THE EFFECTS OF VOLUNTARY DISCLOSURE OF PRODUCT INFORMATION ON FIRM INNOVATION: THE CASE OF FRONT-OF-PACKAGE NUTRITION LABELING INITIATIVE

A Dissertation

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ABSTRACT

In this study, I examine the effects of consumer packaged food manufacturers' voluntary adoption of the Front-of-Package (FOP) nutrition labeling program on firm innovation. Specifically, I study if voluntary participation in the program spurs food manufacturers to be more innovative and introduce more and better new food products.

To empirically investigate my research question, I assemble a unique data set compiled from several sources of secondary data on consumer packaged food products that are introduced in the United States. More specifically, I collected product-specific calorie and nutrient information on all the new products that were introduced by food manufacturers over a 10-year period during which I analyzed several brands and products (more than 600 brands and 7,500 products) in four different food product categories. To disentangle the *self-selection effect* from the *causal effect* of voluntary participation in the program on firms' innovativeness, I employ a quasi-experimental study design using a combination of propensity score matching (PSM) and a series of difference-in-differences (DID) and quantile difference-in-differences (QDID) models.

I focus on two dimensions of innovativeness, quantity and quality of innovation. For quantity of innovation, I look at the number of new product introductions and for quality of innovation, I assess changes in calorie content, levels of individual nutrients and overall nutrition score of new products. The results indicate that firms' participation in FOP nutrition labeling initiative increases their innovativeness on both the quantity and the quality dimensions. I find that participant firms introduce more innovative and

nutritionally better products as compared to non-participant firms. Additional analyses suggest that early adopters of FOP nutrition labeling introduce more new products as compared to late adopters of FOP. I also find that the effect of FOP nutrition labeling is enhanced for products that carry nutrient content claims. The results of my study have important implications for consumers, managers and policymakers, and I hope that this study spurs further examination of the effects of industry-led voluntary initiatives on consumer welfare.

DEDICATION

To my beloved family

I dedicate this dissertation to my dad in heaven, Ki Sang Lim passed away in November 2013 when I was a third-year doctoral student, my mom, Yeon Sook Yun, my grandfather, Jung Mook Lim, my grandmother, Jung Soon Ann, my sister, Heejin Lim, my brother-in-law, Myoung Han Lee and my lovely nephew, Joo Won Lee for their endless love, support, care and sacrifice. Thank you all.

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CHAPTER I

INTRODUCTION

Firms often participate in industry-led voluntary initiatives whereby they disclose the quality of their products to signal their socially responsible management practices. Such examples are replete across many industries. For example, in the context of the appliance industry, firms participate in the voluntary Energy Star program created by the U.S. Department of Energy and the U.S. Environmental Protection Agency that identifies and promotes energy efficient products. Manufacturing companies voluntarily adopt the ISO 14001 Environmental Management System Standard, a voluntary program to signal their commitment towards improving their environmental performance. In the packaged food industry, food manufacturers participate in the Front-of-Package (FOP) nutrition labeling initiative, whereby manufacturers display information on calories and key nutrients on the front of the package of their food products to help consumers make healthier choices. Even in the case of participation in mandatory programs, firms voluntarily adopt practices and standards ahead of the date of mandatory requirement to signal their reputation. For example, many firms voluntarily adopted the International Financial Reporting Standards prior to the cutoff period by which firms were required to be in compliance with the practice. Firms adopt or participate in voluntary programs to reduce information asymmetry in the market and to signal their brand quality or reputation and in turn influence the purchase behavior of their customers. The purpose of this study is to examine the (firm side) consequences of firms’ participation in voluntary programs. I focus on packaged food manufacturers' adoption of FOP nutrition labeling system and examine if firms' participation in the initiative spurs them to introduce more and nutritionally better new products.

FOP nutrition labeling system is a voluntary initiative whereby food manufacturers display information on calories and a set of nutrients in the form of easy-to-read icons on the front of packaged foods.[1] This information about nutrients is in addition to the mandatory *Nutrition Facts* label that is presented on the back or the side of packaging. My decision to focus on (packaged) food manufacturers' adoption of FOP nutrition labeling is driven by the following contextual/public policy and empirical considerations. From the public policy perspective, due to concerns about obesity and diet related diseases, the benefits of providing nutritional information is getting a lot of attention among policymakers around the world. According to the Centers for Disease Control and Prevention estimates, more than one-third of American adults are obese. Childhood and adolescent obesity has also skyrocketed in the last thirty years with more than one third of children and adolescents being overweight or obese in 2012.[2] Government agencies, both at the federal and the state level, have taken several steps to address the issue. For example, in 2004, California passed a state-level regulation that banned soft drinks from schools (Korry 2003). The packaged food industry, on its part, has also voluntarily taken steps to inform consumers about the nutritional value of food products so that consumers can make better choices; one such initiative undertaken by

[1] I provide detailed description of the initiative in the following section.
[2] http://www.cdc.gov/healthyyouth/obesity/facts.htm.

food manufacturers is the FOP nutrition labeling initiative. While a number of extant studies in economics and marketing have focused on the demand side effects of providing calorie and nutrition related information to consumers (Andrews et al. 2011; Van Herpen and Van Trijp 2011; Hawley et al. 2013; Roberto et al. 2012; Sacks et al. 2009; Van Kleef et al. 2008; Draper et al. 2011), I focus on the firm side consequences. More specifically, I focus on the causal relationship between food manufacturers' willingness to disclose product related information and their subsequent innovation. From a public policy perspective, this will help understand whether the industry-led initiative is just a marketing gimmick or whether it encourages food manufacturers to introduce more and better (nutritionally) new products.

From an empirical perspective, unlike the Nutrition Facts label that is mandatory, the adoption of FOP nutrition labeling (henceforth, I simply refer to the initiative as "FOP") is voluntary and therefore requires more scrutiny. On one hand, adoption of FOP allows manufacturers to differentiate themselves from competitors and highlight the key beneficial nutrients in an easy-to-read format. In addition, unlike Nutrition Facts labels which are at the back or the side of the food package, FOP nutrition labels offer greater visibility and readability and can help consumers make informed choices (Golan et al. 2009). On the other hand, there is also some skepticism that adoption of FOP is merely a "marketing gimmick" that may not necessarily lead to nutritionally better products for consumers and therefore can be misleading (Glanz et al. 2012; Hawley et al. 2013). Thus, even if manufacturers introduce new products after FOP adoption, it is critical to examine whether food manufacturers come up with new products that are better in terms of nutrition. Accordingly, my study attempts to uncover if FOP adoption leads to improvement in the quality of new products in terms of introducing products that are high in beneficial nutrients and low in nutrients that consumers seek to avoid.

Against the above background, I position my study as the first to undertake a systematic examination of the effect of food manufacturers' voluntary adoption of FOP on their subsequent innovation in terms of both the quantity and the quality of new products. To meet my research objectives, I collected product-specific calorie and nutrient information on all the new products that were introduced by food manufacturers over a 10-year period (more specifically from January 2003 to May 2013) during which I analyzed several brands and products (more than 600 brands and 7,500 products) in *four* different food product categories. The relationship between FOP adoption and firm innovativeness, if any, could be due to two different reasons: a) *self-selection effect*, whereby firms with ex-ante inherently better organizational capabilities (unobserved to researchers) may self-select into participating in FOP and b) *causal effect* of FOP participation, whereby firms that participate in FOP innovate more subsequent to their participation. Disentangling the self-selection effect from the causal effect of FOP adoption on subsequent innovativeness is important from both the econometric interpretation and the public policy perspectives (more details on this will be discussed in the following sections).

To rule out the endogeneity issue (due to the "self-selection effect") and establish the casual link between FOP adoption and subsequent innovativeness (the "treatment effect"), following recent studies (e.g., Huang et al. 2012), I follow the quasi-experimental approach and create matched sets of adopters and non-adopters (through propensity score matching technique). I then estimate a series of brand specific and product-specific difference-in-differences (DID) models to quantify the impact of FOP adoption on innovation. I focus on two dimensions of innovativeness, quantity or rate of new product introductions and (nutritional) quality of new products. While I analyze the rate of new product introductions at the brand level, I recognize that food brands may have different products nutritionally (e.g., *Kellogg's Raisin Bran* vs. *Kellogg's Frosted Flakes*) and firms may decide to change the nutrition level of these products differently, and thus I analyze the quality of innovation at the individual product level. Furthermore, I realize that the effect of FOP could vary across the distribution of the level of nutrients. For example, it might be easier for firms with poor quality products to improve the nutritional content of their products when compared to firms that have nutritionally better products to begin with. To capture the heterogeneous effect of FOP adoption across the distribution of the level of nutrient content, I employ a series of quantile difference-in-differences (QDID) models.

I would like to acknowledge the following caveat before I present the overview of the results of my study. While the interpretation of the results from the rate of new product introduction models is fairly straightforward, the interpretation of the results from the quality of new product models is not. In my study, I seek to examine if brands that adopt FOP produce nutritionally "better" products, with "better" referring to having lower calories, higher level of beneficial nutrients that consumers seek to increase in their diet (e.g., fiber, protein) and lower level of nutrients that consumers seek to limit (e.g., sugar, fat). To the extent that firms may increase the levels of beneficial nutrients, but may also increase the level of nutrients that consumers seek to avoid, I analyze the levels of each of the nutrients *individually* and also *overall* nutrition. However, I acknowledge that firms can increase beneficial nutrients in ways that may not be healthy and reduce levels of limiting nutrients in a non-healthy manner (for example, reduction in sugar content by the inclusion of artificial sweeteners is not healthy). Given that nutritional quality is a multi-dimensional measure, I do not mean to imply that nutritionally better products are necessarily healthy. By better quality products, I simply refer to products that have lower calories and lower (higher) levels of nutrients that consumers seek to avoid (consume).

The results suggest that firms that adopt FOP introduce more new products subsequent to FOP adoption as compared to firms that do not adopt FOP. I find that FOP adopter firms introduce overall nutritionally better products subsequent to their adoption as compared to firms that do not adopt FOP. However, I find that the improvement in nutritional quality varies across the nutrient type, the level of nutrient content and the product category. I also find that among the firms that adopt FOP, early adopters of the voluntary initiative introduce more new products as compared to late adopters. I also find some evidence that among the products of firms that adopt FOP, those products that have nutrient content claims such as “Low Fat” or “Rich in Fiber” on their products improve the nutritional quality more than products that do not have such claims. Interestingly, I find that among the products of firms that adopt FOP, those products that have non-nutrient content claims (e.g., Environment Friendly Packaging) are less innovative in terms of quality of products, when compared to products that do not have such claims.

My study makes the following contributions. From a theoretical perspective, my study establishes that firms' voluntary participation in initiatives that disclose product quality is not simply a signaling mechanism (driven solely by the self-selection effect) but one by which firms commit to producing more and better products, *subsequent* to their participation. Organizational scholars have long been interested in factors that determine the innovativeness of firms. To the best of my knowledge, this study is one of the first to demonstrate that the relationship between voluntary participation and firm innovativeness which is not just due to the simple self-selection effect but because of the causal effect of firms' participation in socially responsible voluntary programs. The finding that early adopters and those who have structural capabilities to produce more and nutritionally better products respectively highlights the role of organizational capabilities of firms that make such participation more credible and effective.

With respect to food nutrition labeling programs, whereas most extant studies focus on the consumer side, my study is one of the few that looks at the firm side consequences of nutrition related policy changes. Given that the mandatory Nutrition Facts label has not been effective in changing consumer choice behavior (Kiesel et al. 2011), the U.S. Food and Drug Administration (FDA) has increasingly focused on voluntary initiatives by food manufacturers to highlight key nutrients on the front of the food packages to serve the dual purpose of increasing consumer access to nutritional information and improving the quality of the products being produced.[3] However, at the same time, the FDA has sought to avoid the negative consequences associated with the voluntary FOP program such as food manufacturers' misrepresenting information or providing misleading information to consumers. The results suggest that voluntary participation in nutrition labeling initiatives serves as a catalyst for food manufacturers to produce more new products and products that are nutritionally better. Thus, from a public policy perspective, I hope that the results of my study would assuage consumer groups' and policymaker's concern that voluntary adoption of various nutrition related programs is merely a marketing gimmick.

[3] Details on the Front-of-Package labeling initiative and the FDA's guidelines can be accessed at the following link: http://www.fda.gov/Food/IngredientsPackagingLabeling/LabelingNutrition/ucm202726.htm.

CHAPTER II

BACKGROUND AND LITERATURE OVERVIEW

BACKGROUND

Obesity and diet-related diseases have been continuously important social issues in the United States. Nutrition labeling is one of the countermeasures of these problems. The primary goal of nutrition labeling initiative is to provide consumers with accurate nutritional information at the point of purchase and thus help them make a better and healthier choice in grocery stores. Several relevant sectors such as government agencies, non-profit organizations, food manufacturers, and retailers have made an effort to reduce consumers' misleading of untruthful nutritional claims presented in food packages and design a credible and standardized nutrition label. As a part of this effort, in 1994, the U.S. Food and Drug Administration (FDA) mandated food manufacturers to attach Nutrition Facts Panel (NFP) to the back or side of food packages under the Nutrition Labeling and Education Act (NLEA). However, the U.S. Department of Agriculture (USDA) study shows that the use of NFP has declined over ten-year period and Americans' dietary quality level still has to be improved even though consumers have accessed to standardized nutritional information of food products since 1994 (Todd and Variyam 2008; Guenther et al. 2007). Moreover, there have been a lot of skepticism in the academic literature on the effectiveness of NFP on consumers' healthy food choice and nutritional quality improvement of food products due to its illegibility and high level of information search costs (Kiesel et al. 2011; Kiesel and Villas-Boas 2013; Mojduszka et al. 1999; Mojduszka et al. 2001; Balasubramanian and Cole 2002).

In recent years, front-of-package (FOP) nutrition labels have been widely used in the packaged food industry for the purpose of complementing the weak points of NFP. FOP nutrition label is considered as a supplement to NFP because its location and format are more convenient and easier to be recognized by consumers, which in turn aid them in making healthier food choices. Broadly, there are three types of FOP nutrition labeling system: nutrient-specific system, summary indicator system, and food group information system (Institute of Medicine 2010). Nutrient-specific FOP labels "display the amount per serving of selected nutrients from the Nutrition Facts Panel on the front of the food package or use symbols based on claim criteria." Examples of nutrient-specific FOP label are General Mills' Nutrition Highlights and Goodness Corner, Kellogg's Nutrition at a Glance, and UK Traffic Light. Summary indicator FOP labels are in the form of "a single symbol, icon, or score providing summary information about the nutrient content of a product." Examples of these include the NuVal system (that displays a food product's nutritional score on a scale of 1 to 100), Choices Programme logo (that presents a "healthy choice" check mark on food products that meet certain criteria), Kraft's Sensible Solution, PepsiCo's Smart Spot, Smart Choices, Weight Watchers' Points Plus, Hannaford's Guiding Stars, Walmart's Great for You, and American Heart Association's Heart Check. Finally, food group information FOP labels "use symbols that are awarded to a food product based on the presence of a food group or food ingredient.” Examples include ConAgra Start Making Choices and Whole Grain Council’s Whole Grain Stamp.

The benefits of using these FOP nutrition labels are under the spotlight because a FOP nutrition label is simpler, more visible and easier-to-read than NFP, as it is presented on the front of the package of food products. However, over the past few years, too many different types of FOP nutrition labels have been developed and introduced in the market, which in turn increased consumer confusion. In response to the concerns about this issue, in 2009, the Commissioner of Food and Drugs Margaret Hamburg declared that FOP nutrition labeling would be a top priority for the agency. And she encouraged food manufacturers, retailers and others in the food industry to design a standardized, science-based FOP nutrition labeling system that would be in compliance with FDA regulations in order to clean up inconsistencies among several different FOP labeling systems and hence help consumers make a better dietary decision. In 2010, with the initiative of the White House “*Let’s Move!*” campaign to reduce childhood obesity, the FDA undertook a more active role in creating a standardized FOP nutrition labeling system and requested cooperative effort between the agency and food industry. More specifically, the FDA announced a request for research on consumer perceptions on FOP labeling systems, tests of different types of possible FOP labels, and comments from the public about the effectiveness of FOP labeling systems (Food and Drug Administration 2010). In subsequent, Congress directed the Centers for Disease Control and Prevention (CDC) to conduct a study with the Institute of Medicine (IOM) on the development of a uniform FOP nutrition labeling system. The FDA and the

Center for Nutrition Policy and Promotion (CNPP) in the U.S. Department of Agriculture (USDA) also supported the study that consists of two phase reports. In 2011, IOM released its Phase II report that recommended federal agencies develop a new FOP nutrition labeling system that allows only calories and three nutrients to limit such as saturated and trans fat, sodium and sugar. However, while the FDA was waiting for the IOM's next report, two of the leading food industry trade organizations in the U.S.—the Grocery Manufacturers Association (GMA) and the Food Marketing Institute (FMI)—opposed the IOM's recommendation and announced their own voluntary FOP nutrition labeling scheme called "*Facts Up Front*" FOP labeling initiative. In contrast to the FOP nutrition labeling scheme suggested by IOM, Fact Up Front focuses on both nutrients to limit and nutrients to encourage such as vitamins and fiber. In the end, the FDA offered support in the voluntary Facts Up Front program (FoodNavigator-USA 2012). As per the initiative, food manufacturers would present nutritional content of their products in an easy-to-read "call out" format which is based on the Guideline Daily Amounts (GDAs). Food packages would carry four basic icons for calories (per serving), saturated fat (in grams and percent daily value, % DV), sodium (in milligrams and % DV) and sugar (in grams). The basic icons include the set of key nutrients that the U.S. Department of Health and Human Services (HHS) and the U.S. Department of Agriculture (USDA)'s dietary guidance recommends consumers to limit consumption. In addition to these four basic icons, food manufacturers can include up to two icons for "nutrients to encourage" which include fiber, protein and a set of vitamins and minerals. On small food packages and on beverages, due to space limitations, food manufacturers can use just one icon to present calories (per serving) instead of providing all the four basic icons. In fact, Facts Up Front was not a completely brand new FOP label even though it was in the media spotlight in 2011 as it was launched to meet the need for a standardized FOP nutrition labeling system. In 2007, Kellogg and General Mills launched Nutrition at a Glance and Nutrition Highlights which were based on the European Guideline Daily Amounts (GDAs) system and very similar to Facts Up Front label, respectively. Given that nutrient specific FOP labels display quantitative and evaluative information on calories and levels of individual nutrients, for the purpose of my study, I work with nutrient specific FOP labels. Accordingly, I classify a brand as an adopter of FOP if it carries any form of a nutrient specific label on the front of its package.[4] Figure 1 presents examples of FOP nutrition labels examined in this study.

Figure 1 Examples of Front-of-Package (FOP) Nutrition Label

[4] Henceforth, I use the terms "brand" and "firm" interchangeably. For example, Kellogg's Raisin Bran and Kellogg's Frosted Flakes are products of Kellogg's, and I use the terms "brand" and "firm" interchangeably to refer to Kellogg's.

LITERATURE OVERVIEW

I briefly review the relevant literature in two research areas in which my study broadly makes a contribution. First, my study contributes to literature investing firms' participation in voluntary socially responsible initiatives. Muller et al. (2011) and Toffel (2006) argue that voluntary participation in socially responsible initiatives is a signaling mechanism through which participating firms signal their superior management practices to their customers and suppliers. Set in the context of manufacturing firms' adoption of ISO 14001, a voluntary environment friendly standard, Toffel (2006) finds that facilities with better ex ante environmental performance are more likely to adopt the standard. The author argues that it would be less costly for firms with superior management practices to adopt and be in compliance with the voluntary initiative. Levine and Toffel (2010) suggest that voluntary adoption of standards can lead to better outcomes due to organizational learning and restructuring of business practices. Building on similar arguments, I argue that firms that participate in the FOP initiative would invest in improving existing products, reposition existing brands, invest in research and development and introduce more new products with better nutrition. Thus, participating firms would become innovative so that they can further differentiate themselves in the market and make consumers pay attention to their efforts. Adopters of FOP are more likely to commit resources into benchmarking how their products compare with their competitors and are more likely to innovate to appeal to consumers who favor nutritionally better products. However, FOP labeling can be construed as a misleading tactic by firms that want to simply gain consumer attention and increase market share

(Draper et al. 2011; Nestle and Ludwig 2010). And therefore, understanding of the effect of FOP adoption on firm innovation is an empirical issue examined in this study.

Second, I provide empirical evidence brining a new insight into how the implementation of FOP nutrition labeling affects food manufacturers' new product development and reformulation of packaged food products. There have been several studies that examine consumer preferences for and understanding of different forms of FOP labels (Van Kleef et al. 2008; Malam et al. 2009; Lando and Labiner-Wolfe 2007; Feunekes et al. 2008; Gorton et al. 2009; Kelly et al. 2009; Dunbar 2010), relationship between FOP labels and food purchases (Vyth et al. 2010; Sacks et al. 2009), effect of FOP on food consumption (Steenhuis et al. 2010), consumer's willingness to pay for FOP labeled products (Drichoutis et al. 2009; Balcombe et al. 2010), FOP characteristics increasing consumer attention (Bialkova and Van Trijp 2010), relationship between consumer demographics and awareness/use of FOP labels (Gorton et al. 2009; Vyth et al. 2009). All these studies have produced mixed results and focused on the demand side effect of FOP nutrition labeling. As the jury is still out on the impact of FOP labeling initiatives on consumer behavior, I turn my focus to the supply side—the food manufacturers—and examine if their participation in such voluntary programs leads them to produce more and better products for the consumers—products with more beneficial nutrients and with lower level of nutrients that consumers generally seek to avoid or limit. Simply put, my study is concerned with the food manufacturers' strategic reaction to their voluntary participation in product information (i.e., nutrient) disclosure programs with a focus on participant firms' propensity to produce new and better products once they decide to participate. Research has not been nonexistent in the area focusing on the supply side effect of FOP. Young and Swinburn (2002) find that food manufacturers reformulated their products and reduced about 33 tonnes of salt in bread, breakfast cereal, and margarine categories within a year when the Pick the Tick programme of the National Heart Foundation was introduced in New Zealand. In addition, Vyth et al. (2010) conducts a larger study that investigates the effect of the Choices logo on food manufacturers' development of heathier products in New Zealand. They conclude that the food manufacturers joining the new labeling programme are motivated to introduce new healthy products reformulate their existing products which are nutritionally improved. More specifically, after participating in the programme, they noticeably reduce sodium and increase dietary fiber in their products. Although these studies provide meaning insights into food manufacturers' response towards FOP nutrition labeling initiatives, they are based on a model-free descriptive analyses that do not account for potential endogeneity issues that may produce biased results. As a result, their conclusions about the causal relationship between firms' adoption of FOP nutrition labeling and their subsequent reformulation of food products could be questionable. In my empirical examination, it is important to discern the causal effect of FOP participation from the self-selection effect. In the following section, I discuss my approach towards handling the self-selection issue in greater detail.

CHAPTER III

METHODOLOGY

RESEARCH DESIGN: QUASI-EXPERIMENTAL APPROACH

The main empirical challenge in this study is the endogeneity issue: more innovative firms are more likely to adopt the FOP nutrition labeling system and continue to innovate more. Hence, simply regressing the indicators of firm innovativeness on a binary variable indicating whether a firm adopted the FOP nutrition labeling would cause biased estimation results and wrong conclusions. To address the issue of endogeneity due to the self-selection in my context, following recent studies in marketing (e.g., Huang et al. 2012; Kumar et al. 2016), information systems (Rishika et al. 2013), and economics (e.g., O'Keefe 2004), I adopt a quasi-experimental approach with a combination of a difference-in-differences and propensity score matching. Specifically, I utilize a difference-in-differences (hereinafter "DID") estimation on matched samples of treatment and comparison firms based on a propensity score matching (hereinafter "PSM") method to quantify the effect of FOP nutrition labeling adoption on firms' subsequent innovation. PSM helps mimic a randomized experimental study design (Rubin 2006) by pairing a treatment firm and a comparison firm that are as similar as possible on their observed characteristics. PSM avoids the strict assumptions that are often involved with instrumental variable approach.

While PSM has been widely used in quasi-experimental studies to reduce the bias of treatment effect estimates due to confounding factors, it only controls for *observed* factors that affect both treatment assignment and outcome of interest, and thus any unobserved confounding factors may still exist even after conducting PSM. To further control for those unobserved factors, I employ a DID approach that differences out the effects of *time-invariant unobserved* confounding factors (i.e., fixed effects) and any time trends that could be confounded with the treatment effect. Briefly, the DID involves modeling the difference in outcomes (in my context, innovativeness) of food manufacturers during pre and post adoption of FOP between the two groups of firms, the *treatment group* (i.e., firms that adopted FOP) and the *comparison group* (i.e., firms that did not adopt FOP).[5] For the sake of exposition, with respect to the treatment group, I refer to the time periods prior to and post adoption of FOP by a food manufacturer as *pre-FOP* and *post-FOP* respectively. The DID approach uses the comparison group's innovativeness during the post-FOP period as the counterfactual for how the treatment group would have innovated if it had not adopted FOP.

In this study, a combination of PSM and DID enables me to isolate the FOP adoption effect from both observed and unobserved confounding factors. However, if the unobserved factors are not stable over time, the problem can still not be resolved because PSM-DID does not control for *time-variant unobserved* confounding factors that may affect firms' decision on the FOP adoption and their subsequent innovation simultaneously. Although I cannot fully account for the temporal unobserved factors, I

[5] I use the term, *comparison group*, instead of *control group* because the former is generally used in a quasi-experimental study design and the latter is used in a full randomized experimental study design. Although this rule is not hard-and-fast, I follow it to emphasize that there is a lack of full randomization in my study design (Remler and Van Ryzin 2011).

can test whether my results are robust to the presence of any "hidden bias" arising from those factors by conducting a sensitivity analysis. Both time variant and time invariant unobserved factors can be tested by using this approach. I will discuss more details about the sensitivity analysis in later section. In sum, my empirical strategy is rigorous and appropriate to address the endogeneity issues that are concerned in this study.

DATA SOURCES AND SAMPLE

My primary data source is the Mintel Global New Products Database (GNPD), which reports all new beverages and food products introduced in global markets. A highlight of this database is that it provides detailed information on product attributes such as the brand type (private label vs. national brand), calorie and nutritional information, package claims and photographs of the front, side and the back of package for each product. Besides the product attributes, the database also has information on price, unit pack size and the number of units in a multi-pack product.

For the purpose of this study, I focus on the following four food categories in the U.S. market: breakfast cold cereal, bread, sweet biscuit/cookie and potato snack. My decision to work with these four food categories is guided by the following reasons: First, all of the four categories are "fast moving" categories—the four categories feature in the list of 20 largest SymphonyIRI categories (Ma et al. 2013). Cold cereal and salty snack (which includes potato snacks) categories are among the top 5 categories ranked in terms of dollar spending per 1,000 households and percentage of households purchasing in that category (Bronnenberg et al. 2008). Second, recent marketing studies in the area of nutrition have suggested that breakfast cold cereal and bread categories are relatively healthy and functional, and that sweet biscuit/cookie and potato snack categories are regarded as relatively unhealthy and hedonic (Ma et al. 2013; Moorman et al. 2012). This would enable me to examine if the effect of FOP varies systematically across these two types of important category classifications. Third, the key nutrients that food manufacturers may attempt to change after their adoption of FOP could exhibit substantial variation across these four food categories. For example, manufacturers of potato snacks may focus on lowering the sodium content of their products while manufacturers of breakfast cold cereal may focus on increasing the fiber content post-FOP adoption. Finally, the number of brands and products is sufficiently large in the four product categories. To estimate the causal effect of FOP adoption, I use PSM that requires a large sample size for robust implementation (Heinrich et al. 2010). Hence, I use the four different categories for conducting my empirical examination.

In going through the Mintel GNPD carefully, I identified that the first time a food manufacturer adopted FOP was on June 3, 2004 in the breakfast cold cereal category. Since I need sufficient data prior to the adoption of FOP, I started compiling the data on new products for more than a year prior to the date. The study time period is from January 2003 to May 2013. I spent over hundreds of hours putting together FOP adoption and detailed nutrition related information on all of the new brands and products (total of 686 brands and 7,593 products across the four categories) introduced during this long time period. Identification of whether a particular brand adopted FOP or not during the study time period and identification of the actual date of the FOP adoption for all the brands form the crucial steps in my empirical analysis. Other than the key data source, the Mintel GNPD, I collected information on various brands and products from several sources (for the purpose of creating matching variables; I explain these sources in the following section). To assemble the estimation data from the original sample data, I removed treatment brands that introduced new products during *either* only pre-FOP period *or* only post-FOP period so as to circumvent the issue of survival bias. Given my interest in how extant brands responded to FOP adoption, I want to work with brands that were present in the market both prior to and post FOP adoption. I note that DID technique requires the treatment and the control groups to be present before and after an intervention. Applying the above filter enabled me to perform robust construction of similar groups of treatment and comparison brands (via PSM technique) and estimation of proposed econometric models via DID framework. I discuss these two steps in detail in the following sections.

SELF-SELECTION BIAS AND PROPENSITY SCORE MATCHING

Prior literature advocates for the use of instrumental variables or matching techniques to correct for self-selection bias (Angrist and Krueger 1999). In my context, finding good instrumental variables that are correlated with firms' decision to adopt FOP but are uncorrelated with firms' innovativeness would be very difficult. Using weak instruments can only compound the problem (Bound et al. 1995). Another challenge is that even if I am able to find good instruments, given that a focal firm's or brand's decision to adopt FOP is a binary variable, one might face the problem of poor identification (Wooldridge 2002) and/or inconsistent estimates (Angrist and Pischke 2009). I thus follow recent studies in marketing (Bronnenberg et al. 2010; Huang et al. 2012) that take the quasi-experimental study design approach to address the self-selection issue. Specifically, I work with the PSM technique and transform my data to create matched sets of treatment and comparison brands; matching ensures that conditional on the brand specific observed characteristics that are used for matching (referred to as the matching or conditioning variables), a firm's decision to adopt FOP (or not) is independent of the outcome variable (innovativeness in my context).

PSM, a commonly used matching procedure (Rubin 2006), involves the calculation of propensity score which in my context, is the probability of a brand adopting FOP given a set of observables. Matching helps mimic a randomized experimental study design as when the propensity scores for two brands are identical, they are equally likely to be in the treatment group, i.e., adopt FOP (Huang et al. 2012). I estimate propensity scores by specifying a binary logit model of a brand's adoption of FOP as a function of the following brand specific variables: whether the brand is a national brand or a private label, whether the firm is a publicly traded firm or not, whether the firm is a subsidiary or not,[6] whether the brand is a member (or not) of GMA or FMI, the two leading food industry associations, and whether the firm is featured (or not) in the list of Food Processing's Top 100 or Top 75 Retailers & Wholesalers ranking. I also include prior innovativeness of the brand (operationalized by the total number of

[6] A subsidiary is a company that is owned by another company which controls more than 50% of the subsidiary's voting stock.

new products introduced by a focal brand in the 12 months *prior* to the adoption of FOP by the brand) and product line length of the brand (operationalized by the average number of variants of new products launched by a focal firm *prior* to the adoption of FOP). I note that I collected these variables from several sources. In Table 1, I present the description and the data sources of the variables used in the propensity score estimation.

Table 1 Data Sources and Variable Descriptions used for Propensity Score Estimation

Matching Variable	Operationalization	Data Source
Subsidiary	1 if a firm (i.e., brand) has a parent firm or a firm is subsidiary; 0 otherwise. A subsidiary is a company that is owned by another company (i.e., a parent company) that controls more than 50% of the subsidiary's voting stock.	Mintel GNPD, Wikipedia, Company website
PublicFirm	1 if a firm is a publicly traded firm; 0 otherwise.	COMPUSTAT, Wikipedia, Company website
PrivateLabel	1 if a firm has a private label brand; 0 otherwise.	Mintel GNPD, Wikipedia, Company website
GMAFMI	1 if a firm is a member of either GMA or FMI; 0 otherwise.	GMA and FMI membership directory
Ranking	1 if a firm is listed in Food Processing's Top 100 ranking or Top 75 Retailers & Wholesalers ranking; 0 otherwise.	www.foodprocessing.com, www.supermarketnews.com
NumProducts	Total number of new products launched by a firm during one-year period prior to FOP nutrition labeling adoption	Mintel GNPD
NumVariants	Average number of variants for new products launched by a firm prior to FOP nutrition labeling adoption	Mintel GNPD

I now provide a brief discussion on the selection of the variables used for matching. I use a focal brand's prior innovativeness and product line length as proxies for a focal brand's willingness to adopt practices that would help vertically differentiate their products among consumers (Draganska and Jain 2006; Morgan and Rego 2009). The other brand/firm specific variables (national brand vs. private label, publicly traded vs. privately held firm, subsidiary or not, membership in and ranking by industry associations) capture other dimensions of the brand's capabilities and resources and consequently a focal brand's propensity to adopt innovative practices. Although national brands are more likely to participate in voluntary initiatives, retailers are more likely to adopt innovative strategies to remain competitive in non-price dimensions. Public firms are more likely than privately held firms to adopt FOP to signal their commitment towards socially responsible initiatives. With respect to the ownership structure of the firms, studies in the strategy area argue that firms that are subsidiaries (of large companies) have specialized organizational tacit knowledge. In my context, brands that are subsidiaries of other bigger firms are more likely to be focused on consumers' nutrition related preferences and thus are more likely to adopt FOP. Industry associations collect information about changing preferences of the different stakeholders and member firms have easy access to this information. In my context, firms that are members of the two leading food industry associations, GMA and FMI, are more likely to be aware of consumers' preferences for healthier food products and thus are more likely to adopt FOP. With respect to the two continuous variables, namely the number of new products and the product line length, I account for non-linear effects as well by using quadratic terms of the two variables. I note that all the matching variables are measured temporally *before* the treatment period to make sure that these variables themselves are not affected by the treatment. I employ the stepwise estimation procedure to make sure that only the relevant variables are used for matching (Rosenbaum and Rubin 1984). In Table 2, I present the parameter estimates of the binary logit model for PSM.

Table 2 Stepwise Logistic Regression Model of FOP Nutrition Labeling Adoption

	Category			
Matching Variable	*Breakfast Cold Cereal*	*Bread*	*Sweet Biscuit/Cookie*	*Potato Snack*
Subsidiary	1.7169*** (0.6595)	1.5081*** (0.5000)	1.6268*** (0.5649)	–
PublicFirm	0.9194 (0.6262)	–	–	–
PrivateLabel	1.8021*** (0.6838)	1.3621*** (0.4504)	1.1735** (0.5596)	2.0402** (0.8637)
GMAFMI	–	–	–	–
Ranking	–	–	–	–
NumProducts	–	–	–	–
NumVariants	0.7723*** (0.2936)	–	–	1.1094** (0.5384)
NumProducts^2	0.0068 (0.0049)	0.0732*** (0.0269)	0.0204** (0.0085)	–
NumVariants^2	–	0.0528** (0.0245)	–	-0.1031 (0.0797)
Constant	-3.9093*** (0.7684)	-2.4772*** (0.3192)	-3.7729*** (0.4177)	-3.8777*** (0.9577)
N	121	186	298	81
Nagelkerke's R^2	0.4016	0.3311	0.2267	0.1999

Notes. Only coefficient estimates of conditioning variables selected by a stepwise variable selection procedure are shown. Standard errors are in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

For conducting PSM, I follow the steps expounded in Caliendo and Kopeinig (2008) that are implemented by recent studies in the marketing literature (e.g., Huang et al. 2012). I matched the treatment brands to the comparison brands with the closest propensity score (which is equal to the estimated probability) using the *optimal full* *matching* algorithm. I choose to work with the algorithm as it allows for a more general type of matching with one treatment unit matched to one or more comparison units and vice-versa. It also allows for full matching without discarding any observations (Rosenbaum 2002; Hansen 2004). This is particularly important in my context as the number of treatment units is far less than that of the comparison units. After matching, I examined the performance of my matching procedure by checking if the matching variables are well balanced between the treatment and the comparison groups, wherein balance refers to the similarity of their covariate distributions. In Table 3, I present the standardized differences between the treatment and the comparison groups on the matching variables before and after matching and the percentage reduction in the standardized differences after PSM. As can be seen from Table 3, while most of the standardized difference measures are statistically significant prior to matching, the standardized difference measures are not significant after matching, which implies that PSM helps achieve covariate balance between the treatment and the comparison groups. Moreover, a series of the percentage of bias reduction further shows that PSM significantly reduces the imbalance between the treatment and comparison groups on their observed characteristics. The graphical representations of covariate balance (before and after matching are provided in Figure 2) suggest that the degree of covariate balance increases noticeably after PSM (the standardized differences of most matching variables move towards zero).

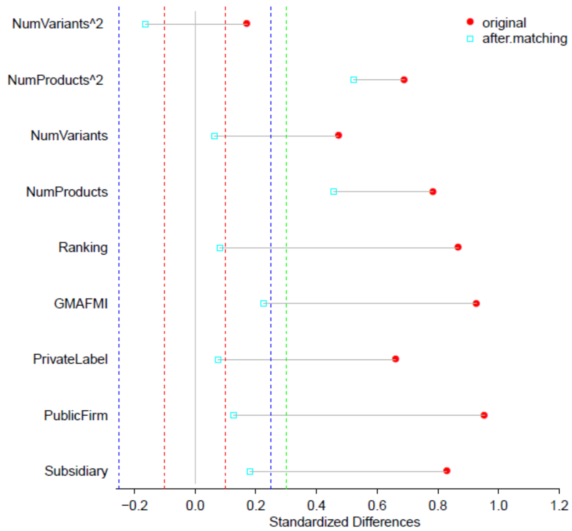
Table 3 Covariate Balance Before and After Matching

Matching Variable	Before Matching		After Matching		Bias Reduction (%)
	Standardized Difference	z-score	Standardized Difference	z-score	
Breakfast Cold Cereal					
Subsidiary	0.8299***	3.4173	0.1806	0.4847	78.23
PublicFirm	0.9534***	3.8661	0.1257	0.5071	86.82
PrivateLabel	0.6609***	2.7714	0.0746	0.3335	88.71
GMAFMI	0.9273***	3.7730	0.2247	1.0346	75.77
Ranking	0.8671***	3.5549	0.0806	0.3572	90.70
NumProducts	0.7844***	3.2467	0.4561	1.0846	41.85
NumVariants	0.4726**	2.0136	0.0640	0.2272	86.46
NumProducts^2	0.6892***	2.8819	0.5225	1.2450	24.19
NumVariants^2	0.1701	0.7358	-0.1642	-0.4865	3.47
Bread					
Subsidiary	0.9539***	4.9464	0.2786	1.1547	70.79
PublicFirm	0.6622***	3.5584	-0.0556	-0.2838	91.60
PrivateLabel	0.7040***	3.7657	-0.1710	-0.8321	75.71
GMAFMI	0.9308***	4.8420	0.2015	1.0000	78.35
Ranking	0.7070***	3.7804	0.0761	0.3870	89.24
NumProducts	0.9000***	4.7013	0.3450	1.3558	61.67
NumVariants	0.5178***	2.8202	-0.0152	-0.0689	97.06
NumProducts^2	0.9202***	4.7940	0.5689*	1.9557	38.18
NumVariants^2	0.3809**	2.0951	0.0195	0.0686	94.88
Sweet Biscuit/Cookie					
Subsidiary	1.1237***	4.3599	0.1970	0.8044	82.47
PublicFirm	0.8981***	3.5255	-0.1889	-0.8298	78.97
PrivateLabel	0.7311***	2.8908	-0.0219	-0.1061	97.00
GMAFMI	1.0665***	4.1513	0.1161	0.4284	89.11
Ranking	1.0928***	4.2474	0.1193	0.3975	89.03
NumProducts	1.3309***	5.0987	0.2832	0.7229	78.72
NumVariants	0.1777	0.7120	-0.0344	-0.1459	80.64
NumProducts^2	1.1921***	4.6069	0.6316	0.9990	47.02
NumVariants^2	0.0842	0.3377	0.0448	0.2080	46.79
Potato Snack					
Subsidiary	0.2117	0.6290	0.2663	0.6748	-25.79
PublicFirm	0.2234	0.6639	-0.0208	-0.0486	90.69
PrivateLabel	0.6909**	2.0061	0.0907	0.3392	86.87
GMAFMI	0.5488	1.6083	0.2610	0.6738	52.44
Ranking	0.3272	0.9690	-0.2354	-0.6203	28.06
NumProducts	0.0585	0.1741	0.0083	0.0273	85.81
NumVariants	0.3224	0.9550	-0.0821	-0.3575	74.53
NumProducts^2	-0.1206	-0.3589	-0.0492	-0.1825	59.20
NumVariants^2	0.0491	0.1464	-0.0326	-0.1496	33.60

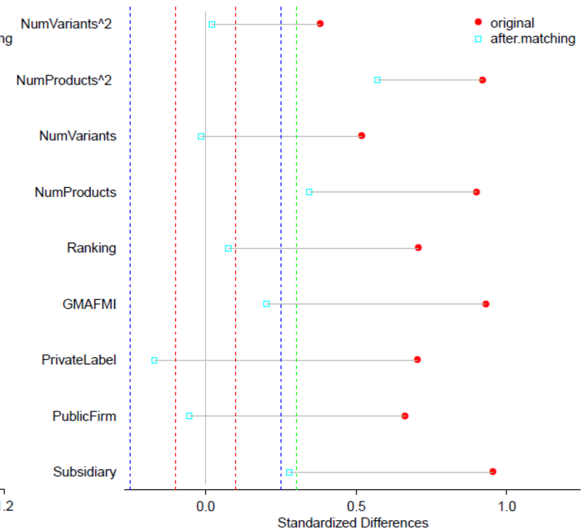
Notes. Please refer to Hansen and Bowers (2008) for full details about standardized difference and z-score calculation.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Figure 2 Balance Assessment Plots

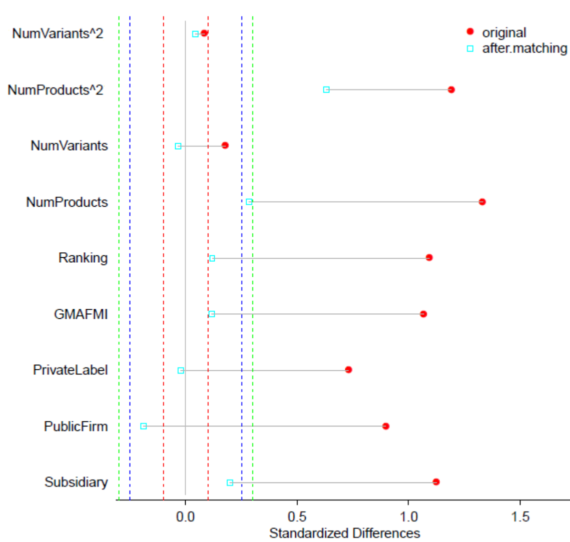
(a) Breakfast Cold Cereal



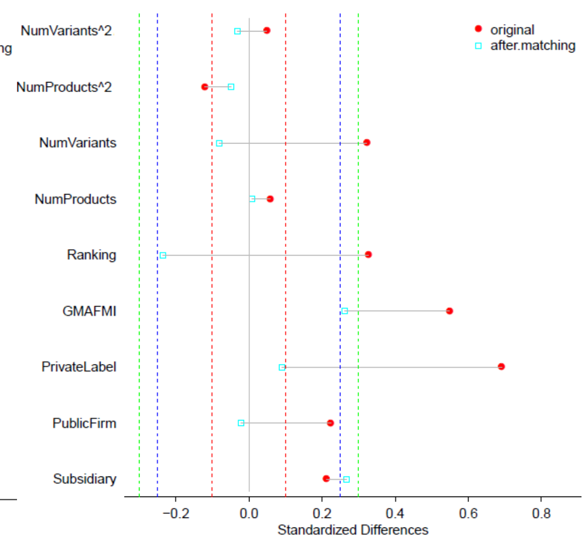
(b) Bread



(c) Sweet Biscuit/Cookie



(d) Potato Snack



Notes. Three types of dotted vertical line pairs are presented in the plot. Each type stands on a specific standardized difference value that serves as the decision criterion for achieving covariate balance after matching. I use 0.10 (D'Agostino 1998), 0.25 (Ho et al. 2007) and 0.30 as decision criteria for covariate balance. A covariate balance is accepted when a standardized difference after matching lies between the two vertical lines for each type of criterion. The smaller a decision criterion value (i.e., |Standardized Difference|), the stricter the condition for achieving covariate balance.

In addition, I follow Hansen and Bowers (2008) and conduct an omnibus test for balance on all of the matching variables *simultaneously* (as opposed to comparing the treatment and the comparison groups on each matching variable separately). In Table 4, I present the results of the omnibus balance test for the four packaged food categories. Large *p*-values of combined baseline difference statistic (d^2) after matching suggest that the null hypothesis of well-balanced matched sets cannot be rejected for all the four categories. All of these results taken together suggest that I am able to achieve statistical balance between the treatment and the comparison brands in the four packaged food categories that I study.

Table 4 Omnibus Covariate Balance Test Results

Category	Before Matching			After Matching		
	Combined Baseline Difference Statistic (d^2)	*df*	*p*-value	Combined Baseline Difference Statistic (d^2)	*df*	*p*-value
Breakfast Cold Cereal	35.0621	9	0.0001	14.6058	9	0.1023
Bread	51.7639	9	0.0000	12.0008	9	0.2133
Sweet Biscuit/Cookie	44.4427	9	0.0000	4.0933	9	0.9052
Potato Snack	10.2956	9	0.3271	5.4291	9	0.7954

As mentioned earlier, the key assumption of the propensity score matching (PSM) is the *ignorable treatment assignment* assumption (Rosenbaum and Rubin 1983). This assumption tells that conditional on a set of observed covariates which are not affected by treatment, the potential outcomes of both treated and non-treated units are independent of the assignment of treatment. This assumption is also known as *selection on observables* (Barnow et al. 1980) which implies that only observed characteristics of units account for the selection process into treatment and control groups and thus the estimated treatment effect could be biased if there are unobserved (to researchers) factors that affect the treatment assignment and the outcomes of interest simultaneously. The bias due to the potential unobservables that are not controlled by PSM is called a *hidden bias*. Although the degree of hidden bias cannot be directly estimated, I can address this issue with a sensitivity analysis that tests how large the hidden bias should be to change the inferences on the treatment effect. If the magnitude of hidden bias that alters the qualitative conclusion of this study is large enough, then I can say that the inferences about the treatment effect are insensitive to the potential hidden bias arising from unobserved factors and thus PSM works effectively. However, if it is too small, I can conclude that PSM is not enough to account for the self-selection issue and thus it is hard to trust the conclusion of the quasi-experimental study using PSM.

Now, I illustrate the basic idea of the sensitivity analysis in my research context (Rosenbaum 1993; Guo and Fraser 2015). Suppose there are two firms, *x* and *y*, that share the same observed covariates, Z, but different probabilities of adopting the FOP nutrition labeling (i.e., $p_x \neq p_y$). Then, PSM would match the two firms to create a matched pair because they are identical in terms of the observables, on the other hand, one of them adopts the FOP nutrition labeling and another does not. The odd of adopting the FOP label for the firm *x* is $p_x/(1- p_x)$ and the odd of adopting the FOP label for the firm *y* is $p_y/(1- p_y)$. And the odd ratio which compares the two odds is $[p_x/(1- p_x)]/[p_y/(1- p_y)]$. The sensitivity analysis further assumes that among the two firms sharing the same

Z, one of the firms is $\Gamma \geq 1$ times more likely to adopt the FOP nutrition labeling than another due to any potential unobserved factors. That is,

$$\frac{1}{\Gamma} \leq \frac{p_x(1-p_x)}{p_y(1-p_y)} \leq \Gamma, \tag{1}$$

where Γ is a sensitivity parameter that is a measure of the degree of the insensitivity towards a hidden bias and thus the study becomes less sensitive to hidden bias as Γ increases. If $\Gamma = 1$ (i.e., $p_x = p_y$), the two matched firms, x and y, have the same chances of adopting the FOP nutrition labeling as in a controlled randomized experiment which is definitely free from hidden bias. However, this is almost impossible in the observational studies. If $\Gamma = 2$, the one of the two firms sharing the same Z is twice as likely to adopt the FOP nutrition labeling as the other. The sensitivity analysis tests a variety set of Γ values to see how the inference about the FOP effect may change. Therefore, the whole idea of conducting the sensitivity analysis is to check how much the study result is robust against any hidden biases caused by unobserved differences between treatment and comparison groups which cannot be controlled by PSM. If the result of my study is not sensitive to the hidden biases, I can admit the validity of PSM and thus I can say that PSM works well in resolving self-selection issues. In this study, I conduct the sensitivity analysis using Huber-Maritz M-statistics (Rosenbaum 2002; Rosenbaum 2007). It provides the upper bounds on the one-sided P-values testing the null hypothesis of no treatment effect along with the different levels of sensitivity parameter (Γ). $\Gamma = 1$ implies a randomized experiment with matched firms having equal chances of treatment (i.e., the absence of unobserved bias). For a certain $\Gamma > 1$, P-value which is slightly above the conventional 0.05 level is large enough to fail to reject the null hypothesis of no treatment effect if a bias of magnitude could be as large as that Γ. The larger the value of Γ corresponding p-value is slightly larger than 0.05, the less the sensitivity of treatment effect to unobserved biases. Please refer to Rosenbaum (2007) for full details about the sensitivity analysis using Huber-Maritz M-statistics. The sensitivity analysis in this study shows that hidden bias is not an overly concern, and the results of the PSM-DID in this study are robust against any unobserved time variant factors that could be possibly related to the self-selection issue.

ECONOMETRIC MODELS

Quantity and Quality of Innovation

I operationalize quantity of innovation by the rate of new product introductions of a particular brand. Table 5 presents the summary statistics of quantity of new products for the four food categories.

Table 5 Summary Statistics of the Number of New Products - Quantity of Innovation

Category	Mean	SD	Min	Max	Total	Obs.
Breakfast Cold Cereal	12.60	37.26	1	320	1764	140
Bread	4.74	6.38	1	43	1089	230
Sweet Biscuit/Cookie	5.10	13.57	1	168	1671	328
Potato Snack	5.01	11.15	1	72	391	78

Notes. The unit of observation is at the brand level. *Total* indicates the total number of new product introductions across brands. *Obs.* refers to the total number of number of observations across pre- and post-FOP adoption (for each brand, there are two observations, pre and post FOP adoption).

With respect to the quality of innovation, I focus on the change in calories and levels of the following five nutrients: fat, sodium, sugar, fiber and protein. To compute these, serving size information is critical. However, the serving size information that is reported in the Nutrition Facts label is not standardized and manufacturers can adjust the serving sizes for marketing purposes (Mohr et al. 2012). The Mintel GNPD lends me a unique advantage as it provides *standardized* information (standardized to a 100g serving size) on each nutrient. In addition to individual nutrient level analysis, I also examine the effect of FOP on overall nutritional quality of food products. To compute this measure, based on a 2,000 calorie daily diet, I first transform the levels of fat, saturated fat, cholesterol, sodium and fiber into Percent Daily Value (%DV) developed by the FDA.[7] I then compute the *overall nutrition score* by treating fat, saturated fat, cholesterol and sodium as "nutrients to limit" and fiber as "nutrient to encourage" as follows (Moorman et al. 2012):[8]

$$\frac{100\times\left(\left(1-\frac{Fat(g)}{65g}\right)+\left(1-\frac{Saturated\ Fat(g)}{20g}\right)+\left(1-\frac{Cholesterol(mg)}{300mg}\right)+\left(1-\frac{Sodium(mg)}{2,400mg}\right)+\frac{Fiber(g)}{25g}\right)}{5}. \quad (2)$$

Table 6 presents the summary statistics of calories, the five focal nutrients and the overall nutrition score for the four packaged food categories.

[7] Based on a 2,000 calorie diet, Daily Values (DVs) for fat, saturated fat, cholesterol, sodium and fiber are 65g, 20g, 300mg, 2,400mg and 25g, respectively. The Percent Daily Value (%DV) in one serving (e.g., standardized to a 100g serving size in this study) of food is calculated by dividing the amount of each nutrient by the maximum or minimum recommended Daily Value (DV) of intakes based on a 2,000 or 2,500 calorie daily diet, and then multiplying by 100. The DVs are listed in the footnote on the bottom of the Nutrition Facts label. For more information on the Nutrition Facts label, visit the following link:
http://www.fda.gov/food/ingredientspackaginglabeling/labelingnutrition/ucm274593.htm.

[8] I note that Moorman et al. (2012) do not include *saturated fat* in their overall nutrition measure calculation. However, I include it in my analysis as the nutrient is an important factor in the evaluation of food products' nutritional quality.

Table 6 Summary Statistics of Nutrient Content - Quality of Innovation

Dependent Variable	Mean	SD	Min	Max	Q10	Q25	Q50	Q75	Q90	Obs.
Breakfast Cold Cereal										
Calorie (kcal/100g)	374.48	58.76	38.71	633.33	334.09	359.62	381.82	400.00	418.18	1160
Fat (g/100g)	4.85	4.22	0.00	33.33	0.00	1.85	3.70	5.77	10.34	1172
Sodium (mg/100g)	432.74	230.45	0.00	1185.19	63.40	254.90	466.67	600.00	703.70	1171
Sugar (g/100g)	26.93	11.91	0.00	55.56	10.00	19.60	27.27	35.85	42.86	1170
Fiber (g/100g)	7.55	6.56	0.00	86.21	3.03	3.33	6.67	10.00	13.33	1164
Protein (g/100g)	7.86	5.22	0.35	61.29	3.33	5.66	7.14	9.38	10.91	1165
OverallNutrition	80.19	5.94	56.69	113.39	73.52	76.67	79.50	82.85	87.66	1141
Bread										
Calorie (kcal/100g)	276.68	65.59	10.00	504.00	211.64	238.10	264.55	299.91	357.14	803
Fat (g/100g)	6.07	6.60	0.00	100.00	1.32	2.40	3.67	7.19	14.63	812
Sodium (mg/100g)	498.27	196.82	0.00	1807.23	316.29	394.74	486.11	575.00	726.02	804
Sugar (g/100g)	5.74	5.91	0.00	100.00	0.00	2.22	5.00	7.69	10.15	805
Fiber (g/100g)	4.67	5.15	0.00	100.00	1.53	2.00	3.13	6.27	10.53	812
Protein (g/100g)	9.08	2.55	0.00	21.05	6.49	7.50	8.89	10.53	11.80	806
OverallNutrition	76.02	6.46	43.22	94.98	67.24	73.43	76.81	79.68	84.02	796
Sweet Biscuit/Cookie										
Calorie (kcal/100g)	466.45	56.49	15.15	625.00	400.00	444.44	471.01	500.00	518.52	1261
Fat (g/100g)	20.12	6.90	0.00	50.00	10.71	16.00	20.69	25.00	28.22	1260
Sodium (mg/100g)	311.74	138.07	0.00	875.00	130.13	214.29	316.67	392.86	482.14	1206
Sugar (g/100g)	33.65	9.46	0.00	75.00	22.00	28.00	34.21	39.47	44.83	1260
Fiber (g/100g)	2.86	2.61	0.00	28.57	0.00	0.00	3.23	3.57	4.76	1237
Protein (g/100g)	5.36	2.11	0.00	18.18	3.23	3.57	5.26	6.67	7.56	1238
OverallNutrition	63.15	7.99	28.59	91.72	52.77	57.79	63.67	68.01	73.84	1183
Potato Snack										
Calorie (kcal/100g)	513.32	44.89	388.01	584.00	451.01	493.83	529.10	535.71	564.37	247
Fat (g/100g)	28.87	7.92	5.36	42.86	16.93	25.00	31.75	35.27	35.71	247
Sodium (mg/100g)	659.08	248.92	3.01	1714.29	390.92	529.10	607.14	776.01	1028.04	247
Sugar (g/100g)	2.87	2.50	0.00	14.11	0.00	0.00	3.53	3.57	7.05	248
Fiber (g/100g)	3.99	1.86	0.00	14.29	3.53	3.53	3.57	3.57	7.05	249
Protein (g/100g)	6.29	1.87	0.01	14.11	3.53	4.92	7.05	7.14	7.14	248
OverallNutrition	63.76	6.62	41.22	83.37	56.81	59.57	63.24	67.22	71.80	247

Notes. The unit of observation is at the product level.

Effect of FOP on the Quantity of Innovation

The unit of analysis of quantity of innovation is at the *individual brand* level. Let L_{mbt} denote the total number of new products introduced by brand *b* that belongs to a matched set *m* at time period *t*. Given that the realization of L_{mbt} is non-negative and discrete, consistent with prior literature on rate of innovation (Hausman et al. 1984), I assume that L_{mbt} follows a Poisson distribution with parameter λ_{mbt} as follows:

$$\mathrm{P}(L_{mbt} = l \mid \lambda_{mbt}) = \frac{e^{-\lambda_{mbt}} \lambda_{mbt}{}^{l}}{l!}, \tag{3}$$

where *l* = 0, 1, ... , and $\lambda_{mbt} > 0$. In my context, the time window of measurement of new products varies across the brands depending on their time of adoption of FOP, and thus the count of new products is measured over different lengths of time. In such a scenario, it is recommended that the Poisson parameter be specified as a rate per time period (months, in my context) as follows (Agresti 2007): λ_{mbt} / h_{mbt}, where h_{mbt} is the number of observed months for a brand *b* of a matched set *m* during time period *t*.

Following a recent study (Anderson et al. 2010), I cast my Poisson regression model in the DID framework. Accordingly, for each matched set (denoted by *m*) of treatment and comparison brands (denoted by *b*), I model the logarithm of the expected rate of new product introductions as follows:

$$\log(\lambda_{mbt} / h_{mbt}) = \alpha_0 + \alpha_1 TB_{mb} + \alpha_2 FOP_{mbt} + \alpha_3 TB_{mb} \times FOP_{mbt} + \theta X_{mbt} + \pi_m + \varepsilon_{mbt}, \tag{4}$$

where TB_{mb} is the treatment dummy variable that is equal to 1 if a brand *b* of a matched set *m* adopts FOP and 0 otherwise. FOP_{mbt} is the post-FOP dummy variable that is equal to 1 if time period *t* is the post-FOP period and 0 if time period *t* is the pre-FOP period for a brand *b* of a matched set *m*. X_{mbt} is a set of control variables for a brand *b* of a matched set *m* at time period *t*. I note that π_m is a series of matched-set fixed effects that capture unobserved time-invariant heterogeneity across matched sets.[9] Lastly, ε_{mbt} denotes the error term. My focal coefficient of interest is α_3 which captures the effect of FOP adoption on a firm's rate of new product introductions.

Effect of FOP on the Quality of Innovation

Before I present the model for assessing the effect of FOP on the quality of innovation, I clarify two points. First, unlike the quantity of innovation model that is at the brand level, the analysis of quality of innovation is at the product level (I use the term "product" to differentiate between Kellogg's brand's *Kellogg's Crunchy Nut* from *Kellogg's Raisin Bran*). The reason is that these different products (brand extensions) of a brand can be very different nutritionally; since my goal is to examine the effect of FOP on the nutritional profile at the individual product level, averaging nutrition level across these products can mask the individual product level differences. Second, I note again that matching is done at the brand level and the analysis of quality of innovation is at the product level. This is because it is extremely difficult to find product-specific (that vary within a brand) matching variables. Moreover, the decision to adopt FOP is likely taken

[9] Inclusion of matched-set fixed effects instead of brand fixed effects makes the model more parsimonious; this helps me to avoid an over-specified model and related problems arising due to small sample size. I also note that the core results are robust to a model with brand fixed effects specification.

at the brand level. Given a brand's decision to adopt FOP, the goal of this study is to examine whether a brand improves the quality of its products subsequent to FOP adoption. Accordingly, I employ the DID modeling framework to analyze the changes in the level of calories and nutrients for a product after FOP adoption.

Let t_m be the first time of FOP adoption across any of products by a treatment brand that is included in the matched set *m* (I note that each matched set has only one treatment brand and that brands can adopt FOP at different points of time). For each matched set of treatment and comparison brands and their products I have:

$$NUTRIENT_{mpbt} = \beta_0 + \beta_1 TB_{mpb} + \beta_2 FOP_{mpbt} + \beta_3 TB_{mpb} \times FOP_{mpbt} + \mu Z_{mpbt} + \nu_m + \eta_t + \xi_{mpbt}. \qquad (5)$$

In Equation (5), $NUTRIENT_{mpbt}$ represents the level of calories and nutrients in a product *p* of a brand *b* of a matched set *m* at time *t* such that $NUTRIENT_{mpbt} \in \{ Calorie_{mpbt},$ Fat_{mpbt}, $Sodium_{mpbt}$, $Sugar_{mpbt}$, $Fiber_{mpbt}$, $Protein_{mpbt} \}$. TB_{mpb} is the treatment brand dummy variable that is equal to 1 if a product *p* of a brand *b* of a matched set *m* is included in the treatment group and 0 otherwise. FOP_{mpbt} is the post-FOP dummy variable that is equal to 1 if $t \geq t_m$ (i.e., the post-FOP period) and 0 if $t < t_m$ (i.e., the pre-FOP period) for a product *p* of a brand *b* of a matched set *m*. I note that both of these dummy variables are product-brand specific. Z_{mpbt} is a set of control variables for a product *p* of a brand *b* of a matched set *m* at time *t*. ν_m is a series of matched-set fixed effects that capture time-invariant unobserved heterogeneity across matched sets. η_t is a series of year fixed effects. ξ_{mpbt} is the error term. I also examine the effect of FOP adoption on the overall nutrition level of the products. I compute $OverallNutrition_{mpbt}$, the overall nutrition score of the focal product using the expression given in Equation (2) and use the following DID model:

$$OverallNutrition_{mpbt} = \beta_0 + \beta_1 TB_{mpb} + \beta_2 FOP_{mpbt} + \beta_3 TB_{mpb} \times FOP_{mpbt} + \mu Z_{mpbt} + \nu_m + \eta_t + \xi_{mpbt}. \qquad (6)$$

The variables presented in Equation (6) are identical to the ones used in Equation (5). I transform my dependent variables (by taking log or by changing the scale) to make the distribution of the dependent variables as close to the normal distribution as possible (I refer the readers to Table A1 in Appendix for details on the transformations of the different dependent variables). As before, the primary coefficient of interest is β_3 that captures the effect of FOP adoption on the change in the level of calories, nutrients and overall nutrition score.

Looking Beyond Average Effects: Quantile Difference-in-Differences Model

DID modeling framework, although very useful in evaluating the treatment effect, helps explain only the average effect. In other words, it helps compare the treatment unit to the comparison unit pre- and post-treatment at the *mean* of the outcome distribution. However, it is possible that the treatment effect itself could vary across the different levels of the distribution of the outcome variable. For example, in my context, the effect of FOP on the change in sugar level may depend on the sugar level prior to FOP adoption. A simple DID model would ignore these potential differential effects. To examine the heterogeneous impact of FOP on the levels of nutrients, based on recent studies (Abadie et al. 2002; Borah et al. 2011; Fan et al. 2012; Atella and Kopinska 2012), I extend the DID model to a quantile difference-in-differences (QDID) model formulation. Other advantages of using QDID stem from the basics of a quantile regression model which does not require any parametric distributional assumption on the error term and allows me to detect changes in the shapes of the distributions of the outcome variable across the covariate variables (Koenker and Machado 1999). Furthermore, in general, a quantile regression model yields more robust and efficient estimates as compared to an ordinary least squares (OLS) regression model, which makes an inference on the conditional mean of the outcome variable. Finally, QDID is less sensitive to outliers in the response measurements.

CHAPTER IV

RESULTS

MODEL FREE EVIDENCE

Before I present the formal econometric models in this study, I provide model free evidence of the impact of FOP on the quantity and the quality of new products. As can be seen from Table 7, FOP adopters, on average, introduced more new products after FOP adoption, when compared to the comparison brands. Whereas the mean number of new products introduced by the adopter brands increased by 20.00 (in breakfast cold cereal), 2.06 (in bread), 3.00 (in sweet biscuit/cookie) and 1.25 (in potato snack), the mean number of new products launched by non-adopters decreased by 5.49 (in breakfast cold cereal), 0.65 (in bread), 0.77 (in sweet biscuit/cookie) and 5.84 (in potato snack).

Table 7 A Comparison of the Quantity of New Products in Pre- and Post-FOP Periods

Category	Treatment Brand			Comparison Brand		
	Pre-FOP	Post-FOP	Change	Pre-FOP	Post-FOP	Change
Breakfast Cold Cereal	16.52 (16.41)	36.52 (84.44)	20.00	8.53 (15.44)	3.04 (3.62)	-5.49
Bread	7.78 (6.64)	9.83 (11.22)	2.06	3.20 (3.52)	2.56 (2.69)	-0.65
Sweet Biscuit/Cookie	18.23 (24.40)	21.23 (45.79)	3.00	4.22 (6.47)	3.45 (10.17)	-0.77
Potato Snack	4.13 (2.30)	5.38 (5.32)	1.25	8.00 (16.99)	2.16 (2.21)	-5.84

Notes. The table presents the mean values of the number of new products introduced during pre- and post-FOP adoption periods for both treatment and comparison brands. *Change* is computed by subtracting the mean number of new products in pre-FOP period from the mean number of new products in post-FOP period. Standard deviations are in parentheses.

In terms of the quality of innovation, Table 8 suggests that the average overall nutrition score of adopter brands increased subsequent to adoption and that the average overall nutrition score of comparison brands decreased across all of the four food categories. Although these preliminary model free evidence results are aligned with the central proposition of my study, I note that these results present only overall trends before and after FOP nutrition labeling adoption and one has to be careful about interpretation of these results. In the subsequent analyses, I develop econometric models that capture the actual causal effect of FOP labeling on product innovation on the quantity and the quality dimensions.

Table 8 A Comparison of Level of Calorie and Nutrient Content in Pre- and Post-FOP Periods

Dependent Variable	Treatment Brand			Comparison Brand		
	Pre-FOP	Post-FOP	Change	Pre-FOP	Post-FOP	Change
Breakfast Cold Cereal						
Calorie (kcal/100g)	380.52 (62.24)	369.80 (61.48)	-10.71	373.46 (53.01)	392.79 (45.54)	19.34
Fat (g/100g)	5.05 (4.29)	4.22 (3.33)	-0.83	5.47 (4.63)	6.59 (6.27)	1.11
Sodium (mg/100g)	462.78 (246.46)	487.41 (205.46)	24.63	318.78 (225.44)	337.71 (230.74)	18.92
Sugar (g/100g)	30.82 (11.05)	27.66 (12.39)	-3.16	23.88 (10.62)	24.14 (10.92)	0.26
Fiber (g/100g)	6.35 (7.86)	7.28 (6.55)	0.93	8.87 (5.93)	7.86 (5.46)	-1.01
Protein (g/100g)	8.63 (8.39)	6.90 (4.23)	-1.73	9.14 (4.66)	9.25 (4.44)	0.11
OverallNutrition	78.64 (5.11)	79.84 (5.99)	1.20	81.88 (6.25)	80.73 (5.23)	-1.15
Bread						
Calorie (kcal/100g)	268.41 (63.29)	262.98 (56.37)	-5.44	293.70 (68.62)	298.54 (73.86)	4.84
Fat (g/100g)	5.33 (5.53)	4.91 (6.70)	-0.42	7.63 (6.67)	7.88 (6.74)	0.25
Sodium (mg/100g)	491.91 (202.72)	470.30 (177.78)	-21.61	542.80 (211.58)	524.78 (206.15)	-18.03
Sugar (g/100g)	5.73 (4.31)	6.53 (6.85)	0.80	4.04 (4.12)	4.54 (5.25)	0.50
Fiber (g/100g)	4.29 (3.41)	5.44 (6.71)	1.15	3.89 (3.95)	4.16 (3.42)	0.27

Table 8 Continued

Dependent Variable	Treatment Brand			Comparison Brand		
	Pre-FOP	Post-FOP	Change	Pre-FOP	Post-FOP	Change
Bread						
Protein (g/100g)	9.18 (2.21)	9.65 (2.49)	0.46	8.42 (2.73)	8.35 (2.55)	-0.07
OverallNutrition	76.27 (6.40)	77.88 (5.64)	1.61	74.00 (6.49)	73.63 (6.87)	-0.37
Sweet Biscuit/Cookie						
Calorie (kcal/100g)	459.27 (66.77)	461.13 (50.97)	1.87	465.23 (62.63)	475.02 (49.59)	9.79
Fat (g/100g)	19.20 (7.43)	19.07 (6.45)	-0.13	20.53 (6.92)	21.13 (6.88)	0.60
Sodium (mg/100g)	331.55 (130.94)	349.83 (134.39)	18.28	283.41 (139.39)	307.661 (135.60)	24.25
Sugar (g/100g)	32.49 (9.04)	35.30 (8.85)	2.81	32.91 (10.96)	33.57 (8.54)	0.66
Fiber (g/100g)	3.21 (2.68)	2.98 (2.34)	-0.22	2.55 (2.75)	2.83 (2.66)	0.28
Protein (g/100g)	5.34 (1.97)	5.16 (2.32)	-0.18	5.64 (2.03)	5.25 (2.08)	-0.39
OverallNutrition	64.92 (8.08)	65.58 (6.53)	0.67	62.09 (8.39)	62.05 (8.01)	-0.04
Potato Snack						
Calorie (kcal/100g)	519.03 (30.69)	494.07 (49.67)	-24.96	514.15 (46.15)	522.61 (38.95)	8.46
Fat (g/100g)	31.39 (3.60)	26.35 (8.81)	-5.04	28.63 (8.32)	30.31 (6.88)	1.68
Sodium (mg/100g)	773.27 (269.93)	664.85 (236.57)	-108.41	621.79 (240.00)	681.21 (284.10)	59.42
Sugar (g/100g)	3.35 (2.95)	2.58 (1.77)	-0.76	2.71 (2.48)	3.28 (2.81)	0.57
Fiber (g/100g)	4.19 (2.27)	4.36 (2.40)	0.17	4.03 (1.84)	3.59 (1.28)	-0.44
Protein (g/100g)	6.91 (1.52)	6.76 (1.92)	-0.14	6.07 (1.97)	6.30 (1.62)	0.23
OverallNutrition	61.43 (5.88)	66.05 (6.53)	4.63	64.17 (6.57)	61.96 (6.46)	-2.21

Notes. The table presents the mean levels of calories, five nutrients and overall nutrition scores during pre- and post-FOP adoption periods for both treatment and comparison brands. *Change* is computed by subtracting the average values of calories, five nutrients and overall nutrition scores in pre-FOP period from the average values of calories, five nutrients and overall nutrition scores in post-FOP period. Standard deviations are in parentheses.

EFFECT OF FOP ON THE QUANTITY OF INNOVATION

Table 9 presents the results of the DID model of quantity of new products (presented in Equation (4)) for the four categories. The DID estimates (α_3 in Equation (4)) are displayed in the first row of Table 9. I find that the coefficients are positive and significant for three of the four categories, the three categories being breakfast cold cereal, bread and potato snack. These results are robust to the inclusion of several control variables such as price, unit pack size and number of units in a multipack. For all the four categories, the model that accounts for control variables fits better than the model without the control variables (based on Akaike Information Criterion (AIC)[10]). I find that the FOP adopters introduced about 388.42% (in breakfast cold cereal), 82.83% (in bread), and 64.31% (in potato snack) more new products per month in post-FOP adoption period than the comparison brands.[11] I find that the effect of FOP on innovation is the greatest in the breakfast cold cereal category. I note that the standard errors that I report in the table are clustered at the matched set level and are heteroskedasticity robust.

Table 9 Impact of FOP Nutrition Labeling Adoption on the Quantity of Innovation

Variable	Model	
	(1) NC	(2) YC
Breakfast Cold Cereal		
TB × FOP	**1.7115*** (0.4369)**	**1.5860*** (0.4191)**
TB	-0.1281 (0.4196)	-0.0418 (0.4702)
FOP	-1.9154*** (0.4382)	-1.8754*** (0.4228)
Price	–	0.0830 (0.0793)
UnitPackSize	–	-0.0005 (0.0010)
UnitsInMultipack	–	0.5851 (0.4422)
Constant	-0.4548** (0.2150)	-1.0584*** (0.3985)
Matched-set fixed effects	Yes	Yes
Log-likelihood	-502.61	-493.11
AIC	1510.45	1497.44

[10] I note that lower AIC indicates better model fit.
[11] This interpretation is based on the results of DID models with control variables. The percentage expression is given by $100 \times (e^{\alpha_3} - 1)$.

Table 9 Continued

Variable	Model	
	(1) NC	(2) YC
Bread		
TB × FOP	**0.5848*** (0.1767)**	**0.6034*** (0.1717)**
TB	0.2220 (0.1661)	0.2009 (0.1616)
FOP	-0.6438*** (0.1114)	-0.6469*** (0.1118)
Price	–	-0.0595 (0.0762)
UnitPackSize	–	0.0007** (0.0003)
UnitsInMultipack	–	-0.1060 (0.0698)
Constant	-2.1013*** (0.0342)	-2.0525*** (0.2110)
Matched-set fixed effects	Yes	Yes
Log-likelihood	-257.62	-251.90
AIC	1266.93	1261.48
Sweet Biscuit/Cookie		
TB × FOP	-0.0763 (0.3088)	-0.0951 (0.3043)
TB	0.4470* (0.2300)	0.4396* (0.2254)
FOP	-0.4632*** (0.1498)	-0.4401*** (0.1580)
Price	–	-0.0372** (0.0183)
UnitPackSize	–	-0.0001 (0.0003)
UnitsInMultipack	–	-0.0070 (0.0450)
Constant	-0.4800*** (0.0845)	-0.3066*** (0.1107)
Matched-set fixed effects	Yes	Yes
Log-likelihood	-549.57	-543.43
AIC	2055.79	2049.51
Potato Snack		
TB × FOP	**0.6174** (0.3064)**	**0.4966* (0.2668)**
TB	-0.3054 (0.2639)	-0.2112 (0.2683)
FOP	-0.9291** (0.3945)	-0.8157*** (0.2155)
Price	–	-0.1813 (0.1471)
UnitPackSize	–	0.0025 (0.0020)
UnitsInMultipack	–	0.4763*** (0.0348)

Table 9 Continued

Variable	Model	
	(1) NC	(2) YC
Potato Snack		
Constant	-0.4947 (0.5412)	-1.1915* (0.6837)
Matched-set fixed effects	Yes	Yes
Log-likelihood	-145.28	-116.39
AIC	536.72	484.96
Notes. The dependent variable is the number of new products introduced by a brand. "NC" and "YC" denote "No (without) Controls" and "Yes (with) Controls" respectively. Robust standard errors that are clustered at the matched-set level are in parentheses. The focal variable of interest and its coefficient estimates that are statistically significant are highlighted in bold. AIC refers to Akaike Information Criterion.		

EFFECT OF FOP ON THE QUALITY OF INNOVATION

Breakfast Cold Cereal Category

I present the results of the DID and the QDID models of quality of new products for breakfast cold cereal category in Table 10. I find that the products of brands that adopt FOP have improved nutritional value along several dimensions as compared to products of brands that do not adopt FOP. More specifically, I find that on average, products of brands that adopt FOP have reduced number of calories, reduced sugar content and an improved overall nutrition score subsequent to FOP adoption when compared to products of brands that do not adopt FOP. I also find that FOP adoption does not lead to an improvement in product quality in terms of the mean levels of fat, sodium, fiber and protein. These results are robust to the addition of the control variables.[12]

[12] Given the number of nutrients and categories that I work with, for the sake of brevity, I present only the estimates of the focal coefficients of interest (i.e., DID and QDID estimates) in Table 10. The extended version of Table 10 that reports the complete set of results of the DID and the QDID models (with the results on the control variables) are available from me upon request.

As mentioned earlier, analysis of the treatment effect at the mean level may be limiting and QDID estimates can shed more light on the heterogeneous effects. Indeed, QDID estimates suggest that the effect of FOP varies across the distribution of the levels of various nutrients. QDID estimates confirm that adoption of FOP leads to a reduction in the number of calories and the level of sugar content at the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} quantiles, and increase in overall nutrition score across the four quantiles (25^{th}, 50^{th}, 75^{th} and 90^{th}). Even with respect to fat, sodium and fiber where I did not find a significant effect of treatment at the mean level, I find an effect of FOP across the different quantiles. In particular, I find that products of brands that adopt FOP have a reduced fat content at the top quantiles of 75^{th} and 90^{th}, lower sodium content at 50^{th}, 75^{th} and 90^{th} quantiles, and higher fiber content at 50^{th}, 75^{th} and 90^{th} quantiles as compared to the products of comparison brands.

For a more detailed understanding of the heterogeneous effect of FOP adoption on the nutrition level of products in the breakfast cereal category, I provide the following numerical interpretation of the estimates of my models (that includes the set of control variables). Adoption of FOP decreases the calorie level by about 26.47kcal/100g, 19.91kcal/100g, 18.34kcal/100g and 30.61kcal/100g at the 10^{th}, 25^{th}, 50^{th} and 90^{th} quantiles of the calorie distribution, respectively. Adopters of FOP also reduce fat content by approximately 31.50% and 29.90% at the 75^{th} and 90^{th} quantiles of the fat distribution, respectively. The QDID results show that adopters of FOP reduce sodium level by roughly 66.61mg/100g and 73.41mg/100g at the 50^{th} and the 75^{th} quantiles of the sodium distribution respectively as compared to non-adopters of FOP, during post-

FOP nutrition labeling adoption time period. FOP nutrition labeling reduces sugar level by about 6.92g/100g, 3.89g/100g, 4.39g/100g and 3.19g/100g at the 10^{th}, 25^{th}, 50^{th} and 90^{th} quantiles of the sugar distribution, respectively. FOP nutrition labeling increases the fiber level by about 34.05%, 33.47% and 30.41% at the 50^{th}, 75^{th} and 90^{th} quantiles of the fiber distribution, respectively. Finally, I can see that FOP nutrition labeling increases the overall nutrition score by about 1.79, 2.59, 3.67 and 4.69 points at the 25^{th}, 50^{th}, 75^{th} and 90^{th} quantiles of the overall nutrition score distribution, respectively.

Overall, the results suggest that products of brands that adopt FOP improve the *overall* nutritional quality of cold cereal products by decreasing the level of nutrients that consumers seek to avoid and increasing the level of fiber which is a nutrient to encourage. I note that since the QDID estimates help capture the heterogeneous treatment effect, the effect is present as long as one of the QDID estimates is significant.

Table 10 Impact of FOP Nutrition Labeling Adoption on the Quality of Innovation - Breakfast Cold Cereal

Dependent Variable	DID estimate		QDID estimate									
			Q10		Q25		Q50		Q75		Q90	
	(1) NC	(2) YC	(3) NC	(4) YC	(5) NC	(6) YC	(7) NC	(8) YC	(9) NC	(10) YC	(11) NC	(12) YC
Calorie	**-0.2348****	**-0.2298****	**-0.2589***	**-0.2647***	**-0.2918****	**-0.1991***	**-0.1951*****	**-0.1834*****	**-0.1406****	-0.1185	**-0.2862***	**-0.3061***
	(0.1030)	**(0.0909)**	**(0.1535)**	**(0.1414)**	**(0.1169)**	**(0.1073)**	**(0.0737)**	**(0.0658)**	**(0.0581)**	(0.0772)	**(0.1517)**	**(0.1635)**
Fat	0.1104	0.1654	0.0000	0.1267	-0.0360	0.0657	-0.2011	-0.1308	**-0.4491*****	**-0.3150****	**-0.4986****	**-0.2990****
	(0.6140)	(0.6489)	(2.1963)	(2.4523)	(1.0195)	(0.2096)	(0.1944)	(0.1561)	**(0.1701)**	**(0.1548)**	**(0.2125)**	**(0.1441)**
Sodium	-0.6557	-0.6975	-0.4409	-0.4844	-0.3504	-0.2535	**-0.6288****	**-0.6661***	**-0.9132****	**-0.7341****	**-0.7055****	-0.5492
	(0.5006)	(0.5271)	(0.2996)	(0.6794)	(0.6905)	(0.5269)	**(0.2895)**	**(0.3623)**	**(0.3872)**	**(0.3712)**	**(0.3138)**	(0.4318)
Sugar	**-3.9867****	**-4.2337***	**-7.0881***	**-6.9218***	-3.3057	**-3.8926****	**-3.4193****	**-4.3852***	**-2.9004***	-1.7369	-1.8135	**-3.1879****
	(1.6134)	**(2.3108)**	**(4.3073)**	**(3.9502)**	(2.9870)	**(1.8808)**	**(1.5741)**	**(2.2982)**	**(1.6989)**	(1.9718)	(2.0507)	**(1.5642)**
Fiber	-0.2026	-0.1741	0.0942	0.0831	0.2262	0.1207	**0.3186****	**0.3405****	**0.1988****	**0.3347****	**0.2899****	**0.3041****
	(0.4579)	(0.5226)	(2.0867)	(2.4795)	(0.1544)	(0.1785)	**(0.1500)**	**(0.1694)**	**(0.0994)**	**(0.1331)**	**(0.1442)**	**(0.1380)**
Protein	0.0180	0.0287	0.0987	0.0811	0.0915	0.1215	0.0431	0.0427	-0.0142	-0.0075	-0.0252	0.0634
	(0.0944)	(0.0952)	(0.1436)	(0.1671)	(0.0995)	(0.0853)	(0.0709)	(0.0617)	(0.0798)	(0.0680)	(0.1240)	(0.1309)
Overall Nutrition	**2.5905****	**2.6982*****	1.0053	1.1513	**1.5930***	**1.7892****	**2.6688****	**2.5902****	**4.1888*****	**3.6708*****	**3.5828****	**4.6895*****
	(1.0085)	**(0.8874)**	(1.5021)	(1.1982)	**(0.9372)**	**(0.8348)**	**(1.0381)**	**(1.2675)**	**(1.5208)**	**(1.3009)**	**(1.7938)**	**(1.7343)**

Notes. This table provides coefficient estimates of the focal two-way interaction term, *TB* × *FOP*. "NC" and "YC" denote "No (without) Controls" and "Yes (with) Controls" respectively. Robust standard errors that are clustered at the matched-set level are in parentheses. Statistically significant coefficient estimates are highlighted in bold.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Bread Category

I present the results of the DID and the QDID models of quality of new products for bread category in Table 11. Results of the DID model suggest that products of brands that adopt FOP in the bread category reduce the fat content and improve their overall nutrition score at the mean level. As before, results from the QDID model offer more nuanced insights. I find that when compared to products of brands that do not adopt FOP, products of brands that adopt FOP improve their nutritional quality by reducing calories, decreasing fat and sugar content, increasing their fiber and protein content and increasing the overall nutrition score (all these effects are at different quantiles). There is no effect of FOP adoption on change in sodium content at any of the five quantiles. To sum up, the DID and the QDID model based results suggest that FOP adoption improves the nutritional quality of bread products by decreasing the level of calories, fat, sugar, the nutrients that consumers seek to avoid, and increasing the level of fiber and protein, the nutrients that consumers seek to increase in their diet.

Table 11 Impact of FOP Nutrition Labeling Adoption on the Quality of Innovation - Bread

Dependent Variable	DID estimate		QDID estimate									
			Q10		Q25		Q50		Q75		Q90	
	(1) NC	(2) YC	(3) NC	(4) YC	(5) NC	(6) YC	(7) NC	(8) YC	(9) NC	(10) YC	(11) NC	(12) YC
Calorie	-0.0329 (0.0966)	-0.0734 (0.0921)	0.1604 (0.1093)	0.1054 (0.1115)	0.1229 (0.0834)	0.1146 (0.0829)	0.0099 (0.1077)	0.0012 (0.1206)	-0.0783 (0.1638)	-0.0778 (0.2006)	**-0.3173**** **(0.1406)**	**-0.3970*** **(0.2091)**
Fat	**-0.5346*** **(0.2846)**	**-0.5519**** **(0.2717)**	**-0.4711*** **(0.2716)**	**-0.4783*** **(0.2472)**	-0.0032 (0.3419)	-0.0073 (0.0620)	0.0590 (0.1128)	0.0739 (0.1251)	-0.0631 (0.1594)	-0.0164 (0.0640)	-0.1053 (0.4153)	-0.0989 (0.2509)
Sodium	0.2835 (0.3412)	0.2338 (0.3374)	0.5096 (0.4611)	0.3454 (0.5050)	0.1957 (0.2622)	0.0418 (0.3201)	0.2225 (0.3943)	-0.0358 (0.3723)	-0.0496 (0.4659)	-0.1445 (0.3744)	-0.2607 (0.6718)	0.3453 (0.7642)
Sugar	0.5984 (0.7056)	0.8442 (0.5320)	0.6378 (2.6898)	0.5482 (2.4773)	-0.1112 (0.1440)	-0.1526 (2.8044)	**-0.3064*** **(0.1572)**	**-0.1743*** **(0.0890)**	**-0.4082**** **(0.1604)**	**-0.2636**** **(0.1111)**	-0.3147 (0.3721)	-0.1696 (0.2730)
Fiber	-0.1492 (0.3621)	-0.0857 (0.3148)	-0.1718 (0.2164)	-0.2440 (0.2152)	-0.1453 (0.1551)	-0.1515 (0.1413)	-0.2327 (0.1726)	-0.1871 (0.2177)	**0.2653**** **(0.1253)**	**0.2629*** **(0.1563)**	0.0664 (0.1354)	0.0226 (0.2306)
Protein	0.4182 (0.4043)	0.4184 (0.3997)	0.1178 (0.1923)	0.0566 (0.6285)	0.1473 (0.1071)	0.0919 (0.3918)	0.1342 (0.1623)	0.2642 (0.3399)	**0.4530***** **(0.1480)**	**0.8128**** **(0.3914)**	**0.3757**** **(0.1860)**	**0.5301*** **(0.3193)**
Overall Nutrition	**1.5471*** **(0.9246)**	**1.8992*** **(0.9796)**	1.8354 (2.8614)	1.7471 (2.5161)	**1.7135**** **(0.8576)**	**1.6548**** **(0.7301)**	0.6457 (0.5340)	0.8749 (0.8433)	**1.6613**** **(0.7655)**	**1.5899**** **(0.7085)**	**1.3554*** **(0.7572)**	**1.8342*** **(1.0302)**

Notes. This table provides coefficient estimates of the focal two-way interaction term, *TB* × *FOP*. “NC” and “YC” denote “No (without) Controls” and “Yes (with) Controls” respectively. Robust standard errors that are clustered at the matched-set level are in parentheses. Statistically significant coefficient estimates are highlighted in bold.
*p < 0.10; **p < 0.05; ***p < 0. 01.

Sweet Biscuit/Cookie Category

I present the results of the DID and the QDID models of quality of new products for sweet biscuit/cookie category in Table 12. FOP adoption does not lead to any significant changes in the nutrition content of sweet biscuit/cookie products at the mean level. However, the results from the QDID model suggest that brands that adopt FOP reduce calorie content (at the 75^{th} and 90^{th} quantiles), lower fat content (at the 75^{th} and 90^{th} quantiles), lower sodium content (at the 10^{th} and 25^{th} quantiles) and enhance the overall nutrition score (at the 10^{th} and 25^{th} quantiles) of their products, as compared to brands that do not adopt FOP. An interesting finding from this category is that there is no effect of FOP adoption on the level of sugar, a key ingredient of this category. There is also no effect of FOP adoption on the fiber and the protein content of the products. I believe that these results attest to the nature of this category as this is a category in which consumers are looking to indulge and not one in which they seek healthier offerings.

Table 12 Impact of FOP Nutrition Labeling Adoption on the Quality of Innovation - Sweet Biscuit/Cookie

Dependent Variable	DID estimate		QDID estimate									
			Q10		Q25		Q50		Q75		Q90	
	(1) NC	(2) YC	(3) NC	(4) YC	(5) NC	(6) YC	(7) NC	(8) YC	(9) NC	(10) YC	(11) NC	(12) YC
Calorie	-0.0539 (0.1139)	-0.0637 (0.1299)	0.0493 (0.2492)	-0.0573 (0.1041)	0.0240 (0.1184)	0.0230 (0.0235)	0.0576 (0.1065)	0.0366 (0.0819)	**-0.1363***** **(0.0520)**	**-0.1469**** **(0.0648)**	**-0.3290***** **(0.0899)**	**-0.2941***** **(0.0971)**
Fat	-0.7694 (1.3454)	-0.8729 (1.3636)	0.0107 (2.2490)	-0.0745 (1.8182)	0.3759 (2.7623)	0.2982 (2.4050)	0.4149 (1.2189)	-0.3049 (1.2659)	**-2.0383**** **(0.1000)**	**-1.6035**** **(0.7717)**	**-3.5524***** **(1.2142)**	**-3.7544**** **(1.5185)**
Sodium	-0.2714 (0.1915)	-0.2714 (0.1908)	**-0.5356**** **(0.2286)**	**-0.5050***** **(0.1616)**	**-0.4388***** **(0.1547)**	-0.3016 (0.3598)	-0.2210 (0.2176)	-0.2399 (0.3315)	-0.2237 (0.1427)	-0.2911 (0.2605)	-0.2625 (0.3845)	-0.2598 (0.3460)
Sugar	1.9236 (2.1407)	2.0800 (2.3662)	-0.6764 (2.7994)	-0.6338 (1.8450)	0.0341 (1.4498)	0.2608 (1.8899)	4.0592 (2.7346)	3.7676 (2.7761)	4.5119 (2.9200)	4.4387 (3.1838)	2.4251 (2.8139)	2.5409 (3.5113)
Fiber	-0.4392 (1.0469)	-0.4677 (0.9797)	0.0000 (0.7132)	-0.0000 (0.0000)	0.0000 (2.7555)	-0.0000 (2.1914)	-0.0381 (0.1136)	-0.0761 (0.3969)	-0.0484 (0.0649)	-0.0412 (0.0421)	-0.1173 (0.1709)	-0.1323 (0.1447)
Protein	0.1918 (0.5572)	0.1800 (0.5049)	-0.1008 (0.2017)	-0.0893 (0.1481)	0.1285 (0.3114)	0.1469 (0.2382)	-0.7092 (0.9509)	-0.3787 (0.7231)	-0.0688 (0.3335)	-0.0429 (0.3073)	-0.0550 (0.5796)	-0.0461 (0.5949)
Overall Nutrition	0.1505 (1.2897)	0.1447 (1.2714)	**3.2819***** **(0.7446)**	**2.7890**** **(1.1066)**	**2.5108**** **(1.1404)**	**2.0710**** **(0.8933)**	-0.9465 (0.6463)	-0.9509 (0.9716)	-0.6962 (1.3351)	-0.2505 (0.9856)	0.1970 (2.1913)	0.4596 (1.1255)

Notes. This table provides coefficient estimates of the focal two-way interaction term, *TB* × *FOP*. "NC" and "YC" denote "No (without) Controls" and "Yes (with) Controls" respectively. Robust standard errors that are clustered at the matched-set level are in parentheses. Statistically significant coefficient estimates are highlighted in bold.
**p* < 0.10; ***p* < 0.05; ****p* < 0. 01.

Potato Snack Category

I present the results of the DID and the QDID models of quality of new products for potato snack category in Table 13. The DID estimates suggest that products of brands that adopt FOP in the potato snack category reduce the level of calories, fat, and sodium and increase their overall nutritional score at the mean level. Results of the QDID model confirm these findings. I also find that such products also increase the fiber content in the 90th quantile. However, there is no effect of FOP adoption on the levels of sugar and protein. Interestingly, all DID and QDID estimates for overall nutrition score are statistically significant. Adopters of FOP increase the average overall nutrition score by about 5.97 points. The overall nutrition score of products of FOP adopters increases by about 5.29, 6.28, 3.33, 6.05 and 10.68 points at the 10th, 25th, 50th, 75th and 90th quantiles of the overall nutrition score distribution respectively, as compared to the non-adopter brands.

Table 13 Impact of FOP Nutrition Labeling Adoption on the Quality of Innovation - Potato Snack

Dependent Variable	DID estimate		QDID estimate									
			Q10		Q25		Q50		Q75		Q90	
	(1) NC	(2) YC	(3) NC	(4) YC	(5) NC	(6) YC	(7) NC	(8) YC	(9) NC	(10) YC	(11) NC	(12) YC
Calorie	**-0.3156****	**-0.3224****	**-0.7091****	**-0.8198*****	**-0.7566*****	**-0.9916*****	-0.0661	-0.0479	-0.0661	-0.0661	-0.0646	-0.0646
	(0.1525)	**(0.1486)**	**(0.3591)**	**(0.2321)**	**(0.2520)**	**(0.2886)**	(0.1948)	(0.2121)	(0.1791)	(0.2456)	(0.0913)	(0.1756)
Fat	**-6.2414*****	**-6.1238*****	**-17.7248****	**-17.8228****	**-10.7086****	**-9.9613****	-0.7938	0.0631	1.3751	1.7651	0.0000	0.0000
	(1.8508)	**(1.8938)**	**(8.2528)**	**(7.2094)**	**(4.2362)**	**(4.8593)**	(1.3638)	(2.0490)	(1.0783)	(1.8482)	(2.4601)	(1.4416)
Sodium	**-1.9143****	**-1.9566****	**-0.8488****	**-1.3221*****	-0.6949	0.2420	**-1.8430***	-1.4026	**-2.0569***	**-3.3115*****	-2.2332	-2.6838
	(0.9538)	**(0.9921)**	**(0.4278)**	**(0.4755)**	(0.7518)	(0.8892)	**(1.0214)**	(1.0303)	**(1.2266)**	**(0.7986)**	(1.6836)	(2.6529)
Sugar	-0.2160	-0.2459	0.0000	-0.0000	0.0000	-0.0000	-0.0124	-0.0124	-0.0124	-0.0124	-0.5379	-0.5379
	(1.3076)	(1.3273)	(5.5162)	(3.4442)	(6.9999)	(3.7497)	(4.4181)	(2.2692)	(2.7668)	(0.2176)	(0.6707)	(0.6051)
Fiber	-0.5444	-0.5339	-0.0124	-0.0536	0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000	**0.2983***	**0.3943***
	(0.7422)	(0.8258)	(3.0201)	(2.3288)	(0.0288)	(0.0058)	(0.0266)	(0.0082)	(0.3156)	(0.0219)	**(0.1555)**	**(0.2043)**
Protein	-0.3518	-0.1717	0.0503	0.0947	-0.0882	-0.0283	-0.0882	-0.0844	-0.0882	-0.0882	0.0000	-0.0000
	(0.4600)	(0.5245)	(1.8111)	(1.9831)	(1.0988)	(0.1026)	(0.5376)	(0.6195)	(0.0667)	(0.0617)	(1.3173)	(1.3837)
Overall	**5.5201*****	**5.9654*****	**7.8934*****	**5.2872*****	**6.4826*****	**6.2785*****	**2.9717*****	**3.3290***	**6.8919*****	**6.0463****	**11.8710*****	**10.6787*****
Nutrition	**(1.9442)**	**(1.8516)**	**(1.9511)**	**(1.9963)**	**(2.1610)**	**(0.6571)**	**(1.1136)**	**(1.8941)**	**(1.8641)**	**(2.5502)**	**(2.6011)**	**(3.8270)**

Notes. This table provides coefficient estimates of the focal two-way interaction term, *TB* × *FOP*. "NC" and "YC" denote "No (without) Controls" and "Yes (with) Controls" respectively. Robust standard errors that are clustered at the matched-set level are in parentheses. Statistically significant coefficient estimates are highlighted in bold.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Summary of DID and QDID Results for the Quality of Innovation

Given the large number of results associated with quality of innovation, I summarize the results in an easy-to-read format in Table 14. As can be seen from the table, the key takeaway is that brands that adopt FOP improve the overall nutrition score of their products across the four categories. Although there is significant variation in the effect of FOP across the four product categories, nutrients and quantiles, I consistently find that adopter of FOP reduces the level of calories, the nutrients that consumers seek to limit such as fat, sodium and sugar, enhance the overall nutrition score of products and the level of nutrients that consumers seek to increase in their diet such as fiber and protein.

Table 14 Summary of the Impact of FOP Nutrition Labeling Adoption on Quality of Innovation

Dependent Variable	Content level			
	Mean	Low	Mid	High
		Breakfast Cold Cereal		
Calorie	▼	▼	▼	▼
Fat	–	–	–	▼
Sodium	–	–	▼	▼
Sugar	▼	▼	▼	▼
Fiber	–	–	▲	▲
Protein	–	–	–	–
OverallNutrition	▲	▲	▲	▲
		Bread		
Calorie	–	–	–	▼
Fat	▼	▼	–	–
Sodium	–	–	–	–
Sugar	–	–	▼	▼
Fiber	–	–	–	▲
Protein	–	–	–	▲
OverallNutrition	▲	▲	–	▲
		Sweet Biscuit/Cookie		
Calorie	–	–	–	▼
Fat	–	–	–	▼
Sodium	–	▼	–	–
Sugar	–	–	–	–
Fiber	–	–	–	–
Protein	–	–	–	–
OverallNutrition	–	▲	–	–
		Potato Snack		
Calorie	▼	▼	–	–
Fat	▼	▼	–	–
Sodium	▼	▼	▼	▼
Sugar	–	–	–	–
Fiber	–	–	–	▲
Protein	–	–	–	–
OverallNutrition	▲	▲	▲	▲

Notes. The table presents the overall direction of the impact of FOP adoption on the mean, low, mid, and high levels of calories, the five nutrients and the overall nutrition score (based on the results in Tables 10, 11, 12 and 13). The quantile ranges for low, mid, and high level are as follows: Low (Q10, Q25), Mid (Q50), High (Q75, Q90). ▲ and ▼ represent a positive and negative FOP effect on the dependent variables, respectively. No arrow is presented in case of no effect of FOP adoption.

CHAPTER V

ROBUSTNESS CHECKS AND ADDITIONAL ANALYSES

ROBUSTNESS CHECKS

In my analysis, I did not disentangle between new product introductions that were radical versus incremental innovations. In this section, I report supplemental analyses that take into account the degree of innovativeness of the new products. The Mintel GNPD classifies new product introductions into the following five types: *New Product*, *New Variety/Range Extension*, *New Packaging*, *New Formulation* and *Relaunch* (Mintel International Group Ltd. 2012). A product is classified as a new product when a totally new range or line or family of products is encountered. A product is classified as a new variety/range extension in cases of extensions to an existing range of products that are listed in the Mintel GNPD. The database classifies a product as a new packaging by a visual inspection of the product for changes and when terms like “New Look,” “New Packaging,” or “New Size” are written on the package of products. A product is classified as a new formulation when terms such as “New Formula,” “Even Better,” “Tastier,” “New and Improved,” or “Great New Taste” are indicated on the pack.[13] A product is classified as a relaunch when a product has been both significantly repackaged and also reformulated based on a secondary source of information (e.g., trade shows, public relations, websites and press). These five types of new products vary in their degree of innovation (Fuller

[13] I note that the Mintel GNPD does not look at the ingredient list to determine a new formulation. If a product is reformulated and repackaged, this is the default launch type to highlight the product’s new ingredient list (Mintel International Group Ltd. 2012).

2004). Of these five different new product launch types, I focus on the three major types, namely new product, new variety/range extension and new packaging[14] and examine the effect of FOP adoption (using DID model) on each of the three types. I report the results of my study in Tables A2, A3, A4 and A5 (see Appendix). I find that FOP adoption has a significant and positive effect on the mean rate of new product introductions across *all* of the three new product launch types in breakfast cold cereal and bread categories. In the potato snack category, FOP adoption leads to a higher rate of new product introductions for the new product launch type only. In the sweet biscuit/cookie category, I find that FOP leads to a reduced rate of new product introductions for only the new packaging launch type. Thus, I find that the effect of FOP is robust (in three of the four product categories) even after classifying the new product introductions into the three different launch types.

A common limitation of Poisson model is that it does not account for the possibility of over dispersion that is common in count data. Therefore, I employ a quasi-Poisson model (for the quantity of innovations) that helps account for overdispersion.[15] I find that the core results are robust to this alternative model formulation. For the quality of innovation model, I note that the QDID modeling approach serves as a robustness check that I discussed in detail in the previous section.

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[14] The three launch types account for the majority of the new product introductions across the four categories that I analyze. More specifically, they account for 92.72%, 95.77%, 97.12% and 94.91% of the entire set of new products in the breakfast cold cereal, bread, sweet biscuit/cookie and potato snack categories, respectively.

[15] Negative binomial model and quasi-Poisson model are commonly used to account for overdispersion in count data. Among the two popular models, I choose quasi-Poisson model because it provides a better fit to the overall mean-to-variance association as compared to negative binomial model (Ver Hoef and Boveng 2007).

ADDITIONAL ANALYSES

In the following, I discuss and examine how the effect of FOP on firm innovation would vary across the adopter firms depending on when they adopt and the effect of firms' commitment towards producing better products.

Quantity of Innovation: Early vs. Late Adopters of FOP Nutrition Labeling

Organizational scholars have argued that the time that firms take to adopt standards is a signal of their resources and capabilities (Bansal and Hunter 2003). Whereas early adopters may be motivated by economic benefits and inherent high willingness to adopt, late adopters may adopt only to obtain legitimacy (Meyer et al. 1981; Tolbert and Zucker 1983; Zucker 1983). In my context, food manufacturers who adopt FOP earlier than later, may have the resources and a stronger commitment towards producing new and better products that may resonate with consumers' preferences for nutritionally better products. Late adopters, on the other hand, may adopt FOP merely to follow suit without committing resources towards innovation. Based on these arguments, I argue that companies with greater (nutrition related) legitimacy may be more likely to adopt FOP earlier than those with lower legitimacy in order to signal their commitment towards producing better products. Hence, I expect that early adopters of FOP would develop and introduce more new products, and hence the effect of FOP adoption on quantity of innovation for early adopters is likely to be stronger than for late adopters.

To test this argument, I classify the treatment group into early and late adopters of FOP by using the median time of adoption by all the treatment brands as the cutoff. I revise the model that I presented in Equation (4) as follows:

$$\log(\lambda_{mbt} / h_{mbt}) = \delta_0 + \delta_1 TB_{mb}^{Early} + \delta_2 TB_{mb}^{Late} + \delta_3 FOP_{mbt} + \delta_4 TB_{mb}^{Early} \times FOP_{mbt} + \delta_5 TB_{mb}^{Late} \times FOP_{mbt} + \phi X_{mbt} + \kappa_m + \psi_{mbt}. \quad (7)$$

In Equation (7), TB_{mb}^{Early} (TB_{mb}^{Late}) is the dummy variable that is equal to 1 if a brand *b* of a matched set *m* is an early (late) adopter of FOP and 0 otherwise (the reference group is a set of comparison brands). X_{mbt} is a set of control variables that I used in Equation (4). κ_m is a set of matched-set fixed effects. ψ_{mbt} is an error term for a brand *b* of a matched set *m* at time period *t*. FOP_{mbt} and X_{mbt} have the same interpretation as in Equation (4). The results (see Table 15) of my model suggest that only early FOP adopter brands introduce more new products when compared to the comparison brands. As can be seen from Table 15, this result holds for three of the four product categories (breakfast cold cereal, bread and potato snack) that I study.

Table 15 Impact of FOP Nutrition Labeling Adoption on the Quantity of Innovation: Early Adopter vs. Late Adopter

Variable	Model	
	(1) NC	(2) YC
Breakfast Cold Cereal		
$TB^{Early} \times FOP$ (early adopter)	**1.8147*** (0.4755)**	**1.4772*** (0.4009)**
$TB^{Late} \times FOP$ (late adopter)	-0.1672 (0.7546)	-0.9872 (1.2809)
TB^{Early}	0.3969 (0.3093)	0.5434* (0.2994)
TB^{Late}	-0.3882 (0.8737)	-0.4604 (0.7912)
FOP	-1.8411*** (0.4563)	-1.7108*** (0.3988)
Price	–	0.0555 (0.1538)

Table 15 Continued

Variable	Model	
	(1) NC	(2) YC
Breakfast Cold Cereal		
UnitPackSize	–	0.0027 (0.0018)
UnitsInMultipack	–	0.5957 (0.4523)
Constant	-0.7751*** (0.1861)	-2.6817*** (0.8300)
Matched-set fixed effects	Yes	Yes
Log-likelihood	-409.27	-382.74
AIC	1327.77	1280.71
Bread		
TB^{Early} × FOP (early adopter)	**0.5589*** (0.1883)**	**0.5493*** (0.1899)**
TB^{Late} × FOP (late adopter)	0.3701 (0.3805)	0.4419 (0.3946)
TB^{Early}	0.3987** (0.1655)	0.3804** (0.1653)
TB^{Late}	-0.0171 (0.3127)	-0.0550 (0.2651)
FOP	-0.6034*** (0.1080)	-0.5995*** (0.1167)
Price	–	-0.0756 (0.0773)
UnitPackSize	–	0.0006** (0.0003)
UnitsInMultipack	–	-0.0953 (0.0862)
Constant	-2.1138*** (0.0341)	-2.0077*** (0.1964)
Matched-set fixed effects	Yes	Yes
Log-likelihood	-253.72	-248.55
AIC	1263.12	1258.79
Sweet Biscuit/Cookie		
TB^{Early} × FOP (early adopter)	-0.1061 (0.3198)	-0.1570 (0.3093)
TB^{Late} × FOP (late adopter)	-0.4192 (0.7888)	-0.4418 (0.7861)
TB^{Early}	0.5936** (0.2946)	0.6274** (0.2816)
TB^{Late}	0.2736 (0.3091)	0.2334 (0.3093)
FOP	-0.4384*** (0.1517)	-0.4098** (0.1612)
Price	–	-0.0395** (0.0181)
UnitPackSize	–	-0.0002 (0.0003)
UnitsInMultipack	–	-0.0106 (0.0430)

Table 15 Continued

Variable	Model	
	(1) NC	(2) YC
Sweet Biscuit/Cookie		
Constant	-0.5091*** (0.0881)	-0.3114*** (0.1143)
Matched-set fixed effects	Yes	Yes
Log-likelihood	-544.55	-537.27
AIC	2049.75	2041.17
Potato Snack		
TB^{Early} × FOP (early adopter)	**0.7075* (0.3882)**	**0.6824** (0.3323)**
TB^{Late} × FOP (late adopter)	0.3157 (1.0237)	-0.4329 (0.9044)
TB^{Early}	-0.5925 (0.4009)	-0.5249** (0.2099)
TB^{Late}	-0.0246 (0.3179)	0.3173** (0.1244)
FOP	-0.9258*** (0.3170)	-0.7977*** (0.1893)
Price	–	-0.1823 (0.1576)
UnitPackSize	–	0.0029** (0.0014)
UnitsInMultipack	–	0.5006*** (0.1495)
Constant	-0.3439 (0.6476)	-1.1560*** (0.3409)
Matched-set fixed effects	Yes	Yes
Log-likelihood	-144.74	-114.81
AIC	539.65	485.79

Notes. The dependent variable is the number of new products introduced by a brand. "NC" and "YC" denote "No (without) Controls" and "Yes (with) Controls" respectively. Robust standard errors that are clustered at the matched-set level are in parentheses. The focal variable of interest and its coefficient estimates that are statistically significant are highlighted in bold. AIC refers to Akaike Information Criterion.

As a robustness check, I estimated a series of Poisson DID models to understand the effect of early versus late adopters on each of the three types of innovations described earlier (i.e., new product, new variety/range extension and new packaging). I present the results in Tables A6, A7, A8 and A9 (see Appendix). I find that early adopters introduce more innovations is fairly robust to categorizing innovations into the three types.

Quality of Innovation: Moderating Effect of Package Label Claims

It is very common for food brands to use various types of claims on the front of packages. Broadly, there are two types of claims: a) nutrient content claims that "*directly or by implication characterize the level of a nutrient in the food*"[16] and b) non-nutrient content claims that do not provide any specific information on nutrients. A key difference between the two is that nutrient content claims require approval by the FDA; only nutrient content claims that are specifically defined in the regulations by the FDA are allowed to be featured on food product packages. Also, the food products need to meet certain threshold levels of nutrients in order for brands to use nutrient content claims. For example, in order for a firm to use the "*High in Fiber*" claim on a product, the product should contain 20% or more of the DV for fiber content.[17] From a signaling perspective, nutrient content claims serve as legitimate signals of brands' commitment towards producing nutritionally better products. This would imply that brands that have nutrient content claims would have higher levels of technological know-how and structural capabilities already implemented to improve nutritional quality of products, as compared to brands who have no nutrient content claims or have non-nutrient content claims. Given that non-nutrient claims are not regulated, it is possible that brands may use such claims as merely a marketing gimmick and they may not have any bearing on the brands' willingness to improve the nutritional quality. Thus, I propose that firms that adopt FOP (a voluntary measure) and have nutrient content claims (regulated by the

[16] http://www.fda.gov/Food/GuidanceRegulation/GuidanceDocumentsRegulatoryInformation/LabelingNutrition/ucm064908.htm.
[17] http://www.fda.gov/Food/GuidanceRegulation/GuidanceDocumentsRegulatoryInformation/LabelingNutrition/ucm064916.htm.

FDA) would be well-positioned towards improving the nutritional quality of their products, as compared to brands who do not use nutrient content claims or have non-nutrient content claims.

The Mintel GNPD reports all the package claims that products carry.[18] Nutrient content claims convey information on nutrition levels by emphasizing addition or increase in nutrients that consumers seek to consume more (e.g., High in Fiber) or addressing decrease in the levels of nutrients that consumers seek to consume less (e.g., Low in Saturated Fat). I refer to all non-nutrient content claims as *other claims*. To examine how the effect of FOP adoption on product quality is moderated by the presence of package label claims, I extend the DID model (see Equation (5)) as follows:

$$\begin{aligned} NUTRIENT_{mpbt} = {} & \gamma_0 + \gamma_1 TB_{mpb} + \gamma_2 FOP_{mpbt} + \gamma_3 NutrientClaim_{mpbt} + \gamma_4 OtherClaim_{mpbt} + \gamma_5 TB_{mpb} \times FOP_{mpbt} \\ & + \gamma_6 TB_{mpb} \times NutrientClaim_{mpbt} + \gamma_7 FOP_{mpbt} \times NutrientClaim_{mpbt} \\ & + \gamma_8 TB_{mpb} \times OtherClaim_{mpbt} + \gamma_9 FOP_{mpbt} \times OtherClaim_{mpbt} \\ & + \gamma_{10} TB_{mpb} \times FOP_{mpbt} \times NutrientClaim_{mpbt} + \gamma_{11} TB_{mpb} \times FOP_{mpbt} \times OtherClaim_{mpbt} \\ & + \chi Z_{mpbt} + o_m + \varphi_t + \varsigma_{mpbt}. \end{aligned} \tag{8}$$

I extend the DID model of overall nutrition score (see Equation (6)) in a similar manner. In Equation (8), $NutrientClaim_{mpbt}$ takes the value of 1 if a product *p* of a brand *b* of a matched set *m* at time *t* has a nutrient content claim and 0 otherwise. $OtherClaim_{mpbt}$ takes the value of 1 if a product *p* of a brand *b* of a matched set *m* at time *t* has any type of claim other than a nutrient content claim and 0 otherwise. o_m is a set of matched-set fixed effects and φ_t is a set of year fixed effects. ς_{mpbt} is the error term. All other

[18] I note that some new products do not carry package label claims.

variables and subscripts in Equation (8) have the same interpretation as in Equation (5). The model presented in Equation (8) is an extension of the model that is presented in Equation (5) as it involves three way interactions. For example, $TB_{mpb} \times FOP_{mpbt} \times NutrientClaim_{mpbt}$ is a three-way interaction between the dummies of the treatment group, FOP adoption and presence of nutrient content claims. Since the model helps examine the difference between the average change over time in the outcome variable for the treatment group and the average change over time in the outcome variable for the comparison group, taking into account the different levels/types of units, the model is commonly referred to as the difference-in-difference-in-differences (DIDID) model. The key coefficients of interest are γ_{10} and γ_{11}. Consistent with the quantile regression approach that I presented earlier, I also estimate the quantile difference-in-difference-in-differences (QDIDID) models to investigate the heterogeneous moderating effect of having package label claims on the calorie and nutrient levels.

In Tables 16, 17, 18 and 19, I only present the DIDID and QDIDID estimates for the four categories.[19] The results indicate that the effect of FOP on the overall nutrition score is enhanced for products with nutrient content claims as compared to products without such claims in three product categories, breakfast cold cereal, bread and the potato snack category. Interestingly, I find that other claims (i.e., non-nutrient content

[19] Given the number of nutrients and categories that I work with, for the sake of brevity, I present only the estimates of the focal coefficients of interest. The extended version of Table 16 that provides the complete set of results of the DIDID and QDIDID models are available from me upon request.

claims) have the opposite effect as that of the nutrient content claims. These results suggest that while nutrient content claims, which are regulated by FDA, serve as credible signals of a brand's commitment towards innovation and highlight organizational capabilities, non-nutrient content claims could perhaps primarily be a marketing tactic to draw consumers' attention towards the products.

Table 16 Moderating Effect of Package Claims on Quality of Innovation - Breakfast Cold Cereal

Dependent Variable	Moderating Variable	DIDID estimate	QDIDID estimate				
			Q10	Q25	Q50	Q75	Q90
Calorie	*NutrientClaim*	**-0.2849**** **(0.1325)**	**-0.2073*** **(0.1075)**	**-0.1007**** **(0.0487)**	**-0.1333***** **(0.0313)**	-0.1219 (0.2953)	-0.3238 (0.3337)
	OtherClaim	0.4104 (0.3029)	**0.9316**** **(0.4526)**	0.3452 (0.3680)	0.1068 (0.1714)	0.0712 (0.1812)	**0.5290*** **(0.2909)**
Fat	*NutrientClaim*	**-0.9424*** **(0.5717)**	**-7.3561*** **(4.1848)**	**-0.9020**** **(0.4308)**	-0.2947 (0.6784)	-0.1590 (0.2597)	-0.0348 (0.5254)
	OtherClaim	**2.9975**** **(1.5207)**	**7.3280*** **(3.8994)**	0.0866 (1.1473)	0.2574 (0.2983)	**0.8157*** **(0.4610)**	**0.7008*** **(0.4190)**
Sodium	*NutrientClaim*	-0.1256 (0.6324)	0.5526 (0.9415)	-0.4942 (0.4720)	-0.3796 (0.7210)	0.8835 (0.6644)	1.4755 (1.0811)
	OtherClaim	**3.6404**** **(1.4593)**	1.9700 (2.8695)	**5.0278*** **(2.7423)**	**3.3563*** **(1.7541)**	**2.3055***** **(0.5969)**	**1.8876***** **(0.5072)**
Sugar	*NutrientClaim*	**-7.6952***** **(2.8522)**	**-15.3014**** **(6.7537)**	-1.9986 (3.8130)	**-5.3912*** **(3.2462)**	**-5.1050***** **(1.6839)**	-2.5301 (2.1375)
	OtherClaim	4.9992 (5.5847)	17.6995 (14.7726)	3.2768 (7.8634)	2.9739 (8.1178)	0.6834 (9.3012)	-13.2895 (9.9172)
Fiber	*NutrientClaim*	0.9980 (0.7274)	0.2217 (5.4570)	0.0348 (0.2388)	**0.2308**** **(0.1100)**	-0.1708 (0.1354)	-0.0058 (0.3675)
	OtherClaim	-0.8277 (2.0666)	-5.7727 (11.4063)	0.1534 (0.2781)	-0.3607 (0.5260)	-0.1173 (0.1241)	**-0.0723*** **(0.0392)**
Protein	*NutrientClaim*	-0.0113 (0.1489)	-0.0599 (0.0378)	**0.2920*** **(0.1718)**	0.0223 (0.1320)	**0.0873*** **(0.0471)**	-0.0414 (0.1987)
	OtherClaim	-0.0137 (0.3098)	0.6577 (1.0845)	0.1427 (0.2564)	-0.1085 (0.3306)	**-0.3864**** **(0.1533)**	-0.1872 (0.8857)
Overall Nutrition	*NutrientClaim*	**2.9073**** **(1.4537)**	**3.7445*** **(2.2498)**	**2.1481**** **(1.0251)**	0.5065 (2.3171)	1.2048 (2.6158)	**3.4648*** **(2.0080)**
	OtherClaim	**-4.7187*** **(2.6929)**	**-6.4404*** **(3.8100)**	**-4.1600*** **(2.1579)**	-2.6814 (1.9564)	-1.7132 (2.5855)	0.3357 (3.1375)

Notes. The table provides coefficient estimates of the focal three-way interaction terms, *TB* × *FOP* × *NutrientClaim* and *TB* × *FOP* × *OtherClaim*. The results presented in the table are based on the models that contain control variables. Robust standard errors that are clustered at the matched-set level are in parentheses. Statistically significant coefficient estimates are highlighted in bold.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Table 17 Moderating Effect of Package Claims on Quality of Innovation - Bread

Dependent Variable	Moderating Variable	DIDID estimate	QDIDID estimate				
			Q10	Q25	Q50	Q75	Q90
Calorie	*NutrientClaim*	0.0654 (0.1848)	-0.0069 (0.2287)	-0.0055 (0.1898)	-0.0361 (0.1777)	0.1283 (0.2709)	-0.1194 (0.5079)
	OtherClaim	-0.1124 (0.2438)	0.1246 (0.3051)	0.0140 (0.2482)	0.0267 (0.2679)	0.0433 (0.4173)	-0.0475 (0.5984)
Fat	*NutrientClaim*	-0.0391 (0.8259)	1.2483 (6.7442)	0.3483 (0.5703)	0.1653 (0.2230)	-0.0223 (0.1879)	-0.2469 (0.3586)
	OtherClaim	**0.4871*** **(0.2940)**	-1.8022 (2.0913)	**0.6886**** **(0.3219)**	**0.7269***** **(0.2101)**	**0.5829***** **(0.1842)**	0.0235 (0.6301)
Sodium	*NutrientClaim*	**-1.0060*** **(0.5195)**	**-0.8589***** **(0.2243)**	**-0.7825**** **(0.3083)**	**-0.5371**** **(0.2410)**	-0.6304 (0.5161)	-0.2902 (0.8144)
	OtherClaim	1.0272 (0.7168)	0.5423 (1.0743)	0.7970 (1.0233)	0.1730 (0.9247)	0.1914 (1.1869)	0.7791 (3.3536)
Sugar	*NutrientClaim*	**-1.4673*** **(0.8622)**	0.0922 (3.5302)	**-2.7811**** **(1.1834)**	-0.4927 (4.8812)	-0.0551 (0.7920)	0.3759 (1.0954)
	OtherClaim	0.6389 (1.7151)	0.7319 (5.1916)	2.1730 (4.7620)	-0.1547 (4.6690)	-0.3023 (0.5787)	-0.4637 (0.4156)
Fiber	*NutrientClaim*	**0.4628***** **(0.1414)**	0.0957 (1.2794)	**0.2893***** **(0.0703)**	**0.5870***** **(0.1491)**	**0.2914***** **(0.0854)**	0.0701 (0.1161)
	OtherClaim	-0.0484 (0.1359)	0.2807 (0.3553)	0.0286 (0.1699)	0.0585 (0.2813)	-0.0362 (0.4485)	**-0.4068*** **(0.2198)**
Protein	*NutrientClaim*	-1.0618 (0.8088)	-2.5887 (1.6593)	-0.4175 (1.4333)	-1.2984 (1.0327)	-0.6975 (1.0120)	-1.1476 (1.3805)
	OtherClaim	0.5026 (0.6961)	1.7796 (1.7466)	-0.5565 (1.0383)	0.9688 (0.9374)	1.9153 (1.2685)	0.3579 (1.4171)
Overall Nutrition	*NutrientClaim*	0.9198 (1.7697)	**4.6489**** **(2.1811)**	-1.2248 (3.6426)	0.7279 (3.8833)	1.3751 (2.6928)	**4.3841*** **(2.2946)**
	OtherClaim	-3.3169 (2.1576)	-6.1659 (6.5509)	-2.6666 (2.5355)	**-3.8670***** **(1.2157)**	-1.8806 (2.5323)	**-4.5295*** **(2.6421)**

Notes. The table provides coefficient estimates of the focal three-way interaction terms, *TB* × *FOP* × *NutrientClaim* and *TB* × *FOP* × *OtherClaim*. The results presented in the table are based on the models that contain control variables. Robust standard errors that are clustered at the matched-set level are in parentheses. Statistically significant coefficient estimates are highlighted in bold.
**p* < 0.10; ***p* < 0.05; ****p* < 0. 01.

Table 18 Moderating Effect of Package Claims on Quality of Innovation - Sweet Biscuit/Cookie

Dependent Variable	Moderating Variable	DIDID estimate	QDIDID estimate				
			Q10	Q25	Q50	Q75	Q90
Calorie	*NutrientClaim*	0.2209 (0.2885)	0.5806 (0.5805)	0.1295 (0.5147)	0.1753 (0.2683)	0.3486 (0.2322)	0.0096 (0.2697)
	OtherClaim	0.1789 (0.2595)	0.2450 (0.6209)	-0.0575 (0.2206)	-0.0541 (0.2242)	-0.1349 (0.3252)	-0.1654 (0.4598)
Fat	*NutrientClaim*	4.5650 (3.2048)	2.5387 (5.3819)	2.3217 (6.7514)	7.4997 (5.5394)	5.3417 (5.4471)	2.2320 (3.9251)
	OtherClaim	-1.8740 (1.9999)	-1.2327 (4.4694)	-4.3721 (4.6883)	-0.4535 (4.3299)	-2.1941 (4.1067)	-1.4984 (3.4995)
Sodium	*NutrientClaim*	0.2781 (0.2667)	0.6773 (0.7119)	0.0209 (0.5123)	0.1691 (0.5713)	0.0856 (0.5764)	0.6438 (0.7745)
	OtherClaim	0.3538 (0.4516)	-0.3638 (0.8592)	0.1260 (0.7641)	0.5707 (0.6059)	0.2648 (0.7414)	0.8667 (0.9321)
Sugar	*NutrientClaim*	-1.7466 (4.0787)	**-6.4584*** **(3.4198)**	1.5729 (7.7595)	2.8894 (4.7312)	**-2.9087***** **(0.9739)**	0.2266 (2.7401)
	OtherClaim	0.1059 (2.5114)	1.7157 (4.1429)	-0.9598 (1.1050)	2.9821 (3.4030)	**3.1682**** **(1.3003)**	**9.4723***** **(2.9309)**
Fiber	*NutrientClaim*	**-3.9930***** **(1.3877)**	-0.0000 (3.2731)	**-8.7310*** **(4.6963)**	-0.1714 (4.2630)	0.0077 (2.3578)	-0.0915 (0.5087)
	OtherClaim	**-3.0337*** **(1.7982)**	-0.0000 (2.8530)	**-15.0497***** **(5.2796)**	-8.1449 (5.6442)	-0.1781 (0.2194)	-0.2124 (0.3959)
Protein	*NutrientClaim*	-0.5751 (0.6162)	-0.1149 (0.5305)	-1.0390 (0.8776)	-0.8040 (0.9877)	-0.0724 (1.1304)	0.0416 (1.8455)
	OtherClaim	0.6446 (0.6960)	-0.4140 (0.3838)	-0.0703 (0.8193)	1.0745 (1.2856)	0.2628 (1.1717)	1.7403 (1.7084)
Overall Nutrition	*NutrientClaim*	-3.0894 (2.6648)	0.2532 (5.9890)	-9.0882 (6.4171)	-5.0641 (4.7667)	-0.5622 (6.5010)	-3.7656 (6.3278)
	OtherClaim	-1.3688 (2.7023)	-4.9278 (4.1758)	0.7785 (3.4858)	-0.1921 (3.4227)	-1.6543 (3.9033)	-1.8188 (7.8312)

Notes. The table provides coefficient estimates of the focal three-way interaction terms, *TB* × *FOP* × *NutrientClaim* and *TB* × *FOP* × *OtherClaim*. The results presented in the table are based on the models that contain control variables. Robust standard errors that are clustered at the matched-set level are in parentheses. Statistically significant coefficient estimates are highlighted in bold.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Table 19 Moderating Effect of Package Claims on Quality of Innovation - Potato Snack

Dependent Variable	Moderating Variable	DIDID estimate	QDIDID estimate				
			Q10	Q25	Q50	Q75	Q90
Calorie	*NutrientClaim*	-0.2834 (0.3076)	**-0.7321** (0.3233)**	-0.6398 (0.5771)	-0.1370 (0.2753)	**-0.3348*** (0.1084)**	**-0.5929*** (0.1890)**
	OtherClaim	0.3883 (0.3407)	-0.3031 (0.4552)	-0.3013 (0.5538)	**0.6188* (0.3739)**	**0.5311** (0.2378)**	**0.7517* (0.4358)**
Fat	*NutrientClaim*	-2.5991 (3.7905)	**-14.9914*** (2.7105)**	-2.4100 (8.1606)	3.0557 (2.3713)	**-3.2483* (1.8862)**	**-1.3717*** (0.4764)**
	OtherClaim	**6.0440* (3.0869)**	**8.2326*** (1.4950)**	**4.3371** (1.7882)**	1.2538 (4.5125)	**5.1990*** (1.3531)**	-2.7173 (3.9390)
Sodium	*NutrientClaim*	**-2.9470** (1.4116)**	-1.3478 (2.9265)	**-4.6027** (2.0865)**	**-4.7954*** (1.1628)**	**-2.8538** (1.1959)**	**-3.0690* (1.8568)**
	OtherClaim	**6.4834*** (1.6852)**	**7.9969*** (2.6542)**	**5.5900** (2.7315)**	**7.8721*** (2.7528)**	**9.3980** (4.2527)**	**8.2567** (4.1481)**
Sugar	*NutrientClaim*	**-3.0771* (1.7402)**	-0.0000 (4.3473)	**-4.9661* (2.8712)**	**-7.4871** (3.2740)**	0.6559 (2.8554)	1.0065 (2.6612)
	OtherClaim	-1.2570 (3.1245)	-0.0000 (3.6932)	-2.7231 (6.9546)	-0.6948 (3.8039)	-0.6769 (4.1658)	0.5992 (4.1359)
Fiber	*NutrientClaim*	**2.9996** (1.2688)**	**14.6245** (5.7292)**	0.0142 (4.2262)	-0.0000 (0.0145)	0.0000 (0.0154)	**0.1296** (0.0590)**
	OtherClaim	**-1.8701* (1.0916)**	**-14.6226** (6.3503)**	-0.0297 (4.2385)	0.0000 (0.0075)	0.4575 (0.3780)	-0.5520 (0.6277)
Protein	*NutrientClaim*	**1.5975** (0.6332)**	**3.2364*** (0.9490)**	**0.9677*** (0.0435)**	**0.2276*** (0.0876)**	**0.0882* (0.0457)**	-0.0882 (0.2814)
	OtherClaim	**-2.6646* (1.5501)**	1.0776 (2.9015)	**-4.4866* (2.6335)**	-0.6991 (0.6699)	-0.0882 (0.4626)	1.7637 (1.7071)
Overall Nutrition	*NutrientClaim*	4.5667 (3.8734)	8.0517 (12.9677)	**3.7827* (1.9412)**	1.1524 (3.9813)	**8.6272*** (3.1485)**	**17.1013*** (5.1805)**
	OtherClaim	**-8.6174*** (2.5340)**	-7.9244 (6.3910)	**-14.2817** (5.7273)**	**-11.4877*** (4.0028)**	-7.7128 (12.3616)	-6.7839 (19.2769)

Notes. The table provides coefficient estimates of the focal three-way interaction terms, *TB* × *FOP* × *NutrientClaim* and *TB* × *FOP* × *OtherClaim*. The results presented in the table are based on the models that contain control variables. Robust standard errors that are clustered at the matched-set level are in parentheses. Statistically significant coefficient estimates are highlighted in bold.
*p < 0.10; **p < 0.05; ***p < 0. 01.

CHAPTER VI

CONCLUSION

SUMMARY

My study is the first to examine the consequences of food manufacturers' participation in voluntary disclosure of nutritional information in the form of FOP nutrition labeling system. I analyzed 7,593 products and 686 brands across four different product categories (breakfast cold cereal, bread, sweet biscuit/cookie and potato snack) over a 10-year time period. I rely on a quasi-experimental study design that is based on a combination of PSM, DID and QDID analyses to overcome the problem of endogeneity due to self-selection. The results suggest that food manufacturers who adopt FOP produce more and nutritionally better products subsequent to participation, as compared to food manufacturers who do not participate in the program. I find that participation in FOP leads firms to produce more new products per month. In terms of changes in nutrition content, I find that firms that adopt FOP improve the overall nutritional profile of their products. More specifically, firms that adopt FOP lower the calorie content and increase (decrease) the level of nutrients that consumers seek to consume more (less). The magnitude of these changes varies across the product categories, the type of nutrient under focus, whether the firm is an early or late adopter of FOP and whether the focal firm has resources committed towards nutritionally better products or not. Based on the results, I offer the following theoretical and policy implications of firms' participation in the FOP nutrition labeling system.

IMPLICATIONS

Participation in Voluntary Initiatives is not a Marketing Gimmick

There is widespread skepticism among consumer groups and the policymakers that FOP labels are only a manufacturer tactic that may not lead to necessarily healthier products and can in fact confuse or mislead consumers (Glanz et al. 2012; Hawley et al. 2013). Manufacturers may highlight only the beneficial nutrients of their products and not the nutrients that consumers seek to avoid consuming thus giving misleading information to the consumers. However, I find that there are significant benefits of participation in voluntary initiatives and that food manufacturers that adopt FOP produce more and nutritionally better products subsequent to their adoption of the voluntary nutrition labeling system. I believe that these results help strengthen the arguments in favor of introducing more voluntary programs for food manufacturers thus aiding in effective policy making. The findings of the study also contribute to the current literature on food and nutrition policies that aims to understand the impact of such policies on consumer behavior and firm (e.g., Kiesel et al. 2011; Moorman et al. 2012).

Indirect Benefits of Participation in FOP Nutrition Labeling System

This paper presents evidence that significant indirect benefits accrue for consumers from food manufacturers' participation in FOP nutrition labeling system. Prior studies have established that NLEA, a mandatory initiative, is confusing and that consumers do not benefit from the information provided in the Nutrition Facts label. While I do not examine whether consumers actually process the information provided in the FOP label, the results suggest that firms that adopt FOP produce nutritionally better products, and hence consumers are better off by consuming products that feature FOP nutrition labels.

Signaling Mechanism behind Participation in Voluntary Initiatives

The results that early adopters produce more new products than late adopters shed light on the signaling mechanism behind voluntary participation. Early adopters are more seriously committed towards the cause behind the voluntary initiative; unlike early adopters, late adopter firms do not innovate which implies that late adopter firms may simply participate to imitate the strategy of early adopters. The result that the effect of FOP is greater for products that carry nutrition content claims also conforms to the notion that firms that have already committed resources to producing better products actually innovate and introduce nutritionally better products subsequent to participation in FOP. This suggests that nutrient content claims on food products, which are regulated by the FDA, serve as credible signals of firms' commitment towards producing nutritionally better products.

LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

While my study is the first to assess the impact of voluntary FOP nutrition labeling programs on firm innovation and has important implications for both the policymakers and the firms, my study is based in only the context of the food industry and hence the results may not be generalizable across other voluntary programs in other industries. Future research could study other settings and contexts to evaluate the efficacy of firms' participation in voluntary initiatives and help advance the understanding of the mechanisms behind the success or failure of such programs. In addition, while I argue that consumers reap indirect benefits from firms' adoption of FOP, I do not explicitly examine the changes on the demand side during the post-FOP period. Future studies can help develop models that answer the question of whether adoption of FOP encourages consumers to make healthier choices. In spite of these limitations, I believe that my study sheds light on the importance of firms' voluntary participation in initiatives that signal stewardship of corporate social responsibility. I hope that my study encourages researchers to examine the consequences of firms' adoption of nutrition related policy changes as public policymakers continue to find ways to encourage consumers to make healthier eating choices.

REFERENCES

Abadie A, Angrist JD, Imbens G (2002) Instrumental variables estimates of the effect of subsidized training on the quantiles of trainee earnings. *Econometrica* 70(1):91−117.

Agresti A (2007) *An Introduction to Categorical Data Analysis*, 2nd ed. (John Wiley & Sons, Inc., Hoboken, NJ).

Anderson ET, Fong NM, Simester DI, Tucker CE (2010) How sales taxes affect customer and firm behavior: The role of search on the Internet. *Journal of Marketing Research* 47(2):229−239.

Andrews JC, Burton S, Kees J (2011) Is simpler always better? Consumer evaluations of front-of-package nutrition symbols. *Journal of Public Policy & Marketing* 30(2):175−190.

Angrist JD, Krueger AB (1999) Empirical strategies in labor economics. In *Handbook of Labor Economics*, 1st ed., Vol. 3, Ch. 23, Edited by Ashenfelter O, Card D 1277−1366 (Elsevier Science, Amsterdam).

Angrist JD, Pischke JS (2009) *Mostly Harmless Econometrics: An Empiricist's Companion* (Princeton University Press, Princeton, NJ).

Atella V, Kopinska J (2012) The impact of cost sharing schemes on drug compliance: Evidence based on quantile regression. CEIS Tor Vergata Research Paper Series 10(11) No. 247.

Balasubramanian SK, Cole C (2002) Consumers' search and use of nutrition information: The challenge and promise of the Nutrition Labeling and Education Act. *Journal of Marketing* 66(3):112−127.

Balcombe K, Fraser I, Falco SD (2010) Traffic lights and food choice: A choice experiment examining the relationship between nutritional food labels and price. *Food Policy* 35(3):211–220.

Bansal P, Hunter T (2003) Strategic explanations for the early adoption of ISO 14001. *Journal of Business Ethics* 46(3):289−299.

Barnow BS, Cain GG, Goldberger AS (1980) Issues in the analysis of selectivity bias. In *Evaluation Studies* 5:42−59, Edited by Stromsdorfer E, Farkas G (Sage , San Francisco, CA).

Bialkova S, Van Trijp H (2010) What determines consumer attention to nutrition labels? *Food Quality and Preference* 21(8):1042–1051.

Borah BJ, Burns ME, Shah ND (2011) Assessing the impact of high deductible health plans on health-care utilization and cost: A changes-in-changes approach. *Health Economics* 20(9):1025−1042.

Bound J, Jaeger DA, Baker RM (1995) Problems with instrumental variables estimation when the correlation between the instruments and the endogeneous explanatory variable is weak. *Journal of the American Statistical Association* 90(430):443−450.

Bronnenberg BJ, Dubé JP, Mela CF (2010) Do digital video recorders influence sales? *Journal of Marketing Research* 47(6):998−1010.

Bronnenberg BJ, Kruger MW, Mela CF (2008) The IRI marketing data set. *Marketing Science* 27(4):745−748.

Caliendo M, Kopeinig S (2008) Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys* 22(1):31−72.

D'Agostino RB, Jr. (1998) Tutorial in biostatistics: Propensity score methods for bias reduction in the comparison of a treatment to a non-randomized control group. *Statistics in Medicine* 17(19):2265−2281.

Draganska M, Jain DC (2006) Consumer preferences and product-line pricing strategies: An empirical analysis. *Marketing Science* 25(2):164−174.

Draper AK, Adamson AJ, Clegg S, Malam S, Rigg M, Duncan S (2011) Front-of-pack nutrition labelling: Are multiple formats a problem for consumers? *European Journal of Public Health* 23(3):517–521.

Drichoutis AC, Lazaridis P, Nayga RM (2009) Would consumers value food-away-from-home products with nutritional labels? *Agribusiness* 25(4):550–575.

Dunbar G (2010) Task-based nutrition labelling. *Appetite* 55(3):431–435.

Fan VY, Karan A, Mahal A (2012) State health insurance and out-of-pocket health expenditures in Andhra Pradesh, India. *International Journal of Health Care Finance and Economics* 12(3):189−215.

Feunekes GIJ, Gortemaker IA, Willems AA, Lion R, van den Kommer M (2008) Front-of-pack nutrition labelling: Testing effectiveness of different nutrition labelling formats front-of-pack in four European countries. *Appetite* 50(1):57–70.

Food and Drug Administration (2010) Front of pack and shelf tag nutrition symbols; Establishment of docket; Request for comments and information. *Federal Register* 75(82): 22602−22606.

FoodNavigator-USA (2012) FDA offers support in industry roll-out of Facts Up Front labeling. Retrieved from http://www.foodnavigator-usa.com/Trends/Food-labeling-and-marketing/FDA-offers-support-in-industry-roll-out-of-Facts-Up-Front-labeling. Accessed January 22, 2016.

Fuller GW (2004) *New Food Product Development: From Concept to Marketplace*, 2nd ed. (CRC Press, Boca Raton, FL).

Glanz K, Hersey J, Cates S, Muth M, Creel D, Nicholls J, Fulgoni V, Zaripheh S (2012) Effect of a nutrient rich foods consumer education program: Results from the nutrition advice study. *Journal of the Academy of Nutrition and Dietetics* 112(1):56−63.

Golan EH, Mancino L, Unnevehr LJ (2009) Food policy: Check the list of ingredients. *Amber Waves* 7(2):16−21.

Gorton D, Mhurchu CN, Chen MH, Dixon R (2009) Nutrition labels: A survey of use, understanding and preferences among ethnically diverse shoppers in New Zealand. *Public Health Nutrtion* 12(9):1359–1365.

Guenther PM, Juan WY, Reedy J, Britten P, Lino M, Carlson A, Hiza HH, Krebs-Smith SM (2007) Diet quality of Americans in 1994-96 and 2001-02 as measured by the healthy eating index-2005. Nutrition Insight 37, Center for Nutrition Policy and Promotion, U.S. Department of Agriculture.

Guo SY, Fraser MW (2015) *Propensity Score Analysis: Statistical Methods and Applications*, 2nd ed. (Sage Publications, Thousand Oaks, CA).

Hansen BB (2004) Full matching in an observational study of coaching for the SAT. *Journal of the American Statistical Association* 99(467):609−618.

Hansen BB, Bowers J (2008) Covariate balance in simple, stratified and clustered comparative studies. *Statistical Science* 23(2):219−236.

Hausman J, Hall BH, Griliches Z (1984) Econometric models for count data with an application to the patents-R&D relationship. *Econometrica* 52(4):909−938.

Hawley KL, Roberto CA, Bragg MA, Liu PJ, Schwartz MB, Brownell KD (2013) The science on front-of-package food labels. *Public Health Nutrition* 16(3):430−439.

Heinrich C, Maffioli A, Vázquez G (2010) A primer for applying propensity-score matching. Inter-American Development Bank Technical Notes, No. IDB-TN-161.

Ho DE, Imai K, King G, Stuart EA (2007) Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis* 15(3):199–236.

Huang Q, Nijs VR, Hansen K, Anderson ET (2012) Wal-Mart's impact on supplier profits. *Journal of Marketing Research* 49(2):131–143.

Institute of Medicine (2010) *Examination of Front-of-Package Nutrition Rating Systems and Symbols: Phase I Report* (The National Academies Press, Washington, DC).

Kelly B, Hughes C, Chapman K, Louie JCY, Dixon H, Crawford J, King L, Daube M, Slevin T (2009) Consumer testing of the acceptability and effectiveness of front-of-pack food labelling systems for the Australian grocery market. Health Promotion International 24(2): 120–129.

Kiesel K, Villas-Boas SB (2013) Can information costs affect consumer choice? Nutritional labels in a supermarket experiment. *International Journal of Industrial Organization* 31(2):153–163.

Kiesel K, McCluskey JJ, Villas-Boas SB (2011) Nutritional labeling and consumer choices. *Annual Review of Resource Economics* 3:141–158.

Koenker R, Machado JAF (1999) Goodness of fit and related inference processes for quantile regression. *Journal of the American Statistical Association* 94(448):1296−1310.

Korry E (2003) California bans soda sales in schools. *NPR*. Retrieved from http://www.npr.org/templates/story/story.php?storyId=1477445. Accessed July 2, 2014.

Kumar A, Ram B, Rishika R, Ramkumar J, and P.K. K (2016) From social to sale: The effects of firm-generated content in social media on customer behavior. *Journal of Marketing* 80(1):7−25.

Lando AM, Labiner-Wolfe J (2007) Helping consumers make more healthful food choices: Consumer views on modifying food labels and providing point-of-purchase nutrition information at quick-service restaurants. *Journal of Nutrition Education and Behavior* 39(3):157–163.

Levine DI, Toffel MW (2010) Quality management and job quality: How the ISO 9001 standard for quality management systems affects employees and employers. *Management Science* 56(6):978−996.

Ma Y, Ailawadi KL, Grewal D (2013) Soda versus cereal and sugar versus fat: Drivers of healthful food intake and the impact of diabetes diagnosis. *Journal of Marketing* 77(3):101−120.

Malam S, Clegg S, Kirwan S, McGinigal S, Raats M, Shepherd R, Barnett J, Senior V, Hodgkins C, Dean M (2009) Comprehension and use of UK nutrition signpost labelling schemes. Food Standards Agency, London, UK.

Meyer JW, Scott WR, Deal TE (1981) Institutional and technical sources of organizational structure: Explaining the structure of educational organizations. In *Organization and the Human Services* Edited by Stein HD 151−178 (Temple University Press, Philadelphia, PA).

Mintel International Group Ltd. (2012) Glossary 2012 (Version 2012.1).

Mojduszka EM, Caswell JA, Harris JM (2001) Consumer choice of food products and the implications for price competition and government policy. *Agribusiness* 17(1):81−104.

Mojduszka EM, Caswell JA, West DB, Harris JM (1999) Changes in nutritional quality of food product offerings and purchases: A case study in the mid-1990's. Technical Bulletin No. 1880, Food and Rural Economics Division, Economic Research Service, U.S. Department of Agriculture.

Mohr GS, Lichtenstein DR, Janiszewski C (2012) The effect of marketer-suggested serving size on consumer responses: The unintended consequences of consumer attention to calorie information. *Journal of Marketing* 76(1):59−75.

Moorman C, Ferraro R, Huber J (2012) Unintended nutrition consequences: Firm responses to the Nutrition Labeling and Education Act. *Marketing Science* 31(5):717−737.

Morgan NA, Rego LL (2009) Brand portfolio strategy and firm performance. *Journal of Marketing* 73 (1):59−74.

Muller KA, Riedl EJ, Sellhorn T (2011) Mandatory fair value accounting and information asymmetry: Evidence from the European real estate industry. *Management Science* 57(6):1138−1153.

Nestle M, Ludwig DS (2010) Front-of-package food labels: Public health or propaganda? *Journal of the American Medical Association* 303(8):771−772.

O'Keefe S (2004) Job creation in California's enterprise zones: A comparison using a propensity score matching model. *Journal of Urban Economics* 55(1):131–150.

Remler DK, Van Ryzin GG (2011) *Research Methods in Practice: Strategies for Description and Causation* (Sage, Los Angeles, CA).

Rishika R, Kumar A, Janakiraman R, Bezawada R (2013) The effect of customers' social media participation on customer visit frequency and profitability: An empirical investigation. *Information Systems Research* 24(1):108−127.

Roberto CA, Bragg MA, Schwartz MB, Seamans MJ, Musicus A, Novak N, Brownell KD (2012) Facts up front versus traffic light food labels: A randomized controlled trial. *American Journal of Preventive Medicine* 43(2):134−141.

Rosenbaum PR (1993) Hodges-Lehmann point estimates of treatment effect in observational studies. *Journal of the American Statistical Association* 88(424):1250–1253.

Rosenbaum PR (2002) Covariance adjustment in randomized experiments and observational studies. *Statistical Science* 17(3):286−327.

Rosenbaum PR (2007) Sensitivity analysis for m-estimates, tests, and confidence intervals in matched observational studies. *Biometrics* 63(2):456-464.

Rosenbaum PR, Rubin DB (1983) The central role of the propensity score in observational studies for causal effects. *Biometrika* 70(1):41−55.

Rosenbaum PR, Rubin DB (1984) Reducing bias in observational studies using subclassification on the propensity score. *Journal of the American Statistical Association* 79(387):516−524.

Rubin DB (2006) *Matched Sampling for Causal Effects* (Cambridge University Press, New York).

Sacks G, Rayner M, Swinburn B (2009) Impact of front-of-pack 'traffic-light' nutrition labelling on consumer food purchases in the UK. *Health Promotion International* 24(4):344−352.

Steenhuis IHM, Kroeze W, Vyth EL, Valk S, Verbauwen R, Seidell JC (2010) The effects of using a nutrition logo on consumption and product evaluation of a sweet pastry. *Appetite* 55(3):707–709.

Todd JE, Variyam JN (2008) The decline in consumer use of food nutrition labels, 1995–2006. Economic Research Report No. 63, Economic Research Service, U.S. Department of Agriculture.

Toffel MW (2006) Resolving information asymmetries in markets: The role of certified management programs. Working paper, Harvard Business School, Harvard University, Boston, MA.

Tolbert PS, Zucker LG (1983) Institutional sources of change in the formal structure of organizations: The diffusion of civil service reform, 1880-1935. *Administrative Science Quarterly* 28(1):22–39.

Van Herpen E, Van Trijp HCM (2011) Front-of-pack nutrition labels. Their effect on attention and choices when consumers have varying goals and time constraints. *Appetite* 57(1):148–160.

Van Kleef E, Van Trijp H, Paeps F, Fernández-Celemín L (2008) Consumer preferences for front-of-pack calories labelling. *Public Health Nutrition* 11(2):203–213.

Ver Hoef JM, Boveng PL (2007) Quasi-Poisson vs. negative binomial regression: How should we model overdispersed count data? *Ecology* 88(11):2766–2772.

Vyth EL, Steenhuis IH, Vlot JA, Wulp A, Hogenes MG, Looije DH, Brug J, Seidell JC (2010) Actual use of a front-of-pack nutrition logo in the supermarket: Consumers' motives in food choice. *Public Health Nutrition* 13(11):1882–1889.

Vyth EL, Steenhuis IH, Mallant SF, Mol ZL, Brug J, Temminghoff M, Feunekes GI, Jansen L, Verhagen H, Seidell JC (2009) A front-of-pack nutrition logo: A quantitative and qualitative process evaluation in the Netherlands. *Journal of Health Communication* 14(7):631–645.

Wooldridge JM (2002) *Econometric Analysis of Cross Section and Panel Data* (MIT Press, Cambridge, MA).

Young L & Swinburn B (2002) Impact of the Pick the Tick food information programme on the salt content of food in New Zealand. *Health Promotion International* 17(1):13–19.

Zucker LG (1983) Organizations as institutions. In *Research in the Sociology of Organizations* Edited by Bacharach SB 2:1−42 (JAI Press, Greenwich, CT).

APPENDIX

Table A1 Transformations on Dependent Variables for the Quality of Innovation Models

Dependent Variable (Y)	Breakfast Cold Cereal	Bread	Sweet Biscuit/Cookie	Potato Snack
Calorie (kcal/100g)	Y / 100	Y / 100	Y / 100	Y / 100
Fat (g/100g)	$\log_e(Y + 0.001)$	$\log_e(Y + 0.001)$	Y	Y
Sodium (mg/100g)	Y / 100	Y / 100	Y / 100	Y / 100
Sugar (g/100g)	Y	$\log_e(Y + 0.001)$	Y	$\log_e(Y + 0.001)$
Fiber (g/100g)	$\log_e(Y + 0.001)$	$\log_e(Y + 0.001)$	$\log_e(Y + 0.001)$	$\log_e(Y + 0.001)$
Protein (g/100g)	$\log_e(Y + 0.001)$	Y	Y	Y
OverallNutrition	Y	Y	Y	Y

Table A2 Impact of FOP on the Quantity of Innovation by Launch Type - Breakfast Cold Cereal

Variable	Dependent Variable: Number of New Products of the Three Launch Types					
	New Product		New Variety/ Range Extension		New Packaging	
	(1) NC	(2) YC	(5) NC	(6) YC	(7) NC	(8) YC
TB × FOP	**1.4276***** **(0.4501)**	**1.4258***** **(0.4945)**	**1.0867**** **(0.4757)**	**1.0319*** **(0.5982)**	**2.2893***** **(0.7732)**	**1.9722***** **(0.6300)**
TB	-0.3036 (0.3593)	-0.2329 (0.4089)	0.0415 (0.3253)	0.0783 (0.4591)	-0.1054 (0.7764)	0.0655 (1.0002)
FOP	-1.5813*** (0.4077)	-1.6042*** (0.4311)	-2.0678*** (0.5049)	-2.0355*** (0.5739)	-1.9089*** (0.6064)	-1.7944*** (0.6120)
Price	–	0.1998 (0.1310)	–	-0.0554 (0.3400)	–	0.0869 (0.3490)
UnitPackSize	–	-0.0011 (0.0012)	–	-0.0003 (0.0015)	–	-0.0002 (0.0041)
UnitsInMultipack	–	0.0864 (0.8367)	–	0.4312 (1.3318)	–	1.1885 (1.6901)
Constant	-1.1944 (0.7941)	-1.2681 (1.3667)	-1.1545 (2.4771)	-1.3525 (3.2034)	-3.4773 (6.5686)	-4.8125 (6.3625)
Matched-set fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-163.97	-160.05	-258.51	-257.35	-213.82	-202.54
AIC	652.75	650.91	843.55	847.21	663.79	647.24

Notes. "NC" and "YC" denote "No (without) Controls" and "Yes (with) Controls" respectively. Robust standard errors that are clustered at the matched-set level are in parentheses. The focal variable of interest and its coefficient estimate that is statistically significant is highlighted in bold. AIC refers to Akaike Information Criterion.
*p < 0.10; **p < 0.05; ***p < 0. 01.

Table A3 Impact of FOP on the Quantity of Innovation by Launch Type - Bread

Variable	Dependent Variable: Number of New Products of the Three Launch Types					
	New Product		New Variety/ Range Extension		New Packaging	
	(1) NC	(2) YC	(5) NC	(6) YC	(7) NC	(8) YC
TB × FOP	**0.8658**** **(0.3076)**	**0.7438**** **(0.3767)**	**0.5028*** **(0.2830)**	**0.5067*** **(0.2790)**	**0.5756**** **(0.2575)**	**0.6023**** **(0.2490)**
TB	0.3017 (0.2535)	0.4936 (0.3146)	0.0943 (0.1923)	0.0793 (0.2006)	0.5732 (0.5462)	0.5205 (0.4238)
FOP	-1.0590*** (0.2639)	-1.1273*** (0.2991)	-0.7911*** (0.1829)	-0.7819*** (0.1881)	0.2419* (0.1399)	0.2295 (0.2464)
Price	–	0.0245 (0.1689)	–	-0.0763 (0.1004)	–	-0.0392 (0.1871)
UnitPackSize	–	0.0006 (0.0007)	–	0.0007* (0.0004)	–	0.0007 (0.0008)
UnitsInMultipack	–	-1.4835 (2.3680)	–	-0.1431 (0.2939)	–	0.0288 (0.1463)
Constant	-18.8459*** (2.5005)	-17.7003*** (3.4608)	-2.6461 (2.9168)	-2.5274 (2.7536)	-3.2749*** (1.0622)	-3.4244 (8.9632)
Matched-set fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-173.15	-164.57	-184.97	-181.40	-125.80	-124.95
AIC	736.66	725.49	916.35	915.20	539.34	543.63

Notes. "NC" and "YC" denote "No (without) Controls" and "Yes (with) Controls" respectively. Robust standard errors that are clustered at the matched-set level are in parentheses. The focal variable of interest and its coefficient estimate that is statistically significant is highlighted in bold. AIC refers to Akaike Information Criterion.
*p < 0.10; **p < 0.05; ***p < 0. 01.

Table A4 Impact of FOP on the Quantity of Innovation by Launch Type - Sweet Biscuit/Cookie

Variable	Dependent Variable: Number of New Products of the Three Launch Types					
	New Product		New Variety/ Range Extension		New Packaging	
	(1) NC	(2) YC	(3) NC	(4) YC	(5) NC	(6) YC
TB × FOP	0.0574 (0.5254)	0.0552 (0.4592)	0.3626 (0.5843)	0.3425 (0.6829)	**-0.8216**** **(0.3607)**	**-0.8462**** **(0.4263)**
TB	0.6341* (0.3702)	0.6108* (0.3181)	0.1737 (0.3024)	0.1850 (0.3018)	0.8813*** (0.2859)	0.8794** (0.4000)
FOP	-0.7199*** (0.2645)	-0.6941*** (0.2398)	-0.7100*** (0.2114)	-0.7061*** (0.2327)	0.2935 (0.2029)	0.3548 (0.2470)
Price	–	-0.0450 (0.0511)	–	-0.0101 (0.0178)	–	-0.0952* (0.0491)
UnitPackSize	–	0.0004 (0.0005)	–	-0.0003 (0.0007)	–	-0.0001 (0.0009)
UnitsInMultipack	–	-0.0173 (0.0820)	–	-0.0149 (0.1172)	–	0.0301 (0.0951)
Constant	-1.6314 (2.5632)	-1.5822 (3.6053)	-0.9877 (3.1761)	-0.8400 (3.3710)	-2.7350 (4.2526)	-2.4343 (3.7332)
Matched-set fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-299.47	-297.32	-400.29	-399.21	-257.87	-250.61
AIC	1053.69	1055.39	1403.56	1407.39	894.38	885.87

Notes. "NC" and "YC" denote "No (without) Controls" and "Yes (with) Controls" respectively. Robust standard errors that are clustered at the matched-set level are in parentheses. The focal variable of interest and its coefficient estimate that is statistically significant is highlighted in bold. AIC refers to Akaike Information Criterion.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Table A5 Impact of FOP on the Quantity of Innovation by Launch Type - Potato Snack

Variable	Dependent Variable: Number of New Products of the Three Launch Types					
	New Product		New Variety/ Range Extension		New Packaging	
	(1) NC	(2) YC	(3) NC	(4) YC	(5) NC	(6) YC
TB × FOP	**1.2425** **(0.6230)**	**1.4424*** **(0.7909)**	0.2625 (0.4014)	0.1681 (0.4998)	0.8622 (5.6180)	0.6824 (18.8223)
TB	0.7347 (5.0735)	0.6764 (4.9176)	-0.2515 (0.4116)	-0.1931 (0.4822)	-1.5071 (10.9302)	-1.1440 (27.3212)
FOP	-0.9594*** (0.2866)	-1.0587*** (0.3653)	-0.8590*** (0.2255)	-0.7930** (0.3083)	-0.8892 (1.2296)	-0.5612 (6.7991)
Price	–	-0.2653 (0.3214)	–	-0.1243 (0.3492)	–	-0.1467 (69.7481)
UnitPackSize	–	-0.0006 (0.0023)	–	0.0011 (0.0026)	–	0.0051 (0.7790)
UnitsInMultipack	–	0.2438 (0.3591)	–	0.3691 (3.9646)	–	0.7390 (92.0636)
Constant	-3.6547 (5.0004)	-3.3669 (5.2380)	-0.7397 (0.6565)	-1.1296 (4.5270)	-3.0121 (6.0583)	-4.6340 (116.0347)
Matched-set fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-64.12	-59.84	-87.28	-79.42	-73.03	-54.95
AIC	227.91	225.36	356.67	346.93	258.58	228.43

Notes. "NC" and "YC" denote "No (without) Controls" and "Yes (with) Controls" respectively. Robust standard errors that are clustered at the matched-set level are in parentheses. The focal variable of interest and its coefficient estimate that is statistically significant is highlighted in bold. AIC refers to Akaike Information Criterion.
**p* < 0.10; ***p* < 0.05; ****p* < 0. 01.

Table A6 Impact of FOP on the Quantity of Innovation by Launch Type: Early vs. Late Adopters **-** Breakfast Cold Cereal

Variable	Dependent Variable: Number of New Products of the Three Launch Types					
	New Product		New Variety/ Range Extension		New Packaging	
	(1) NC	(2) YC	(3) NC	(4) YC	(5) NC	(6) YC
TB^{Early} × FOP (early adopter)	**1.6323*** (0.4698)**	**1.5726*** (0.4575)**	**1.2223** (0.5171)**	**1.0744** (0.4347)**	**2.3981*** (0.6783)**	**1.4917*** (0.5634)**
TB^{Late} × FOP (late adopter)	-0.3004 (0.8203)	-0.3441 (0.8958)	-0.4803 (0.9805)	-1.2775 (1.6577)	-0.3674 (1.0929)	-2.3647 (1.6897)
TB^{Early}	-0.1368 (0.2468)	-0.0264 (0.2889)	0.4507** (0.2018)	0.4718** (0.2011)	0.6689* (0.3614)	0.9979*** (0.3804)
TB^{Late}	-0.3605 (1.1084)	-0.3736 (1.1733)	-0.3032 (0.9447)	-0.4808 (0.7886)	-0.0850 (1.2769)	-0.1330 (0.9827)
FOP	-1.5449*** (0.4461)	-1.5436*** (0.4244)	-2.0288*** (0.5054)	-1.9671*** (0.4546)	-1.7671*** (0.6192)	-1.4116*** (0.5284)
Price	–	0.1838** (0.0816)	–	-0.1235 (0.2749)	–	0.1647 (0.2164)
UnitPackSize	–	0.0002 (0.0009)	–	0.0028 (0.0027)	–	0.0053* (0.0027)
UnitsInMultipack	–	0.0184 (0.3841)	–	0.2419 (0.6408)	–	1.5821*** (0.4400)
Constant	-1.3126*** (0.1287)	-1.8641*** (0.6069)	-1.3856*** (0.1223)	-2.5596** (1.0606)	-4.0578*** (0.2305)	-8.2894*** (1.5233)
Matched-set fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-151.49	-147.93	-236.00	-229.10	-158.44	-130.02
AIC	631.78	630.65	802.52	794.71	557.02	506.18

Notes. "NC" and "YC" denote "No (without) Controls" and "Yes (with) Controls" respectively. Robust standard errors that are clustered at the matched-set level are in parentheses. The focal variable of interest and its coefficient estimate that is statistically significant is highlighted in bold. AIC refers to Akaike Information Criterion.
*p < 0.10; **p < 0.05; ***p < 0. 01.

Table A7 Impact of FOP on the Quantity of Innovation by Launch Type: Early vs. Late Adopters - Bread

Variable	Dependent Variable: Number of New Products of the Three Launch Types					
	New Product		New Variety/ Range Extension		New Packaging	
	(1) NC	(2) YC	(3) NC	(4) YC	(5) NC	(6) YC
TB^{Early} × FOP (early adopter)	**1.1487*** (0.3244)**	**0.9576** (0.3735)**	0.3660 (0.2833)	0.3311 (0.2965)	**0.8581** (0.4121)**	**0.9128** (0.4522)**
TB^{Late} × FOP (late adopter)	-0.2400 (0.5661)	-0.1932 (0.5658)	0.6957 (0.4561)	0.7582 (0.4712)	-0.0221 (0.5729)	-0.0753 (0.6712)
TB^{Early}	0.3813 (0.2538)	0.6006* (0.3146)	0.2732 (0.2262)	0.2766 (0.2297)	0.4702 (0.5832)	0.3811 (0.5789)
TB^{Late}	0.0304 (0.2822)	0.1253 (0.2482)	-0.1784 (0.4103)	-0.2161 (0.3695)	0.6425 (0.7090)	0.6299 (0.5957)
FOP	-1.0133*** (0.1936)	-1.0706*** (0.2230)	-0.7578*** (0.1532)	-0.7405*** (0.1458)	0.2632 (0.2556)	0.2437 (0.3016)
Price	–	0.0048 (0.1336)	–	-0.0955 (0.0805)	–	-0.0152 (0.1590)
UnitPackSize	–	0.0006 (0.0004)	–	0.0007** (0.0003)	–	0.0005 (0.0004)
UnitsInMultipack	–	-1.3967** (0.6052)	–	-0.1798 (0.1565)	–	0.1082 (0.0797)
Constant	-18.8580*** (1.01481)	-17.7357*** (1.2070)	-2.6554*** (0.0434)	-2.4307*** (0.3020)	-3.2860*** (0.1337)	-3.5443*** (0.4485)
Matched-set fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-165.07	-158.21	-183.37	-179.37	-124.13	-123.23
AIC	724.49	716.78	917.14	915.15	539.99	544.19

Notes. "NC" and "YC" denote "No (without) Controls" and "Yes (with) Controls" respectively. Robust standard errors that are clustered at the matched-set level are in parentheses. The focal variable of interest and its coefficient estimate that is statistically significant is highlighted in bold. AIC refers to Akaike Information Criterion.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Table A8 Impact of FOP on the Quantity of Innovation by Launch Type: Early vs. Late Adopters - Sweet Biscuit/Cookie

Variable	Dependent Variable: Number of New Products of the Three Launch Types					
	New Product		New Variety/ Range Extension		New Packaging	
	(1) NC	(2) YC	(3) NC	(4) YC	(5) NC	(6) YC
TB^{Early} × FOP (early adopter)	-0.0916 (0.4385)	-0.1150 (0.4458)	0.3472 (0.6438)	0.2837 (0.5979)	**-0.7624***** **(0.1945)**	**-0.8360***** **(0.2280)**
TB^{Late} × FOP (late adopter)	-0.0558 (0.6330)	-0.0575 (0.6393)	0.0331 (1.0195)	0.0163 (1.0119)	**-1.4245***** **(0.4928)**	**-1.5057***** **(0.4747)**
TB^{Early}	0.8963** (0.4503)	0.8981** (0.4458)	0.3640 (0.5009)	0.4391 (0.4499)	0.8925*** (0.1978)	0.9600*** (0.2210)
TB^{Late}	0.3421 (0.3570)	0.3060 (0.3580)	0.0017 (0.2276)	-0.0185 (0.2219)	0.7999 (0.6320)	0.6790 (0.6407)
FOP	-0.6940*** (0.2059)	-0.6634*** (0.2182)	-0.6880*** (0.1962)	-0.6822*** (0.2108)	0.3162* (0.1854)	0.3964* (0.2030)
Price	–	-0.0478 (0.0381)	–	-0.0118 (0.0092)	–	-0.0990*** (0.0316)
UnitPackSize	–	0.0004 (0.0003)	–	-0.0004 (0.0004)	–	-0.0002 (0.0006)
UnitsInMultipack	–	-0.0245 (0.0575)	–	-0.0272 (0.0538)	–	0.0357 (0.0379)
Constant	-1.6646*** (0.1248)	-1.5881*** (0.1936)	-1.0226*** (0.1249)	-0.8311*** (0.1361)	-2.7591*** (0.1260)	-2.4542*** (0.1576)
Matched-set fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-297.98	-295.65	-397.29	-395.58	-256.36	-248.30
AIC	1054.71	1056.06	1401.55	1404.14	895.38	885.26

Notes. "NC" and "YC" denote "No (without) Controls" and "Yes (with) Controls" respectively. Robust standard errors that are clustered at the matched-set level are in parentheses. The focal variable of interest and its coefficient estimate that is statistically significant is highlighted in bold. AIC refers to Akaike Information Criterion.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A9 Impact of FOP on the Quantity of Innovation by Launch Type: Early vs. Late Adopters **-** Potato Snack

Variable	Dependent Variable: Number of New Products of the Three Launch Types					
	New Product		New Variety/ Range Extension		New Packaging	
	(1) NC	(2) YC	(3) NC	(4) YC	(5) NC	(6) YC
TB^{Early} × FOP (early adopter)	**2.1450** (0.8448)**	**2.3113*** (0.8827)**	0.3112 (0.4924)	0.2508 (0.6373)	0.3372 (0.9312)	0.4843 (0.4097)
TB^{Late} × FOP (late adopter)	-17.2226 (11.5653)	-17.7098 (46.3454)	0.2942 (2.1269)	-0.0763 (2.4895)	19.6368 (14.5739)	20.8632 (15.8401)
TB^{Early}	16.2290*** (1.3659)	16.3049 (53.1995)	-0.6897 (0.5855)	-0.6876 (0.8403)	-0.2697 (1.6384)	0.4749 (26.8955)
TB^{Late}	1.1887 (13.6574)	1.2818 (34.8421)	0.1529 (2.3449)	0.3739 (2.7670)	-36.2169** (14.2330)	-39.2746** (15.8258)
FOP	-0.9762 (13.7012)	-1.0042 (16.9579)	-0.8464*** (0.2109)	-0.7662** (0.3474)	-0.8921*** (0.3429)	-0.5578** (0.2455)
Price	–	-0.3242 (18.4259)	–	-0.1188 (0.4689)	–	-0.2102 (0.1423)
UnitPackSize	–	0.0024 (0.1809)	–	0.0012 (0.0030)	–	0.0070*** (0.0012)
UnitsInMultipack	–	0.3542 (50.5604)	–	0.3886 (0.6511)	–	0.7995*** (0.0318)
Constant	-19.7662 (13.3203)	-20.2192 (98.2579)	-0.4923 (0.9269)	-0.9065 (1.6474)	-3.5149 (13.4272)	-6.0924 (25.4049)
Matched-set fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-59.26	-54.55	-86.35	-78.17	-68.47	-48.39
AIC	222.19	218.78	358.80	348.43	253.47	219.31

Notes. "NC" and "YC" denote "No (without) Controls" and "Yes (with) Controls" respectively. Robust standard errors that are clustered at the matched-set level are in parentheses. The focal variable of interest and its coefficient estimate that is statistically significant is highlighted in bold. AIC refers to Akaike Information Criterion.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.