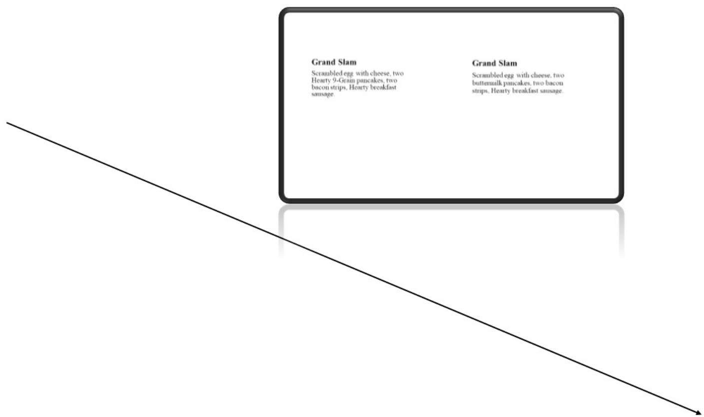
Table B3: Calorie distance and temptation in the lab experiment

	Dependent variable:	
	Temptation Distance	
	(1)	(2)
Calorie distance	0.230***	0.190**
	(0.084)	(0.087)
Male		0.245*
		(0.129)
BMI		0.001
		(0.014)
High Income (dummy)(>60,000 USD)		0.042
		(0.131)
Constant	0.502***	0.387
	(0.068)	(0.361)
Observations	8,630	8,110
R^2	0.003	0.005
Adjusted R^2	0.003	0.005
Residual Std. Error	2.209 (df = 8628)	2.202 (df = 8105)
Note:		*p<0.1; **p<0.05; ***p<0.01

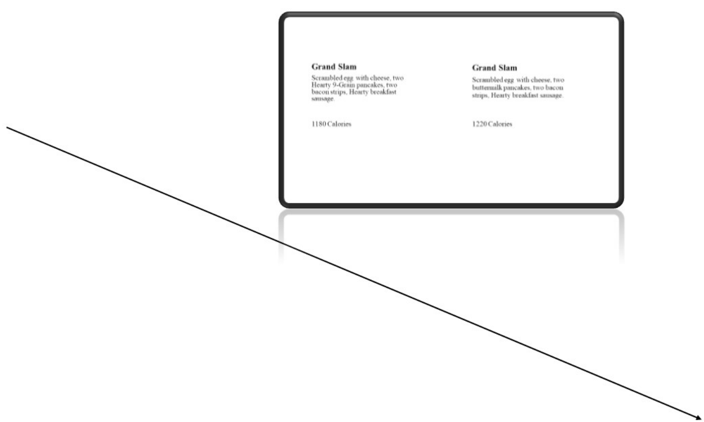
Note: The table shows the results of OLS regression analysis and errors were clustered on subject level. The clustering helps to account the possible serial correlation among repeated measures. Calorie distance variable is the actual (except Homegrown condition) calorie distance between the alternatives and normalized by 100 calories. The dependent variable is the difference between self-reported temptation scores of high and low-calorie snacks.

Table B4: Balance test of the randomization of subjects across the experimental conditions (Lab-in-the-field experiment)

	(1) No Information	(2) Accurate Information	(3) p-value from joint orthogonality test of experimental conditions
Male	0.450	0.525	0.416
White	0.517	0.492	0.787
High Income (dummy)(>60,000 USD)	0.271	0.357	0.326
BMI	26.814	28.411	0.245
N	60	61	



[a] No Information



[b] Accurate Information

The figure depicts the sequence of stimuli across experimental stages in the lab in the field experiment.

Figure B2: Stimuli in the lab-in-the-field experiment.

Table B6 and B7 present the list of beverage and dessert products used in the restaurant experiment, respectively.

Table B8 reports the relationship between hunger level and temptation to snacks in the

Table B5: The list of meals in each choice trial in the lab-in-the-field experiment

Trial	Left	Right	LeftCal	RightCal	CalDiff
T1	Fit Slam	Grand Slam	430	790	360
T2	Grand Slam	Grand Slam	930	790	140
T3	Grand Slam	Grand Slam	930	1030	100
T4	Grand Slam	Fit Slam	1030	430	600
T5	Fit Slam	Grand Slam	430	1220	790
T6	Grand Slam	Grand Slam	1220	1030	190
T7	Grand Slam	Grand Slam	1180	1220	40
T8	Grand Slam	Fit Slam	1180	430	750
T9	Lumberjack Slam	Fit Slam	1610	430	1180
T10	Lumberjack Slam	Lumberjack Slam	1610	1660	50
T11	Fit Slam	Lumberjack Slam	430	1660	1230
T12	Lumberjack Slam	Lumberjack Slam	1750	1660	90
T13	Lumberjack Slam	Fit Slam	1750	430	1320
T14	Lumberjack Slam	Fit Slam	1640	430	1210
T15	Lumberjack Slam	Grand Slam	1640	1180	460
T16	Lumberjack Slam	Grand Slam	1750	1180	570
T17	All-American Slam	Lumberjack Slam	1230	1660	430
T18	All-American Slam	Lumberjack Slam	1230	1750	520
T19	Fit Slam	All-American Slam	430	1750	1320
T20	All-American Slam	Grand Slam	1230	1180	50
T21	Tres Leches Pancake	Tres Leches Pancake	1370	1560	190
T22	Tres Leches Pancake	Leche Crunch Pancake	1500	2100	600
T23	Tres Leches Pancake	Choconana Pancake	1370	1500	130
T24	Choconana Pancake	Choconana Pancake	1500	1450	50
T25	Choconana Pancake	Choconana Pancake	1500	1980	480
T26	Berry Banana Pancake	Choconana Pancake	890	1790	900
T27	Tres Leches Pancake	Choconana Pancake	1370	1980	610
T28	Choconana Pancake	Choconana Pancake	1450	1980	530
T29	Choconana Pancake	Berry Banana Pancake	1450	1420	30
T30	Leche Crunch Pancake	Berry Banana Pancake	2100	1420	680
T31	Wild West Omelette	Wild West Omelette	990	1120	130
T32	Wild West Omelette	Wild West Omelette	1330	990	340
T33	Ultimate Omelette	Wild West Omelette	1535	990	545
T34	Ultimate Omelette	Ultimate Omelette	1535	1580	45
T35	Hammy & Cheese Omelette	Wild West Omelette	1705	1120	585
T36	Wild West Omelette	Veggie Omelette	1120	860	260
T37	Wild West Omelette	Ultimate Omelette	1120	1375	255
T38	Hammy & Cheese Omelette	Veggie Omelette	1705	1070	635
T39	Veggie Omelette	Ultimate Omelette	860	1375	515
T40	Wild West Omelette	Hammy & Cheese Omelette	990	1705	715
T41	Grand Slamwich	Fit Slam	1420	430	990
T42	Grand Slamwich	Grand Slam	1420	790	630
T43	Lumberjack Slam	Grand Slamwich	1660	1420	240

lab experiment.

Table B5 (contd.): The list of meals in each choice trial in the bab in the field experiment.

Trial	Left	Right	LeftCal	RightCal	CalDiff
T44	All-American Slam	Grand Slamwich	1230	1420	190
T45	All-American Slam	Country-Fried Stake & Egg	1230	1340	110
T46	Grand Slam	Country-Fried Stake & Egg	790	1340	550
T47	Country-Fried Stake & Egg	Fit Slam	1340	430	910
T48	Country-Fried Stake & Egg	All-American Slam	1340	1750	410
T49	Country-Fried Stake & Egg	T-bone Stake & Egg	1340	1610	270
T50	T-bone Stake & Egg	T-bone Stake & Egg	1310	1610	300
T51	T-bone Stake & Egg	T-bone Stake & Egg	780	1610	830
T52	T-bone Stake & Egg	Country-Fried Stake & Egg	780	1340	560
T53	Fit Fare Veggie Skillet	Santa Fe Skillet	390	900	510
T54	Supreme Skillet	Santa Fe Skillet	940	900	40
T55	Supreme Skillet	Santa Fe Skillet	985	900	85
T56	Supreme Skillet	Fit Fare Veggie Skillet	985	390	595
T57	Diner Cheeseburger	Double Cheeseburger	1335	1380	45
T58	Fit Burger	Double Cheeseburger	830	1380	550
T59	Fit Burger	Diner Cheeseburger	830	1335	505
T60	Diner Cheeseburger	Double Cheeseburger	1425	1380	45
T61	Pot Roast Melt Sandwich	The Super Bird Sandwich	1425	870	555
T62	Pot Roast Melt Sandwich	Club Sandwich	1425	1335	90
T63	Cali Club Sandwich	Club Sandwich	1455	1335	120
T64	Cali Club Sandwich	The Super Bird Sandwich	1455	870	585
T65	Cali Club Sandwich	Grilled Tuscan Sandwich	1455	1385	70
T66	The Super Bird Sandwich	Grilled Tuscan Sandwich	870	1385	515
T67	Slow-Cooked Pot Roast	Slow-Cooked Pot Roast	725	1310	585
T68	Homestyle Meatloaf	Homestyle Meatloaf	915	1500	585
T69	Mediterrenian Chicken	Mediterrenian Chicken	935	1550	615
T70	Chicken Strips	Chicken Strips	1490	890	600
T71	Slow-Cooked Pot Roast	Slow-Cooked Pot Roast	1220	1310	90
T72	Homestyle Meatloaf	Homestyle Meatloaf	1410	1500	90
T73	Mediterrenian Chicken	Mediterrenian Chicken	1550	1460	90
T74	Chicken Strips	Chicken Strips	1115	1490	375
T75	Country-Fried Stake & Egg	Country-Fried Stake & Egg	1550	945	605
T76	Country-Fried Stake & Egg	Country-Fried Stake & Egg	1550	1460	90
T77	T-Bone Stake	T-Bone Stake	1480	825	655
T78	T-Bone Stake	T-Bone Stake	1480	1165	315
T79	Garlic Peppercorn Sirlion	Garlic Peppercorn Sirlion	805	1340	535
T80	Garlic Peppercorn Sirlion	Garlic Peppercorn Sirlion	1115	1340	225
T81	Grand Slam	Wild West Omelette	930	1120	190
T82	Ultimate Omelette	Grand Slam	1375	790	585
T83	Chicken Strips	Mediterrenian Chicken	1115	935	180
T84	Chicken Strips	Mediterrenian Chicken	1490	935	555
T85	Fit Fare Veggie Skillet	Fit Slam	390	430	40
T86	Supreme Skillet	Fit Slam	985	430	555

Table B6: The list of beverages in the lab-in-the-field experiment

Signature Diner Blend Regular Coffee	0 Calories
Signature Diner Blend Decaf Coffee	0 Calories
Cold Brew Coffee Sweetened	130 Calories
Cold Brew Coffee Unsweetened	60 Calories
Minute Maid Lemonade	150 Calories
Mango Lemonade	210 Calories
Strawberry Lemonade	210 Calories
Fresh Brewed Iced Tea	160 Calories
Lemonade Iced Tea	80 Calories
Fuze Raspberry Tea	110 Calories
Coca Cola	180 Calories
Water	0 Calories
Diet Coke	0 Calories
Sprite	170 Calories
Dr. Pepper	140 Calories
Fanta	190 Calories
Hot Tea/Herbal Tea	0 Calories
Hot Chocolate	190 Calories
Minute Maid Premium Berry Blend	230 Calories
Minute Maid Orange	210 Calories
Apple Juice	210 Calories
Ruby Red Grapefruit	240 Calories
Tomato	90 Calories
2% Milk	230 Calories
Chocolate Milk	290 Calories
Horchata Milk Shakes	670 Calories
Peanut Butter Banana Milk Shake	1150 Calories
Chocolate Peanut Butter Milk Shake	1200 Calories
Cake Butter Milk Shake	1090 Calories
Oreo Milk Shake	1050 Calories
Chocolate Milk Shake	870 Calories
Strawberry Milk Shake	760 Calories
Vanilla Milk Shake	800 Calories

Table B7: The list of desserts in the lab-in-the-field experiment

New York Style Cheesecake with Strawberry topping and Whipped Cream	600 Calories
Chocolate Lava Cake	700 Calories
Caramel Apple Pie Crisp	760 Calories
Sundae – chocolate ice cream (two scoops), hot fudge, Oreo and whipped Cream	775 Calories

Table B8: The effect of the hunger level on temptation to snacks

	Dependent variable:			
	Temptation to Low-Calorie Snacks		Temptation to high-Calorie Snacks	
	(1)	(2)	(3)	(4)
Entry hunger level	0.046***		0.033***	
	(0.008)		(0.008)	
Exit hunger level		0.103***		0.129***
		(0.012)		(0.013)
Constant	3.896***	3.533***	4.583***	3.987***
	(0.052)	(0.079)	(0.054)	(0.082)
Observations	8,200	8,200	8,200	8,200
R^2	0.004	0.009	0.002	0.013
Adjusted R^2	0.004	0.009	0.002	0.012
Residual Std. Error (df = 8198)	2.362	2.357	2.462	2.449
F Statistic (df = 1; 8198)	35.553***	71.339***	17.040***	103.926***

Note: *p<0.1; **p<0.05; ***p<0.01

Table B9: The effect of fatigue on low-calorie choices (lab-in-the-field experiment)

	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male	−0.04***	−0.04	−0.04	−0.04	−0.04	−0.04
	(0.01)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
BMI	−0.00***	−0.00	−0.00	−0.00	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
High Income dummy (>60,000 USD)	0.07***	0.07*	0.06	0.06	0.06	0.06
	(0.01)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Calorie distance		−0.02***		−0.02***	−0.02***	−0.02***
		(0.00)		(0.00)	(0.00)	(0.00)
Accurate Information			0.11***	0.11***	0.09***	0.09***
			(0.03)	(0.03)	(0.03)	(0.03)
Calorie distance * Accurate Information					0.00	0.00
					(0.01)	(0.01)
Order						−0.00*
						(0.00)
AIC	13221.41	13131.86	13116.26	13025.68	13026.21	13025.42
BIC	13250.10	13167.72	13152.13	13068.72	13076.42	13082.80
Log Likelihood	−6606.71	−6560.93	−6553.13	−6506.84	−6506.10	−6504.71
Deviance	13213.41	13121.86	13106.26	13013.68	13012.21	13009.42
Num. obs.	9632	9632	9632	9632	9632	9632

stars.

Note: This table displays the analysis of choices in the restaurant setting. The table shows the results of the Logit regression analysis across all experimental conditions with clustering at the subject level. Order variable represents the presentation order of stimuli (binary menus) for each subject and controls the impact of fatigue effect on food choices, if any. The clustering helps to account the possible serial correlation among repeated measures. Calorie distance variable is the actual calorie distance between the alternatives and normalized by 100 calories. Thus, the marginal effect shown in the table indicates the probability change due to a 100 calorie increase in Calorie distance variable.

APPENDIX C

We used eye-tracking technology in both experiments. Tobii Spectrums tracked the eye movements of the subjects with the 300 Hz sampling rate and the data was extracted with iMotions software. Tobii Spectrums were attached to the bases of the computer screens and with the help of near-infrared technology Eye movements were recorded through visible reflections in the cornea (Huseynov et al., 2019a; Ramsoy, 2015). In this study, we focus on the total time subjects spent fixating on different parts of the screen. We also use eye-fixation counts metrics. Eye-fixation counts measures how many times a subjects fixated on the particular part of the screen. One eye-fixation count happens when when a subject fixates on the particular point of interest and then leaves that part of the screen. For example, if eye-fixation counts is four, it means that the subjects fixated four times on the particular part of the screen during the choice trial.

In the lab experiment, we defined one Area of Interest (AOI). Our AOI was product pictures in the all experimental conditions. In the analysis, we do not include eye-fixation time and eye-fixation counts on the parts of the screens with calorie information (in the Accurate and Homegrown Information conditions), because subjects were explicitly directed to consider them in the treatments. Therefore, eye-fixation time and counts on the calorie information mostly stemmed from the compliance to experimental instructions. Since eye-fixation time and counts on the snack product pictures occurred without external influence, their moderation effect in the relationship of treatment variables and low-choice choices is the object of interest.

In the restaurant experiment, we defined the part of the screens with product descriptions and with the calorie information (only in the Accurate Information condition) as AOIs.

Appendix D1

Proof . Consider any $x, x' \in X$ such that $x = \{a, b\}$, $x' = \{a', b'\}$, $u(a) > u(b)$, $v(a) < v(b)$, $u(a') > u(b')$, $v(a') < v(b')$, $u(a) = u(a')$, $u(b) = u(b')$, $v(b') \geq v(b)$ and $v(b') - v(a') > v(b) - v(a)$. Since $\psi(\cdot)$ is weakly increasing, $\psi(v(b')) \geq \psi(v(b))$. Then, consider the following:

$$v(b') - v(a') > v(b) - v(a)$$

$$\psi(v(b'))[v(b') - v(a')] > \psi(v(b))[v(b) - v(a)]$$

$$u(a') - \psi(v(b'))[v(b') - v(a')] < u(a) - \psi(v(b))[v(b) - v(a)]$$

$$u(a') - u(b') - \psi(v(b'))[v(b') - v(a')] < u(a) - u(b) - \psi(v(b))[v(b) - v(a)]$$

Then, from equation (2) and F is an increasing function, we get $\Pr[C(x') = \{a'\}]$ is less than $\Pr[C(x) = \{a\}]$.

Appendix D2

Proof. Consider any $x \in X$ such that $x = \{a, b\}$, a and b are the low-calorie and high-calorie items, respectively. Then, $u(a) > u(b)$ and $v(a; \lambda) < v(b; \lambda)$ for $\lambda \in \{0, 1\}$. By definition of *salient* and *non-salient* choice-contexts, we have:

$$\psi(v(b; \lambda); \tau = 1) < \psi(v(b; \lambda); \tau = 0)$$

Using the above inequality, we get: $u(a) - u(b) - \psi(v(b; \lambda); \tau = 1)(v(b; \lambda) - v(a; \lambda)) > u(a) - u(b) - \psi(v(b; \lambda); \tau = 0)(v(b; \lambda) - v(a; \lambda))$

Then, by (4) and since F is an increasing function, we get:

$\Pr\left[C\left(x;\tau=1,\lambda\right)=\{a\}\right]>\Pr\left[C\left(x;\tau=0,\lambda\right)=\{a\}\right]$.

Appendix D3

Proof. Consider any $x\in X$ such that $x=\{a,b\}$ with $u\left(a\right)>u\left(b\right)$ and $v\left(b;\lambda\right)>v\left(a;\lambda\right)$ for $\lambda\in\{0,1\}$. Then, a and b are low and high calorie items, respectively. By definition of *satiated* and *non-satiated* agents, we have the following:

$$v\left(b;\lambda=1\right)>v\left(b;\lambda=0\right)$$
$$v\left(b;\lambda=1\right)-v\left(a;\lambda=1\right)\geq v\left(b;\lambda=0\right)-v\left(a;\lambda=0\right)$$

Since $\psi\left(\cdot\right)$ is weakly increasing, we get the following:

$$u\left(a\right)-u\left(b\right)-\psi\left(v\left(b;\lambda=1\right);\tau\right)\left[v\left(b;\lambda=1\right)-v\left(a;\lambda=1\right)\right]$$

should be less than or equal to

$$u\left(a\right)-u\left(b\right)-\psi\left(v\left(b;\lambda=0\right);\tau\right)\left[v\left(b;\lambda=0\right)-v\left(a;\lambda=0\right)\right]$$

Then, from (4) and an increasing F, we get $\Pr\left[C\left(x;\tau,\lambda=1\right)=\{a\}\right]\leq\Pr\left[C\left(x;\tau,\lambda=0\right)=\{a\}\right]$.

Appendix D4

Proof of **Proposition 4**: Consider any $x\in X$ such that $x=\{a,b\}$ where $u\left(a\right)>u\left(b\right)$ and $v\left(a;\lambda\right)<v\left(b;\lambda\right)$. Suppose $\psi\left(\cdot;\tau\right)=M>0$. For *unbiased temptation difference*, on average, we have the following:

$$u\left(a\right)-u\left(b\right)-M\times E\left[\tilde{v}\left(b;\lambda\right)-\tilde{v}\left(a;\lambda\right)\right]=u\left(a\right)-u\left(b\right)-M\left[v\left(b;\lambda\right)-v\left(a;\lambda\right)\right]$$

Then, by (4), (5) and an increasing F, $\Pr\left[EC\left(x;\tau,\lambda\right)=\{a\}\right]=\Pr\left[C\left(x;\tau,\lambda\right)=\{a\}\right]$ for *unbiased temptation difference*. For *over-estimated temptation difference*, we have the following:

$$u(a) - u(b) - M \times E[\tilde{v}(b;\lambda) - \tilde{v}(a;\lambda)] < u(a) - u(b) - M[v(b;\lambda) - v(a;\lambda)]$$

Then, by (4), (5) and an increasing F, $\Pr[EC(x;\tau,\lambda) = \{a\}] < \Pr[C(x;\tau,\lambda) = \{a\}]$ for *over-estimated temptation difference*. For *under-estimated temptation difference*, we have the following:

$$u(a) - u(b) - M \times E[\tilde{v}(b;\lambda) - \tilde{v}(a;\lambda)] > u(a) - u(b) - M[v(b;\lambda) - v(a;\lambda)]$$

Then, by (4), (5) and an increasing F, $\Pr[EC(x;\tau,\lambda) = \{a\}] > \Pr[C(x;\tau,\lambda) = \{a\}]$ for *under-estimated temptation difference*.

Define bias as $E[\tilde{v}(\cdot)] - v(\cdot)$ i.e. difference in expected value of estimate and actual value, then: (1) *unbiased temptation difference* says that bias in temptation of the low-calorie and high-calorie item is the same, (2) *over-estimated temptation difference* says that bias in temptation of the low-calorie item is smaller than bias in temptation of high-calorie item, and (3) *under-estimated temptation difference* says that the bias in the temptation of the low-calorie item is larger than bias in the temptation of the high-calorie item.

Appendix D5

Definition 4. Temptation utilities are said to be *unbiased* if $E[\tilde{v}(a;\lambda)] = v(a;\lambda)$ and $E[\tilde{v}(b;\lambda)] = v(b;\lambda)$.

Lemma. If $f(x)$ is an increasing and convex function, defined for $x \geq 0$, then $g(x) = f(x)(x-c)$ is convex for $x > c$.

Proof. Since $f(\cdot)$ is convex, we have:

$$f(\theta x + (1-\theta) y) \leq \theta f(x) + (1-\theta) f(y) \;\; \forall \theta \in [0,1]$$

To show that $g(x) = f(x)(x-c)$ is convex, consider any $\theta \in [0,1]$ and $x > y > c \geq 0$, without loss of generality, for the following:

$$f(\theta x + (1-\theta) y)(\theta x + (1-\theta) y - c) - \theta f(x)(x-c) - (1-\theta) f(y)(y-c)$$

$$= \theta [f(\theta x + (1-\theta) y) - f(x)](x-c) + (1-\theta)[f(\theta x + (1-\theta) y) - f(y)](y-c)$$

$$\leq \theta [f(\theta x + (1-\theta) y) - f(x)](x-c) + (1-\theta)[f(\theta x + (1-\theta) y) - f(y)](x-c)$$

$$= [f(\theta x + (1-\theta) y) - \theta f(x) - (1-\theta) f(y)](x-c) \leq 0$$

This proves convexity of $f(x)x$. In the above working, $f(\theta x + (1-\theta) y) \geq f(y)$ because $x > y$, $f(\cdot)$ is an increasing function and $\theta \in [0,1]$. This leads to the first inequality after replacing y with x. The second inequality arises from convexity of $f(\cdot)$ and $x > c$.

Proposition 5. For an increasing and convex $\psi(\cdot;\tau)$ and *unbiased* temptation utilities, an agent with incomplete information chooses the healthy menu item with at least as much probability as an agent with complete information.

Proof. Consider any $x \in X$ such that $x = \{a,b\}$ where $u(a) > u(b)$ and $v(a;\lambda) < v(b;\lambda)$. An agent with incomplete information bases his choice on the sign of $u(a) - u(b) - \psi(\tilde{v}(b;\lambda);\tau)[\tilde{v}(b;\lambda) - \tilde{v}(a;\lambda)]$. He chooses a if this expression is positive and b if negative.

For *unbiased* temptation utilities, on average, we have the following:

$$
\begin{aligned}
u(a) - u(b) - E\left[\psi\left(\tilde{v}(b;\lambda);\tau\right)\left(\tilde{v}(b;\lambda) - \tilde{v}(a;\lambda)\right)\right] &= u(a) - u(b) - \\
-E\left[\psi\left(\tilde{v}(b;\lambda);\tau\right)\left(\tilde{v}(b;\lambda) - \tilde{v}(a;\lambda)\right)\right] & \\
&\geq u(a) - u(b) - \\
-\psi\left(v(b;\lambda);\tau\right)\left(v(b;\lambda) - v(a;\lambda)\right) &
\end{aligned}
$$

The equality utilizes independence of $\tilde{v}(a;\lambda)$ and $\tilde{v}(b;\lambda)$. The inequality arises from convexity of $f(\tilde{v}(b;\lambda)) = \psi(\tilde{v}(b;\lambda))(\tilde{v}(b;\lambda) - v(a;\lambda))$ which is established in Lemma. Then, by (4), (5) and an increasing F, $\Pr[EC(x;\tau,\lambda) = \{a\}] \geq \Pr[C(x;\tau,\lambda) = \{a\}]$ for *unbiased* temptation utilities.

APPENDIX E

Table E1 and E2 also confirm the previous analyses. According to Table E1, if the actual calorie distance between the food alternatives becomes greater, subjects tend to have more upward-bias in estimating calories of low-calorie snacks. Conversely, Table E2 shows that the magnitude of the bias for high-calorie products shrinks as the distance becomes greater.

Table E1: The analysis of calorie estimates for low-calorie products

	Dependent variable:			
	Bias for low-calorie alternative			
	(1)	(2)	(3)	(4)
Male	−0.755	−0.678	−2.652	−2.667
	(17.360)	(17.367)	(17.836)	(17.834)
BMI	0.277	0.289	0.193	0.191
	(2.093)	(2.093)	(2.113)	(2.113)
High Income (dummy)(>60,000 USD)	22.874	22.764	22.484	22.499
	(17.206)	(17.214)	(17.319)	(17.318)
True Calorie Distance		0.450***	0.450***	0.509***
		(0.049)	(0.049)	(0.068)
More Tempted			9.648	15.402
			(17.653)	(18.233)
True Calorie Distance * More Tempted				−0.123
				(0.097)
Constant	37.481	16.122	14.820	12.092
	(53.761)	(53.834)	(54.192)	(54.231)
Observations	2,630	2,630	2,630	2,630
Log Likelihood	-16,262.180	-16,222.200	-16,218.270	-16,218.880
Akaike Inf. Crit.	32,536.360	32,458.410	32,452.530	32,455.760
Bayesian Inf. Crit.	32,571.610	32,499.530	32,499.530	32,508.640
Note:				*p<0.1; **p<0.05; ***p<0.01

Note: The table shows the results of the mixed-effect logit regression analysis across all experimental conditions with clustering at the subject level.

Table E2: The analysis of calorie estimates for high-calorie products

	Dependent variable:			
	Bias for high-calorie alternative			
	(1)	(2)	(3)	(4)
Male	6.116	6.065	2.251	2.247
	(21.326)	(21.320)	(21.815)	(21.815)
BMI	2.011	2.003	1.817	1.816
	(2.571)	(2.570)	(2.584)	(2.584)
High Income (dummy) (>60,000 USD)	30.302	30.374	29.832	29.836
	(21.137)	(21.132)	(21.184)	(21.184)
True Calorie Distance		-0.294^{***}	-0.294^{***}	-0.278^{***}
		(0.058)	(0.058)	(0.081)
More Tempted			18.645	20.125
			(21.593)	(22.270)
True Calorie Distance * More Tempted				-0.032
				(0.116)
Constant	-7.487	6.443	3.926	3.224
	(66.043)	(66.083)	(66.282)	(66.331)
Observations	2,630	2,630	2,630	2,630
Log Likelihood	-16,700.560	-16,689.780	-16,685.420	-16,686.620
Akaike Inf. Crit.	33,413.110	33,393.570	33,386.840	33,391.230
Bayesian Inf. Crit.	33,448.360	33,434.690	33,433.840	33,444.110
Note:				*p<0.1; **p<0.05; ***p<0.01

Note: The table shows the results of the mixed-effect logit regression analysis across all experimental conditions with clustering at subject level.

Table E3: Low-calorie choice tendency in Homegrown and Accurate Information

	(1)	(2)	(3)
(Intercept)	0.00^{***}	0.00^{***}	0.00^{***}
	(0.00)	(0.00)	(0.00)
Bias in low-calorie snack	-0.07^{*}	-0.08^{*}	-0.08^{*}
	(0.04)	(0.04)	(0.04)
More Tempted	−0.01	−0.01	−0.02
	(0.04)	(0.05)	(0.04)
Bias in high-calorie snack	0.04	0.04	0.05
	(0.04)	(0.04)	(0.04)
Homegrown Information	−0.02	−0.02	−0.02
	(0.04)	(0.05)	(0.05)
Bias in low-calorie snack*More Tempted	0.06	0.06	0.06
	(0.06)	(0.06)	(0.06)
Bias in high-calorie snack*More Tempted	−0.04	−0.03	−0.04
	(0.05)	(0.05)	(0.05)
Male		-0.10^{**}	-0.10^{**}
		(0.04)	(0.04)
BMI			0.00
			(0.01)
High Income (dummy) (>60,000 USD)			−0.04
			(0.04)
AIC	7859.03	7264.49	7253.65
BIC	7905.63	7317.17	7319.50
Log Likelihood	−3922.52	−3624.24	−3616.83
Deviance	7845.03	7248.49	7233.65
Num. obs.	5750	5350	5350

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: The table shows the results of the logit regression analysis in Homegrown and Accurate Information condition with clustering on the subject level.

Table E3 shows that the observed bias indeed has consequences. Interestingly, according to Table E3, only the bias in the calorie estimates of low-calorie snacks appear to be important in the calorie intake. We confirm that the bias in calorie estimates of low-calorie choices are mainly driven by temptation distance. But we cannot detect a difference between Homegrown and Accurate Information conditions.

APPENDIX F

Table F1 shows that the effect of calorie distance is “harmful” only for sugar products. Interestingly, the calorie information helps to reduce calorie intake in the sugar sub-sample as well. We do not detect non-zero effects in other sub-samples related to the the calorie distance variable. Nevertheless, Homegrown Information increase the calorie intake only in the undisclosed sub-sample. It confirms the previous discussion that consumers are more vulnerable to consuming high-calorie food products when they can bring their individual beliefs or information into food decision-making.

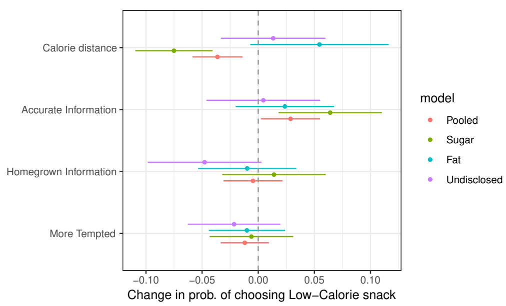
Figure F1 shows that subjects exhibit more bias in calorie estimates of low-calorie products, especially in the sugar sub-sample.

Table F1: Low-calorie choice tendency in product sub-samples

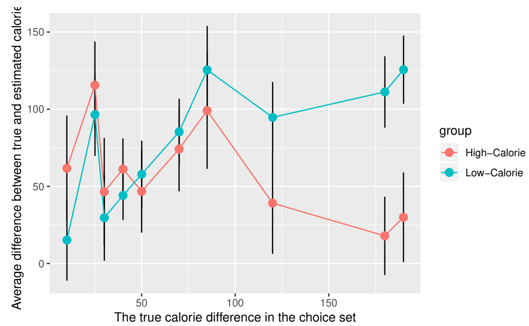
	(Sugar)	(Fat)	(Undisclosed)
(Intercept)	0.00^{***}	0.00^{***}	0.00^{***}
	(0.00)	(0.00)	(0.00)
Male	-0.08^{**}	-0.14^{***}	-0.10^{***}
	(0.04)	(0.05)	(0.03)
BMI	0.01	0.01^{**}	0.00
	(0.00)	(0.00)	(0.00)
High Income (dummy) (>60,000 USD)	0.00	−0.07	0.01
	(0.04)	(0.05)	(0.03)
Calorie distance	-0.09^{**}	−0.02	−0.04
	(0.04)	(0.09)	(0.07)
More Tempted	0.03	−0.02	−0.03
	(0.05)	(0.05)	(0.03)
Accurate Information	0.01	−0.04	−0.05
	(0.06)	(0.07)	(0.04)
Homegrown Information	−0.01	−0.02	−0.06
	(0.06)	(0.07)	(0.04)
Calorie distance*More Tempted	−0.06	0.02	0.01
	(0.05)	(0.07)	(0.06)
Calorie distance*Accurate Information	0.08^{*}	0.18	0.12
	(0.05)	(0.11)	(0.09)
Calorie distance*Homegrown Information	0.05	0.03	0.02
	(0.06)	(0.09)	(0.07)
AIC	3516.05	4388.53	3064.44
BIC	3580.71	4455.45	3127.25
Log Likelihood	−1747.03	−2183.26	−1521.22
Deviance	3494.05	4366.53	3042.44
Num. obs.	2639	3241	2230

stars

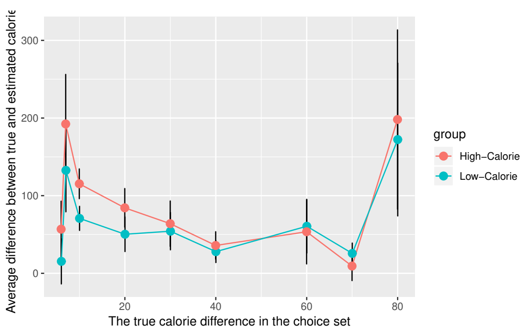
Note: The table shows the results of the logit regression analysis across product types with clustering on subject level. The clustering helps to account the possible serial correlation among repeated measures. Calorie distance variable is the actual (except Homegrown condition) calorie distance between the alternatives and normalized by 100 calories. Thus, the marginal effect shown in the table indicates the probability change due to a 100 caloie increase in Calorie distance variable. Moreover, for Homegrown Information condition Calorie Distance variable includes estimated calories by subjects, since subjects acted on their believes in this condition.



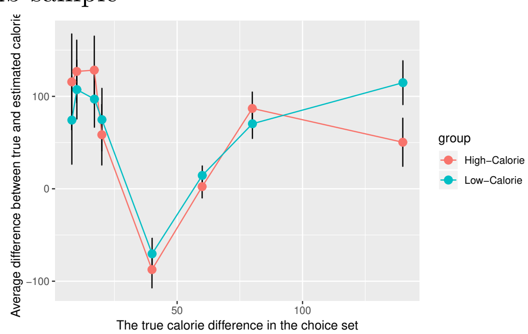
(a) Average marginal effects



(b) Average misestimation of calories in sugar sub-sample



(c) Average misestimation of calories in fat sub-sample



(d) Average misestimation of calories in undisclosed sub-sample

Figure F1: Calorie estimations across product types.

APPENDIX G

Table G1: Calorie budgeting

	Dependent variable:	
	Calorie of Beverage	Calorie of Dessert
	(1)	(2)
Male	75.421***	3.537
	(6.434)	(2.650)
BMI	−6.756***	2.493***
	(0.452)	(0.187)
High Income (dummy)(>60,000 USD)	14.078**	−31.259***
	(7.012)	(2.878)
Accurate Information	411.615***	−110.532***
	(24.792)	(10.665)
Chosen Entree	0.070***	−0.019***
	(0.013)	(0.005)
Calorie of Beverage		0.046***
		(0.006)
Chosen Entree*Accurate Information	−0.311***	0.076***
	(0.018)	(0.008)
Calorie of Beverage*Accurate Information		0.004
		(0.008)
Constant	301.233***	622.419***
	(21.856)	(9.044)
Observations	9,632	9,632
R^2	0.076	0.048
Adjusted R^2	0.076	0.047
Residual Std. Error	312.514 (df = 9625)	127.754 (df = 9623)
F Statistic	132.650*** (df = 6; 9625)	60.674*** (df = 8; 9623)
Note:		*p<0.1; **p<0.05; ***p<0.01

Note: The table shows the results of the logit regression analysis across product types with clustering on subject level.