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The Organic Wheat Market: Three Essays on Pricing, Consumer Segments, and the Importance of Labels

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THE ORGANIC WHEAT MARKET: THREE ESSAYS ON PRICING, CONSUMER

SEGMENTS, AND THE IMPORTANCE OF LABELS

by

Tatiana Drugova

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ABSTRACT

The Organic Wheat Market: Three Essays on Pricing, Consumer Segments, and the Importance of Labels

by

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This dissertation focuses on the issues related to supply and demand of the organic wheat market and consists of three essays. In the first essay, organic and conventional wheat price series were used to evaluate the uncertainty associated with organic wheat premiums and how it affects organic wheat profitability. Data simulation revealed that there are occasions when organic premiums may not cover the additional costs of producing organic, but the losses can be offset over time. Further, results provide some evidence that conventional futures can be used to cross hedge organic wheat price risk, but results depend on the method used to impute the missing organic prices. Finally, it was found that conventional futures prices contain some information useful in predicting organic prices in the short run.

The second and third essay used data from an online consumer survey, conducted in the summer of 2017 across 16 U.S. western states. In the second essay, latent class

modeling was used to perform market segmentation and identify "very likely," "likely" and "unlikely" consumers of organic bread and cookies. Consumer attitudes toward organics, past consumption, and stated preferences for organic bread and cookies were used as segmentation variables. The results revealed that significant differences, which are not product-specific, exist across the segments in terms of willingness to pay values, preferences for product attributes and labels, socio-demographics, lifestyles, and consumption habits.

In the third essay, multinomial and random parameter logit models were used to investigate the impact of including additional health promoting labels (gluten-free, sugar-free or low-carb) and the non-GMO label on the consumer preferences and willingness to pay for organic bread and cookies. It was found that the combinations of the labels do not increase overall consumer willingness to pay on average, however, there are consumers who find these combinations appealing. Familiarity with and knowledge of organic, as well as wheat or gluten intolerance or avoidance, were among the factors found to influence average willingness to pay for the organic label alone and combinations of labels.

(222 pages)

PUBLIC ABSTRACT

The Organic Wheat Market: Three Essays on Pricing, Consumer Segments, and the Importance of Labels

Tatiana Drugova

This dissertation aims to address issues related to supply and demand of organic wheat either as a commodity or contained in the final consumer products. Objectives for the first essay are to evaluate organic wheat price and premium risk, how it affects the profitability of organic wheat production, and examine whether hedging and forecasting can be used to manage the organic wheat price risk. A side objective is to apply and evaluate several data imputation methods to recover missing organic wheat price observations. Objectives for the second essay are to identify "very likely," "likely," and "unlikely" consumers of organic wheat products, examine the differences across the consumer groups to understand which sociodemographic characteristics and other factors drive demand for organic wheat products, and which product characteristics and labels are important to consumers. Objectives for the third essay are to obtain willingness to pay values for organic label alone, examine whether combining organic label with other labels (non-GMO, gluten-free, sugar-free or low-carb) is beneficial for consumers, and evaluate whether knowledge and familiarity with organic, wheat or gluten intolerance or avoidance, and other sociodemographic characteristics affect how consumers value the organic label alone and in combination with other labels. The analyses in the second and third essay are

performed using two wheat product categories (bread and cookies) to examine how findings differ across different product categories.

This dissertation provides several societal benefits. The findings provide insights that may play an important role in supporting growth of the organic wheat production through reduction of uncertainty associated with wheat commodity prices and final consumer demand. Understanding the dynamics of organic wheat prices, how they can affect profitability of organic wheat production and what can be done to reduce the uncertainty is critical to organic wheat growers and food manufacturers when they make production decisions. The findings in the second and third essay will assist food manufacturers and marketers as they develop new products and marketing strategies and make labelling decisions. The findings in this dissertation may allow them to match consumers' needs better, and thus use the limited organic wheat supply more efficiently.

DEDICATION

This dissertation is dedicated to my husband Hamza Abdellaoui, who encouraged me to pursue the degree from the very beginning and believed in my ability to complete it. It is also dedicated to my mother Anna Drugova, my father Štefan Druga, and my brother Štefan Druga—you will always be in my heart.

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INTRODUCTION

Organic food consumption has become one of the most significant trends in the food industry. The growth in the sales of organic foods has outpaced that of conventional foods in recent years (Organic Trade Association, 2018), despite the premiums that organic foods usually command. While increasing demand coupled with organic premiums have encouraged growers to adopt organic production practices, some growers have experienced challenges which has slowed down the supply growth needed to satisfy demand. Organic wheat growers in U.S. western states face some of these challenges, which affects the welfare of other actors along the supply chain including food manufacturers, retailers and final consumers. The purpose of this dissertation is to address issues related to supply and demand in the organic wheat market that will facilitate the decision-making process and contribute to the welfare of actors along the supply chain.

The overall objective of the first essay is to evaluate the impact of organic premium uncertainty on the profitability of organic wheat production and examine options that growers may have to reduce uncertainty. Improving growers' understanding of these issues may benefit them as they make production decisions, and in turn contribute to increasing the organic wheat supply. Specifically, we address three objectives: (1) examine the uncertainty associated with organic wheat prices and organic premiums and how they affect the profitability of organic wheat production relative to conventional wheat production, (2) examine whether hedging in conventional wheat futures mitigates the organic wheat price risk and whether conventional futures prices can be used to predict organic prices, and (3) apply and evaluate different methods for imputing missing observations in the historical organic wheat price data. This study is the first one to examine

the possibility to cross hedge price risk of an organic commodity using the futures market for its conventional counterpart, in the absence of its own futures market. Further, previous studies have typically examined dynamics between spot and futures prices for the same commodity. This study adds to the current literature by examining the dynamics between qualitatively differentiated commodities.

The overall objective for the second essay is to segment consumers into groups to understand who “very likely,” “likely,” and “unlikely” consumers of organic wheat products are and how they differ to identify what factors determine an interest in organic wheat products. Past studies have examined the factors associated with preferences for organic products, and there tends to be a consensus that characteristics such as lifestyle and attitudinal factors may explain consumer behavior better than demographics (Gil, Gracia, and Sanchez, 2000; Li, Zepeda, and Gould, 2007; Ureña, Bernabéu, and Olmeda, 2008; Bitzios, Fraser, and Haddock-Fraser, 2011; Gracia and de Magistris, 2013). This essay adds to the current literature by shedding light on what factors determine preferences for organic foods in the context of wheat products. Further, it contributes to the existing literature by performing the analysis and contrasting the results for two different wheat product categories, bread and cookies, since past studies have found that preferences for and perceptions of organic label depend on whether the product is classified as a virtue or a vice (Van Doorn and Verhoef, 2011; Ellison et al., 2016). In this essay, bread is considered a virtue product and cookies are considered a vice product (Hui, Bradlow, and Fader, 2009). In addition, this study is the first one to examine whether organic wheat products are appealing to consumers who avoid wheat or gluten. Finally, we differentiate consumers

based on factors affecting their likelihood to prefer organic bread and cookies specifically, which has not been addressed in the previous literature. This knowledge can be used to assist manufacturers and marketers in making production and marketing decisions when allocating the limited supply of organic wheat to match consumers' needs, as well as gauge the growth potential. In addition, it will allow wheat growers to better understand the current economic conditions and perspective on the market growth potential in organic wheat.

Specifically, the second essay addresses four objectives: (1) cluster consumers into segments based on their attitudes toward organic products and production systems, their past purchases of organic wheat products and importance of certified organic labels, (2) examine the differences across the segments in terms of their preferences, reasons for purchasing/not purchasing organic wheat products, socio-demographics, lifestyle characteristics, and shopping and consumption behavior, (3) calculate willingness to pay (WTP)[1] values for certified organic products for whole sample and for each segment, and (4) examine the differences in findings across the two types of wheat products.

The overall objective of the third essay is to examine consumer WTP for the organic label alone and in combination with other related labels to understand whether combining the organic label with other labels is beneficial for consumers or whether it confuses them, and what factors may affect it. Past studies have examined consumer WTP for the combination of organic and non-GMO labels, but with somewhat contrasting findings.

[1] Willingness to pay for a product attribute is the additional dollar amount that a consumer would pay to obtain the product with the attribute, while keeping the overall utility of the consumer constant. The WTP amount is determined by finding the utility that consumer gains from the additional attribute and then finding the dollar amount (i.e., increase in cost to the consumer) that will decrease the utility by the same magnitude.

While Conner and Christy (2004) found that organic consumers specifically are willing to pay more for this combination of labels than for the organic label alone, McFadden and Lusk (2017) found out that consumers in general tend to perceive these labels as substitutes and are not willing to pay extra for the combination. In the third essay, we add to the existing literature by examining whether knowledge that organic is non-GMO by definition plays a role in consumer valuation of the organic and non-GMO labels combination. Since past studies found that consumers in general perceive organic products as healthier relative to conventional products (Magnusson et al., 2001; Lea and Worsley, 2005; Krystallis, Fotopoulos, and Zotos, 2006; Lee et al., 2013), we further examine whether combinations of the organic label with some health promoting labels have any effect on consumer preferences for organic bakery products. Gluten-free and low-carb or sugar-free labels are chosen to reflect some of the recent trends in consumer food demand (Asioli et al., 2017), and this study is the first one to examine consumer preferences for combinations of these labels with organic label.

For the third essay we consider the following four objectives: (1) obtain consumers' WTP for organic label on bread and cookies, (2) examine the impact of combining organic and non-GMO labels on the WTP for organic products and whether it depends on consumers' prior knowledge that organic must be non-GMO, (3) examine the impact of including gluten-free, sugar-free or low-carb labels on the WTP for organic products, and (4) evaluate the effect of factors including overall knowledge and familiarity with organic and gluten/wheat intolerance/avoidance on the WTP. The findings will benefit food manufacturers and marketers as they develop new products and marketing strategies. The

number of labels on the products newly introduced to the U.S. market has greatly increased in the recent years (U.S. Department of Agriculture Economic Research Service, 2017), but consumers may or may not value specific label combinations. The insights regarding multiple labeling that involves the organic label specifically may be of great importance to manufacturers and marketers of products containing organic wheat.

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CHAPTER 1

ORGANIC WHEAT PRICES AND PREMIUM UNCERTAINTY: DO CROSS HEDGING AND FORECASTING PLAY A ROLE?

1.1 Abstract

We compare the volatility of organic wheat prices to that of conventional wheat prices using historical measures. To reduce uncertainty associated with organic wheat prices and organic premium, we examine the possibility of cross hedging using conventional wheat futures and the ability of futures to forecast the organic prices. Results provide some evidence that conventional futures can be used to cross hedge organic wheat price risk, but results depend on the method used to impute the missing values and time period. Similarly, we find a long-run equilibrium relationship between organic wheat prices and conventional wheat futures prices. Finally, futures prices contain some information useful in predicting organic prices in the short run.

1.2 Introduction

Organic foods have gained popularity among consumers in the US during the last two decades, documented by the significant increase in consumers' demand for organic food. For example, the sales of organic foods have increased more than 10-fold in the period between 1997 and 2017, from $3.4 billion to $45.2 billion (Organic Trade Association, 2018), despite the significant organic premiums that most organic food products command. Many studies have investigated what drives consumer demand for organic food. As summarized in Hughner et al. (2007), the common reasons include beliefs that organic food

is healthier, safer, and tastes better than conventionally produced food. Also, consumers of organic food believe that organic production is better for the environment, promotes animal welfare, and supports local economies. The interest in organic foods coupled with organic premiums has encouraged some producers to switch from conventional to organic production, but in many markets the supply increases have not kept up with increases in consumer demand.

The organic wheat market has experienced increased scarcity as demand for organic wheat products has grown. Organic wheat acreage for both food and feed production represented just 1% of total U.S. wheat acreage and 6.7% of total U.S. organic acreage in 2016 (U.S. Department of Agriculture, 2017a), but bread and grains accounted for 9% of overall organic food consumption in 2012 (U.S. Department of Agriculture, 2017b). The Organic Trade Association (OTA) found that growth in the organic grain market "could have been even more robust in 2015 if greater supply had been available" (OTA, 2016), suggesting that demand growth in the organic grain market has outpaced supply growth in recent years.

Agricultural production is inherently risky since yields are largely affected by factors outside of producers' control, such as weather, pests, and diseases. In addition, agricultural commodity prices and market conditions at harvest are unknown when production decisions are made. Producers who adopt organic production practices face additional challenges and restrictions from the National Organic Program (U.S. Department of Agriculture, 2002), which defines national standards for the organic production system. These restrictions include limited use of chemical inputs such as

fertilizers and pesticides and usually lead to reduced yields (Lotter, 2003; Korsaeth, 2008; Seufert, Ramankutty, and Foley, 2012; De Ponti, Rijk, and Van Ittersum, 2012) and higher total production costs per bushel as a result. While limits on fertilizer and pesticide use may decrease the per acre operating costs of organic compared to conventional grain production, the total per acre economic costs of producing organic grains may be higher when other costs—such as labor and land—are included (McBride et al., 2015). Lower per acre yields in organic production further increase total costs per bushel compared to conventional production.

Looking at wheat specifically, McBride et al. (2012) find that the additional operating, capital, and economic costs of producing organic wheat were \$2–\$4/bu over conventional wheat in 2009,[2] while the organic wheat premium was \$3.79/bu, indicating that the higher costs of producing organic wheat can be offset with higher organic prices. Thus, organic wheat production can be more profitable than the conventional production, assuming the transition period to organic production has already been made. But it also indicates that the relative profitability of the organic wheat production depends on the organic premium, which in turn depends on how organic and conventional wheat prices develop over time. Organic wheat prices have changed rapidly in past years, leading to an overall increase in excess of 140% between 2010 and 2017 and positively affecting the organic premium. Although current organic wheat prices allow for profitable organic wheat production in the West, growers face uncertainties regarding the length of favorable market

[2] The authors used data from 2009 Agricultural Resource Management Survey (ARMS) of organic and conventional wheat growers. The higher cost to produce organic wheat was driven by lower yields of organic wheat production (30 bu/acre) compared to those of conventional wheat production (44 bu/acre). The authors also accounted for the cost of transitioning to organic wheat production.

conditions, which potentially affect their decision to begin or continue dryland organic wheat production. This study evaluates the uncertainty associated with organic prices and premiums and explores options that growers may have to manage this uncertainty.

This essay has three primary objectives. First, we compare the risks associated with organic and conventional wheat prices by examining the historical volatilities and evaluate the organic premium risk by calculating the probability that the organic premium falls below additional costs of producing organic wheat. We hypothesize that organic wheat prices are more volatile than conventional wheat prices, making organic wheat production riskier from the perspective of growers, possibly affecting negatively growers' perceptions about organic wheat profitability and acting as a barrier to adopting organic wheat production practices.

Second, we explore some options that growers considering conversion to or maintaining organic wheat production have to manage the price risk associated with organic wheat. More specifically, we investigate whether hedging in conventional wheat futures mitigates the organic wheat price risk and whether conventional futures prices can be used to predict organic cash prices. Since the number of cash transactions on the organic wheat market is likely not large enough to support trading in organic wheat futures, we consider the alternative of using conventional wheat futures to cross hedge organic price risk. To estimate the optimal hedge ratio, we use a cointegration approach, which is based on the concept of market integration.

Our analysis is complicated by the limited availability of historical organic wheat price data and missing observations in the data that are available. Our third objective is to

simulate missing organic wheat prices. We use three methods to add robustness to our analysis and to help determine whether our results are sensitive to the methods. This will allow us to highlight possible limitations and provide more validity to our results. In addition, we investigate which method is the optimal one.

1.3 Background and Literature Review

1.3.1 Price Volatility as a Measure of Price Uncertainty

Price volatility is defined as the deviation of a price from its mean value or price movements within a short period of time (Balcombe, 2010). Higher volatility makes it harder to predict future prices and creates more uncertainty associated with future price expectations. In general, commodity prices are highly volatile (Deaton and Laroque, 1992; Pindyck, 2004). The main factors that contribute to price volatility for agricultural commodities are instability of supply due to weather, pests, and weeds; inelastic short-run demand and supply; changes in food and agricultural policies; and current prices that affect production decisions (Demeke et al., 2012). McKay (2016) compares the price volatility of organic commodities and their conventional counterparts from 2007–2015 and finds that organic corn, soybeans, and oats prices were less volatile than conventional prices, while organic wheat and barley prices were more volatile. Higher volatility of prices for organic commodities can affect the risk perceptions associated with the relative profitability of organic production. We compare the volatilities of wheat prices using historical volatilities, while McKay (2016) uses a coefficient of variation.

1.3.2 Organic versus Conventional Production Profitability and Risk Perceptions

While some studies have found that organic production is less profitable than conventional production (Dobbs and Smolik, 1997), other studies have found the opposite. Mahoney et al. (2004) find that net returns for selected organic crops are significantly larger than those for conventional crops, and they are statistically equal when organic price premiums were not considered. Delbridge et al. (2013) consider the possible differences in the size of organic and conventional farms to evaluate whole-farm net returns for a corn–soybean rotation and find that risk-averse growers would be better off adopting organic production practices. However, this result is sensitive to the changes in the organic premium and yields. Similarly, Archer et al. (2007) find that during the period of transitioning to organic—when growers do not receive organic premiums for their crops—the rotation systems of corn, soybean, and wheat generate lower net present values than do conventional systems. However, results for organic production are more positive when organic premiums are considered. These studies suggest that the profitability of organic production depends on the price premiums, which in turn depend on how organic and conventional prices develop over time. Thus, higher volatility and uncertainty of organic prices, if found, can affect rates of adoption or continuation of organic production and confirms the value of having tools to manage the uncertainty associated with organic price premiums.

1.3.3 Hedging and Optimal Hedge Ratio

Investments in agricultural production generally occur well before harvest; in the interim, prices usually change. Hedging is one tool used to mitigate the risk associated with price

changes in agriculture. Often, the most efficient hedge is not a one-to-one hedge. In other words, not all the spot risk is hedged in the futures market. Instead, hedgers apply an optimal hedge ratio (OHR). Traditionally, it is calculated as the ratio of the covariance between spot and futures prices, S_t and F_t, to the variance of the futures prices, F_t, (Myers and Thompson, 1989) with the goal to minimize the variance of the portfolio, expressed as

$$(1\text{-}1) \quad \lambda^* = \frac{Cov(S_t, F_t)}{Var(F_t)}.$$

OHR can be estimated using regression analysis, but several techniques using different assumptions have been used in the literature. Some studies assume a constant (static) OHR over time, which can be estimated using ordinary least squares (OLS) estimation methods (e.g., Rolfo, 1980; Wilson, 1982; Benninga, Eldor, and Zilcha, 1984; Figlewski, 1994). Other studies relax this assumption by allowing the distribution of spot and futures prices to vary over time, making it possible to estimate a time-variant (dynamic) OHR using variations of generalized autoregressive conditional heteroskedasticity (GARCH) and stochastic volatility models (Cecchetti, Cumby, and Figlewski, 1988; Baillie and Myers, 1991; Park and Switzer, 1995; Chang, McAleer, and Tansuchat, 2011; Revoredo-Giha and Zuppiroli, 2014).[3] Although some studies show that assuming a time-invariant OHR is not appropriate (Baillie and Myers, 1991), others show that using more complex models to account for a time-variant OHR does not lead to significant reduction in portfolio variance (Lien, Tse, and Tsui, 2002; Lien and Tse, 2002; Cotter and Hanly, 2012). Lien and Luo (1994) compare the hedging performance of a GARCH model and a

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[3] Lien and Tse (2002) provide a thorough review of the traditional (static) and recently developed (dynamic) hedging frameworks.

vector error correction (VEC) model in the presence of conditional heteroskedasticity using data from major foreign exchange markets. While the GARCH model has been found to have better statistical performance when estimating OHRs, it has not been found to have better hedging performance, which is what ultimately matters to a hedger. Hence, we start with the assumption that the OHR is constant over time and examine the validity of that assumption by performing specification tests.

Regardless of methodology, most studies find that the OHR is less than unity, meaning that the naïve method of hedging all expected production using futures contracts is usually not appropriate. Looking at wheat specifically, Wilson (1982) examines the efficiency of the U.S. futures markets for several wheat varieties and finds that the time-invariant OHR is less than unity and the risk is reduced more if nearby futures contracts are used as opposed to those in the more distant future. Revoredo-Giha and Zuppiroli (2014) compare the effectiveness of short-term hedging of wheat price risk using U.S. and European futures markets, while considering time-varying OHRs. They find that U.S. futures markets can reduce the price variance of the portfolio by 77% with the OHR close to unity, while European markets reduce the variance by only 30% with the OHR significantly less than unity.

1.3.4 Cross Hedging

The organic wheat market is considered thin. Because of the lack of liquidity, there is no futures market for organic wheat. Thus, we evaluate the possibility of cross hedging, which involves hedging in a futures market for a related commodity. The challenging task is to find a related commodity. According to Anderson and Danthine (1981), the correlation

between prices of the hedged commodity and the related futures commodity must be significantly different from 0.

Several studies have examined the possibility of cross hedging when no futures contract is established for the commodity in question. Blake and Catlett (1984) simulate a routine cross hedge and find that the use of corn futures to manage the price risk of hay increased gross returns per ton of hay. Zacharias et al. (1987) apply a numerical simulation approach and find that growers can benefit from cross hedging the price risk of rough rice using wheat futures. On the other hand, Coffey, Anderson, and Parcell (2000) find that cross hedging the price risk of grain by-products (corn gluten feed, hominy, distiller's dried grain) using corn futures fails to perform efficiently.

This study builds on the previous literature by examining the possibility of cross hedging organic wheat price risk using conventional wheat futures. To estimate the OHR, we use the cointegration approach, which is based on the concept of market integration. Understanding market integration not only allows us to estimate cross-hedge OHR but also investigate the dynamics between organic spot prices and conventional futures prices. This, in turn, can be used to evaluate the potential of conventional futures prices to predict organic spot prices.

1.3.5 Market Integration

If the same information is used to form expectations about supply and demand in two different markets, these markets and their prices become linked. The strength of the linkage between prices can be examined by investigating their long-run and short-run relationships. If nonstationary prices share a stable long-run equilibrium, then the markets are said to be

cointegrated. In this case, if one of the prices deviates from this equilibrium due to a shock in the market, an adjustment will take place to re-establish the equilibrium relationship.

For cointegration between two markets to exist, the prices need to be nonstationary in levels. Given two nonstationary series, x_t and y_t, the series are said to be cointegrated if there exists a unique β_1 that renders the difference $y_t - \beta_0 - \beta_1 x_t = u_t$ stationary. In this case, β_1 is a cointegrating parameter and the difference $y_t - \beta_0 - \beta_1 x_t$ is a cointegrating regression.[4]

Traditionally, market integration has been examined between spot markets for the same commodity connected horizontally across space (Gonzalez-Rivera and Helfand, 2001; Rapsomanikis, Hallam, and Conforti, 2006; Asche et al., 2012; Rosa, Vasciaveo, and Weaver, 2014) or vertically along the supply chain (Cramon-Taubadel, 1998; Pozo, Schroeder, and Bachmeier, 2013) and between different commodities acting as substitutes (Campiche et al., 2007; Rosa, Vasciaveo, and Weaver, 2014). Some studies have examined market integration specifically between spot markets for organic and conventional commodities, which are qualitatively differentiated but can potentially act as substitutes to some extent (Kleemann and Effenberger, 2010; Singerman, Lence, and Kimble-Evans, 2014; Würriehausen, Ihle, and Lakner, 2015; Nemati and Saghaian, 2016; Ankamah-Yeboah, Nielsen, and Nielsen, 2017).

Other studies have used the cointegration concept to investigate whether futures prices can be used to forecast spot prices and to examine the efficiency of futures markets

[4] Maddala and Kim (1999) provide detailed review of cointegration. Rapsomanikis, Hallam, and Conforti (2006) offer a brief review of cointegration and testing for cointegration.

in transmitting price signals to spot markets (Bessler and Covey, 1991; Lai and Lai, 1991; Wahab and Lashgari, 1993; Beck, 1994; Fortenbery and Zapata, 1997; Aulton, Ennew, and Rayner, 1997; McKenzie and Holt, 2002; Wang and Ke, 2005; Carter and Mohapatra, 2008). Understanding the relationships between futures and cash markets can be helpful in determining how changes in futures markets can impact spot prices. If current futures prices are unbiased forecasts of future spot prices, then the futures markets are said to be efficient and can be used to forecast future spot prices. Fewer studies have used cointegration specifically to estimate OHRs, and their overall aim was to compare the effectiveness of cointegration and conventional approaches in the process of OHR estimation (see the Methods section).

1.4 Data

We use monthly farm gate/FOB organic and conventional food grade wheat prices as spot prices, which were collected from the Agricultural Marketing Service (AMS) and the Economic Research Service (ERS) agencies of the U.S. Department of Agriculture (USDA) between January 2008 and August 2017. In total, 116 pricing observations were obtained for conventional wheat and 85 observations for organic wheat, with 26.7% of the organic wheat prices missing.

To add robustness to our analysis and to examine whether the results are sensitive to the methods used, we imputed values for the missing organic prices using three methods: i) spline interpolation, ii) exponential weighted moving average, and iii) an expectation-

maximization with bootstrapping (EMB) algorithm.[5] While the first two methods consider only observations in the proximity of the missing values, the EMB algorithm utilizes the whole distribution of the data in the imputation process. In addition, it accounts for the time series nature of the data.

Futures prices for conventional wheat correspond to the soft red winter variety traded at the Chicago Board of Trade (CBOT) and are collected from the Commodity Research Bureau (CRB) with monthly frequency. Futures contracts are available for 5 delivery months in each year—March, May, July, September, and December. The futures price series is a collection of nearby futures prices between January 2008 and August 2017, with a total of 116 observations. We roll over to the contract with the next available delivery month in the month of an actual delivery period. For example, for the futures contract with a maturity date in March, we record futures prices up to February. In March, we use the price of the May contract.

All spot and futures prices used in the analysis are deflated using the seasonally adjusted consumer price index for cereals and bakery products. Figure 1-1 shows the plot

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[5] The spline interpolation method fills in missing values by connecting observed values immediately before and after the missing values using a smooth curve. The exponential weighted moving average method calculates a missing value by taking the average of several observed values before and after the missing value, with the observations immediately before and after the missing observation receiving the highest weight. Weights decline exponentially with more distant observations. The EMB algorithm works under the assumption that the complete data (observed and unobserved) follow a multivariate normal distribution with the distribution parameters $(\mu,\Sigma) = \theta$ and that the data are missing at random. First, the algorithm finds the posterior distribution of the complete-data parameters θ given the observed data and then it takes m draws of θ from this posterior distribution. In the next step, missing data are obtained by drawing values from the complete-data distribution conditional on the observed data and the draws of θ, creating m sets of complete data. In the last step, we combine m imputed values by taking a simple average using the Amelia II package developed by Honaker, King, and Blackwell (2011). We choose $m = 10$ in our analysis, but the Honaker, King, and Blackwell (2011) note that $m = 5$ is usually adequate.

of observed organic wheat spot prices and conventional wheat spot and nearby futures prices. Organic and conventional wheat prices tend to move in the same direction, suggesting a potential long-run relationship between the price series. But the difference between the prices (i.e., the organic premium) varies over time. The plots show no clear trend in the development of prices, as periods of price increases and decreases follow one another. Lastly, the plots suggest that organic prices are less stable than conventional prices. Also, as expected, conventional futures and spot prices follow each other closely. Figure 1-2 depicts observed organic prices as well as prices obtained using the three imputation methods. There are some differences in the imputed organic prices across the three methods, particularly around 2016, when no data were observed for several consecutive months.

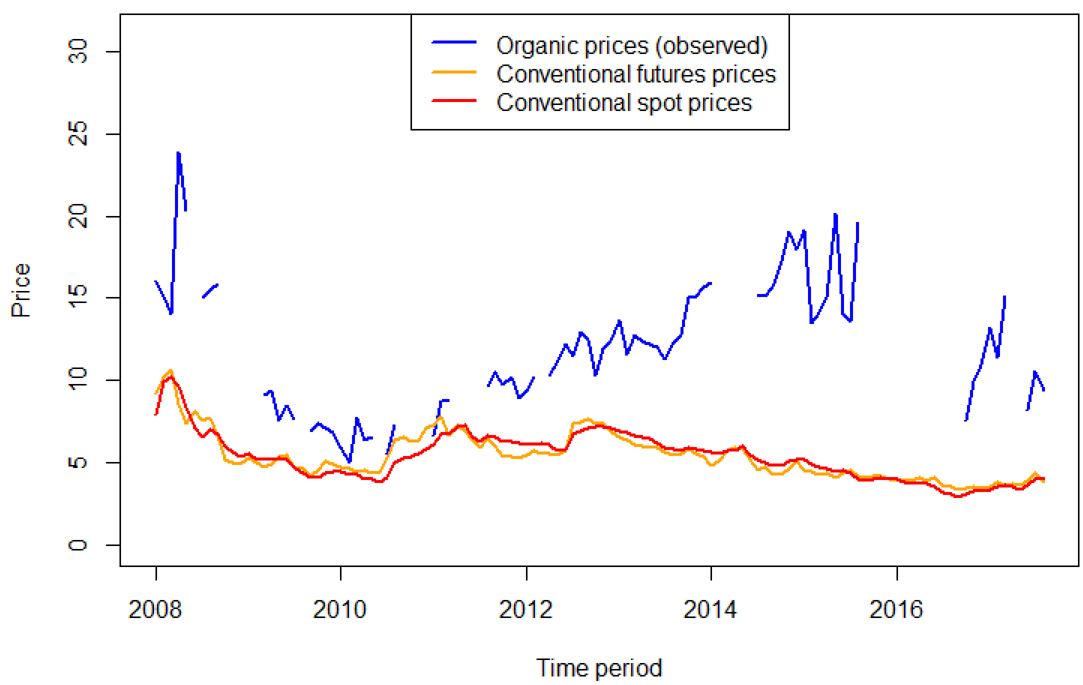

Figure 1-1. Observed monthly organic wheat spot prices, and conventional wheat spot and futures prices, 01/2008–08/2017 ($/bu)

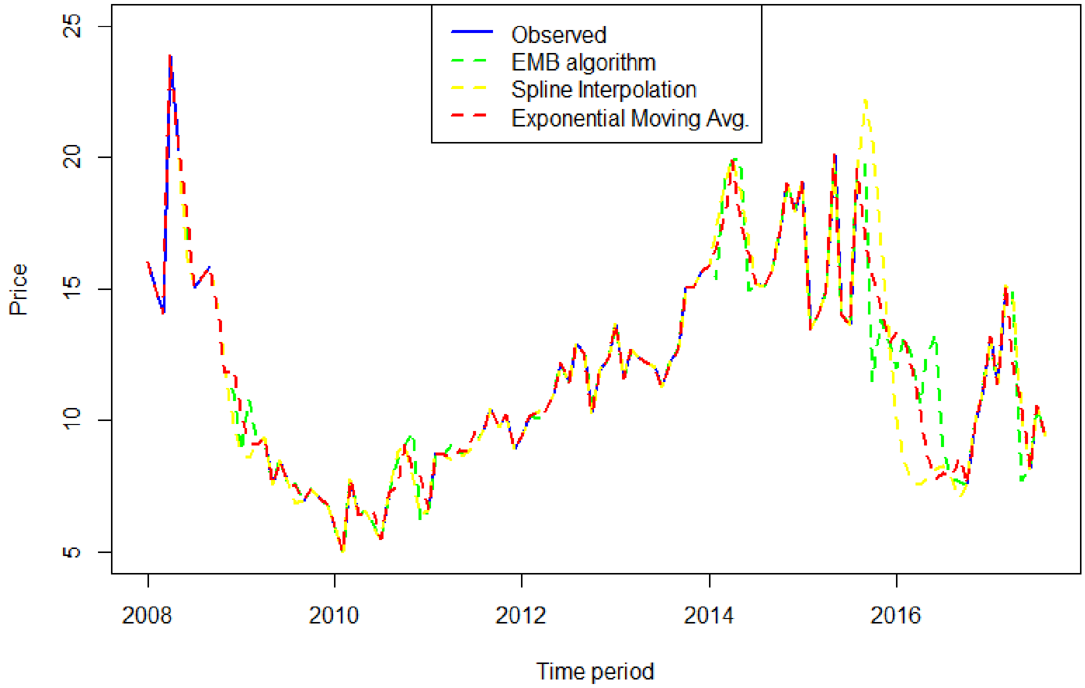

Figure 1-2. Observed monthly organic wheat prices compared to complete organic prices obtained using three imputation methods ($/bu)

Table 1-1 reports summary statistics for all price series and the organic premium, calculated as the difference between organic spot prices (observed and imputed) and conventional spot prices. Organic wheat prices are on average double conventional wheat prices. Similarly, the range of the organic prices is double the range of conventional prices. The standard deviation for each organic price series is relatively large compared to conventional wheat (spot and futures) prices, indicating higher uncertainty associated with organic prices. Using an *F*-test, we find that the differences in variance between organic prices and conventional spot and futures prices are statistically significant.

Table 1-1. Summary Statistics for Conventional Wheat Futures and Spot Prices, Organic Wheat Spot Prices, and Organic Premium, January 2008–August 2017 ($/bu)

	No. of Obs.	Mean	St. Dev.	Min.	Max.	Range
Conventional futures prices[a]	116	5.41	1.44	3.38	10.70	7.32
Conventional spot prices	116	5.38	1.44	2.93	10.19	7.27
Organic spot prices						
Observed	85	11.96	3.96	5.02	23.91	18.89
EMB algorithm	116	11.92	3.92	5.02	23.91	18.89
Spline interpolation	116	11.80	4.18	5.02	23.91	18.89
Exponential weighted moving avg.	116	11.85	3.85	5.02	23.91	18.89
Organic premium						
Observed	85	6.41	3.72	0.55	15.66	15.11
EMB algorithm	116	6.54	3.77	0.29	15.86	15.57
Spline interpolation	116	6.42	4.00	0.50	18.27	17.77
Exponential weighted moving avg.	116	6.48	3.67	0.55	15.66	15.11

Note: [a] Nearby futures prices (soft red winter variety); that is, prices for the nearest futures contract. The contract is rolled over to the second-nearest contract the day before an actual delivery period.

As mentioned previously, the price risk of a commodity can be cross hedged by taking a position on the futures market for a related commodity, under the condition that the correlation between the prices of the two commodities be significantly different from 0 (Anderson and Danthine, 1981). In general, stronger correlations create more effective hedges. Table 1-2 reports the correlations between conventional futures prices and the three organic spot price series. We find the correlations to be significant at the 90% confidence level and between 0.15 and 0.17, depending on the method used to impute missing organic prices. Positive correlations indicate that the spot and futures prices move in the same direction more than half the time, implying that hedging could be risk-reducing.

Table 1-2. Correlations between Conventional Futures Prices and Organic Spot Prices

	Conventional Futures	Organic EMB Algorithm	Organic S.I.[a]	Organic E.W.M.A.[b]
Conventional Futures	1.000	0.152*	0.157*	0.166*
Organic EMB Algorithm		1.000	0.940***	0.968***
Organic S.I.[a]			1.000	0.963***
Organic E.W.M.A.[b]				1.000

Note: *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.
[a] Spline Interpolation
[b] Exponential Weighted Moving Average

1.5 Methods

1.5.1 Organic Premium Risk and Price Risk Evaluation

To evaluate the risk associated with the organic premium, we first find the best-fitting probability density. Since four organic wheat price series are available (one observed and three imputed using the three imputation methods), we obtain four organic premium series. We use kernel density to fit each organic premium set because it does not impose any potentially limiting assumptions about the distribution of the data.[6] In the next step, we sample 10,000 values from each kernel density. The values are drawn from each fitted kernel density with the probability that is attached to each value of the fitted density, so that the density of the simulated values comes close to the fitted kernel density. The simulated values are then used to calculate the probability that the organic premium falls below the additional costs of producing organic.

[6] The Epanechnikov (quadratic) kernel is chosen for the kernel function, since it can be shown that it is an optimal kernel, but in general the choice of kernel is not critical (Cameron and Trivedi, 2005). The unbiased cross-validation method is used for the bandwidth selection, as it is entirely data-driven and minimizes the integrated squared error, which is a global measure evaluating the performance of the kernel smoothing at all data points (Cameron and Trivedi, 2005).

Next, we calculate historical volatilities of organic and conventional prices. This enables us to compare how much prices change from one period to another and how much uncertainty is associated with the change. Since we have monthly data, we calculate monthly historical volatilities and we calculate the moving volatilities over a period of 12 months, following the standard procedure (described, e.g., in Figlewski, 1994).

1.5.2 Estimation of Optimal Hedge Ratio

Historically, an OLS regression of spot prices, S_t, on futures prices, F_t, at time *t*, with both prices either in levels, differences, or as percentage changes, has been used to estimate the OHR, expressed as

(1-2) $S_t = \mu + \lambda F_t + \varepsilon_t,$

where slope coefficient λ is the OHR. However, the effectiveness of this approach is limited since the OHR obtained from equation (1-2) does not account for the past information available to the hedger at time *t* (Myers and Thompson, 1989), and it likely yields an unreliable OHR if the relationships between the spot and futures prices are not specified correctly (Ghosh, 1993). Thus, we apply a method that extends this simple OLS approach and include lags of futures and spot prices that may play a role in explaining the movements in spot prices and capture the short-run relationships between the prices. We also incorporate the cointegration relation, when it exists, between spot and futures prices, to account for the long-run relationships between the prices. As summarized in Lien and Tse (2002), several studies (e.g., Lien and Luo, 1994; Ghosh, 1993; Wahab and Lashgari, 1993; Chou, Denis, and Lee, 1996) have found that this cointegration approach performs

better than the simple OLS approach in equation (1-2). If cointegration is not found, we estimate

$$(1\text{-}3) \quad \Delta OS_t = \mu + \lambda \Delta CF_t + \sum_{i=1}^{k} \beta_i \Delta OS_{t-i} + \sum_{j=1}^{l} \gamma_j \Delta CF_{t-j} + \varepsilon_t,$$

as proposed by Myers and Thompson (1989). If cointegration is found, we add the error correction term to obtain

$$(1\text{-}4) \quad \Delta OS_t = \mu + \lambda \Delta CF_t + \sum_{i=1}^{k} \beta_i \Delta OS_{t-i} + \sum_{j=1}^{l} \gamma_j \Delta CF_{t-j} + \alpha Z_{t-1} + \varepsilon_t,$$

as described in Lien and Tse (2002). In each case, the OHR is the estimate of the slope coefficient λ. In these equations, ΔOS_t is the difference between the organic wheat spot prices in two time periods $OS_t - OS_{t-1}$, ΔCF_t is the difference between the conventional wheat futures prices in two time periods $CF_t - CF_{t-1}$, ΔOS_{t-i} is the *i*th lag of the organic spot price difference, and ΔCF_{t-j} is the *j*th lag of the conventional futures price difference. The number of lags, *k* and *l*, is determined by the Akaike Information Criterion (AIC), and Z_{t-1} in equation (1-4) is the lagged error correction term, obtained from the regression between OS_t and CF_t,

$$(1\text{-}5) \quad OS_t = \alpha + \beta CF_t + z_t.$$

The regression analysis applied is a part of either a structural vector autoregressive (SVAR) or a structural vector error correction (SVEC) model, depending on whether equation (1-3) or (1-4) is estimated, respectively. Typically, estimating SVAR and SVEC models in the case of a bivariate price analysis involves a simultaneous estimation of the system of two equations, where each price variable is in function of its own lags and lags

of the other price variable, and the contemporaneous relationship between the two price variables is captured in one of these two equations only. Given our interest in estimating the OHR, we only consider equations with organic price set as the dependent variable. Following the theory behind OHR calculation, we include the contemporaneous effect of conventional futures prices in the equation.

1.5.3 Examination of Relationships between Prices

In addition to estimating the OHR, equations (1-3) and (1-4) also allow us to examine long-run and short-run relationships between organic spot and conventional futures prices. Understanding these relationships provides insights into the possibility of predicting organic spot prices using conventional futures prices. Following Rapsomanikis, Hallam, and Conforti (2006), we perform short-run and long-run causality tests to determine whether futures prices can be used to predict organic prices (or vice versa). Short-run causality is examined using Granger causality tests, following Toda and Yamamoto (1995). Using this procedure, we apply a Wald test to determine whether prediction of one price variable improves if lags of the other price variable are included in the vector autoregressive (VAR) model. The model is estimated using prices in levels. If the joint effect of past lags of price series x_t is significantly different from 0 in the equation with the price series y_t as the dependent variable, then x_t is said to Granger-cause y_t, and past values of x_t can be used to improve the prediction of y_t.

If cointegration is found between the prices, then we examine long-run causality by applying a standard *t*-test to the coefficient of the error correction term estimated using equation (1-4). If the coefficient on the error correction term is significantly different from

0 in the equation with price series y_t as dependent variable, then the long-run causality runs from x_t to y_t.

1.6 Results

1.6.1 Risks Associated with Organic Premium and Prices

The best-fitting kernel densities for organic premiums are in figure 1-3. Densities of organic premiums are far from being normal, as they are visibly skewed to the left, indicating that an organic premium of lower value is more likely to occur. The fitted density of organic premium calculated with organic prices imputed using the exponential weighted moving average is closest to the fitted density of the observed organic premium.

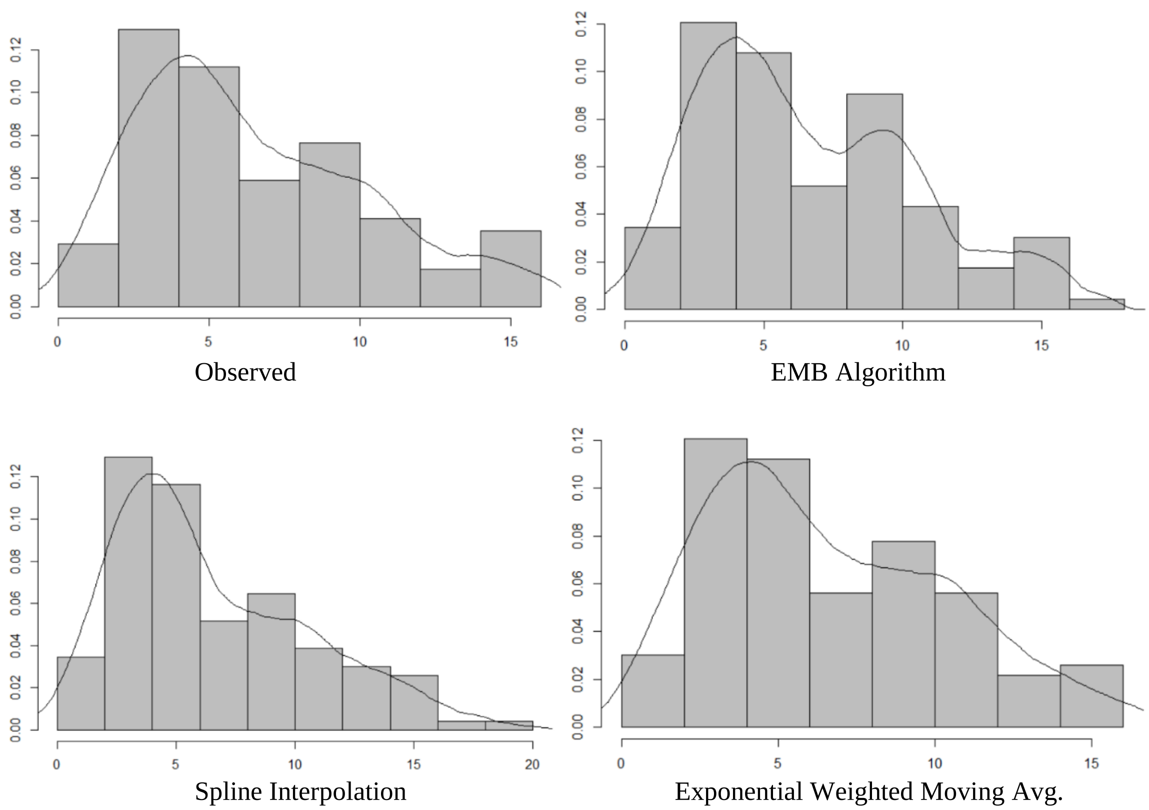

Figure 1-3. Histogram of data and kernel density for organic premiums

In the next step, 10,000 draws are taken from each estimated kernel density to obtain the probability of the premium being less than $4/bu as an upper limit and less than $2/bu as a lower limit (the estimated increased costs for organic wheat, following McBride et al., 2012).[7] We also obtain the probability of organic premiums above $8/bu. This allows growers to cover organic costs across two periods. Table 1-3 reports the mean values, standard deviations and probabilities, calculated using the simulated organic premiums. With a simulated mean organic premium of $6.47–$6.63/bu, organic wheat growers would more than offset the higher cost per bushel by producing organic wheat. However, the calculated probabilities need to be examined to understand the risk associated with the premium.

Table 1-3. Means, Standard Deviations, and Probabilities Calculated Using Simulated Organic Premiums

Organic Premium	Mean ($/bu)	St. Dev. ($/bu)	Pr(<$2) (%)	Pr(<$4) (%)	Pr(>$8) (%)
Observed	6.52	3.97	10.44	30.64	32.37
EMB algorithm	6.62	3.92	9.37	30.24	34.83
Spline interpolation	6.47	4.21	11.40	33.31	31.85
Exponential weighted moving avg.	6.63	3.98	10.86	30.45	35.18

The probability of observing an organic premium below the maximum additional cost of $4/bu is 30.2%–33.3%. In other words, if the premium falls below $4/bu, which happens approximately one-third of the time, the grower may be unable to cover the additional costs, resulting in lower profitability of the organic wheat compared to

[7] The probabilities were calculated as follows: First, all 10,000 values were ordered from the lowest to the highest and then, to calculate the probability of organic premium being below $*x*/bu, the count of all drawn values below or equal to $*x* was divided by 10,000.

conventional. Results also show that the probability of organic premiums below $2/bu is 9.4%–11.4%, which means that in 10% of the time, wheat growers will not receive organic premiums sufficient to cover the additional costs. However, the lower relative profitability in one period is likely compensated by higher profitability in other periods. As results in table 1-3 show, the probability of organic premiums being above $8/bu, which is enough to cover the additional costs of producing organic for two periods, is 31.9%–35.2%.

It is important to note that all calculated probabilities are unconditional, which means they represent the probability of an event occurring over the entire observed period, not taking into consideration specific values observed today. For example, if a premium below $4/bu is observed today, the probability of observing a premium below $4/bu in the next month is more than 30% due to the time series nature of the data and strong dependence between observations in two adjacent time periods. However, as the time passes, the dependence weakens, and higher premiums may be more likely to be observed.

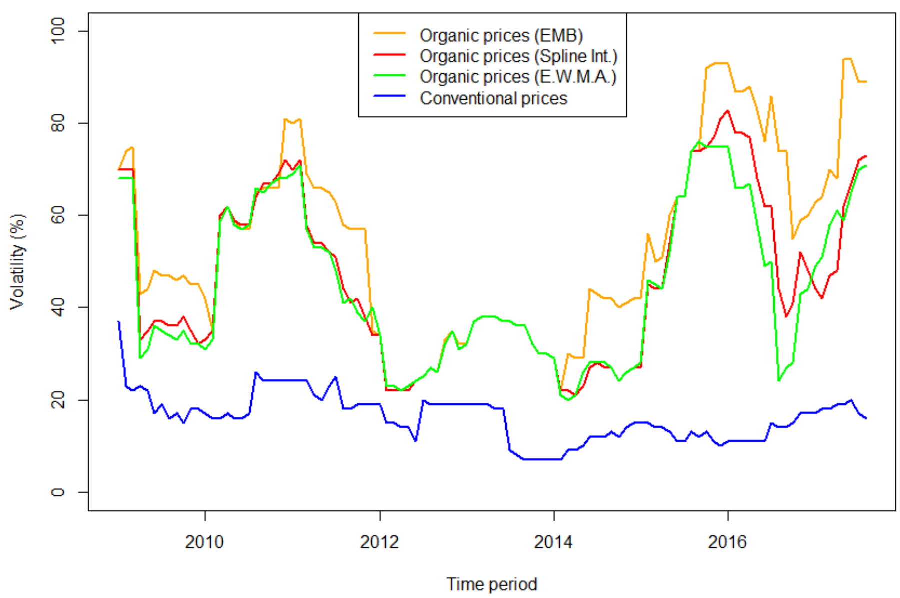

Figure 1-4. Annualized historical volatilities

Next, we calculated monthly historical volatilities of organic and conventional wheat prices and annualized them by multiplying each calculated volatility by $\sqrt{12}$, plotted in figure 1-4. The plots provide visual evidence that organic prices are more volatile than conventional prices. Annualized volatilities of conventional prices are 10%–40%, while the annualized volatilities of organic prices are 20%–90%, double that of conventional prices. This shows that organic prices tend to change more dramatically and are less stable over a short horizon. The plots also show that periods of higher volatility are followed by periods of lower volatility in the case of organic prices, while the volatilities of conventional prices are relatively stable over time. This suggests that if more organic wheat production is desired, more risk-averse growers may need tools that will enable them to efficiently manage the risk associated with organic prices and premiums.

1.6.2 Time Series Properties of the Data

As a first step in any regression analysis involving time series, it is necessary to examine whether the time series are stationary using unit root tests. We apply three commonly used tests to determine whether the price series used in the analysis are stationary: the Augmented Dickey–Fuller (1979) ADF test, the Phillips–Perron (1988) PP test, and the Kwiatkowski–Phillips–Schmidt–Shin (1992) KPSS test. We use all three since some tests perform better in certain circumstances.[8]

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[8] For example, some studies suggest that the Augmented Dickey–Fuller test may perform poorly and tend to accept the null of nonstationarity in the presence of serial correlation or heteroskedasticity (Rapsomanikis, Hallam, and Conforti, 2006; Esposti and Listorti, 2013).

For each set of organic cash and conventional futures prices, we confirm that the prices are nonstationary in levels and stationary after first differencing.[9] This leads us to test for cointegration between cash and futures prices. We apply the maximum likelihood method developed by Johansen (1988, 1991). We use the AIC to determine the number of lags, k, to be used. We estimate the trace and maximum eigenvalue statistics using a constant in the cointegrating equation. Table 1-4 reports trace test statistics, λ_{trace}, and maximum eigenvalue test statistics, λ_{max}, for each pair of prices. The null hypothesis of no cointegrating relationship ($r = 0$) is rejected for all three pairs of conventional futures prices with organic spot prices using at least one of the two estimated statistics; we therefore estimate equation (1-4) for each pair.

Table 1-4. Johansen Cointegration Test Results

	Number of Cointegrating Vectors = Rank (r)			
	Null	Alterna-tive	λ_{trace}	λ_{max}
Conventional futures and organic spot prices (EMB algorithm)	$r = 0$	$r = 1$	16.65	13.99*
	$r = 1$	$r = 2$	2.65	2.65
Conventional futures and organic spot prices (spline interpolation)	$r = 0$	$r = 1$	22.07**	15.03*
	$r = 1$	$r = 2$	7.04	7.04
Conventional futures and organic spot prices (exponential weighted moving avg.)	$r = 0$	$r = 1$	20.71**	14.87*
	$r = 1$	$r = 2$	5.85	5.85

Note: * and ** denote significance at the 10% and 5% level, respectively.

[9] Unit root test results are available from the authors upon request.

1.6.3 Cross Hedge for Organic Wheat Using Conventional Wheat Futures

Table 1-5 reports the results of estimating the OHRs. The AIC selected 3 lags, 1 lag, and 1 lag as optimal for the regressions involving organic prices imputed using the EMB algorithm (Model 1), the spline interpolation (Model 2), and the exponential weighted moving average (Model 3), respectively. Table 1-5 also reports results of misspecification tests. We fail to reject the null of no autocorrelation using the Box–Ljung test for all three models. This means the models are well specified in terms of the number of included lags.

Table 1-5. Regression Results

$$\Delta OS_t = \mu + \lambda \Delta CF_t + \sum_{i=1}^{k} \beta_i \Delta OS_{t-i} + \sum_{j=1}^{l} \gamma_j \Delta CF_{t-j} + \alpha Z_{t-1} + \varepsilon_t$$

	Model 1 (EMB Algorithm)		Model 2 (Spline Interpolation)		Model 3 (Exponential Weighted Moving Avg.)	
	Estimate	SE	Estimate	SE	Estimate	SE
μ	-0.041	0.194	-0.007	0.192	-0.062	0.180
ΔCF_t	0.276	0.456	-0.841**	0.408	-0.879**	0.381
ΔOS_{t-1}	-0.272***	0.097	0.024	0.092	-0.219**	0.090
ΔOS_{t-2}	-0.290***	0.095	-	-	-	-
ΔOS_{t-3}	-0.145	0.089	-	-	-	-
ΔCF_{t-1}	0.793*	0.403	1.385***	0.382	1.092***	0.358
ΔCF_{t-2}	0.518	0.408	-	-	-	-
ΔCF_{t-3}	0.095	0.409	-	-	-	-
Z_{t-1}	-0.022	0.039	-0.008	0.017	0.000	0.014
Misspecification tests						
Autocorrelation						
Q-stat (lags = 2)	0.186		0.912		1.006	
Conditional heteroskedasticity						
$Q(m)$	6.093		12.771		11.591	
Rank test	18.653**		29.037***		24.369***	
$Q_k(m)$	45.049		53.059*		46.221	
$Q_k^r(m)$	52.473*		46.040		45.799	
Q-stat (lags = 2)	7.036**		3.238		0.803	

Note: *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

The coefficient estimate on the differenced futures price in the current period, ΔCF_t, is of primary interest because it represents the OHR. In Model 1, the coefficient estimate is not statistically significant, implying that organic wheat price risk cannot be cross hedged using conventional futures. In Models 2 and 3, the coefficient estimate is statistically significant and large, but negative. Based on the calculation of OHR shown in equation (1-1), the covariance between organic spot prices and conventional futures prices is negative, after controlling for lags and the error correction term included in the estimated regressions. Thus, if there is an increase in futures prices, the organic spot prices decrease and vice versa. Typically, spot and futures prices for the same commodity are positively correlated. In that case, growers first sell futures contracts and later, when both spot and futures prices decline, losses in the spot market can be offset with a gain in the futures market. But a negative OHR coefficient means that spot and futures prices move in opposite directions, making a typical strategy of first selling futures contracts not applicable. However, if growers purchase futures contracts first, then growers can offset the loss in the spot market with gains in the futures market if spot prices decline and futures prices increase. This means that cross hedging organic price risk using conventional futures prices can be applied in practice, even if spot and futures prices move in opposite directions. However, we find only limited evidence for the possibility of cross hedging organic prices using conventional futures, since only two of the three estimated models show an OHR significantly different from 0.

1.6.4 Relationships between Organic Spot and Conventional Futures Prices

The significance of the lagged price variables in table 1-5 suggests that there are short-run relationships between organic spot and conventional futures prices. The results differ slightly based on the method used to impute missing organic prices, but there is agreement across the three models that past futures prices affect organic prices. The results of the Wald test, applied to examine short-run Granger causality (reported in table 1-6), provide some evidence that futures prices Granger-cause organic prices, meaning that past futures prices contain information that helps predict current organic prices in the short run. On the other hand, results show clearly that organic prices do not affect futures prices in the Granger sense, regardless of the method used to impute the organic prices.

Table 1-6. Short-Run Granger Causality Tests

	No. of Lags in VAR Model	χ^2 Statistic	*p*-Value
Futures prices Granger-cause organic prices			
EMB algorithm	4	5.3	0.260
Spline interpolation	1	10.3***	0.001
Exponential weighted moving avg.	2	12.5***	0.002
Organic prices Granger-cause futures prices			
EMB algorithm	4	2.0	0.740
Spline interpolation	1	0.8	0.380
Exponential weighted moving avg.	2	3.2	0.200

Note: *** denotes significance at the 1% level. H_0: X does not Granger-cause Y (= dependent variable in VAR model). Number of lags in VAR models (in levels) is determined based on AIC.

Results further show that coefficients from the error correction term in all three models are not significant, although a cointegrating relationship has been found between organic spot and conventional futures prices. The insignificance of the error correction term in the models with organic prices as dependent variables suggests that if there is a shock to

the system, it is the futures price that adjusts to the deviation from the long-run equilibrium. This has been confirmed by the significance of the error correction term in the regressions with the conventional wheat prices as the dependent variable (not reported).[10] Although the long-run relationship from organic prices to futures prices means that futures prices adjust to the deviation from the long-run equilibrium, it happens slowly, over a longer period of time. On the other hand, the relatively large short-run effect from futures prices to organic prices means that information from the conventional futures market is passed to the organic spot market quickly, in a relatively short time. Thus, we find some evidence that futures prices can be used to predict organic prices, but only for short horizons.[11]

1.6.5 Evaluation of Imputation Methods

Since we find that results are not robust to the methods used to impute missing organic prices, we evaluate the performance of each imputation method based on how accurately it predicts the values for the missing observations. First, 10% of the originally observed organic prices (9 of 85 total observations) are dropped randomly. Then, each method is applied to impute the values of the observations dropped from the dataset. Lastly, the root mean squared error (RMSE)[12] is calculated using the imputed and observed values and compared across the three methods.

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[10] These results are based on the specification of the cointegrating relationship in equation (1-5), where organic spot price is set as dependent variable. However, we verified that the results are robust to the specification of the cointegrating relationship.

[11] We repeated the whole analysis using hard red winter futures, finding similar results in terms of negative OHRs and the existence of dynamic relationships.

[12] The RMSE is the root of the mean of the squared deviations between the imputed and observed values of the organic prices: $RMSE = \sqrt{\frac{1}{N}\sum_1^N \left(P_{imputed} - P_{observed}\right)^2}$.

The lowest RMSE (= 2.45) is found for the exponential weighted moving average method. The RMSE value for the EMB algorithm method is 2.75, and the largest RMSE (= 2.87) is found for the spline interpolation method. We therefore consider the results obtained using the exponential weighted moving average method to have the highest validity and to be the most appropriate to conclude with.

1.6.6 Further Examination of OHRs

Since we find negative OHR, which had not been expected given the positive unconditional correlations between the conventional futures and organic spot prices (reported in table 1-2), we further examine the unconditional correlations and OHRs in selected subperiods to determine the significance of the obtained result and whether it is driven by any particular time period. We split the sample in two subperiods: i) January 2008–December 2012 and ii) January 2013–August 2017. We choose to split the data in this way for two reasons. First, the initial, pooled sample is relatively small, with only 116 observations; splitting it into two subsamples of similar sizes (60 and 56 observations) will yield estimates of comparable statistical validity. Second, based on the plot of organic spot and conventional futures prices in figure 1-1, the development of prices appears to become more divergent starting in the second half of 2013. Table 1-7 reports the unconditional correlations between the conventional futures and organic spot prices in the two subperiods. All correlations are positive and statistically more significant than correlations found for the pooled prices series.

Table 1-7. Correlations between Conventional Futures Prices and Organic Spot Prices

	EMB Algorithm	Spline Interpolation	Exponential Weighted Moving Avg.
01/2008–12/2012	0.63***	0.64***	0.63***
01/2013–08/2017	0.35***	0.34***	0.36***

Note: *** denotes significance at the 1% level.

For each subperiod, we estimate the same models in terms of number of lags and presence of cointegration as those estimated using the whole sample, with the justification that all observations come from the same data-generating process. Table 1-8 reports models estimated for the 2008–2012 subperiod. The magnitude of the estimated OHR remains negative and significant in Models 2 and 3, despite strong positive unconditional correlations. In contrast with results obtained for the whole period, 2008–2017, there is a clear indication that there is no short-run relationship between organic spot and conventional futures prices in 2008–2012, regardless of the methods used to impute missing prices. However, organic prices are now found to adjust to the deviations from long-run equilibrium, and the speed of adjustment is significantly high. Table 1-9 reports the results of models estimated for the 2013–2017 subperiod. The OHR is positive but insignificant, regardless of the method used to impute missing prices. Additionally, there is no clear pattern of short-run and long-run relationships across the three methods.

To summarize, considering the results obtained using the exponential weighted moving average method—since it has been found to be the most accurate in predicting missing organic prices—the possibility of cross hedging organic wheat price risk is dependent on the time period. However, there is evidence of short-run and/or long-run relationships between the prices, depending on the time period.

Table 1-8. Regression Results, 01/2008–12/2012

	Model 1 (EMB Algorithm)		Model 2 (Spline Interpolation)		Model 3 (Exp. Weighted Moving Avg.)	
	Estimate	SE	Estimate	SE	Estimate	SE
μ	-0.005	0.152	-0.066	0.192	-0.065	0.190
ΔCF_t	0.022	0.281	-0.692**	0.331	-0.654*	0.329
ΔOS_{t-1}	-0.165	0.105	-0.092	0.111	-0.234**	0.111
ΔOS_{t-2}	-0.063	0.098	-	-	-	-
ΔOS_{t-3}	-0.159*	0.084	-	-	-	-
ΔCF_{t-1}	0.278	0.298	0.415	0.396	0.035	0.382
ΔCF_{t-2}	0.279	0.294	-	-	-	-
ΔCF_{t-3}	0.066	0.294	-	-	-	-
Z_{t-1}	-0.207***	0.071	-0.264***	0.074	-0.276***	0.071
Misspecification tests						
Autocorrelation						
Q-stat (lags = 2)	1.012		0.442		0.151	
Conditional heteroskedasticity						
Q-stat (lags = 2)	0.496		1.032		0.464	

Note: *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 1-9. Regression Results, 01/2013–08/2017

	Model 1 (EMB Algorithm)		Model 2 (Spline Interpolation)		Model 3 (Exp. Weighted Moving Avg.)	
	Estimate	SE	Estimate	SE	Estimate	SE
μ	-0.363	0.420	-0.164	0.315	-0.149	0.289
ΔCF_t	1.255	1.394	0.524	1.093	0.229	0.998
ΔOS_{t-1}	-0.360**	0.148	0.140	0.135	-0.159	0.131
ΔOS_{t-2}	-0.431***	0.141	-	-	-	-
ΔOS_{t-3}	-0.165	0.148	-	-	-	-
ΔCF_{t-1}	2.541**	1.253	1.640	1.090	2.185**	0.986
ΔCF_{t-2}	0.812	1.372	-	-	-	-
ΔCF_{t-3}	-1.827	1.424	-	-	-	-
Z_{t-1}	-0.032	0.025	-0.165**	0.069	-0.132*	0.068
Misspecification tests						
Autocorrelation						
Q-stat (lags = 2)	0.485		0.559		0.868	
Conditional heteroskedasticity						
Q-stat (lags = 2)	3.689		5.550*		1.389	

Note: *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

1.7 Conclusions

In this study, we examine the profitability risk associated with organic wheat, focusing on organic prices and premiums. As expected, we find organic prices to be more volatile than conventional wheat prices, indicating there is more uncertainty associated with organic wheat prices. Simulating organic premiums reveals that, depending on the method used to impute missing prices, there is a 30%–33% probability of observing a premium below \$4/bu, assumed to be the maximum additional cost of producing organic wheat, and a 9%–11% probability that the premium will be below \$2/bu, assumed to be the minimum additional cost of producing organic wheat. Thus, there are occasions when organic wheat production is relatively less profitable per bushel than conventional wheat production. On the other hand, there are more occasions when organic wheat production is more profitable per bushel and the gains from organic premiums cover the additional costs. We find that the probability of observing an organic premium above \$8/bu is 32%–35%. However, these probabilities are unconditional, not taking into consideration the observed premium in a particular time period. For example, if the observed premium is low in one period, it is likely to be low in the next time period as well.

The analysis suggests that tools to manage the risk associated with the organic prices and premium may be needed if more organic wheat production is desired. Since the organic premium and the organic wheat price are linked and there is no futures market established for organic wheat, we examine the possibility of hedging the organic wheat price risk using conventional wheat futures contracts. Results suggest that the coefficient representing OHR is significantly different from 0 but negative. This means that there is

an inverse relationship between changes in organic spot and conventional futures prices. In this case, growers looking to mitigate losses from a decrease in spot prices could cross hedge using conventional futures prices, but they need to purchase conventional futures contracts as their hedge. However, the statistical significance of the estimated OHRs is sensitive to the methods used to impute the missing organic prices and the time period, providing only limited evidence that organic price risk can be cross hedged using conventional futures prices.

In addition to examining OHRs, the estimated models allow us to investigate the short-run and long-run dynamics between the organic spot and conventional futures prices. We find complex relationships between the two prices. Considering the entire studied time period, tests of short-run Granger causality reveal that futures are weakly exogenous, meaning that they contain some information to help predict organic spot prices in the short run. Our analysis also provides some evidence of cointegration between organic spot and conventional futures markets. However, we find organic prices to be weakly exogenous in the long run, meaning that futures prices adjust to the deviations from the long-run equilibrium relationship rather than organic prices, but the speed of adjustment is slow. Further examination of the dynamic relationships in different time periods reveals that their nature has been changing over time. The organic wheat market was developing in the studied period and its lack of maturity and stability could have affected the dynamic relationships.

We conclude that cross hedging the risk associated with organic prices using conventional futures market might be useful to growers, but the evidence is limited. Recent

changes in the federal crop insurance program, which allow wheat growers to use prices agreed to in a contract or organic wheat price election established by USDA in calculating their compensation, make the crop insurance program likely a better option. Conventional futures prices can be used to predict organic wheat prices, but only over a short timeframe, based on our examination of the dynamic relationships in recent years.

This essay is the first one to examine dynamic relationships between futures and spot prices of two qualitatively differentiated commodities—conventional and organic, respectively. Further, it is the first study to examine the possibility of hedging the price risk of an organically grown commodity using futures market of the same commodity but grown conventionally. However, there are some limitations: First, we did not observe the organic wheat prices completely and the imputed prices contain some error. Second, our results are limited to the studied ten-year period. An extension of the dataset with additional, future prices might affect the results, in particular since we find that the results differ across the studied subperiods. Thus, the results need to be considered with caution. Nevertheless, these findings are useful in providing direction for future research to examine in more detail how conventional wheat futures prices might affect the development of organic prices in the short run. This can be of great importance to growers and food manufacturers as they attempt to predict the movement of organic wheat prices. Also, future research can identify other commodities that might be more closely correlated with organic wheat prices and could potentially be examined for cross-hedge possibilities.

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CHAPTER 2

HOW DO CURRENT AND POTENTIAL CONSUMERS OF ORGANIC WHEAT PRODUCTS DIFFER FROM NON-CONSUMERS? A MARKET SEGMENTATION ANALYSIS

2.1 Abstract

We use latent class modeling to identify groups of "very likely," "likely," and "unlikely" consumers of organic wheat products based on factors indicating their preferences for organic wheat products and attitudes toward organics in general. We perform the analysis for two types of wheat products—bread and cookies—using data from an online survey conducted across the western United States in Summer 2017. The results show that significant differences, which are not product-specific, exist across the segments. "Very likely" consumers rank price and taste as less important compared to the other two groups, who tend to believe that organic products are too expensive, regular products taste better, and organic products are not better. These groups value local and natural labels over organic label. In addition, significant differences in willingness to pay (WTP) for certified organic, socio-demographics, lifestyles, and shopping and consumption habits are found across the segments. Finally, we find that those with some wheat/gluten intolerance/avoidance tend to be "very likely" consumers of organic wheat products.

2.2 Introduction

The demand for organic wheat in the US is currently stronger than domestic supply. There is an initiative to stimulate and support organic wheat production in the U.S. western states

by addressing grower concerns regarding yields, soil quality, weed management and productivity (U.S. Department of Agriculture – National Institute of Food and Agriculture, 2014-2020). However, it is also important to understand who current and potential consumers of organic wheat products are, what product attributes are important to them, and what determines or limits their interest in organic foods. This knowledge can help manufacturers and marketers to make production and marketing decisions when allocating the limited supply of organic wheat and to better understand market growth potential.

A large body of research characterizes consumers of organic foods and assesses the determinants of their interest in and WTP for organics across a variety of products (e.g., Jolly, 1991; Gil, Gracia, and Sanchez, 2000; Lockie et al., 2004; Krystallis and Chryssohoidis, 2005; Hughner et al., 2007). However, studies disagree in their assessments of which consumer characteristics and factors play a role in identifying consumers of organic foods versus non-consumers. For example, some studies find that demographics do not explain organic shopping behavior well and that attitude and lifestyle factors tend to explain it better (Li, Zepeda, and Gould, 2007; Gracia and de Magistris, 2013), while others find significant relationships between demographics and organic food demand (Govindasamy and Italia, 1999; Loureiro, McCluskey, and Mittelhammer, 2001; Onyango, Hallman, and Bellows, 2007; Ngobo, 2011).

The overall purpose of this essay is to segment consumers into “very likely,” “likely,” and “unlikely” consumers of organic bread and cookie products to examine the differences between the segments and identify factors that determine their interest level and preferences for organics. To our knowledge, this study is the first one to perform such

analysis with the focus on products containing organic wheat.

This study has four objectives: (1) We cluster consumers into segments based on their attitudes toward organic products and production systems, their past purchases of organic wheat products, and the importance they place on certified organic labels to identify groups of "very likely," "likely," and "unlikely" consumers of organic wheat products. We use factor analysis to reduce the number of attitudinal variables used in the segmentation process, and then we apply latent class modeling to carry out the segmentation. (2) We examine the differences among the groups in terms of their preferences for labels and product characteristics, reasons for purchasing or not purchasing organic wheat products, socio-demographics, lifestyle characteristics, and shopping and consumption behavior. Finally, we (3) calculate WTP values for certified organic products for the entire sample and for each segment; and (4) examine the differences in findings across the two types of wheat products.

2.3 Background and Literature Review

2.3.1 Determinants of Organic Food Choice and Consumption

The literature on organic food consumption (Hughner et al., 2007) indicates that organic consumers are in general female and have children living with them, while the effects of age, education, and income are either insignificant or inconsistent across the studies. The discrepancies may be a result of different methodologies, samples of respondents from culturally different regions, or the category of product analyzed. For example, using a sample of respondents in Sweden, Magnusson et al. (2001) found that respondents aged 18–25 demonstrated stronger intentions to purchase organic bread, while gender, education

level and presence of children played no role.

However, some studies find that other consumer characteristics such as lifestyle and attitudinal factors can explain consumer behavior and sometimes better than socio-demographics (Gil, Gracia, and Sanchez, 2000; Li, Zepeda, and Gould, 2007; Gracia and de Magistris, 2013). Gil, Gracia, and Sanchez (2000) segmented Spanish consumers by lifestyle attributes and found that consumers who were concerned about a healthy diet and the environment were most likely to purchase organic food and pay a premium. On a similar note, Gracia and de Magistris (2013) found that attitudes towards organic foods regarding health and environmental benefits affected intention to purchase organic foods and the final decision. Li, Zepeda, and Gould (2007) found that consumer beliefs that organic foods are more nutritious was an important determinant of organic food purchases.

Attitudes toward organic products and production systems have been found to play a role in motivating purchase of organic food products in general, but positive attitudes do not necessarily translate into purchasing decisions. Some studies have found that many respondents express positive attitudes toward organic production, but their purchase frequency is still low (Magnusson et al., 2001; Bellows et al., 2008; Aertsens et al., 2009). We use attitudes toward organic production systems in conjunction with the consumer purchase history of organic wheat products to identify consumers who have positive attitudes toward organic food but do not necessarily purchase organic wheat products, to explore their characteristics and preferences and identify possible barriers to purchasing organic wheat products.

2.3.2 Consumer Preferences Related to Wheat Products and WTP for Certified Organic

Few studies examine the attributes consumers consider when purchasing or consuming bread products specifically. Magnusson et al. (2001) found that 97% and 94% of respondents in Sweden selected taste and freshness, respectively, as important or very important, while only 17% selected organic production. Using organic bread as the food item presented to respondents, Lusk and Briggeman (2009) found that safety, nutrition, taste, and price were among the most important food values for U.S. consumers. Bitzios, Fraser, and Haddock-Fraser (2011) found that the key attributes that UK consumers considered when purchasing bread were the type of flour, price, texture, taste, aroma, and perceived healthiness, while the organic production method did not matter to them. Based on these studies, it appears that taste is considered universally important.

Several studies examined also consumer WTP for organic bread and cookies, although they were conducted either outside of the United States or they obtained WTP estimates for a whole sample rather than by consumer segment. Krystallis, Fotopoulos, and Zotos (2006) found that a sample of Greek consumers were willing to pay 75.5% more for organic bread than for conventional. Ureña, Bernabéu, and Olmeda (2008) found that a sample of Spanish consumers were willing to pay an average of 9.2% more for organic bread, biscuits, and sweets, with significant differences between men and women, and segments of regular, occasional, potential, and non-consumers, where regular male consumers were willing to pay the highest premium (19.2%) and probable female consumers the lowest (2.8%). Similarly, Zheng (2014) found that Canadian consumers were willing to pay 9.5% for certified organic whole grain bread, while Hasselbach and

Roosen (2015) found that consumers in Germany were not willing to pay for organic bread unless it was produced locally. Bitzios, Fraser, and Haddock-Fraser (2011) found that UK consumers do not care much about the organic label on bread, but a combination of functional ingredient and organic label yielded positive utility for consumers in one of the three segments they identified. Finally, Lee et al. (2013) found that U.S. consumers were willing to pay 50% more for organic cookies.

2.3.3 Motivations and Barriers to Purchasing Organic Products

Another topic that has been researched in the literature is motivations and barriers to purchasing and consuming organic products. Health and environmental concerns are among the main reasons that people purchase organic foods (Lea and Worsley, 2005; Padel and Foster, 2005; Zepeda, Chang, and Leviten-Reid, 2006). Other reasons include concerns about animal welfare, support for the local economy (Padel and Foster), and the belief that organic foods taste better (Lea and Worsley). Price and familiarity/availability of organic products are key barriers to purchasing organic foods (Lea and Worsley; Zepeda, Chang, and Leviten-Reid; Bellows et al., 2008), in addition to quality issues and lack of trust (Bellows et al.). For bread, price is a major barrier to purchasing organic (Magnusson et al., 2001; Kihlberg and Risvik, 2007). Kihlberg and Risvik found that a majority of consumers in Sweden think organic bread tastes better than conventional bread after a sensory assessment, but they would not buy it if the price were too high relative to conventional. In a sensory evaluation of whole grain bread, Teuber, Dolgopolova, and Nordström (2016) found that once taste was accounted for, a sample of German respondents were not willing to pay a premium for the organic label, suggesting that taste

is an important attribute for bread and consumers are not willing to compromise on it.

2.3.4 Effects of Product Type on Consumer Preferences for Organic Products

Past studies have found that consumers have different WTP for organic virtue and vice foods (Van Doorn and Verhoef, 2011), as well as divergent taste and nutritional expectations (Ellison et al., 2016). Thus, we perform the analysis using bread and cookies. Following Hui, Bradlow, and Fader (2009), bread can be classified as a virtue food item and cookies as a vice food item, in relation to long-term health outcomes and immediate pleasure from consumption. Analyzing two product categories will also allow us to examine in one study whether organic food consumers share common characteristics and preferences across virtue and vice products.

2.4 Data and Survey Methodology

The data used in the analysis come from an online survey conducted in 16 U.S. western states in June 2017. The same data are used in Essay 3; thus, the following survey description is relevant to both essays. The survey was designed and administered using the Qualtrics platform and a pretest of the survey was performed using a group of graduate students at Utah State University. A link to the final survey was sent to Qualtrics panelists in an email invitation to participate in the study. In return for the completion of the survey, they received points that they could trade later for rewards including cash and gift cards.

In total, 1,009 valid responses were received. The respondents were selected so that the sample was representative of the population in the western United States based on three criteria: age group, gender, and state of residence. Only respondents at least 18 years of

age were allowed to participate. Table 2-1 reports the share of respondents by state compared to the share of the population by state. Table 2-2 reports selected sociodemographic characteristics for the sample and population. The sample is fairly representative of the population in the western United States in terms of origin, gender, age group, marital status, household size, presence of children, and unemployment rate. The share of those with some college education or higher is greater in the sample than in the general population, while the share of those with household income above $100,000 and the labor force participation rate is lower. Organic consumers tend to be wealthier (e.g. Dettmann and Dimitri, 2009; Ngobo, 2011; Dimitri and Dettmann, 2012), likely to have busier schedules, and consequently have less time or interest to participate in online surveys. Thus, it appears that the organic consumers are underrepresented in the sample which needs to be considered when interpreting the results.

Table 2-1. Respondents and Population in the U.S. Western States by State

State	Sample count	Population count	Sample share	Population share
Arizona	92	5,206,537	9.1%	8.1%
California	512	30,028,400	50.7%	46.7%
Colorado	71	4,199,802	7.0%	6.5%
Idaho	21	1,222,749	2.1%	1.9%
Kansas	42	2,191,407	4.2%	3.4%
Montana	9	806,722	0.9%	1.3%
Nebraska	19	1,425,560	1.9%	2.2%
Nevada	21	2,222,290	2.1%	3.5%
New Mexico	26	1,585,693	2.6%	2.5%
North Dakota	11	585,614	1.1%	0.9%
Oklahoma	53	2,950,241	5.3%	4.6%
Oregon	52	3,167,825	5.2%	4.9%
South Dakota	3	648,789	0.3%	1.0%
Utah	32	2,083,586	3.2%	3.2%
Washington	40	5,558,381	4.0%	8.6%
Wyoming	5	446,607	0.5%	0.7%
All 16 states	1,009	64,330,203	100.0%	100.0%

Note: Population data are sourced from the U.S. Census Bureau, 2015 American Community Survey 1-Year Estimates, and exclude individuals less than 18 years of age.

Table 2-2. Socio-Demographic Characteristics of Respondents Compared to the Population in U.S. Western States

Characteristic	Sample mean	Population in U.S. western states
Female (%)	51.6	50.6
Age group (%)		
18–24 yrs.	11.8	13.0
25–44 yrs.	35.2	35.8
45–64 yrs.	35.5	32.8
>64 yrs.	17.5	18.4
Annual household income (%)		
<$10,000	5.9	6.1
$10,000–$49,999	44.7	36.6
$50,000–$99,999	32.9	30.3
$100,000–$149,999	10.7	14.4
>$149,999	5.7	12.6
Married (%)	50.1	52.2[a]
Household size (persons)	2.7	2.8
Presence of children <18 years (%)	33.6	32.9
Education attainment (%)		
Less than high school	0.5	14.0
High school	16.7	24.2
Some college or associate's degree	43.1	33.3
4-year college	26.6	18.5[b]
Graduate degree or higher	13.2	10.0
Labor force participation rate (%)	56.2	63.3[c]
Unemployment rate (%)	6.8	6.5[c]
Ethnic background (%)[d]		
African American	5.4	4.8
American Indian	1.0	1.7
Asian	6.3	8.8
Hawaiian	0.2	0.3
Other, one	0.5	7.6
Other, two or more	3.4	3.1
White (non-Hispanic)	72.2	58.6
White (Hispanic)	9.2	15.1

Note: Population data are sourced from the U.S. Census Bureau, 2015 American Community Survey 1-Year Estimates, and exclude individuals less 18 years of age, unless indicated otherwise.
[a] Sample includes persons 18+, population data for persons 20+.
[b] Includes graduate degree for the population between 18–24 years.
[c] Sample includes persons 18+, population data for persons 16+.
[d] Data source: U.S. Census Bureau, 2011–2015 American Community Survey 5-Year Estimates.

Respondents were asked a variety of survey questions about their shopping and

consumption habits, preferences related to labels and characteristics of bread and cookies, reasons for purchasing or not purchasing organic bread and cookies in the past, attitudes toward organic food and organic production in general, knowledge of organic production system and products, and lifestyle and sociodemographic questions. To determine consumer WTP and further examine preferences for selected labels (including organic), we employed a hypothetical choice experiment in which we repeatedly asked respondents to choose which alternative they would purchase in a real shopping scenario, considering their budget.

2.4.1 Choice Experiment Design

In each choice question, a respondent could choose from three alternatives: "conventional," "organic," and "none." Alternatives labeled "conventional" and "organic" varied in four attributes—"price" and the presence or absence of three labels: "non–GMO," "gluten-free," and "low-carb" for bread or "sugar-free" for cookies.

Price was drawn randomly from a range based on the national average price for each combination of product (bread or cookies) and production method (conventional or organic). The basis for the price range determination was the April 2017 U.S. average price point of $2.00/lb for high quality bread and $3.40/lb for chocolate chip cookies (Bureau of Labor Statistics, 2017). Following Carlson and Jaenicke (2016), who found an organic premium for bread of around 30% over conventional bread, we applied a 30% premium to conventional prices to obtain the price points for organic bread and organic cookies. Using these prices, we then established the price ranges based on an approximately 50% discount and a 100% premium above the obtained price points. Table 2-3 lists the attributes with

their levels or ranges.

Table 2-3. Attributes and Their Levels or Ranges

Attributes	Levels and ranges
Non–GMO label	Present/Absent
Gluten-free label	Present/Absent
Low-carb or sugar-free label	Present/Absent
Price	
Conventional bread	\$1.00–\$5.00
Organic bread	\$2.00–\$7.00
Conventional cookies	\$2.00–\$7.00
Organic cookies	\$3.00–\$8.00

Not considering the price attribute, each product alternative (conventional and organic) in each choice set could vary in three attributes with two levels per each attribute, resulting in $2^3 = 8$ possible specifications of each product alternative. Since two product alternatives were available in each choice set, there were $8 * 8 = 64$ total possible combinations of product alternatives and thus 64 possible choice sets, which we split into eight blocks with eight choice sets per block, while preserving the balance and orthogonality, which is necessary for optimal design with maximum statistical efficiency. Then, we added the price attribute to each alternative in each choice set by drawing the price randomly from the determined price ranges. Each respondent received one block of the choice sets for bread and one block for cookies, assigned randomly and independently of each other. In total, each respondent evaluated 16 choice sets. An example of the complete questionnaire is in Appendix A; the questionnaires differed across respondents only in terms of the assigned blocks of the choice sets.

2.5 Model Specification and Methodology

2.5.1 Latent Class Modeling

We employed a latent class model (LCM) within a discrete choice modeling framework. LCM combines the multinomial logit (MNL) model (McFadden, 1974; Train, 2009), which is a basic approach to modeling consumer preferences, and latent class analysis, which is an alternative to clustering techniques (Magidson and Vermunt, 2002). As such, LCM serves two purposes (Swait, 1994; Boxall and Adamowicz, 2002; Greene and Hensher, 2003): First, it allows to cluster consumers into latent (unobserved) classes (segments) based on selected segmentation characteristics. Second, during the segmentation process, a MNL model is estimated for each segment simultaneously. This procedure results in segments with homogeneous consumer preferences and characteristics within a segment and heterogeneous preferences and characteristics across segments, allowing to capture some of the heterogeneity in preferences which is not accounted for when a MNL model is estimated for the whole sample (see Ruto and Garrod, 2009; Hidrue et al., 2011).

Respondent n's utility from bread alternative *i* among *j=1,…,J* alternatives, U_{ni}, is

(2-1) $U_{ni} = V_{ni} + \varepsilon_{ni} = \beta X_{ni} + \varepsilon_{ni}$,

where V_{ni} is part of the utility that is observed by the researcher and ε_{ni} is unobserved and random. V_{ni} is linear in parameters and comprises a vector of attributes of bread alternative i (labels and price) faced by respondent n, X_{ni}, and a vector of taste parameters, β, associated with the attributes and assumed not to vary across respondents within the MNL framework.

A utility-maximizing respondent will choose bread alternative i among $j=1,\ldots,J$ bread alternatives if the utility from this alternative, U_{ni}, is greater than utility from all other available alternatives, U_{nj}, for all $j \neq i$. Following McFadden (1974) and Train (2009), the probability that the respondent *n* will choose bread alternative *i* is

$$(2\text{-}2) \quad P_{ni} = P\left(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}\ \forall j \neq i\right) = P\left(\varepsilon_{nj} < \varepsilon_{ni} + V_{ni} - V_{nj}\ \forall j \neq i\right).$$

Under the assumption that the unobserved ε's in equation (2-2) are i.i.d. type I extreme value, equation (2-2) can be rewritten as the product of cumulative density functions, $F(\varepsilon_{nj})$, for each $\varepsilon_{nj}\ \forall j \neq i$, where $F\left(\varepsilon_{nj}\right) = \exp\left(-exp\left(-\varepsilon_{nj}\right)\right) = \exp\left(-exp\left(-(\varepsilon_{ni} + V_{ni} - V_{nj})\right)\right)$. The resulting expression is further integrated over all possible values for ε_{ni}, and it can be manipulated to calculate the logit choice probability of choosing alternative *i* by respondent *n*, P_{ni}, as (Train, 2009)

$$(2\text{-}3) \quad P_{ni} = \frac{\exp(V_{ni})}{\sum_{j=1}^{J} \exp(V_{nj})} = \frac{\exp(\beta X_{ni})}{\sum_{j=1}^{J} \exp(\beta X_{nj})}.$$

Next, assuming that respondent *i* belongs to a latent class *q* ($q=1,\ldots,Q$, where Q is the number of latent classes), the logit choice probability is calculated as (Boxall and Adamowicz, 2002)

$$(2\text{-}4) \quad P_{ni|q} = \frac{\exp\left(V_{ni|q}\right)}{\sum_{j=1}^{J} \exp(V_{nj|q})} = \frac{\exp\left(\beta_q X_{ni}\right)}{\sum_{j=1}^{J} \exp(\beta_q X_{nj})},$$

where β_q becomes a class-specific vector of taste parameters, allowing the taste parameters to vary across classes. Further, assuming a vector of observed respondent-specific characteristics, Z_n, that determines class membership and a vector of the parameters for the respondent-specific characteristics in class q, θ_q, the probability of assigning

respondent *n* to latent class q can be calculated as (Boxall and Adamowicz, 2002; Greene and Hensher, 2003)

$$(2\text{-}5) \quad P_{nq} = \frac{\exp(\theta_q Z_n)}{\sum_{q=1}^{Q} \exp(\theta_q Z_n)}.$$

In this essay, the vector Z_n contains attitudes toward organic products and production systems, past purchases of organic breads/cookies, and ranked importance of the organic label in bread/cookies. The respondent-specific characteristics that are not observed but affect the assignment of respondent *n* to a latent class q, ε_{nq}, are assumed to be i.i.d. type I extreme value, as in the case of a MNL model (Boxall and Adamowicz, 2002; Greene and Hensher, 2003). Finally, the probability that any respondent *n* chooses a bread alternative *i* is calculated as (Boxall and Adamowicz, 2002)

$$(2\text{-}6) \quad P_{ni} = \sum_{q=1}^{Q} P_{nq}\, P_{ni|q} = \sum_{q=1}^{Q} \left[\frac{\exp(\theta_q Z_n)}{\sum_{q=1}^{Q} \exp(\theta_q Z_n)}\right]\left[\frac{\exp(\beta_q X_{ni})}{\sum_{j=1}^{J} \exp(\beta_q X_{nj})}\right].$$

The number of latent classes Q must be specified but is usually not known in advance. Therefore, we estimate models with two to eight classes and evaluate each model using several fit criteria, including the Akaike information criterion (AIC), Bayesian information criterion (BIC), Hannan-Quinn criterion (HQC), log-likelihood value, and pseudo-R^2. Lower AIC, BIC, and HQC and higher log-likelihood and pseudo-R^2 values indicate better overall fit. However, BIC has been found to perform relatively better compared to the other criteria considered (Nylund, Asparouhov, and Muthén, 2007; Jung and Wickrama, 2008).

2.5.2 Willingness to Pay

After the estimation of LCM, we calculate mean WTP values for the organic label within each class using two methods. Applying the first method, mean WTP for the organic label within a latent class q ($q = 1,\dots,Q$) is calculated as the negative ratio of the coefficient estimate for the organic label in class q, $\beta_{organic,q}$, to the coefficient estimate for price in class q, $\beta_{price,q}$,

$$(2\text{-}7)\quad WTP_{organic,q} = -\frac{\beta_{organic,q}}{\beta_{price,q}}.$$

For the WTP values calculated using equation (2-7), we use Delta method to construct confidence intervals around the mean WTP estimates and determine the significance of the mean WTP within each class.

Applying the second method, we use individual WTP values obtained for each respondent in the sample and calculate mean of the respondents' WTP values within each class. First, each respondent is assigned to one of the Q classes, so that $\sum_{q=1}^{Q} M_q = 1009$, where M_q is the number of respondents assigned to class q. For each respondent m_q ($m_q = 1, \dots, M_q$) in class q, we obtain the coefficient estimates for the organic label, $\beta_{organic,m_q}$, and price, β_{price,m_q}.[13] The individual WTP is then calculated as

$$(2\text{-}8)\quad WTP_{organic,m_q} = -\frac{\beta_{organic,m_q}}{\beta_{price,m_q}}.$$

Finally, the WTP within each class q is calculated as the average of the individual WTP values for all respondents m_q assigned to class q

[13] More details on how these individual level estimates are calculated can be found in Greene (2012).

$$(2\text{-}9) \quad WTP_{organic,q} = \frac{\sum_{m_q=1}^{M_q} WTP_{organic,m_q}}{M_q}.$$

We do not obtain standard errors for the mean WTP values which are calculated using this method, but the individual WTP values are useful for evaluating the statistical significance of the differences in WTP values across the groups of respondents.

2.5.3 Factor Analysis and Factor Scores

In total, respondents answered nine attitudinal questions, but some of the attitudes may be correlated. Before the estimation of LCM, we employed factor analysis to extract underlying latent factors describing the attitudes, with the aim to reduce the number of variables in vector Z_n in equation (2-6) while explaining sufficient amount of variance contained in the originally observed variables. First, we subjected the first half of the sample (n = 504) to exploratory factor analysis (EFA). The minimum residual method was used to extract potential factors[14] and the number of factors was determined using parallel analysis, scree test, selected fit indices,[15] and following common practice in the literature.[16] To enable possible nonzero correlations between factors, we applied the oblique rotation to the solution with desired number of factors. Next, to verify the EFA solution, we

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[14] Revelle (2017) suggests the minimum residual method as a good alternative to maximum likelihood method for factor extraction. Fabrigar et al. (1999) and Costello and Osborne (2005) cite maximum likelihood method as the best choice, but it assumes the data are multivariate normal. In this study, the assumption of multivariate normality does not hold.

[15] We used the Tucker–Lewis index (TLI), root mean squared error of approximation (RMSEA), and root mean square of the residuals (RMSR).

[16] 1) We retain variables with a minimum loading of 0.32 (Costello and Osborne, 2005; Tabachnick and Fidell, 2007), but prefer 0.50 for a strong factor (Costello and Osborne, 2005). 2) At least three variables need to load on a factor, and two variables only may load on a factor only if their correlation is above 0.70 (Yong and Pearce, 2013). 3) Variables with multiple correlations below 0.30 may need to be removed from analysis (Yong and Pearce, 2013).

subjected the second half of the sample (n = 505) to confirmatory factor analysis (CFA) (Fabrigar et al., 1999) and evaluated selected fit indices.[17]

In the next step, we proceeded to obtain each respondent's scores associated with the factors—factor scores—which were to be used in the LCM instead of the original attitudinal variables. There are several approaches to obtaining factor scores but no clear direction in the current literature regarding a preferred method (DiStefano, Zhu, and Mindrila, 2009; Yong and Pearce, 2013). First, factor scores can be obtained after either EFA or CFA. We opted to calculate factor scores after CFA (using the whole sample) because only the variables that load significantly on the factor are used in the calculation of the factor score, which eliminates the noise from weakly loading variables. Second, several methods of calculating factor scores are available (DiStefano, Zhu, and Mindrila discuss advantages and disadvantages). A major issue with factor scores is their indeterminacy (i.e., the possibility to obtain infinite number of scores that would be consistent with the same correlation pattern between the variables and underlying factors; Grice, 2001; DiStefano, Zhu, and Mindrila). Considering this issue, we chose to apply the Bartlett method,[18] which produces unbiased factor scores with high validity (Grice; DiStefano, Zhu, and Mindrila).

[17] We used the Tucker–Lewis index (TLI), root mean squared error of approximation (RMSEA), standardized root mean squared residual (SRMR), and comparative fit index (CFI).

[18] We found that the correlation between factor scores produced using Bartlett method after CFA (-0.44) came close to the correlation found between latent factors after EFA (-0.49). The approximation is referred to as correlational accuracy and is one of the measures that can be used to assess the degree of factor indeterminacy (Grice, 2001; DiStefano, Zhu, and Mindrila, 2009).

2.5.4 Differences across Groups

After the classes were identified using LCM, we organized them into groups of “very likely,” “likely,” and “unlikely” consumers based on the similarities and differences in terms of the preferences for the organic label and past purchases of organic bread and cookies. From now on, “class” or “segment” is used to refer to one of the latent classes obtained from LCM, and “group” to refer to the grouping of classes. After identifying the groups of respondents, we examined the statistical significance of the differences in selected characteristics between the respondents in the “very likely” group on one side and the respondents in the “likely” and “unlikely” groups on the other to determine which factors play a role in differentiating consumers from non-consumers. Where applicable, we also compared groups across product categories and/or contrasted the results within the bread and cookies product category to determine whether differences are product specific.

We examined differences in these characteristics: WTP for organic label in bread and cookies—calculated as mean of the individual WTP values of respondents in each group, based on equation (2-9); preferences for labels and characteristics of bread and cookies; interest in organic versions of bread, cookies, and other wheat product categories; possible motivations and barriers to purchasing organic bread and cookies; lifestyles; and consumption behavior. We used Welch’s *t*-test and Wilcoxon (Mann-Whitney) test to evaluate the significance of the differences. Both tests allowed us to compare the means or proportions for two groups under the assumption of unequal variance, but while the Welch test assumes that the data are normally distributed, the Wilcoxon test does not.

2.6 Results

2.6.1 Factor Analysis and Factor Scores

We performed Bartlett's test of sphericity ($\chi^2(36) = 2{,}095$, p-value < 0.001) and the Kaiser–Meyer–Olkin (KMO) test of factor adequacy (overall measure of sampling adequacy MSA = 0.80, MSA per variable > 0.67) and concluded that the factor analysis was appropriate. Following recommendations in the literature during EFA and using only the first half of the sample, we found that two attitudinal statements needed to be removed from analysis. Consequently, we obtained a satisfactory 2-factor solution. To confirm that this solution was appropriate, we performed CFA using the second half of the sample. Obtained fit statistics (Tucker–Lewis index TLI = 0.922, comparative fit index CFI = 0.951, root mean squared error of approximation RMSEA = 0.077, and standardized root mean squared residual SRMR = 0.048) indicated a moderately good fit .[19]

Table 2-4 summarizes the 2-factor solution after performing EFA on the whole sample and seven attitudinal statements. The first factor is strongly and positively correlated with beliefs that organic products are healthier and fresher than conventional ones, do not contain harmful substances, and the organic production is better for the environment. In summary, this factor represents a positive view of organic products and production; a belief that organic products and production are differentiated from conventional products and production.

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[19] We followed Hooper, Coughlan, and Mullen (2008), who summarized fit indices and their recommended cut-off values. Reported TLI and RMSEA indices were found to miss the recommendations; however, these indices were obtained using only one half of the sample. After performing EFA using the whole sample, all recommendations were met (see table 2-4 notes).

Table 2-4. Rotated 2-Factor Solution Applying EFA on the Whole Sample (n=1009)

Statement	Factor 1	Factor 2	Uniqueness
Organic products are healthier than conventional	0.75	-0.12	0.34
Organic products are fresher than conventional	0.72	0.15	0.57
Organic production is better for the environment	0.64	-0.11	0.50
Organic products do not contain harmful substances	0.63	0.04	0.63
Organic products are not safer than conventional	-0.09	0.67	0.49
Buying organic food does not benefit local farmers	0.09	0.64	0.64
Organic products do not taste better than conventional	-0.05	0.62	0.58
Variance explained	0.27	0.18	-

Note: TLI = 0.962 (>0.95), RMSEA = 0.058 (<0.07), RMSR = 0.02 (<0.05). Cut-off values for fit indices, in parentheses, are based on Hooper, Coughlan, and Mullen (2008).

The second factor is strongly and positively correlated with beliefs that organic products are not safer and do not taste better than conventional products and that buying organic food does not benefit local farmers. This factor represents a neutral view toward organic products and production, since it indicates a belief that organic products and production do not differentiate from conventional products and production. The two factors together account for 46% of total variance in the data.

The correlation between the factors is -0.49, indicating a relatively strong negative relationship. This exceeds the $\pm$0.32 threshold, which is used to warrant an oblique as opposed to orthogonal rotation (Tabachnick and Fidell, 2007). This finding of nonzero correlation is also supported by the theoretical reasoning that positive and neutral beliefs toward organic products and production may be negatively correlated. In addition, examining the correlation pattern between variables (see table 2-5) shows that correlations between statements loading on factors 1 and 2 are negative and the correlations involving

the two statements dropped from the factor analysis are relatively weak. Finally, we performed CFA to obtain the factor scores.

Table 2-5. Correlations between Statements

	Healthier	Fresher	Better for environment	No harmful substances	Not safer	No benefits for local farm	Not better taste	Too expensive	Selection not good
Healthier[a]	1.00	0.51	0.57	0.49	-0.39	-0.23	-0.36	-0.13	0.02
Fresher[a]	0.51	1.00	0.45	0.38	-0.17	-0.06	-0.20	-0.05	0.08
Better for environment[a]	0.57	0.45	1.00	0.42	-0.35	-0.26	-0.27	-0.09	0.03
No harmful substances[a]	0.49	0.38	0.42	1.00	-0.28	-0.10	-0.16	-0.08	0.05
Not safer[b]	-0.39	-0.17	-0.35	-0.28	1.00	0.41	0.47	0.22	0.12
No benefits for local farm[b]	-0.23	-0.06	-0.26	-0.10	0.41	1.00	0.38	0.15	0.19
Not better taste[b]	-0.36	-0.20	-0.27	-0.16	0.47	0.38	1.00	0.31	0.19
Too expensive	-0.13	-0.05	-0.09	-0.08	0.22	0.15	0.31	1.00	0.26
Selection not good	0.02	0.08	0.03	0.05	0.12	0.19	0.19	0.26	1.00

Note: [a,b] The same superscript indicates that the statements load on the same factor. Statements without superscripts were dropped from factor analysis and used in the subsequent analysis as is.

2.6.2 Latent Class Modeling

We estimated the LCM using NLOGIT 5.0 (Greene, 2012). Table 2-6 reports values for the criteria used to evaluate the model fit. For both bread and cookies, starting with a 2-class model all fit criteria improved with every additional class up to the 7-class model. Statistically, 7-class models appear to be best. However, considering 5% minimum size of class membership (Nasserinejad et al., 2017) and our focus on segments of current and potential consumers of organic products and interpretability of results (Jung and Wickrama, 2008), we chose 6-class models for bread and cookies.

Table 2-6. Criteria Used in Determining Number of Latent Classes (LC) in the LCM

	2 LC	3 LC	4 LC	5 LC	6 LC	7 LC	8 LC
Bread							
AIC	13,061	11,623	11,135	10,919	10,798	10,651	10,631
BIC	13,194	11,847	11,450	11,324	11,295	11,239	11,310
HQC	13,106	11,700	11,243	11,057	10,968	10,852	10,863
Log-Likelihood	-6,511	-5,780	-5,522	-5,401	-5,328	-5,242	-5,219
Pseudo R^2	0.266	0.348	0.377	0.391	0.399	0.409	0.412
Parameters[a]	19	32	45	58	71	84	97
Cookies							
AIC	12,046	11,249	10,715	10,586	10,435	10,286	10,256
BIC	12,179	11,473	11,029	10,992	10,931	10,874	10,935
HQC	12,092	11,325	10,822	10,725	10,604	10,487	10,488
Log-Likelihood	-6,004	-5,592	-5,312	-5,235	-5,146	-5,059	-5,031
Pseudo R^2	0.323	0.369	0.401	0.410	0.420	0.430	0.433
Parameters[a]	19	32	45	58	71	84	97

Note: Sample size is 8,072 choices from 1,009 individuals.
[a] Number of parameters in the estimated model.

2.6.2.1 Latent Class Modeling for Bread

Table 2-7 reports results of the LCM for bread. The results are organized in two sections: 1) MNL model estimates, and 2) latent class parameter estimates, obtained for each latent class. In the section with the MNL model estimates, the focus is on the stated preferences for the organic attribute, but all attributes presented to respondents in the choice experiment were included in the estimation process to account for the effect of these attributes on respondents' choices. The MNL model estimates for each segment are interpreted relative to a base product—a conventionally produced bread ("organic" = 0) without any labels ("non–GMO" = 0, "gluten-free" = 0, "low-carb" = 0). "No choice" measures the utility of choosing no bread relative to the base product. Table 2-7 also reports the mean WTP values for organic label for each segment, calculated based on equations (2-7) and (2-9).

Table 2-7. Latent Class Model Parameter Estimates, Bread

	Unlikely		Likely		Very likely	
Variable	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
Multinomial Logit Model Estimates						
Price	-1.02***	-1.50***	-2.88***	-0.63***	-0.32***	-0.48***
	(0.08)	(0.12)	(0.31)	(0.09)	(0.04)	(0.10)
Organic	-0.79***	-0.93***	1.96***	1.72***	0.49***	4.01***
	(0.19)	(0.13)	(0.40)	(0.27)	(0.09)	(0.42)
Non-GMO	0.00	0.25*	0.77**	-0.01	0.35***	0.62***
	(0.12)	(0.14)	(0.35)	(0.21)	(0.08)	(0.23)
Gluten-free	-0.80***	0.11	0.28	-0.46**	0.33***	0.72***
	(0.14)	(0.13)	(0.28)	(0.23)	(0.09)	(0.27)
Low-carb	-0.14	0.11	0.34	-0.15	0.38***	0.13
	(0.13)	(0.17)	(0.30)	(0.20)	(0.08)	(0.20)
No choice	-3.38***	-9.70***	-10.39***	1.50***	-2.89***	0.20
	(0.30)	(0.62)	(1.18)	(0.40)	(0.27)	(0.46)
WTP for organic[a]	-$0.77 ***	-$0.62 ***	$0.68 ***	$2.74 ***	$1.52 ***	$8.33 ***
WTP for organic[b]	-$0.54	-$0.50	$0.57	$2.56	$1.50	$7.99
Latent Class Parameter Estimates						
Intercept	-1.20***	-1.02***	-1.54***	0	-0.98**	-0.93*
	(0.42)	(0.37)	(0.55)		(0.39)	(0.49)
Factor 1[c] (organic better)	0.14 (0.16)	0.13 (0.14)	0.31 (0.21)	0	0.55*** (0.16)	1.11*** (0.23)
Factor 2[c] (organic not better)	0.60*** (0.17)	0.33** (0.15)	0.07 (0.22)	0	0.52*** (0.15)	0.08 (0.19)
Organic food is too expensive[c]	0.17 (0.14)	0.15 (0.13)	0.60*** (0.21)	0	-0.28** (0.12)	-0.50*** (0.15)
Selection of organic is not good[c]	-0.01 (0.12)	0.17 (0.11)	0.05 (0.15)	0	0.10 (0.12)	0.12 (0.14)
Rank of organic label in bread[d]	0.26*** (0.08)	0.28*** (0.07)	0.05 (0.10)	0	0.12 (0.07)	-0.19* (0.10)
Past purchase of organic bread	-0.75** (0.36)	-0.39 (0.29)	-0.08 (0.38)	0	1.63*** (0.29)	1.33*** (0.39)
Class probability	18.2%	24.2%	9.2%	17.6%	20.8%	9.9%
% purchased organic bread	13.3%	18.6%	31.8%	35.8%	76.1%	83.7%

Note: Standard errors are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.
[a] Mean WTP calculated according to equation (2-7); significance determined using Delta method.
[b] Mean WTP calculated according to equation (2-9); significance not available.
[c] The variables represent attitudes toward organic food and production systems either as a composite measure (“Factor 1” and “Factor 2”) or as an individual attitude if they did not load on any factor during factor analysis.
[d] 1 = highest, 7 = lowest.

The section with latent class parameter estimates in table 2-7 reports differences across segments with respect to the covariates used in the segmentation process. Significance and magnitude of each coefficient within a segment indicate whether and how the covariate affects the likelihood of a respondent being assigned to the segment, relative to the reference segment. Here, segment 4 is the reference segment, with its coefficients normalized to 0 to allow identification. The reference segment was selected arbitrarily by the software during the estimation process, but it did not affect choice and class probabilities. Ultimately, the interest is to identify differences in preferences for organic label on bread and how they relate to attitudes and past purchases of organic bread. Table 2-7 also reports the probability of assigning a respondent to each class and the percentage of respondents in each class who actually purchased organic bread in the past month.

In the next step, the six classes or segments were split into three groups, labeled "unlikely," "likely," and "very likely." The classes were grouped based on their similarities with respect to the combination of three criteria: "past purchase of organic bread", "% purchased organic bread in past month", and mean WTP values, given the interest to differentiate between respondents based on their likelihood to purchase organic bread.

Looking at table 2-7, consumers in segment 1 (18.2%) are very unlikely to be interested in organic bread. Among all segments, they tend to hold the strongest beliefs that organic products in general are not better than conventional products and they are least likely to have purchased organic bread in the past month. They also rank importance of the organic label in bread lower than the "very likely" and "likely" segments. On average, they chose the organic alternative only in one of eight choice scenarios. Looking at the results

of the MNL models, they do not show interest in any other labels offered to them in the choice scenarios and appear to be satisfied with basic bread products.

Consumers in segment 2 (24.2%) are also unlikely to be interested in organic bread, choosing the organic alternative only once in eight choice scenarios. Compared to segment 1, they tend to rank the importance of an organic label on bread similarly low, but they are less convinced that organic products are not better than conventional products and they show an interest in the non–GMO attribute, which is one of the components of organic. Similarly, as consumers in segment 1, they chose the organic alternative only once out of eight choice scenarios.

Among all segments, consumers in segment 3 (9.2%) are most likely to believe that organic products are too expensive. They derive positive utility from the organic attribute, but their perception that organic products are too expensive might act as a barrier to actual purchase. On average, in comparison to the "very likely" segments, they tend to believe less that organic products are better than conventional products. In our survey, they chose organic bread in three of the eight choice scenarios. They are also interested in the non–GMO label.

Segment 4 (17.6%) also constitutes a segment of "likely" organic bread consumers. They chose organic bread once in eight choice scenarios, not because they prefer conventional bread but rather due to their strong preference for no bread at all. Consumers in this segment are the only ones who prefer no bread to conventional; if they choose bread at all, they prefer organic.

Consumers in segment 5 (20.8%) are highly interested in organic bread. In

comparison to the two “likely” segments, they tend to hold more positive attitudes toward organics and disagree more that organic products are too expensive, but not as strongly as consumers in segment 6. In comparison to segment 6, they also tend to believe more that organic products are not better than conventional products. On average, they selected organic bread in four of eight choice scenarios. Besides organic, they gain positive utility from all labels offered to them in the choice scenarios.

Consumers in segment 6 (9.9%) are very enthusiastic about organic bread; on average, they selected organic bread in seven of eight choice scenarios. Among all segments, they tend to hold the strongest beliefs that organic products are better than conventional products, give the highest importance to the organic attribute, and disagree the most with the statement indicating that organic products are too expensive. They are also interested in non–GMO and gluten-free labels.

Among “very likely” and “likely” segments of organic bread consumers, segment 6 stands out as the one with the highest utility for organics. In terms of estimated WTP for an organic label on a loaf of bread (approx. 1 lb.), based on equation (2-7), segment 6 (WTP = \$8.33) is followed by segments 4 (WTP = \$2.74), 5 (WTP = \$1.52), and 3 (WTP = \$0.68). Segment 4 (“likely”) has higher WTP for the organic label than segment 5 (“very likely”), but since it contains a smaller share of respondents who purchased organic bread in the past month and they have positive utility from no bread at all, they are classified as “likely” rather than “very likely” consumers. Both segments in the “unlikely” group have negative WTP for the organic label.

2.6.2.2 Latent Class Modeling for Cookies

Table 2-8 reports results from the estimation of LCM for cookies—the MNL model estimates and latent class parameter estimates. Following the convention established for bread, we label segments 1, 2 and 3 "unlikely," segments 4 and 5 "likely," and segment 6 "very likely" consumers of organic cookies.

Looking at table 2-8, consumers in segments 1, 2, and 3 hold, on average, significantly weaker beliefs that organic products are better than conventional products, agree more that organic products are too expensive, rank importance of the organic label in cookies lower, and are less likely to have purchased organic cookies in the past month, relative to consumers in segment 6. In addition, consumers in these segments derive negative utility from the organic attribute in cookies (although this is not statistically significant for segment 2). Consumers in segment 1 (25.5%) do not like any of the cookie labels provided to them in the choice scenarios, preferring a basic product. On average, they did not select organic cookies in any of the eight choice scenarios. These consumers are very unlikely to be interested in organic cookies. Among "unlikely" segments, segment 2 (15.5%) differs in that they gain some positive utility from the non–GMO label (a component of organic). They chose the organic alternative in one of eight choice scenarios and their WTP for the organic label in cookies is negative, but insignificant. Consumers in segment 3 (26.5%) chose the organic cookie alternative in two of eight choice scenarios, but their estimated WTP for the organic label is negative and significant.

Table 2-8. Latent Class Model Parameter Estimates, Cookies

	Unlikely			Likely		Very likely
Variable	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
Multinomial Logit Model Estimates						
Price	-0.98***	-1.69***	-1.27***	-0.57***	-0.22***	-0.08
	(0.13)	(0.20)	(0.10)	(0.07)	(0.06)	(0.14)
Organic	-0.86***	-0.24	-0.41***	0.46*	0.29**	3.30***
	(0.28)	(0.28)	(0.09)	(0.25)	(0.12)	(0.38)
Non-GMO	-0.51**	0.26*	0.04	0.17	0.33***	0.02
	(0.21)	(0.15)	(0.10)	(0.15)	(0.11)	(0.30)
Gluten-free	-1.00***	-0.15	0.16	-1.05***	0.40***	0.74**
	(0.28)	(0.18)	(0.11)	(0.27)	(0.12)	(0.33)
Sugar-free	-1.12***	-0.15	-0.28***	-2.30***	0.61***	-0.12
	(0.34)	(0.20)	(0.11)	(0.42)	(0.16)	(0.39)
No choice	-2.33***	-7.33***	-10.88***	-3.15***	-2.85***	0.48
	(0.44)	(1.07)	(0.70)	(0.45)	(0.43)	(0.87)
WTP for organic[a]	-$0.88 ***	-$0.14	-$0.32 ***	$0.81 **	$1.35 ***	$42.88
WTP for organic[b]	-$0.80	-$0.13	-$0.30	$0.58	$1.19	$34.89
Latent Class Parameter Estimates						
Intercept	1.61***	0.75	1.04*	2.19***	0.96	0
	(0.59)	(0.66)	(0.58)	(0.59)	(0.62)	
Factor 1[c]	-1.32***	-1.14***	-0.93***	-1.06***	-0.17	0
(organic better)	(0.30)	(0.30)	(0.30)	(0.32)	(0.31)	
Factor 2[c]	-0.21	-0.25	-0.10	-0.21	0.42**	0
(organic not better)	(0.22)	(0.23)	(0.21)	(0.21)	(0.21)	
Organic food is too	0.95***	0.99***	0.70***	0.67***	0.38**	0
expensive[c]	(0.18)	(0.21)	(0.17)	(0.20)	(0.18)	
Selection of	-0.23	-0.03	-0.18	-0.09	-0.20	0
organic is not good[c]	(0.18)	(0.18)	(0.17)	(0.19)	(0.18)	
Rank of organic	0.22*	0.27**	0.38***	-0.06	0.16	0
label in cookies[d]	(0.12)	(0.13)	(0.12)	(0.13)	(0.13)	
Past purchase of	-3.63***	-2.56***	-1.96***	-1.94***	-0.79*	0
organic cookies	(0.51)	(0.49)	(0.42)	(0.44)	(0.45)	
Class probability	25.5%	15.5%	26.5%	13.4%	13.3%	5.8%
% purchased organic cookies	4.6%	12.7%	19.6%	26.9%	56.8%	79.0%

Note: Standard errors are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

[a] Mean WTP calculated according to equation (2-7); significance determined using Delta method.

[b] Mean WTP calculated according to equation (2-9); significance not available.

[c] The variables represent attitudes toward organic food and production systems either as a composite measure ("Factor 1" and "Factor 2") or as an individual attitude if they did not load on any factor during factor analysis.

[d] 1 = highest, 7 = lowest.

Consumers in segments 4 (13.4%) and 5 (13.3%) are “likely” consumers of organic cookies. In comparison to consumers in segment 6, they agree more that organic products are too expensive, are less likely to have purchased organic cookies in the past month, and either agree less that organic products are better (segment 4) or agree more that organic products are not better (segment 5). But in contrast to “unlikely” segments, they gain positive utility from organic cookies. Their ranking of importance of the organic label is not significantly different on average from the ranking of “very likely” segment 6. Consumers in segment 4 have a significant mean WTP of $0.81 for an organic label on a 1 lb. bag of cookies. They do not care for non–GMO label, but they clearly dislike gluten-free and sugar-free labels. In the survey, they chose the organic alternative in two of eight choice scenarios. Consumers in segment 5 have a significant mean WTP of $1.35 for the organic label on cookies. In contrast to consumers in segment 4, they also gain positive utility from other labels. On average, they chose organic cookies in four of eight choice scenarios.

The “very likely” consumers in segment 6 (5.8%) love organic cookies and they prefer them to conventional ones. Their high utility from the organic label on cookies, combined with their low sensitivity to price, results in extremely high mean WTP values using both equations (2-7) and (2-9). However, since the estimated price coefficient is insignificant, the WTP measure is not meaningful (Hensher, Rose, and Greene, 2005). Further, the applied Delta method provides evidence that the mean WTP based on equation (2-7) is insignificant. Nevertheless, consumers in segment 6 have the highest utility from organic cookies among all segments and in the survey, they chose organic cookies in seven

of eight scenarios. Although we do not obtain a meaningful mean WTP value for consumers in this segment, we can conclude that they are willing to pay any reasonable amount for the organic cookies and more than any other segment. In addition to organic, they also have relatively strong preferences for the gluten-free label.

2.6.3 Comparisons across "Very Likely," "Likely," and "Unlikely" Groups

2.6.3.1 WTP for the Organic Label

Table 2-9 summarizes average WTP values for the organic label on bread and cookies across all groups and for the whole sample. The mean WTP values were calculated (on a group level) based on equation (2-9). We find significant differences in average WTP values across groups within a product category and between groups across the two products. Within bread category, the "very likely" group has a mean WTP for the organic label $4.00 higher than that of the "unlikely" group. Within cookie category, note that "the very likely" group corresponds to segment 6. As discussed in the previous section, we did not find a meaningful mean WTP estimate for the organic label for this segment; however, we report their WTP value for the illustration purposes, considering the previous discussion which indicates that they are WTP more for the organic label than the other two groups.

Looking at the mean WTP values for the entire sample hides the differences found across groups, indicating that it can be more appropriate to obtain WTP estimates for consumer segments than for the whole sample. Also, this shows that consumer segmentation can be very important, and further analysis of differences among groups is necessary to understand how segments with high WTP differ from those with low WTP.

Table 2-9. WTP Values by Group and Product Category

	Very likely	Likely	Unlikely	Whole sample
Bread	$3.57^{b}	$1.91***^{b}	-$0.52***^^^^{b}	1.37^{a(b)}$
Cookies	$34.89^{b}	$0.88***^{b}	-$0.46***^^^^{b}	2.06^{a(b)}$

Note: *** denote significance of the differences between "very likely" group (reference group) and "likely" and "unlikely" groups at the 1% level within each product category. ^^^ denote significance of the differences between "likely" group and "unlikely" group at the 1% level within each product category. ^{a,b} denote significance of the differences between particular groups across product categories at the 5% and 1% level, respectively.
If a difference in the significance is found between the Welch and Wilcoxon tests, the result obtained using the Wilcoxon test is reported in parentheses.

2.6.3.2 Preferences for Wheat Products

Next, we examined how preferences for selected product labels and characteristics differed across the groups within and across product categories. We asked respondents to rank the importance of seven labels, where 7 = "most important" and 1 = "least important." Figure 2-1 plots the average ranking of each label within each group, and table 2-10 provides additional details.

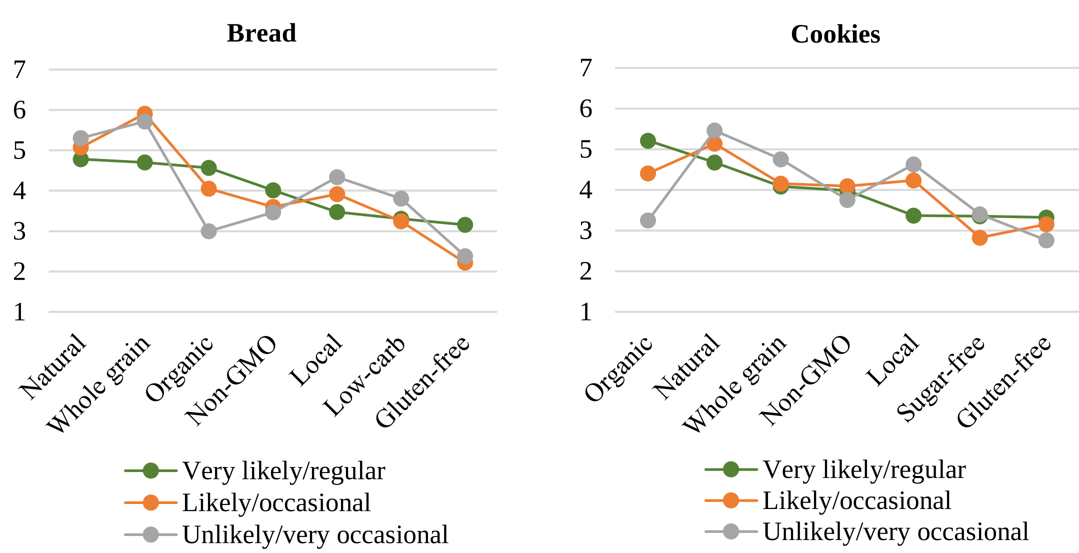

Figure 2-1. Average preferences for labels on bread and cookie products

Note: Respondents were asked to rank the importance of the labels, where 7 = "most important" and 1 = "least important."

Table 2-10. Average Importance Ranking of Labels across Groups

Label	Bread			Cookies		
	Very likely	Likely	Unlikely	Very likely	Likely	Unlikely
Natural	**4.78**^{ab}	**5.07**^{ac}	**5.30**^{bc}	**4.68**^{ab}	**5.14**^{ac}	**5.46***^{bc}
Whole grain	**4.70**^{ab}	**5.91**$^{a(c)}$	**5.72**$^{b(c)}$	**4.08***^{b}	4.15*^{c}	**4.76***^{bc}
Organic	**4.57**^{ab}	**4.05**^{ac}	3.00^{bc}	**5.21***^{ab}	**4.41***^{ac}	3.25*^{bc}
Non–GMO	4.01^{ab}	3.60^{a}	3.46^{b}	3.98	4.09*^{c}	3.75*^{c}
Local	3.47^{ab}	3.91^{ac}	**4.34**^{bc}	3.37^{ab}	**4.23***^{ac}	**4.63***^{bc}
Low-carb/sugar-free	3.31^{b}	3.24^{c}	3.81^{bc}	3.36^{a}	2.83*^{ac}	3.40*^{c}
Gluten-free	3.16^{ab}	2.22$^{a(c)}$	2.38$^{b(c)}$	3.32^{b}	3.16*^{c}	2.76*^{bc}

Note: Top three labels within each group are in bold. * denotes significant differences in rank for cookies compared to bread within the group at the 10% level or better. ^{a,b,c} denote significant differences between group of "very likely" and "likely," "very likely" and "unlikely," and "likely" and "unlikely," respectively, at the 10% level or better. If a difference in the significance is found between the Welch and Wilcoxon tests, the result obtained using the Wilcoxon test is reported in parentheses.

In the "very likely" group, "natural," "whole grain," and "organic" labels are the most important labels, regardless of product category. As expected, "organic" is ranked highest by this group and lowest by the "unlikely" group. Interestingly, the "natural" and "local" labels are both ranked significantly higher in the "likely" group and highest in the "unlikely" group for both bread and cookies. As the importance of "organic" increases, the importance of "natural" and "local" appears to decline, and vice versa.[20] This could be a result of how the question was formulated, forcing those who find "organic" very important to rank the other labels lower, but not necessarily meaning that they do not care for "local" and "natural."[21] "Gluten-free" and "low-carb" or "sugar-free" are ranked least important

[20] Using a sample of consumers in Germany, Hempel and Hamm (2016) found that consumers who do not regard organic production as very important had higher WTP values for local than for organic. On the other hand, consumers who regard organic production as very important had overall higher WTP values for organic than for local if the alternative product was from Germany, but their WTP for local increased above WTP for organic when the alternative product was from a neighboring country.

[21] For example, Lusk and Briggeman (2009) found a positive correlation between importance of naturalness and WTP for organic bread. Similarly, Onyango, Hallman, and Bellows (2007) found a positive association between naturalness and organic food purchases.

by “very likely” and “likely” groups for both products. The “unlikely” group ranks “gluten-free” as least important but “organic” as second least important for both products. Finally, average rankings for “whole grain” are significantly lower and for “organic” are significantly higher for cookies than for bread across all three consumer groups. “Whole-grain” is important for bread within the “likely” group in particular, and these consumers might find bread labeled both “organic” and “whole-grain” appealing.

Table 2-11 reports the share within each group of those who had purchased the product with the specific label in the previous month. For bread, “whole grain” and “non-organic” are among the top three labels in all three groups. For cookies, only “local” is among the top three labels across all three groups. “Organic” is among the top three labels in the “very likely” and “likely” groups for both bread and cookies.

Table 2-11. Labels and Types of Purchased Bread and Cookie Products

	Bread			Cookies		
Label or type	Very likely	Likely	Unlikely	Very likely	Likely	Unlikely
Organic	**79%**	**34%*****	16%***	**79%**	**41%*****	12%***
Whole grain	**54%**[b]	**58%**	**45%****	29%[b]	15%**(***)	6%***
Non-organic	**41%**	**39%**	**38%**	32%	**36%**	**31%**
Local	38%	27%***	**27%*****	**34%**	**32%**	**21%****
Non–GMO	31%	15%***	9%***	**40%**	21%***	8%***
Gluten-free	31%	7%***	6%***	27%	20%	7%***
Home-baked	22%	9%***	16%**	31%	30%	**28%**
Low-carb/ sugar-free	20%(a)	6%***	8%***	31%(a)	20%(*)	15%**(***)

Note: Values represent share of those who purchased bread/cookies with the specific label or characteristic in the past month. *, **, *** denote significance of the differences between “very likely” group (reference group) and “likely” and “unlikely” groups at the 10%, 5%, and 1% level, respectively, within each product category. [a,b] denote significance of the differences between “very likely” groups across product categories at the 10% and 1% level, respectively. If a difference in significance is found between the Welch and Wilcoxon tests, the result obtained using the Wilcoxon test is reported in the parentheses.

Although the “very likely” group ranks “local” as significantly less important

compared to the other two groups, a higher share of them actually purchased "local" bread and/or cookies. Further, the share of those within the "very likely" group who purchased bread with "organic," "non–GMO," "gluten-free," "home-baked," and "low-carb" labels, and cookies with "organic," "non-GMO," and "whole-grain" labels, is significantly higher than in the other two groups, although the "very likely" consumers rank some of these labels as less or equally important in comparison to the other two groups. This suggests that they are overall more likely to be interested in various labels. Finally, considering the shares of those who purchased products with specific labels in the "very likely" group, there are no significant differences across the two product types, with the exception of the "whole grain" label, which appears to be more important for bread than for cookies. "Whole grain" is also found to be more important for bread among the other two groups.

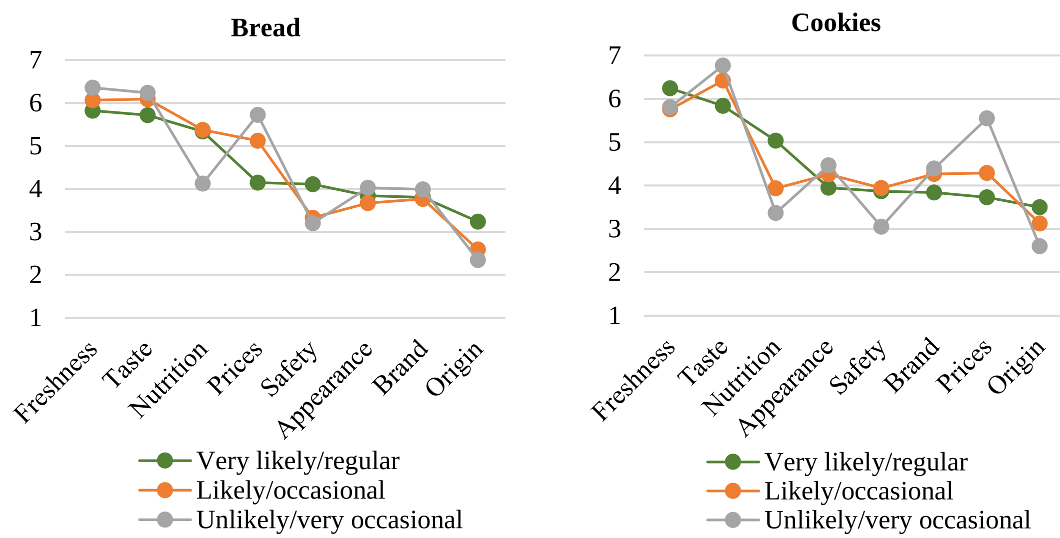

Figure 2-2. Preferences for characteristics of bread and cookie products

Note: Respondents were asked to rank the importance of the labels, where 8 = "most important" and 1 = "least important."

Next, we asked respondents to rank the importance of eight product characteristics (where 8 = "most important" and 1 = "least important"). Figure 2-2 summarizes the average rankings of the product characteristics, and table 2-12 provides additional details.

Table 2-12. Average Importance Ranking of Product Characteristics across Groups

Product characteristic	Bread			Cookies		
	Very likely	Likely	Unlikely	Very likely	Likely	Unlikely
Freshness	**5.82**^{b}	**6.06**^{c}	**6.35**^{bc}	**6.24**$*^{(ns)ab}$	**5.76**$*^{a}$	**5.81**$*^{b}$
Taste	**5.71**^{ab}	**6.09**^{a}	**6.23**^{b}	**5.84**$^{a(ns)b}$	**6.42**$*^{a(ns)c}$	**6.77**$*^{bc}$
Nutrition	**5.34**^{b}	**5.37**^{c}	4.12^{bc}	**5.03**^{ab}	3.93$*^{ac}$	3.37$*^{bc}$
Price	4.14^{ab}	5.12^{ac}	**5.73**^{bc}	3.73^{ab}	**4.29**$*^{ac}$	**5.55**^{bc}
Safety	4.11^{ab}	3.33^{a}	3.20^{b}	3.87^{b}	3.94$*^{c}$	3.05^{bc}
Appearance	3.84	3.67^{c}	4.03^{c}	3.95^{b}	4.26$*^{(c)}$	4.47$*^{b(c)}$
Brand	3.80	3.77	3.99	3.84^{b}	4.27$*$	4.39$*^{b}$
Origin	3.24^{ab}	2.59$^{ac(ns)}$	2.35$^{bc(ns)}$	3.50$^{(a)b}$	3.13$*^{(a)c}$	2.60$*^{bc}$

Note: Top three characteristics within each group are in bold. * denotes significant differences in rank for cookies compared to bread within the group at the 10% level or better. ^{a,b,c} denote significant differences between group of "very likely" and "likely," "very likely" and "unlikely," and "likely" and "unlikely," respectively, at the 10% level or better. If a difference in the significance is found between the Welch and Wilcoxon tests, the result obtained using the Wilcoxon test is reported in parentheses. ^{ns} denotes "not significant".

All groups rank "freshness" and "taste" as two most important, regardless of product category. The "likely" and "unlikely" groups rank "taste" as more important for cookies compared to bread. Also, the average ranking of "taste" in these groups tends to be higher compared to the "very likely" group. If they find organic versions to be less tasty compared to conventional, this may affect their choice.

Among all groups, the "very likely" group ranks "price" as least important, while the "unlikely" group ranks "price" as most important, regardless of the product category. This indicates that consumers of organic products tend to be less price-sensitive than non-consumers, and the higher price of organic may act as a barrier to consumption for some potential consumers.

2.6.3.3 Motivations and Barriers to Purchase Organic Bread and Cookies

Within each group identified for bread/cookies, some respondents had purchased organic bread/cookies in the past month, and some had not. We examined motivations for purchasing organic bread/cookies (table 2-13), potential barriers to purchasing (table 2-14), and any significant differences across consumer groups.

Table 2-13. Reasons for Purchasing Organic Bread (B) and Cookies (C)

	Bread			Cookies		
Reason	Very likely	Likely	Unlikely	Very likely	Likely	Unlikely
Organic B (C) is (are) healthier.	**61%**	**61%**	**49%***	**57%**	**51%**	**53%**
Organic B (C) do(es) not contain harmful substances.	**44%**	**53%**	**35%**	**47%**	**38%**	**44%**
Organic B (C) taste(s) better.	**37%**	37%	17%***	41%	32%	22%**
My family members like organic B (C).	31%	29%	34%	33%	28%	33%
Organic food production is better for the environment.	30%[b]	**38%**	23%	**51%**[b]	33%**	31%**
I like to try new food alternatives.	29%	29%	**37%**	29%	**34%**	**41%**
Organic B (C) is (are) more visually attractive.	14%	7%**(*)	10%	16%	18%	18%
Organic food is trendy or in fashion.	10%(a)	7%	10%	18%(a)	9%	7%*(**)
Purchased organic B (C) in the past month	241 (79%)	92 (34%)	71 (16%)	49 (79%)	107 (41%)	85 (12%)

Note: Values represent share of those who selected a specific reason among those who purchased organic bread/cookies. The total number of those who purchased organic bread/cookies per each group and their share in the group are reported in brackets in the last row. Top three reasons per each group are in bold. *, **, *** denote significance of the differences between "very likely" group (reference group) and "likely" and "unlikely" groups at the 10%, 5%, and 1% level, respectively, within each product category. [a,b] denote significance of the differences between "very likely" groups across product categories at the 10% and 1% level, respectively. If a difference in the significance is found between the Welch and Wilcoxon tests, the result obtained using the Wilcoxon test is reported in parentheses.

Across all six groups, among the top three reasons for purchasing organic bread

and cookies are that these options are "healthier" and that they "do not contain harmful substances." For "very likely" consumers, the belief that "organic bread tastes better" is in the top three for bread and "organic food production is better for the environment" for cookies. Compared to the "very likely" group, a significantly smaller share of consumers in the "unlikely" group believes that "organic bread/cookies taste better". As found previously, all groups rank "taste" as one of the most important characteristics, but among all groups, the "unlikely" group tends to care most about taste. As it turns out, they are also less likely to believe that organic bread/cookies taste better.

Next, we examined why consumers did not purchase organic bread and cookies (see table 2-14). "I did not think about it" is among the three most cited reasons across all six groups, without any significant differences. "Organic bread (cookies) is (are) too expensive" is also among the top three reasons for "likely" and "unlikely" groups regardless of the product category, while the share of those who selected this reason in the "very likely" group is significantly smaller. This further indicates that higher prices of organic bread and cookies may act as a barrier to growth in the organic market. Similarly, the share of those in the "likely" and "unlikely" groups, who selected that "organic bread (cookies) is (are) not better than regular" and "regular bread (cookies) taste(s) better than organic", is higher compared to the "very likely" group. However, we did not examine whether these negative expectations regarding taste are based on an actual experience or a belief. Depending on that, organic bread/cookie tastings in stores might help increase the sales.

Table 2-14. Reasons for Not Purchasing Organic Bread (B) and Cookies (C)

Reason	Bread			Cookies		
	Very likely	Likely	Unlikely	Very likely	Likely	Unlikely
I did not think about it.	**30%**	**31%**	**31%**	**23%**	**30%**	**33%**
Organic B (C) is (are) too expensive.	**27%** b(ns)	**54%** ***	**52%** ***	8% b(ns)	**29%** **(*)	**41%** ***(**)
I am not familiar with organic B (C).	**20%**	11%(*)	23%	**23%**	25%	26%
Organic B (C) is (are) not available in the store where I shop.	15%	14%	7% *(**)	8%	16%	11%
I do not think organic B (C) is (are) better than regular B (C).	14% c(ns)	**28%** ***(**)	**33%** ***	0% c(ns)	**28%** ***(**)	26% ***(**)
It is difficult to find the variety I like.	12% a(b)	9%	7%	**38%** a(b)	13% (**)	11% *(***)
Organic B (C) has (have) a shorter shelf life.	11% c(ns)	10%	11%	0% c(ns)	7% ***(ns)	7% ***(ns)
I am not familiar with organic foods.	8% b(ns)	6%	14%	0% b(ns)	7% ***(ns)	8% ***(ns)
Regular B (C) taste(s) better than organic.	6%	14% **(*)	20% ***	8%	26% **(ns)	**28%** **(ns)
I do not trust that it is really organic.	6% b(ns)	12%	11%	0% b(ns)	9% ***(ns)	10% ***(ns)
My family members do not like organic food.	5% a(ns)	6%	8%	0% a(ns)	8% ***(ns)	6% ***(ns)
Organic B (C) is (are) not visually attractive.	2%	1%	4%	0%	4% **(ns)	4% ***(ns)
Did not purchase organic B (C) in the past month	66 (22%)	175 (66%)	364 (84%)	13 (21%)	152 (59%)	603 (88%)

Note: The values represent share of those who selected a specific reason among those who did not purchase organic bread/cookies. The total number of those who did not purchase organic bread/cookies per each group and their share in the whole group in the brackets are reported in the last row. Top three reasons per each group are in bold. *, **, *** denote significance of the differences between "very likely" group (reference group) and "likely" and "unlikely" groups at the 10%, 5%, and 1% level, respectively, within each product category. a,b,c denote significance of the differences between "very likely" groups across product categories at the 10%, 5%, and 1% level, respectively. If a difference in the significance is found between the Welch and Wilcoxon tests, the result obtained using the Wilcoxon test is reported in parentheses. ns denotes "not significant".

Overall, the share of those who hold a somewhat negative view toward organic bread and cookies within the "very likely" group tends to be smaller. Instead, they select the lack of familiarity with organic bread and cookies as one of the most important reasons for not purchasing, suggesting that promoting organic bread and cookies to these groups

may increase sales. For cookies, they select difficulty in finding the variety they like as most important, suggesting that further research examining their preferences in more detail may be necessary.

2.6.3.4 Consumer Interest in Organic Versions of Wheat Products

Next, we asked respondents to rank importance of having a certified organic option for different wheat product categories, where 9 = "most important" and 1 = "least important." The results in table 2-15 reveal that the importance of having a certified organic option for different products is similar across all six groups, with only a few differences. In summary, across all groups identified within bread and cookies, "specialty bread," "white bread," and "pasta" are the three most important products in terms of having a certified organic version, while "pastries," "breadsticks," and "pies" (and, also "cookies" among "likely" consumers within bread product category) are ranked least important. This provides an evidence that consumers view organic versions of virtue and vice products differently.

Table 2-15. Importance of Certified Organic Option by Wheat Product Category

Organic wheat product category	Bread			Cookies		
	Very likely	Likely	Unlikely	Very likely	Likely	Unlikely
Specialty bread	**6.87**	**7.03**	**6.18*****	**7.02**	**6.79**	**6.51**(*)
White bread	**6.85**	**6.95**	**6.60**	**6.52**	**6.69**	**6.82**
Pasta	**5.35**	**5.35**	**5.41**	**5.15**	**5.28**	**5.43**
Bagels	4.83	4.94	4.82	5.02	4.81	4.86
Cookies	4.77	***4.13******	4.53	5.13	4.68	4.37**
Crackers	4.50	4.90**	4.54	4.47	4.65	4.63
Pastries	***4.29***	***4.13***	***4.52***	***4.23***	***4.39***	***4.34***
Breadsticks	***3.95***	***3.76***	***4.15***	***4.27***	***3.92***	***3.98***
Pies	***3.60***	***3.83***	***4.25******	***3.21***	***3.78***(**)	***4.06*****(***)

Note: Reported values represent average ranking of importance for each product category within a group of consumers. The three most important product categories per group are in bold and the three least important product categories are in bold and italic. *, **, *** denote significance of the differences between "very likely" group (reference group) and "likely" and "unlikely" groups at the 10%, 5%, and 1% level, respectively, within each product category. If a difference in the significance is found between the Welch and Wilcoxon tests, the result obtained using the Wilcoxon test is reported in parentheses.

2.6.3.5 Socio-Demographic Characteristics

Table 2-16 reports selected sociodemographic characteristics for all groups. We also compared the characteristics of "very likely" consumers across bread and cookies, but no significant differences were found.

Table 2-16. Sociodemographic Characteristics across Groups for Bread and Cookies

	Bread			Cookies		
Characteristic	Very likely	Likely	Unlikely	Very likely	Likely	Unlikely
Female	52%	53%	51%	47%	54%	51%
Married	52%	52%	48%	57%	50%	50%
Income above $60k	47%	43%	31%***	53%	46%	35%***
4-year college or higher	48%	47%	30%***	50%	48%	36%**
Employed (full and part-time)	73%	49%***	49%***	69%	66%	51%***
Resident of California	56%	47%**	49%**	65%	56%	48%***(**)
Age below 45 years	66%	31%***	43%***	58%	57%	42%**
Children 0–17 years	82%	44%***	56%***	86%	72%	54%*(**)
Household size	2.89	2.42***	2.74(*)	2.92	2.79	2.65
Ethnicity (=1 if "white," 0 otherwise)	66%	80%***	72%*	66%	69%	74%
N	307	267	435	62	259	688

Note: The values reported are either shares or means. *, **, *** denote significance of the differences between "very likely" group (reference group) and "likely" and "unlikely" groups at the 10%, 5%, and 1% level, respectively, within each product category. If a difference in the significance is found between the Welch and Wilcoxon tests, the result obtained using the Wilcoxon test is reported in parentheses.

The differences in proportion of females and those who are married are not statistically significant across the groups for bread and cookies, suggesting that gender and marital status do not determine interest in organic bread and cookies. Past studies have also found no connection between gender and decision to purchase organic foods (Zepeda and Li, 2007; Nasir and Karakaya, 2014), but others have found a positive relationship for female gender (Govindasamy and Italia, 1999) or married (Dimitri and Dettmann, 2012) and likelihood to pay more for or buy organic food. However, higher income and education levels positively impact interest in organic bread and cookies. While the differences

between the "very likely" and "likely" groups are not statistically significant, they are significant between "very likely" and "unlikely" groups. This finding is consistent with the previous findings in the literature that higher income and education positively affect likelihood of purchasing organic foods (Dettmann and Dimitri, 2009; Ngobo, 2011; Dimitri and Dettmann, 2012), although some studies have found no effects of income and education on the intention to purchase (Nasir and Karakaya, 2014). Our results further suggest that being employed (full-time or part-time) and California residence increase interest in organic bread and cookies, but the significance of the differences between groups depends on product type.

The effects of age and presence of children in the household are more ambiguous, but they appear to be related. The proportion of respondents less than 45 years old and with children in the household are lowest in the "unlikely" group for cookies, which is in line with the previous findings in the literature that younger consumers (Zepeda and Li, 2007) and consumers with younger children in the household (Hughner et al., 2007) are more likely to purchase organic products. But the shares of younger consumers and consumers with children in the household are lowest in the "likely" group for bread, suggesting that the effects of age and the presence of children depend on the product category. Older respondents who are less likely to have children living with them appear to be more interested in organic versions of staple products, such as bread, which might be due to their financial situation or health concerns.[22]

Household size appears to have a small effect on interest in organic bread and

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[22] Health concern has been identified as a major reason for consumers' positive attitudes toward or choice of organic foods (Magnusson et al., 2003; Honkanen, Verplanken, and Olsen, 2006; Hughner et al., 2007).

cookies. Only for bread, the average household size of respondents in the "likely" group is significantly smaller from the household size of the "very likely" group, which makes sense since the "likely" group contains the lowest share of respondents with children in the household.

Since the majority of our respondents selected "white" as their ethnic background, we further examined whether there are differences across groups in the proportion of whites. Significant differences are found only for bread, where the proportion of whites in the "very likely" group is lower than in the other two groups. Overall, it appears that the effect of ethnicity is weak, which was also found by Dimitri and Dettmann (2012).

2.6.3.6 Lifestyle Choices

Respondents were asked to evaluate their level of agreement with 16 lifestyle statements on a 5-point scale (see table 2-17). On average, all groups somewhat agree that they "eat grains daily," with no significant differences across the groups, regardless of the product category. The "very likely" group agrees more that they control their "fat consumption" and that "supporting local farmers is important" to them compared to the other two groups for both bread and cookies. Similarly, respondents in this group also agree significantly more that they avoid eating "processed foods" and "food products with additives," they are more concerned about the "safety" and "origin" of their food, "physical activity and exercise" and "agricultural open space" are more important to them, and they "buy products with low environmental impact" more, but the "very likely" group within the cookies category agrees with these statements significantly more than the same group within the bread category.

Table 2-17. Average Level of Agreement with Lifestyle Statements by Group

	Bread			Cookies		
Statement	Very likely	Likely	Unlikely	Very likely	Likely	Unlikely
I control my salt and sugar intake.	3.85	3.84	3.59 ***	4.02	3.78	3.70 **
I control my fat consumption.	3.78(a)	3.61 *	3.34 ***	4.02(a)	3.67 **	3.45 ***
I follow a vegetarian or vegan diet.	2.32	1.63 ***	1.48 ***	2.37	2.15	1.58 ***
I eat fresh produce daily.	4.02	3.72 ***(**)	3.52 ***	4.19	3.89 **(ns)	3.62 ***
I eat grains daily.	3.71	3.83	3.69	3.92	3.79	3.69(*)
I avoid eating processed foods.	3.48[a]	3.16 ***	2.62 ***	3.76[a]	3.32 ***(**)	2.85 ***
I avoid eating food products with additives.	3.66[b]	3.22 ***	2.65 ***	4.03[b]	3.43 ***	2.91 ***
I am concerned about my health.	4.10	4.01	3.88 ***	4.26	4.08 (*)	3.91 **(***)
I am concerned about the safety of my food.	4.18 a(b)	3.82 ***	3.66 ***	4.40 a(b)	4.06 **(***)	3.73 ***
I am concerned about the origin of my food.	3.81[c]	3.51 ***	3.27 ***	4.23[c]	3.66 ***	3.38 ***
I eat out infrequently.	3.25	3.15	3.10	3.44	3.20	3.12*
Physical activity or exercise is an important part of my routine.	3.96 c(b)	3.64 ***	3.43 ***	4.32 c(b)	3.75 ***	3.55 ***
I buy products with low environmental impact.	3.48[c]	3.04 ***	2.82 ***	3.85[c]	3.27 ***	2.94 ***
Recycling is a priority for me.	4.07	3.93	3.70 ***	4.19	3.93 *(ns)	3.82 ***(**)
Supporting local farmers is important to me.	4.07	3.76 ***	3.68 ***	4.24	3.95 **	3.73 ***
Agricultural open space is important to me.	3.88[b]	3.71 *	3.51 ***	4.18[b]	3.86 **	3.56 ***
N	307	267	435	62	259	688

Note: The reported values represent group means of the responses ranging from 1 to 5, where 1 = “strongly disagree,” 2 = “somewhat disagree,” 3 = “unsure,” 4 = “somewhat agree,” 5 = “strongly agree.”
*, **, *** denote significance of the differences between “very likely” group (reference group) and “likely” and “unlikely” groups at the 10%, 5%, and 1% level, respectively, within each product category. [a,b,c] denote significance of the differences between “very likely” groups across product categories at the 10%, 5%, and 1% level, respectively. If a difference in the significance is found between the Welch and Wilcoxon tests, the result obtained using the Wilcoxon test is reported in parentheses. [ns] denotes “not significant”.

Further, respondents in the “very likely” group agree more, on average, that they control their “salt and sugar intake” and that they are concerned about their “health” when

compared to the “unlikely” group, but the level of agreement with these statements is not different statistically when compared to the “likely” group. They also agree more that they “follow a vegetarian or vegan diet,” “eat fresh produce daily,” and “recycling is a priority” compared to the other groups. When it comes to frequency of eating out, overall there are no major differences except that consumers in the “unlikely” group agree less that they “eat out infrequently” at the 10% level.

Examining lifestyle statements across consumer groups confirms that lifestyle plays an important role in distinguishing consumers of organic food from non-consumers, which was previously found in Gil, Gracia, and Sanchez (2000) and Sanjuán et al. (2003). The authors in these studies segmented Spanish consumers based on lifestyle and found that those who were concerned about healthy diet and environment were more likely to purchase organic food (Gil, Gracia, and Sanchez, 2000), and those with higher health awareness and balanced lifestyles consumed organic food more frequently. Although we have not segmented survey respondents based on lifestyles, we find comparable results and clear differences in lifestyle across the three groups of consumers, regardless of the examined product. It appears that “very likely” consumers are, on average, more inclined toward making lifestyle choices considered to be healthier and better for the environment, and they care more about the origin, safety, and production aspects of their food. Our results also support previous findings in de Magistris and Gracia (2008) and Chen (2009) that healthy lifestyle plays a role in positively affecting consumer attitudes toward organic foods.

2.6.3.7 Shopping and Consumption Behavior

We asked respondents to select the store type(s) where they typically shop for bread and cookies. Table 2-18 reports the share of respondents in each group who selected each store type. “Very likely” consumers are significantly more likely to purchase bread/cookies in specialty stores, bulk stores, and local bakeries in comparison to “likely” and “unlikely” consumers for bread and “unlikely” consumers for cookies.

Table 2-18. Group Percentage Shares and Means Related to Consumer Shopping Habits

	Bread			Cookies		
	Very likely	Likely	Unlikely	Very likely	Likely	Unlikely
Store type						
Grocery store	71%[a(b)]	72%	76%	53%[a(b)]	59%	69%**
Multipurpose store	49%	35%***	49%	40%	46%	46%
Specialty store	38%	23%***	11%***	34%	30%	16%***
Bulk store	30%	17%***	15%***	32%	23%	16%**(***)
Local bakery	23%	9%***	11%***	29%	23%	10%***
Discount store	11%	10%	12%	11%	17%	14%
Reviewed information[c]						
Nutrition facts panel	69[a]	62***	50***	78[a]	66***	55***
Ingredient list	68[b(a)]	61***(**)	48***	77[b(a)]	66***(**)	53***
Serving size	55	49**	46***	62	53**	47***
Package size	58	57	61	62	59	58
Allergy warnings	47	25***	25***	54	41**(***)	26***
Front labels	71[b(a)]	56***	40***	79[b(a)]	65***	47***
Other						
Bread/cookies purchase frequency[d]	2.79[b]	2.45***	2.74	2.31[b]	2.02*	1.79***
Bread/cookies cost	$9.10	$4.40***	$5.72***	$8.95	$7.99	$5.00***
Household grocery shopping	83%	81%	82%	85%	83%	81%

Note: *, **, *** denote significance of the differences between “very likely” group (reference group) and “likely” and “unlikely” groups at the 10%, 5%, and 1% level, respectively, within each product category. [a,b] denote significance of the differences between “very likely” groups across product categories at the 5% and 1% level, respectively. If a difference in the significance is found between the Welch and Wilcoxon tests, the result obtained using the Wilcoxon test is reported in parentheses.

[c] 0 = “never,” 25 = “sometimes,” 50 = “about half the time,” 75 = “most of the time,” 100 = “always.” Reported values are group means.

[d] 0 = “never,” 1 = “once a month or less,” 2 = “several times a month,” 3 = “once a week,” 4 = “several times a week.” Reported values are group means.

We also asked respondents to indicate on a 100-point scale how often they review specific product information, where 0 = “never” and 100 = “always.” Table 2-18 also reports the averages per group and information type. As expected, we find that “very likely” consumers review nutrition facts panels, ingredient lists, serving sizes, allergy warnings, and front labels significantly more frequently than the other two groups, regardless of product category. We also find that, on average, “very likely” consumers within each product category purchase bread/cookies as frequently as or more than and spend as much as or more per purchase than the other two groups. The average percentage of household grocery shopping that each respondent is responsible for is 81%–85%, and there are no significant differences across the groups. This indicates that the results are not affected by the overall involvement in grocery shopping.

We also asked respondents how often they consume sustainable foods in general (e.g., labeled as organic, locally grown, GMO–free, natural, grass-fed, free-range, etc.). As shown in table 2-19, “very likely” consumers of both bread and cookies consume sustainable foods significantly more frequently than consumers in the other two groups, as expected, and significant differences are found between these two groups as well (not reported).

Finally, we asked respondents whether they or any member of their household suffers from wheat/gluten intolerance, celiac disease, or avoids wheat/gluten for other reasons. The aim was to determine whether consumers with these limitations, which certainly affect their choice and consumption of wheat products, found organic versions of wheat products appealing. Table 2-19 reports the share of consumers within each group

who indicated a specific limitation. As it turns out, for bread, the share of respondents with limitations is significantly higher in the group of "very likely" consumers of organic bread than in the other two groups. For cookies, there are differences in share of respondents with these limitations between the groups as well, but these are not necessarily significant. These results suggest that indeed those who need to or choose to avoid wheat/gluten products might be substituting the regular wheat products with organic versions, as they are concentrated in the "very likely" group. However, it appears that this may hold more for staple wheat product categories like bread and less for "optional" products, like cookies.

Table 2-19. Group Percentage Shares and Means Related to Consumer Consumption Behavior and Limitations

	Bread			Cookies		
	Very likely	Likely	Unlikely	Very likely	Likely	Unlikely
Sustainable food consumption frequency[b]	3.02[a]	2.13***	1.35***	3.55[a]	2.71***	1.69***
Wheat intolerance/allergy	21%	4%***	5%***	27%	15%**	6%***
Wheat avoidance	22%	6%***	4%***	23%	19%	5%***
Gluten intolerance/allergy	19%	7%***	6%***	13%	13%	8%
Gluten avoidance	28%	9%***	6%***	29%	19%*	10%***
Celiac disease	4%	1%***	1%***	2%	4%	1%

Note: *, **, *** denote significance of the differences between "very likely" group (reference group) and "likely" and "unlikely" groups at the 10%, 5%, and 1% level, respectively, within each product category.
[a] denotes significance of the differences between "very likely" groups across product categories at the 1% level.
[b] 0 = "never," 1 = "once a month or less," 2 = "several times a month," 3 = "once a week," 4 = "several times a week." Reported values are group means.

2.7 Conclusions

This study attempts to understand the factors that determine consumer interest in organic wheat products, the product characteristics and labels that matter to current and potential consumers, and how potential consumers (who represent growth potential in the market)

differ from current organic consumers by examining the differences across consumer segments. The analysis is performed for bread (a staple or virtue product) and cookies (a hedonistic or vice product) to assess whether the findings may be broadly applicable or product specific. We use latent class modeling for discrete choice analysis to cluster respondents based on their attitudes toward organics in general and their preferences for the organic label in selected organic wheat products, resulting in three groups: "very likely," "likely," and "unlikely" consumers, each indicating the likelihood of purchasing a wheat product with an organic label. Welch tests and Wilcoxon tests are used to evaluate the significance of the differences between the groups. Data were collected using an online survey administered in 16 U.S. western states during Summer 2017 that yielded 1,009 valid responses.

The analysis reveals significant differences that are not product specific among groups. First, all groups have significantly different WTP for organic labels, indicating that focusing on WTP among the whole sample may be misleading; in some cases, it may be more appropriate to obtain WTP estimates by segment. Second, as the importance of the organic label on bread and cookies increases, the importance of local and natural labels decreases (and vice versa). However, we also find that a higher share of "very likely" consumers purchased local bread and cookies compared to "unlikely" consumers. Apart from the local label, we find that they have a higher interest in labels in general, since an equal or a larger share of "very likely" consumers purchased bread and cookies with some labels, although they rank them equally or less important as the other two groups.

Third, those classified as "very likely" consumers of organic bread and cookies

rank price and taste overall as less important than the other two groups. Among those who had purchased organic bread and cookies in the past month, “unlikely” consumers selected that “organic tastes better” less frequently than consumers in the “very likely” and “likely” groups. Among those who did not purchase organic versions of the products, “likely” and “unlikely” consumers believe more frequently that organic products are too expensive, organic is not better than regular (conventional), and regular tastes better. In summary, it appears that the higher price of organic wheat products and expected inferior taste compared to non-organic versions may act as a barrier to the consumption of organic wheat products. This is in line with findings by Ellison et al. (2016), who also find that the organic versions of vice products are perceived to be more nutritious than conventional ones, which provides some background for our finding that the “very likely” group ranks nutritional value in cookies (a vice product) as significantly more important than the other two groups.

Fourth, consumers in all three groups, on average, select specialty bread, white bread, and pasta as the three wheat products they would most like to have a certified organic option. Fifth, higher income, higher education, employment, and California residence are related to higher interest in organic bread and cookies, while gender and marital status play no role. Sixth, as expected, “very likely” consumers tend to have lifestyles that are considered healthier and more environmentally responsible, be more concerned about the safety and origin of their food, and support local agriculture more compared to other consumers, particularly in the “unlikely” group.

Finally, “very likely” consumers review nutrition fact panels, ingredient lists, serving sizes, allergy warnings, and front labels, and they purchase bread and cookies in

specialty stores, bulk stores, and local bakeries significantly more frequently than consumers in the other two groups. Also, we find that the share of respondents who need to or choose to avoid gluten/wheat is the highest in the “very likely” groups, indicating that they find organic wheat products appealing and that they may be substituting regular wheat products with organic versions.

We draw several conclusions to assist food manufacturers and marketers in production and marketing decisions: First, it may be worth investing in research and development to improve the taste of organic wheat products, particularly for hedonistic products such as cookies, which may help justify the higher price tag. All groups rank “organic” as more important for cookies than bread, yet smaller share of respondents purchased organic cookies than bread and expected taste is one of the reasons. At the same time, “likely” and “unlikely” consumers rank “taste” as more important in cookies than bread. However, we did not examine whether consumers’ expectations that organic products are less tasty are based on an actual experience or a belief. Marketers may also want to conduct organic cookie sample tastings, which will allow consumers to experience and personally evaluate the taste of organic cookies, and it may help convince “likely” consumers, who appear to be more price conscious than “very likely” consumers, that organic cookies are worth the extra cost.

Second, our results suggest that organic bread produced with whole-grain flour may appeal to “likely” consumers, who rank the whole-grain label in bread as most important. To further attract “likely” consumers, organic bread should be advertised as fresh, tasty, and nutritious, and organic cookies as fresh and tasty, since nutrition does not play an

important role for them.

One of our contributions is that we identify consumer segments for bread and cookies based on their likelihood of purchasing organic bread and cookies, which had not been done previously. Second, this study contributes to the vast literature examining which consumer characteristics determine consumption of organic products in the context of wheat products, which have not received much attention in the literature so far. Specifically, we identify and discuss differences in socio-demographics and lifestyles across consumer segments. Third, we provide recommendations for food manufacturers and marketers regarding preferred product characteristics and labels. Fourth, we contrast the findings for two wheat product categories to determine whether our findings are broadly applicable or product specific. However, there are some limitations which need to be considered while interpreting the results. First, we suspect that organic food consumers are underrepresented in our sample and the groups of “very likely” and “likely” consumers may be larger. Second, since the employed choice experiment was hypothetical, i.e. it did not involve actual purchases, there is a possibility that respondents evaluated the attributes, in particular price, less thoroughly. Consequently, the calculated WTP values may be higher than the actual WTP.

This study is one of few examining consumer segments and/or their preferences for organic wheat products in more detail, but more work can be done. Future research may build on our findings and examine whether consumers’ beliefs that organic wheat products are less tasty are based on expectations or on actual experience, and what aspects of taste they would like to improve, if any. Depending on the outcome, sample tastings or careful

improvements to taste could be undertaken, while considering the needs and preferences of current consumers. It would also be worth investigating whether consumers value the organic label in whole-grain bread significantly more than in white bread. Finally, it would be interesting to examine why respondents with gluten/wheat consumption limitations are interested in organic versions of wheat products, particularly bread, to provide further recommendations for marketing organic wheat products to the growing segment of gluten/wheat-avoiding consumers, which appears to find organic versions of wheat products appealing.

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CHAPTER 3

DO EXTRA LABELS PAY? THE IMPACT OF NON-GMO AND HEALTH RELATED LABELS ON CONSUMER WILLINGNESS TO PAY FOR ORGANIC WHEAT PRODUCTS

3.1 Abstract

In this essay, consumer preferences and willingness to pay (WTP) for the organic label alone and in combination with other labels in the context of wheat products are explored. The investigated labels are either directly related to the organic label (non-GMO), or perceived as health promoting (gluten-free, low-carb and sugar-free). The analysis is performed for two products (bread and cookies) to examine whether results depend on product type (virtue vs. vice). The data used comes from an online survey conducted in 2017 across 16 U.S. western states. The analysis is completed using multinomial logit and random parameter logit models. It is found that the combinations of the labels with the organic label are not widely accepted and they may reduce overall consumer WTP, however, there are consumers who find these combinations appealing. Also, consumer knowledge that organic is also non-GMO can increase overall WTP for the combination of organic and non-GMO labels above WTP for the organic label alone. Finally, it is found that those with some gluten or wheat intolerance or avoidance represent a profitable market for organic wheat products.

3.2 Introduction

Consumption of organic foods has become one of the most significant trends in the food industry, and consumer demand for organic food continues to increase each year. In 2017, the total sales of organic foods were at $45.2 billion in the United States, up 6.4% compared to the sales in 2016, outpacing the growth in the sales of conventional foods (Organic Trade Association, 2018). In general, organic foods are more expensive than their conventional counterparts so the additional costs of producing organics are usually covered. And, previous studies have found that consumers are willing to pay extra for the organic label alone in a variety of products, ranging from fresh products such as produce (Jolly, 1991; Govindasamy and Italia, 1999; Govindasamy, DeCongelio, and Bhuyan, 2006) and meats (Van Loo et al., 2011) to processed, multi-ingredient food products (Batte et al., 2007).

Like the organic label, the non-GMO (genetically modified organism) label has also gained importance in the US food market in recent years. According to a report by Nielsen, sales of non-GMO products jumped from $12.9 billion in 2012 to $21.1 billion in 2016 (USA Today, 2016).[23] The non-GMO label is related to the organic label in the sense that the absence of GMOs is listed as one of the conditions that each product labelled as organic must meet, as established by the National Organic Program (NOP) in the United States in 2002. That is, the non-GMO label complements the organic label.

However, findings of a recent study by McFadden and Lusk (2017) suggest that consumers do not recognize the difference between organic and non-GMO labels, and they

[23] At the same time, the number of non-GMO labels in new products introduced to the market increased by 558% between 2012 and 2016 (U.S. Department of Agriculture Economic Research Service – USDA ERS, 2017).

confuse the two. Consumers preferring non-GMO over organic labels might be doing so based on perception rather than actual facts and knowledge, and organic food producers may be losing sales to non-GMO labeled foods, which represent a cheaper alternative (Roseboro, 2013). A possible solution to this problem—to provide both labels together—may not help either, as McFadden and Lusk (2017) find that in the case of products with both labels, the overall WTP is close to the WTP for organic alone. On the other hand, Conner and Christy (2004) found that the average WTP for the combination of organic and non-GMO labels was higher than the WTP for organic alone, but the authors focused on organic food consumers. Other studies show that when the definitions of the labels are provided to consumers, they may be willing to pay significantly more for organic labeled foods relative to non-GMO foods (He and Bernard, 2011), or they may not (Bernard, Zhang, and Gifford, 2006), but the authors did not examine the effect of organic knowledge on consumer WTP for the labels alone and together.

Overall, it seems that consumers care greatly about the non-GMO component of organics and/or they perceive the organic and non-GMO labels as substitutes. To our knowledge the effect of having both labels together on a product has not been examined separately for consumers with and without prior knowledge that organic must be non-GMO[24], which may be correlated with their interest in these labels and thus affect their WTP values. This analysis is one of the objectives of this study. Further, we examine whether consumer overall knowledge of organic products and production systems

[24] In this study, we do not consider specifically that consumers may be aware of and concerned about possible contamination of organic with GMOs. This could lead them to prefer "Non-GMO Project Verified" (NGPV) label over organic label, since the NGPV label verifies that the GMOs are not present in the final product, while the organic label examines that GMOs are not used in the production process only.

influences their WTP for the labels alone and in combination. Since it has been found previously that subjective (self-reported) knowledge affects consumer interest in organic foods more than objective (actual or tested) knowledge (Pieniak, Aertsens, and Verbeke, 2010; Aertsens et al., 2011), we examine the impact of both on consumer preferences for organic and non-GMO labels. We expect that our findings will provide insights regarding why some “natural food” retailers experience positive consumer responses to products that contain both labels (Roseboro, 2015), despite recent research suggesting otherwise.

In addition to organic and non-GMO labels, other labels have received increased attention recently. Food manufacturers and marketers have been increasing the number of labels or claims on new food products introduced to the market, recognizing the potential of labels to attract consumers. For example, in 2009 a new food product had on average 2.1 claims[25], but in 2016 it was 3.7 claims (USDA ERS, 2017). This indicates that there is a trend of increased claims on a single product, but the question is whether multiple labels provide any benefit to consumers and whether they are helpful in deciding to purchase a product or not, or whether they are instead causing confusion.

In addition to the already mentioned interaction of organic and non-GMO labels, of which the consumer interest has been driven to a considerable extent by their health concerns (Gil, Gracia, and Sanchez, 2000; Torjusen et al., 2001; Magnusson et al., 2003; Baker et al., 2004; Lesch, Anderson, and Wachenheim, 2006; Zepeda, Chang, and Leviten-Reid, 2006), we examine the interaction of the organic label with other labels perceived as healthy. We focus on gluten-free, low-carb and sugar-free labels, which appeal to

[25] Calculated as the ratio of total number of claims on new products introduced to the market in that year to number of new products.

consumers who seek to avoid ingredients that may cause allergies or lead to a food related disease, which have been identified as some of the major trends in consumer food demand in recent years (Asioli et al., 2017). We examine the impact of these labels on the WTP for organic in the context of two wheat product categories: bread as a staple item, where organic attribute may appeal to those who by default prefer a gluten-free diet (for other than health reasons); and cookies as a hedonistic item, where the sugar-free attribute may appeal to those who by default prefer food labelled as organic.

In summary, we consider these objectives for this study: (1) obtain consumers' WTP for the organic label alone in two types of organic wheat products—bread and cookies, (2) examine the impact of combining organic and non-GMO labels on the WTP for organic products and whether it depends on consumers' prior knowledge that organic must be non-GMO, (3) examine the impact of including additional labels perceived by consumers as healthier (gluten-free, sugar-free or low-carb) on the WTP for organic products, and (4) evaluate the effect of several factors, including overall tested (objective) knowledge of organic, self-reported (subjective) familiarity with organic, and wheat/gluten intolerance/avoidance, on the WTP for the organic label and in combination with other labels.

3.3 Background and Literature Review

3.3.1 The Complexity of the Organic Label, Consumer Preferences for Components of Organic and Associations with Other Labels

In the United States, the organic label can be used only on products that are produced following strict rules developed by the National Organic Program (USDA, 2002). These

rules specify the substances, methods and practices that are allowed and prohibited in the organic farming, including use of genetic engineering, synthetic pesticides and fertilizers, growth hormones, sewage sludge and irradiation. Thus, the organic label is composed of multiple characteristics that jointly define organic. The complexity of the organic label has inspired researchers to examine consumer valuation of the organic label as a whole relative to its parts, in particular non-GMO.

Some studies find that consumers are not willing to pay significantly more for organic relative to non-GMO alone (Bernard, Zhang, and Gifford, 2006, using potato chips, tortilla chips and milk chocolate), and the WTP values for parts of organic are likely not additive because the sum of WTP for two selected components of organic (non-GMO and pesticide-free) is found to be significantly not different from WTP value for organic (Bernard and Bernard, 2010, using potatoes and sweet corn). On the other hand, He and Bernard (2011) found that products labeled organic elicited significantly higher premiums on average than products only labeled non-GMO, with the difference in premiums ranging from 6.80% for tortilla chips to 17.57% for potato chips. In these studies, respondents were given a neutrally phrased definition of each label, but consumers do not necessarily have accurate knowledge of labels during a real shopping scenario. In addition, these studies do not examine the interaction of organic and non-GMO labels, which could be valuable for those who do not know that by definition organic implies non-GMO.

Conner and Christy (2004) examined the WTP for a bag of organic corn chips that had a non-GMO label in addition to organic, and found that current consumers of organic food, who were targeted specifically in this study, are willing to pay on average $0.75 more

for a product with both labels relative to the base product with the organic label only, which cost $1. The respondents were not provided definitions of the labels and only 53% knew that organic is non-GMO by definition. However, the impact of knowledge on WTP values has not been discussed in more detail. In a more recent study, McFadden and Lusk (2017) examined the effect of the interaction of organic and non-GMO labels as well. In contrast to the findings of the study by Conner and Christy (2004), they found that consumers, not limited to organic food consumers only, are not willing to pay for non-GMO and organic labels together significantly more than for each label alone. In fact, they seem to value non-GMO and organic labels similarly, suggesting the two labels are perceived to be substitutes rather than complements, but the impact of their prior knowledge of the organic label was not assessed.

In summary, previous research suggests that consumers care greatly about a few components of organic and/or they do not have a clear understanding of what organic really means. As discussed in Stanton and Guion (2015), some segments of the population have a good understanding of what organic means. But the general population is still confused about its meaning, which may be exacerbated by companies which, in an attempt to advertise organic products, include claims that add to the confusion. For example, consumers in general appear to confuse organic with other labels that are perceived as sustainable, such as "local" (Risku-Norja and Løes, 2017), or excluding some undesirable practices during the production process (e.g. no antibiotics or pesticide-free), such as "all-natural" (Abrams, Meyers, and Irani, 2010) and "natural" (Gifford and Bernard, 2011), although it is not clear whether they confuse them because they are placed together on a

product. However, previous research also suggests that when organic and local labels are combined together, they may be appealing to specific consumer segments that view the labels as complements (Hasselbach and Roosen, 2015; Hempel and Hamm, 2016), which could also be the result of their better understanding of the organic label (Holmes and Yan, 2012). Also, regarding the relationship between organic and natural labels, findings of Lusk and Briggeman (2009) suggest that "naturalness" is a key value motivating consumer preferences for organic food. In this study, we examine whether consumers find the combination of organic and non-GMO labels confusing, or helpful, conditional on their actual knowledge that organic implies non-GMO.

3.3.2 Organic Food Perceived as Healthier by Consumers

Many studies have looked at consumers' perceptions of organic foods to provide insights into why consumers value organics and what motivates their purchase decisions. A common finding across the studies is that organic food is perceived as healthier and more nutritious when compared to the conventional alternatives (Magnusson et al., 2001; Lea and Worsley, 2005; Krystallis, Fotopoulos, and Zotos, 2006; Lee et al., 2013). For example, Lee et al. (2013) found that consumers evaluated organic versions of processed foods (cookies, potato chips and yogurt) as more nutritious and having less calories than the conventional versions, solely based on the organic label, and their WTP for the organic version was higher. It has been found that people who are concerned about their health tend to have more positive attitudes toward organic foods (Zepeda, Chang, and Leviten-Reid, 2006), affecting positively their intention to purchase and/or WTP for organic (Gil, Gracia,

and Sanchez, 2000; Magnusson et al., 2003; Akgüngör, Miran, and Abay, 2010; Gracia and de Magistris, 2013; Nasir and Karakaya, 2014).

As shown in the studies above, consumers in general perceive organic products to be healthier than the conventional alternatives. We aim to explore the impact of including other labels, perceived by consumers as health promoting, on consumers' preferences and WTP for organic, by examining the interactions of the organic label with the other health claims. The labels we examine are gluten-free, and low-carb in case of bread and sugar-free in case of cookies. These labels are chosen to represent two different trends driven by consumers' health concerns and issues as one of the major tendencies in the food consumption in the developed countries (Grunert, 2013)—avoidance of some ingredients due to allergies and intolerances, and due to concerns about or as a result of suffering from a food related disease (Asioli et al., 2017). We investigate whether these additional labels in combination with organic are desirable for consumers.

3.3.3 Increasing Importance of Gluten-Free Foods

Gluten-free foods were developed to address needs of people with celiac disease, or intolerances or allergies to gluten, but over time, more and more consumers became convinced that gluten-free diet is a healthy lifestyle option and shifted their preferences towards these types of foods (Potter, Stojceska, and Plunkett, 2014). According to The Hartman Group's Health & Wellness report (2015), 26% of consumers in US claim that they purchase gluten-free foods because they believe they are a "healthier option", which was the second most cited reason for purchasing gluten-free foods, following the most frequently cited "no reason at all" by 35% of respondents, while only 8% stated "I have a

gluten sensitivity." This study also found that in 2015 one in five consumers in the US claim that they avoid or reduce gluten in their daily diet. The increasing consumer interest in the foods with gluten-free label is also documented by 36% annual growth in the U.S. gluten-free foods market between 2010 and 2015 (Berry, 2017).

Given the importance that the gluten-free diet has gained over the past few years, we aim to examine if there is any connection between preferences for bakery products labeled as gluten-free and those labeled organic, as both labels are perceived to be healthy, which to our knowledge has not yet been addressed in the literature. We aim to examine whether organic wheat products may serve as an alternative to gluten-free bakery products for consumers who prefer gluten-free products for other than gluten/wheat intolerance reasons, given that gluten-free bakery products are generally perceived among consumers to be of lower quality when compared to conventional bakery products (Arendt et al., 2002; Potter, Stojceska, and Plunkett, 2014).

3.3.4 Increasing Importance of Food with no or Reduced Sugar

Health concerns and issues gave rise to another trend in food consumption, which is controlling sugar intake and interest in foods with reduced/no sugar labels. Despite mixed scientific evidence (Stanhope, 2016), many consumers believe that high sugar intake leads to health issues including diabetes, cardiovascular diseases and obesity. However, as the number of diabetics in US increased from 25.8 million in 2010 (U.S. Department of Health and Human Services, Centers for Disease Control and Prevention – HHS CDC, 2011) to 30.3 million in 2015 (HHS CDC, 2017), more and more consumers need to watch closely their overall carbohydrate intake, including sugars. There is evidence that consumers in the

US have decreased their consumption of added sugars (Welsh et al., 2011). And, while only 30% of US consumers of all ages met the recommendations for daily intake of added sugars in the period 2007-2010 (HHS and USDA, 2015), this share increased to 42% in the period 2013-2014 (Bowman et al., 2017), indicating a trend toward decreased consumption of added sugars. Given the consumers' perception of organic as health promoting, we are interested in examining whether consumers value the combination of organic and low-carb or sugar-free labels, which to our knowledge has not yet been considered in the literature.

3.3.5 Impact of Knowledge of Organic Label on Organic Food Choice

Previous studies have investigated the effect of objective and/or subjective knowledge of organic food production systems on the consumption of organics.[26] Pieniak, Aertsens, and Verbeke (2010) and Aertsens et al. (2011) found that subjective knowledge directly affects the likelihood of consuming organic vegetables. Objective knowledge did not affect the consumption of organic vegetables directly but contributed significantly to forming positive attitudes towards organics. Thus, it appears that subjective knowledge has a stronger impact on the consumption of organic vegetables than objective knowledge. Similarly, Gracia and de Magistris (2013) found that higher self-reported knowledge of organic products is associated with an increase in the willingness to purchase organic products. Further, Gil and Soler (2006) and Mesías Díaz et al. (2012) found positive relationship between consumers' tested organic knowledge and their WTP for organic

[26] As defined in the discussed studies (Pieniak, Aertsens, and Verbeke, 2010; Aertsens et al., 2011), objective knowledge is what a consumer actually knows about organic (e.g. it can be evaluated using a test) and subjective knowledge is what a consumer thinks he/she knows and is influenced by perceptions (e.g. it can be a self-reported familiarity with organic).

products. On the other hand, Li, Zepeda, and Gould (2007) found that the knowledge of organic production practices does not play a role in organic food purchasing behavior. In this study, we examine how objective and subjective knowledge of organics affects WTP for the organic alone and in combination with the other labels. Understanding how knowledge of organic production systems is related to consumer choice and consumption is important, since it can provide insights for the marketing of organic food in terms of whether campaigns aimed at educating consumers about organic can be an effective tool to increase sales of organic foods or not.

3.3.6 WTP for Organic Wheat Products

In this section, studies examining consumer WTP for products containing organic wheat are reviewed. For example, average WTP for 1kg whole wheat flour was estimated at 7.5% over the price of conventional flour in Rodríguez, Lacaze, and Lupín (2007), using a convenience sample of food shoppers in Argentina. Hempel and Hamm (2016) found that organic-minded consumers in Germany were willing to pay on average approximately €1 extra for 1kg organic flour, while the non-organic minded consumers were not willing to pay extra.

Several studies examined WTP for organic bread. Krystallis, Fotopoulos, and Zotos (2006) extracted a sub-sample of organic food buyers from a sample of primary household grocery shoppers in Greece and found that their stated WTP for 0.5kg of organic bread was 75.5% above the price of conventional bread. Boxall et al. (2007) used a sample of regular consumers of wheat bread products in Edmonton, Canada, intercepted at various shopping outlets and public venues, to elicit WTP a predetermined value for the whole wheat organic

bread above the price for conventional bread, either before or after tasting a sample of organic and conventional bread, while providing information about health or environmental aspects of organic production, resulting in four treatments. The mean WTP was 63% above the price of conventional bread, but it differed based on the treatment. They found that before the tasting occurred, environmental information yielded higher WTP (86%) than the health information (42%), but after the tasting occurred, health information yielded higher WTP (79% vs. 43%). This suggests that consumers care about the taste, and once they confirm it is desirable, health information has a greater effect on WTP values.

Using a sample of primary grocery shoppers in Canada, Zheng (2014) found that they were willing to pay on average 9.5% above the price of the conventional whole wheat bread for the certified organic label but were not willing to pay extra for the non-certified organic label. Teuber, Dolgopolova, and Nordström (2016) used an experimental auction to elicit students' and university staff' bids for 0.5kg whole grain bread with selected attributes, including organic. The average WTP for organic bread was €0.80 under a blind tasting scenario, €1.22 when extrinsic quality cues (e.g. info about labels and packaging) were provided, and €1.19 after both blind tasting and extrinsic quality cues were provided.

Few studies examined the interaction of the organic label combined with other claims on bread. Bitzios, Fraser, and Haddock-Fraser (2011) examined the interaction of the organic claim with claims of health benefits and functional ingredients in three consumer segments, extracted from the stratified sample of UK households. They found that consumers in all segments were not willing to pay extra for the organic claim alone and with added claims of health benefit and functional ingredient, only one segment was

willing to pay £1 GBP for bread with organic and health benefit claims together. Hasselbach and Roosen (2015) used a sample of organic food buyers, intercepted at various shopping outlets in Germany, and found that consumers were not willing to pay extra for the organic attribute alone in bread, but the estimated premium for organic bread from the region, considered local, was €4.66.

In summary, the review of studies shows that there is a large variability in consumer WTP for the organic label on bread. We build on the previous research by examining the WTP values for the organic attribute alone and when combined with other labels, which has not been done previously in the US. In contrast to the majority of reviewed studies, we use a sample of consumers selected from the general population in the U.S. western states, not limiting the sample to primary household shoppers/organic food buyers/wheat bread consumers. In addition, the analysis is performed for two different types of wheat products – bread and cookies, with the goal to examine the impact of a product category on WTP values (staple vs. hedonistic), since previous studies have found that consumer preferences for organic attribute depend on the type of product (Ellison et al., 2016).

3.4 Data and Survey Methodology

The data used in the analysis comes from an online survey that was administered in the U.S. western states in the summer of 2017. The data and survey methodology are described in more detail in Essay 2.

3.5 Model Specification and Methodology

In this essay, the choices of respondents from a set of given alternatives are analyzed to understand how individual labels and prices contribute to the utility from an alternative and probability of the choice of an alternative. The choice is a binary variable, equal to 1 when the alternative is chosen and 0 otherwise, and the analysis is performed using a discrete choice modeling framework. Within this framework, multinomial logit (MNL) and random parameter logit (RPL) models are used in this study, as described below.

3.5.1 Multinomial Logit Model

The MNL model is considered a base model within the discrete choice modeling framework in a situation when the decision maker faces more than two alternatives from which he/she can choose. The MNL model is useful to identify what factors affect the decision maker's level of utility.

The utility of decision maker n from bread/cookies alternative i among $j=1,\dots,J$ bread/cookies alternatives, presented in a choice scenario t, U_{nit}, is

(3-1) $U_{nit} = V_{nit} + \varepsilon_{nit} = \beta X_{nit} + \varepsilon_{nit}$.

Here, V_{nit} is the observed portion of the utility and ε_{nit} is unobserved and assumed to be i.i.d. type 1 extreme value, i.e. uncorrelated across decision makers, alternatives and choice scenarios. The value of V_{nit} depends on the vector of attributes of the bread/cookies alternative i presented to decision maker n in a choice scenario t, X_{nit}, and the vector of marginal utilities associated with the attributes, β, which are assumed to not vary across respondents within the MNL framework. The goal is to estimate β given the observed attributes and choices made.

In this essay, three specifications of the observed utility function are used. In MNL1 model, X_{nit} is a vector of attributes in levels only, which includes dummies for organic, non-GMO, gluten-free and low-carb (for bread) or sugar-free (for cookies) labels equal to 1 when the label is present and 0 otherwise, alternative specific constant for opt-out option—none, and price. In MNL2 model, X_{nit} is expanded to include also two-way interactions of organic label with a) non-GMO, b) gluten-free and c) low-carb (bread) or sugar-free (cookies) labels equal to 1 when both labels are present and 0 otherwise. The aim is to examine whether a combination of the organic label with another label has any impact on the overall level of utility and to gain insights regarding whether the labels are perceived as complements, substitutes, or independent. If the parameter for the interaction term of two labels is positive, consumers derive additional utility from both labels that is beyond the sum of utilities from individual labels, and they are considered complements. If the interaction term is negative, the labels are considered substitutes and if it is zero, the labels are independent (McFadden and Lusk, 2017).

In MNL3 model, a three-way interaction of the organic label, the non-GMO label and knowledge that the organic product should be non-GMO by definition is added to the vector X_{nit} to examine whether this knowledge has any impact on the utility from the combination of organic and non-GMO labels.[27] The knowledge is a dummy variable equal

[27] This specification omits the main effect of knowledge and two-way interactions of knowledge with non-GMO and organic labels, respectively. First, the justification for omitting the main effect of knowledge is that when neither organic nor non-GMO labels are present (i.e. “organic”=0 and “non-GMO”=0), the knowledge that organic is also non-GMO does not affect the choice. Second, the justification for omitting the interaction of knowledge with non-GMO label is that when only the non-GMO label is present, the knowledge that organic is non-GMO does not affect the choice. And third, when only the organic label is present, the knowledge that organic is non-GMO does not affect the choice. In summary, the knowledge is assumed to affect the choice only when both organic and non-GMO labels are present.

to 1 when the decision maker knows that organic is non-GMO by definition and 0 otherwise. In the context of discrete choice models, only the differences in utility are identifiable (Train, 2009) and the conventional version of bread/cookies without any labels (i.e. “organic”=0, “non-GMO”=0, “gluten-free”=0, “low-carb”/”sugar-free”=0, “none”=0) is set as the reference product. The utility of the reference product is 0, and the utility associated with any label is interpreted relative to that.

In each choice scenario *t*, a rational and utility-maximizing decision maker *n* will choose the bread/cookie alternative *i* among $j=1,\ldots,J$ bread/cookie alternatives if and only if the utility from this alternative, U_{nit}, is greater than the utility from all other available alternatives, U_{njt}, for all $j \neq i$. The algebraic derivation of the logit choice probability of decision maker *n* choosing alternative *i* is described in more detail in Essay 2 and the resulting formula for the probability is (Train, 2009)

$$(3\text{-}2) \quad P_{nit} = \frac{\exp(V_{nit})}{\sum_{j=1}^{J}\exp(V_{njt})} = \frac{\exp(\beta X_{nit})}{\sum_{j=1}^{J}\exp(\beta X_{njt})}.$$

In this essay, each decision maker faces eight choice scenarios within each product category, making a sequence of choices. Since the unobserved portion of utility is assumed to be i.i.d. type 1 extreme value, it is uncorrelated over choice scenarios. Thus, the probability of decision maker *n* choosing a sequence of alternatives $\mathbf{i} = \{i_1, \ldots, i_T\}$, where i_t is an alternative with attributes $X_{ni_t t}$ chosen in choice scenario *t*, is a product of logit choice probabilities over choice scenarios (Train, 2009)

$$(3\text{-}3) \quad P_{n\mathbf{i}} = \prod_{t=1}^{T}\left[\frac{\exp\left(V_{ni_t t}\right)}{\sum_{j=1}^{J}\exp\left(V_{njt}\right)}\right] = \prod_{t=1}^{T}\left[\frac{\exp\left(\beta X_{ni_t t}\right)}{\sum_{j=1}^{J}\exp\left(\beta X_{njt}\right)}\right].$$

The vector β is estimated by applying maximum likelihood estimation (MLE) procedure to

(3-4) $$LL(\beta) = \sum_{n=1}^{N} \sum_{t=1}^{T} \sum_{j=1}^{J} y_{njt} \ln P_{njt}.$$

Equation (3-4) represents the log-likelihood function of observing the choices that are made by $N(= 1009)$ decision makers in the sample, in $T(= 8)$ choice scenarios and from $J(= 3)$ alternatives, where $y_{njt} = 1$ when decision maker *n* chooses alternative *j* in choice scenario t and $y_{njt} = 0$ otherwise. The values of β are estimated by maximizing the log-likelihood function.

The advantage of a MNL model is that it can be easily implemented. However, there are several assumptions related to this model which limit its application as described following Train (2009). First, it is required that the independence from irrelevant alternatives (IIA) property holds, meaning that when a new alternative is introduced to the choice set, the ratio of the probability of choice of any other two options in the choice set will not be affected. Second, it is assumed that the preferences of decision makers are homogeneous, i.e. β values are fixed across the population of decision makers. Third, in case when the decision maker makes a sequence of choices, MNL model assumes that there is no correlation between the unobserved factors that affect the choices made. The Hausman and McFadden (1984) test of IIA property is performed to determine whether the MNL model is valid, or whether the RPL model is more appropriate.

3.5.2 Random Parameter Logit Model

If the assumptions of a MNL model are found to be too restrictive, RPL model, also known as mixed logit model, can be implemented. In contrast to MNL model, RPL model does not require that the IIA assumption holds, it allows consumer preferences for product attributes to vary randomly across decision makers, and it can accommodate the correlation in the unobserved factors over the sequence of choices made by the same decision maker and over the choice alternatives in a choice scenario (Train, 2009).

In case of a RPL model, the vector of preferences for product attributes, i.e. taste parameters, is individual-specific and β_n instead of β is used. However, the vector β_n may also contain coefficients that are fixed. The distribution $f(\beta_n|\Theta)$ represents the density of β_n in the population, with Θ representing the parameters of the density that are to be estimated. The researcher specifies whether preferences for each attribute are random or fixed, the type of the distribution for each random parameter, and whether the preferences for individual attributes are correlated or not, which affects the number of parameters to be estimated and the overall complexity of the model. Preferences for some attributes can be specified as fixed either due to practical reasons (e.g. for the purposes of deriving WTP distribution as described later), or when it is found to be appropriate (e.g. when the estimated standard deviation is statistically insignificant as described later). The choice of the distribution for each parameter specified as random depends on the assumption of a reasonable range of the utility associated with the attribute in the population, as well as whether it is strictly positive or negative. Normal, triangular, uniform and log-normal distributions are commonly used (Hensher and Greene, 2003).

In the context of a RPL model, the probability that decision maker n makes a sequence of observed choices $\mathbf{i} = \{i_1, \dots, i_T\}$ is (Revelt and Train, 1998; Train, 2009)

$$(3\text{-}5) \quad P_{n\mathbf{i}} = \int \prod_{t=1}^{T} \left(\frac{\exp\left(V_{ni_t t}\right)}{\sum_{j=1}^{J} \exp\left(V_{njt}\right)} \right) f(\beta_n|\Theta) d\beta_n$$

$$= \int \prod_{t=1}^{T} \left(\frac{\exp\left(\beta_n X_{ni_t t}\right)}{\sum_{j=1}^{J} \exp\left(\beta_n X_{njt}\right)} \right) f(\beta_n|\Theta) d\beta_n \, .$$

Here, β_n is a vector of both fixed and random parameters, distributed as $f(\beta_n|\Theta)$, thus the RPL choice probability is the integral of the MNL choice probability over all possible β_n values. Here, the main interest is to estimate the set of parameters Θ, which describe the distribution of individual taste parameters β_n in the population (Revelt and Train, 1998).

The integral in equation (3-5) does not have a closed form solution. Thus, in case of the RPL model, a simulated maximum likelihood estimation (SMLE) procedure is used instead of the MLE procedure outlined in equation (3-4) for the MNL model. For each decision maker, SMLE starts with a draw of many values for each β_n value from its assumed distribution and each value is used to evaluate the logit choice probability in equation (3-3). The average of these probabilities is obtained for each decision maker, and these simulated averages are then used to construct the simulated log-likelihood function of the observed choices for all decision makers in the sample (Revelt and Train, 1998; Train, 2009).

Using the RPL framework, models RPL1, RPL2, and RPL3 are estimated following the specification of MNL models described previously but allowing for random

preferences. However, the decision needs to be made whether each individual parameter should be random or fixed, and for a random parameter, what distribution it should follow.

Initially, starting with RPL1 model, it is assumed that preferences for each attribute vary in the population following a normal distribution, except price which is specified to be fixed, following previous literature (e.g. Revelt and Train, 1998; Lusk and Schroeder, 2004; Van Loo et al., 2011; Janssen and Hamm, 2012; Hasselbach and Roosen, 2015).[28] The normal distribution is chosen under the assumption that decision makers can value each label either positively or negatively. In the next step, parameters with insignificant standard deviations are re-specified as fixed and the model is re-estimated (Barreiro-Hurle, Gracia, and de Magistris, 2010; Janssen and Hamm, 2012). Ultimately, the Bayesian Information Criterion (BIC) is used to select the best model within the RPL1 specification. In the next step, two-way interaction terms are added to this model to obtain the starting RPL2 model. Again, the preferences for the interactions of labels are assumed to be random and normally distributed, and different specifications for the parameters with insignificant standard deviations (random vs. fixed) are tested. Finally, the same procedure is applied to determine the specification of RPL3 model. In this essay, it is also assumed that the preferences for attributes are uncorrelated. The set of distribution parameters Θ to be estimated contains a vector of mean values of taste parameters, β, and a variance-covariance matrix, Σ. In Σ, the diagonal terms represent variance σ^2 of each taste parameter indicating how preferences vary in the population. The off-diagonal terms equal 0,

[28] For example, Revelt and Train (1998) state that the specification of fixed price parameter "allows easy derivation of the distribution of the WTP."

assuming that the preferences for attributes are uncorrelated. During the simulation process, 2000 Halton sequences are used to draw the β_n values.

3.5.3 Willingness to Pay

After the estimation of MNL and RPL models, we use the Hausman and McFadden (1984) test of the IIA property and model selection criteria (Akaike Information Criterion – AIC, Bayesian Information Criterion – BIC, and log-likelihood) to determine the final model. The mean coefficients of the selected final model are then used to calculate mean WTP values. For example, the mean WTP value for the organic label is calculated as the negative ratio of the parameter estimate for the organic label, $\beta_{organic}$, to the price parameter estimate, β_{price},

(3-6) $$WTP_{Mean,organic} = -\frac{\beta_{organic}}{\beta_{price}}.$$

To determine the significance of the calculated mean WTP values, we use the Delta method (Oehlert, 1992).

In the case of MNL models, the preferences are fixed and the value of β is the same for every decision maker. In the case of RPL models, the preferences for labels may vary over decision makers, following a normal distribution with mean β and standard deviation σ as discussed in the previous section. As a result, the WTP values for these labels vary as well and the distribution of WTP values can be derived. For example, assuming that the preferences for the organic label follow a normal distribution with standard deviation $\sigma_{organic}$ and the price coefficient β_{price} is fixed, the standard deviation of the WTP values for the organic label is calculated as (Hensher and Greene, 2003)

(3-7) $$WTP_{SD.,organic} = -\frac{\sigma_{organic}}{\beta_{price}}.$$

This convenience in finding the WTP distribution is the reason why the price coefficient β_{price} is set as fixed.[29]

We are also interested in understanding what factors affect consumers' mean WTP values for the labels alone and in combination. The examined factors include overall level of organic knowledge and familiarity, wheat and/or gluten intolerance and/or avoidance, and socio-demographics. The final model is estimated for each subgroup of decision makers formed based on the above factors, and mean WTP values are compared across these subgroups. For example, to examine the effect of gender on mean WTP values, the model is estimated separately for males and females, and then mean WTP values for each gender group are compared. The reason for not including these factors in the utility function directly is to avoid issues associated with the estimation of a large number of parameters.

[29] Alternatively, the price coefficient can be set as random following log-normal distribution, but past studies find that in this case the parameters of WTP distribution can become unrealistically high (Hess, Bierlaire, and Polak, 2005; Hole and Kolstad, 2012). A relatively new approach is to estimate models in "WTP space" (Train and Weeks, 2005), where the models are re-specified in a way that WTP values are estimated directly, allowing the assumptions to be made about the distribution of WTP values and not restricting the price coefficient to be fixed. It appears that models estimated in the WTP space yield more reasonable WTP distributions, but on the other hand, estimates obtained in the preference space tend to have a better fit (Train and Weeks, 2005). In addition, Hole and Kolstad (2012) find that mean WTP values derived from simpler models in the preference space (that is, MNL and RPL models with uncorrelated coefficients and fixed price) are similar to the mean WTP values estimated directly in WTP space using more complicated specification (all coefficients are random and uncorrelated/some correlated). Nevertheless, estimation in WTP space approach has not been applied widely in the past literature. In this essay, an attempt was made to apply this approach; however, convergence issues were encountered during estimation.

3.6 Results

Results from the estimation of the MNL and RPL models for bread and cookies are reported in tables 3-1 and 3-2, respectively. Within the group of RPL models, in RPL1 models all standard deviations for labels alone are statistically significant. Thus, no other specifications within RPL1 models were tested. In case of the RPL2 and RPL3 models, some standard deviations of the interaction terms are found to be insignificant, which indicates fixed preferences. Tables B-1 and B-2 in the Appendix B report all models that were considered within the RPL2 and RPL3 specifications for bread and cookies, respectively. BIC was used to select the best models.

Next, results from the estimation of MNL and RPL models in tables 3-1 and 3-2 are compared. The Hausman-McFadden test statistics and values of log-likelihood, AIC, and BIC across MNL and RPL models within each product category show clearly that RPL specifications are better. In addition, significant and large standard deviations of some coefficients imply that some preferences are indeed heterogeneous and not homogeneous, as assumed by MNL. Also, MNL and RPL models yield different coefficient estimates. Allowing the preferences to be random results in coefficients that are larger in magnitude, and in some cases the magnitude is more than double. For some coefficients, the significance is affected as well. These differences in estimates indicate that in this essay the model specification matters, and we focus on RPL models next.

Table 3-1. MNL and RPL Models, Bread

	MNL1	MNL2	MNL3	RPL1	RPL2	RPL3
Means						
Price	-0.46***	-0.45***	-0.45***	-1.03***	-1.03***	-1.03***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)
None	-1.76***	-1.69***	-1.70***	-5.06***	-4.90***	-4.89***
	(0.09)	(0.09)	(0.09)	(0.23)	(0.23)	(0.23)
Organic	0.14***	0.21***	0.21***	0.33***	0.55***	0.55***
	(0.05)	(0.07)	(0.07)	(0.10)	(0.14)	(0.14)
Gluten-free	-0.01	-0.08*	-0.07	-0.13*	-0.20**	-0.20**
	(0.03)	(0.04)	(0.04)	(0.07)	(0.09)	(0.09)
Low-carb	0.04	0.02	0.02	0.09	0.10	0.09
	(0.03)	(0.04)	(0.04)	(0.06)	(0.08)	(0.08)
Non-GMO	0.17***	0.31***	0.31***	0.33***	0.58***	0.58***
	(0.03)	(0.04)	(0.04)	(0.06)	(0.08)	(0.08)
Gluten-free×Organic	-	0.14***	0.14*	-	0.13	0.13
		(0.05)	(0.05)		(0.11)	(0.11)
Low-carb×Organic	-	0.02	0.02	-	-0.05	-0.05
		(0.05)	(0.05)		(0.11)	(0.10)
Non-GMO×Organic	-	-0.32***	-0.51***	-	-0.60***	-0.78***
		(0.05)	(0.07)		(0.12)	(0.14)
Non-GMO×Organic× Knowledge[1]	-	-	0.45*** (0.11)	-	-	0.42** (0.17)
Standard deviations						
None	-	-	-	4.54***	4.54***	4.54***
				(0.22)	(0.22)	(0.23)
Organic	-	-	-	2.52***	2.57***	2.55***
				(0.11)	(0.12)	(0.12)
Gluten-free	-	-	-	1.37***	1.40***	1.40***
				(0.10)	(0.10)	(0.10)
Low-carb	-	-	-	0.69***	0.75***	0.74***
				(0.11)	(0.11)	(0.11)
Non-GMO	-	-	-	0.71***	0.66***	0.65***
				(0.11)	(0.13)	(0.13)
Non-GMO×Organic	-	-	-	-	0.75***	0.76***
					(0.24)	(0.24)
Log-Likelihood	-8,160.8	-8,148.3	-8,129.6	-5,603.0	-5,588.5	-5,585.3
AIC	16,333.6	16,314.6	16,279.3	11,228.0	11,206.9	11,202.6
BIC	16,382.2	16,387.5	16,360.2	11,317.0	11,328.4	11,332.1
IIA test 1 statistic[2]	23.2***	21.8***	22.3***	-	-	-
IIA test 2 statistic[2]	48.8***	46.8***	49.2***	-	-	-

Note: *, **, *** denote significance of the coefficients at 10%, 5% and 1% level, respectively. Standard errors are in the parentheses. The number of observations used in the estimation of each model is 24,216.

[1] Knowledge = 1 if respondent knows that organic is also non-GMO and 0 otherwise.

[2] Hausman-McFadden test of IIA property: Test 1 statistic is obtained after excluding "organic" alternative. Test 2 statistic is obtained after excluding "none" alternative. *H0*: Difference in coefficients not systematic.

Table 3-2. MNL and RPL Models, Cookies

	MNL1	MNL2	MNL3	RPL1	RPL2	RPL3
Means						
Price	-0.44***	-0.44***	-0.44***	-1.06***	-1.08***	-1.08***
	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)
None	-2.17***	-2.15***	-2.16***	-6.16***	-6.21***	-6.22***
	(0.11)	(0.11)	(0.11)	(0.25)	(0.27)	(0.27)
Organic	-0.01	0.02	0.02	-0.06	0.11	0.10
	(0.05)	(0.07)	(0.07)	(0.10)	(0.13)	(0.13)
Gluten-free	-0.08**	-0.08*	-0.08*	-0.28***	-0.25***	-0.25***
	(0.03)	(0.04)	(0.04)	(0.08)	(0.10)	(0.10)
Sugar-free	-0.31***	-0.29***	-0.29***	-0.85***	-0.77***	-0.77***
	(0.04)	(0.04)	(0.04)	(0.10)	(0.11)	(0.11)
Non-GMO	0.04	0.04	0.04	0.12*	0.18**	0.18**
	(0.03)	(0.04)	(0.04)	(0.06)	(0.08)	(0.08)
Gluten-free×Organic	-	-0.01	-0.01	-	-0.12	-0.12
		(0.06)	(0.06)		(0.12)	(0.12)
Sugar-free×Organic	-	-0.05	-0.05	-	-0.41***	-0.41***
		(0.06)	(0.06)		(0.15)	(0.15)
Non-GMO×Organic	-	0.00	-0.10	-	-0.10	-0.15
		(0.05)	(0.07)		(0.12)	(0.14)
Non-GMO×Organic× Knowledge[1]	-	-	0.24**	-	-	0.12
			(0.11)			(0.17)
Standard deviations						
None	-	-	-	4.68***	4.69***	4.69***
				(0.22)	(0.21)	(0.21)
Organic	-	-	-	2.27***	2.24***	2.24***
				(0.11)	(0.12)	(0.12)
Gluten-free	-	-	-	1.43***	1.49***	1.49***
				(0.11)	(0.11)	(0.11)
Sugar-free	-	-	-	1.99***	1.98***	1.98***
				(0.12)	(0.12)	(0.12)
Non-GMO	-	-	-	0.68***	0.67***	0.68***
				(0.12)	(0.12)	(0.12)
Sugar-free×Organic	-	-	-	-	1.36***	1.37***
					(0.24)	(0.24)
Log-Likelihood	-8,097.7	-8,097.5	-8,093.0	-5,489.2	-5,482.3	-5,482.0
AIC	16,207.4	16,212.9	16,205.9	11,000.4	10,994.5	10,996.0
BIC	16,256.0	16,285.8	16,286.9	11,089.5	11,115.9	11,125.6
IIA test 1 statistic[2]	113.8***	579.1***	586.8***	-	-	-
IIA test 2 statistic[2]	90.4***	98.0***	97.8***	-	-	-

Note: *, **, *** denote significance of the coefficients at 10%, 5% and 1% level, respectively. Standard errors are in the parentheses. The number of observations used in the estimation of each model is 24,216.
[1] Knowledge = 1 if respondent knows that organic is also non-GMO and 0 otherwise.
[2] Hausman-McFadden test of IIA property: Test 1 statistic is obtained after excluding “organic” alternative. Test 2 statistic is obtained after excluding “none” alternative. *H0*: Difference in coefficients not systematic.

Within RPL models for both bread and cookies, the addition of the two-way interactions of labels affects the values of some coefficients in RPL2 models relative to RPL1 models, while the addition of the three-way interaction in RPL3 models affects the coefficients only marginally relative to RPL2 models. Given our interest to examine how mean WTP values for labels alone and the interactions of labels vary over consumer subgroups and considering the marginal changes in coefficient estimates going from RPL2 to RPL3 model, the RPL3 model is chosen as the final model. Although RPL3 model does not have the lowest BIC, the change in BIC from RPL2 to RPL3 model is marginal and RPL3 model has the lowest AIC and/or the highest log-likelihood. The discussion of results from RPL3 models follows next, and it is supplemented with means and standard deviations of WTP values, which are reported in table 3-3. The mean WTP values were calculated based on the equation (3-6) and the standard deviations (SD) based on the equation (3-7).

Table 3-3. WTP Distributions Derived from the Results of RPL3 Models

Labels/Label Interactions	Bread		Cookies	
	Mean	SD	Mean	SD
Organic	$0.54	$2.49	$0.10[a]	$2.07
Gluten-free	-$0.19	$1.36	-$0.23	$1.38
Low-carb/Sugar-free	$0.09[a]	$0.73	-$0.71	$1.83
Non-GMO	$0.56	$0.64	$0.17	$0.63
Gluten-free×Organic	$0.13[a]	-	-$0.11[a]	-
Low-carb×Organic/Sugar-free×Organic	-$0.05[a]	-	-$0.38	$1.26
Non-GMO×Organic	-$0.76	$0.74	-$0.14[a]	-
Non-GMO×Organic×Knowledge	$0.41	-	$0.11[a]	-

Note: [a] Values are not statistically significant at 10% or better.

3.6.1 Consumer Preferences for Individual Labels

First, the utility function coefficients and WTP values for individual labels alone are examined. On average, consumers value the organic label significantly positively in bread, but for cookies the positive coefficient is insignificant. Estimated mean WTP for the organic label on bread is $0.54 and $0.10[30] for cookies. This result supports previous findings of Van Doorn and Verhoef (2011) that consumers in general find the organic label less attractive in hedonistic food items. In both bread and cookies, the non-GMO label alone is valued on average positively and gluten-free label negatively. However, these labels are valued more positively and less negatively for bread. Mean WTP for the non-GMO label is $0.56 and $0.17 and for the gluten-free label -$0.19 and -$0.23 for bread and cookies, respectively.

Interestingly, in the case of bread, mean WTP for the non-GMO label is close to the WTP for the organic label. This suggests that on average, consumers either do not have a good understanding of what constitutes organic, or they care mostly about the non-GMO component of organic. The latter may be related to concerns about possible contamination of organic products with GMOs. In that case, consumers may choose the non-GMO label over the organic label, as it requires testing for possible contamination, while the organic label ensures that the GMOs are not used in the production process only. For cookies, it is even more interesting to find that consumers value the non-GMO attribute positively, yet they are not willing to pay extra for the organic label, although it covers non-GMO and more. Again, it might be because they are not aware that organic must be non-GMO, but

[30] In cookies, the estimated WTP is not statistically significant.

also it might be that they associate organic with a healthy diet, which does not correspond well with the hedonistic nature of cookies. It appears that consumers like the idea of a safer product, but perhaps they feel that organic label negatively affects some of the features they expect from cookies, e.g. enjoyable taste, relative to the non-GMO label.

Furthermore, mean estimate for the low-carb label parameter in bread is insignificant, while the sugar-free label parameter in cookies is negative and significant. Mean WTP for low-carb label in bread is \$0.09 and insignificant, but consumers need a discount of \$0.71 for a sugar-free label in cookies. There is likely a connection between generally lower consumer preferences for organic and sugar-free labels in cookies as a hedonistic product, relative to bread. However, the standard deviations of the parameters and WTP values for all labels alone are significant and large for both bread and cookies, meaning that there are some consumers who value each of these labels alone positively/negatively and may have a positive/negative WTP for each one.

3.6.2 Consumer Preferences for Combinations of Labels

Next, we examine the effect of combining the organic label with the remaining labels on the overall utility and WTP values. The overall utility/WTP value for a combination of two labels is calculated as the sum of the marginal utilities/WTP values for the labels alone and their interaction. First, we find that the interactions of organic and gluten-free labels on bread and cookies, organic and low-carb labels on bread, and organic and non-GMO labels on cookies are all insignificant, which means that these label combinations do not increase nor decrease the overall consumer utility/WTP value beyond the sum of the utilities/WTP values for these labels alone and the labels are perceived as independent. In addition, in

these cases the standard deviations of the interaction coefficients are not different from zero (not included in the reported final models), which means that consumers have similar preferences regarding these label interactions.

On the other hand, for bread, the interaction of organic and non-GMO label is negative on average. Thus, when both organic and non-GMO labels are provided on bread, the overall utility is lower than the sum of the utilities from the labels alone and these labels are perceived as substitutes. In terms of WTP, overall mean WTP for the combination of both labels on bread is $0.34 (= $0.54 + $0.56 - $0.76), which is lower than the mean WTP for each label alone ($0.54 for organic and $0.56 for non-GMO). This result is in line with the findings of McFadden and Lusk (2017). However, the standard deviation of the interaction term is significant and of a similar magnitude as the mean of the interaction term. Given the properties of normal distribution, this means that there is a segment of consumers who derive additional positive utility beyond the sum of the individual utilities from these labels alone and they are willing to pay more than the sum of WTP for the individual labels. These consumers view organic and non-GMO labels as complements.

Further, we find that the specific knowledge that organic must be non-GMO reduces the negative impact of combining these two labels on the overall utility and WTP. Total mean WTP for the combination of organic and non-GMO labels, conditional on the knowledge that organic is non-GMO, increases to $0.75 (= $0.34 + $0.41) and becomes greater than the WTP for each label alone, but smaller than the sum of WTP for each label. The moderating effect of knowledge is consistent across respondents since the standard deviation is insignificant (not included in RPL3 models). On the other hand, for cookies,

the interaction of the organic and non-GMO labels does not have any (negative or positive) effect on the overall utility and WTP, and the knowledge that organic must be non-GMO does not play a role either. In summary, consumer preferences for the combination of organic and non-GMO label depend on the product category, and it may or may not depend on the knowledge that organic is also non-GMO.

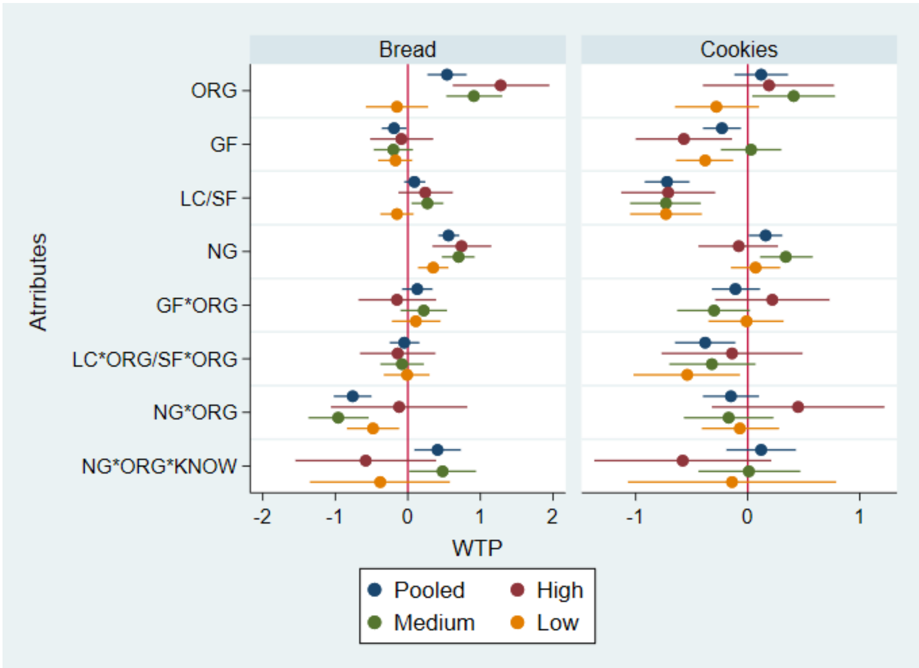
As mentioned previously, consumers on average dislike the sugar-free label on cookies, and in combination with the organic label the overall utility and WTP decrease even more. When the two labels are combined, consumers require a discount of \$1.09 (= \$0.71 + \$0.38). However, the significant and large standard deviation of the interaction term implies that there is a heterogeneity in preferences for the combination of these two labels. Again, given the properties of the normal distribution, there exists a segment of consumers who value this combination beyond the sum of the utilities and WTP values associated with these labels alone.

3.6.3 Impact of Objective and Subjective Knowledge of Organic Label on WTP

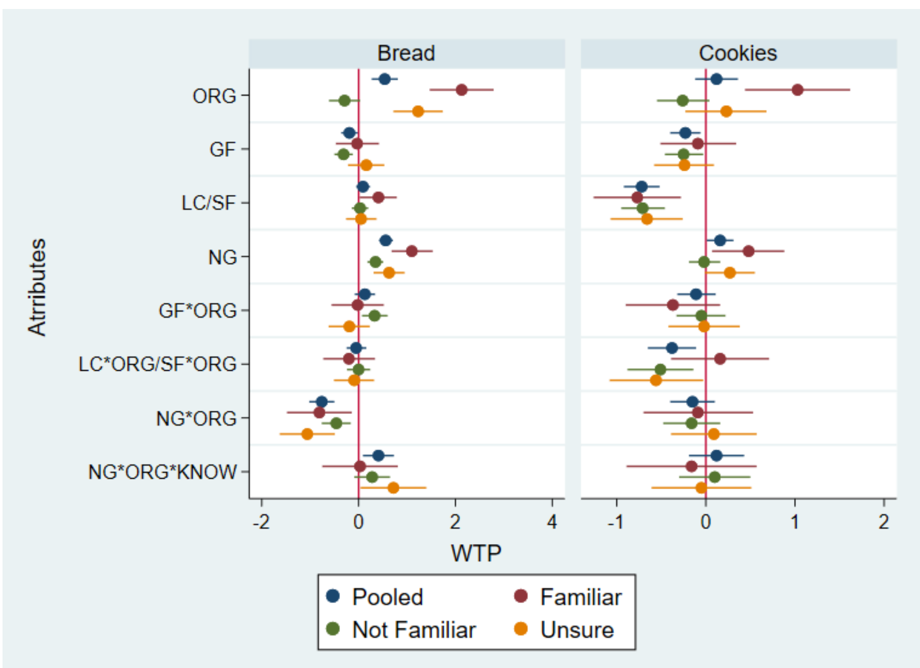
RPL3 models have been estimated for subgroups of consumers, formed based on different criteria to examine the impact of various factors on the mean WTP values for the labels alone and combinations of labels. In this section, the impact of tested knowledge of organic label (objective knowledge) and self-reported familiarity with organic label (subjective knowledge) are evaluated and compared. To test the knowledge of respondents, they were asked six questions related to organic food production and products (including whether organic production allows for the use of GMOs). Respondents with zero to one correct answer were assigned to the group of “low” knowledge (N=356), respondents with two to

three correct answers were assigned to the group of “medium” knowledge (N=490), and respondents with four correct answers or more were assigned to the group of “high” knowledge (N=163). Respondents were also asked about their familiarity with organic food production standards, and they were divided into groups of “familiar” (N=288), “not familiar” (N=493) and “unsure” (N=228). Overall, despite the mainstream nature of organic foods, the share of those who have a relatively good understanding of or consider themselves familiar with organics is relatively low at 16% and 23%, respectively.

Mean WTP values for labels alone and interactions of labels along with the 95% confidence intervals per each consumer subgroup are plotted in figure 3-1. Consumers with a medium and high knowledge of organic production standards are willing to pay more for the organic label on bread, while those with low knowledge are not. For cookies, only those with medium knowledge are willing to pay more for the organic label. This suggests that objective knowledge plays a role in consumer interest in the organic label only for specific products. It is different for subjective knowledge. Those who think that they are familiar with organic production standards are willing to pay more for the organic label in both bread and cookies. Thus, it appears that the link between the subjective knowledge of organic and the interest in organic is stronger than in case of the objective knowledge. This result supports findings of Pieniak, Aertsens, and Verbeke (2010) and Aertsens et al. (2011) that subjective knowledge affects the likelihood of consuming organic vegetables more than objective knowledge. It is possible that those who already purchase organic food consider themselves familiar with organic and are willing to pay more, but they do not necessarily have high factual knowledge of organics.



a) Objective knowledge



b) Subjective knowledge

Figure 3-1. Mean WTP values and 95% confidence intervals per consumer subgroup based on a) objective knowledge and b) subjective knowledge

Note: "ORG" = organic, "GF" = gluten-free, "LC/SF" = low-carb (bread) or sugar-free (cookies), "NG" = non-GMO. Numbers are reported in tables B-3 and B-4 in Appendix B.

Finally, those with low knowledge and those who claim that they are unfamiliar with organics are not willing to pay extra for organic bread nor cookies, indicating that lack of organic knowledge, either objective or subjective, limits interest in organics.

The WTP for the non-GMO label is positive within all subgroups for bread, but for cookies only within the group of those with medium knowledge and those who claim they are familiar with organics. Comparison of mean point estimates of WTP values shows that only those with low knowledge and those unfamiliar with organics are willing to pay more for the non-GMO label than the organic label. This finding suggests that both objective and subjective knowledge affect whether organic and non-GMO labels are confused, as expected.

Next, the effects of label interactions on the overall mean WTP (i.e. WTP for the combination of two labels) are examined across groups, with focus on those that are significantly different from zero. Only those who are not familiar with organics have positive mean WTP for the interaction of organic and gluten-free labels on bread equal to $0.33, but their mean WTP for these labels alone is $0 and -$0.31, respectively, resulting in overall mean WTP for both labels equal to $0.02. The interaction of organic and sugar-free labels on cookies is negative and significant within the group of consumers with low knowledge (-$0.54) and those who are unfamiliar (-$0.51) or unsure (-$0.56) about organic, resulting in overall negative WTP for the combination of these labels, given also their zero WTP for the organic label and negative WTP for the sugar-free label alone.

Further, in bread only, the coefficient for the interaction of organic and non-GMO labels, ranging from -$1.06 to -$0.46 within five of the six groups identified based on

perceived and tested knowledge, reduces the overall mean WTP for both labels, except for those with high objective knowledge of organics. Considering these five groups, the negative interaction coefficient reduces the WTP for the combination of these labels below the WTP for organic alone, except for those who claim that they are familiar with organics. They see some value in having both labels together (+$0.30 above their mean WTP for the organic label alone) regardless of their knowledge that organic is non-GMO. Further, the negative interaction effect is partially offset within the group of those with medium knowledge and those who are unsure about organic if they know that organic is non-GMO, and their overall WTP for both labels exceeds their WTP for the organic label alone by $0.22 and $0.28, respectively. This discussion illustrates the complexity of the issue of evaluating consumer WTP for combination of organic and non-GMO labels, and how knowledge that organic is also non-GMO can affect overall WTP positively.

Finally, the interaction terms for the remaining subgroups for bread and cookies, which have not been discussed, are not statistically different from zero—the labels are evaluated independently from each other. However, the mean WTP for all labels alone (besides the organic label) is either negative or zero for the majority of the subgroups, which means that the overall WTP for the combination of the organic label with these labels is either lower than or equal to the WTP for the organic label alone. Only those familiar with organic and those with medium knowledge of organic are WTP extra for low-carb on bread and non-GMO on cookies, resulting in overall mean WTP for a product with both labels greater than WTP for a product with organic label only.

3.6.4 Impact of Wheat and/or Gluten Intolerance and/or Avoidance on WTP

In this section, the impact of wheat and/or gluten intolerance and/or avoidance (WGIA) on mean WTP values for labels alone and their combinations is examined. Respondents were asked to indicate whether they have any wheat or gluten intolerance and whether they avoid wheat or gluten for any other reasons. They were split into two groups – one group made of those with WGIA (N=230) and another group made of those with no WGIA, i.e. NWGIA (N=779). Mean WTP values for labels alone and their combinations, along with 95% confidence intervals, are plotted in figure 3-2.

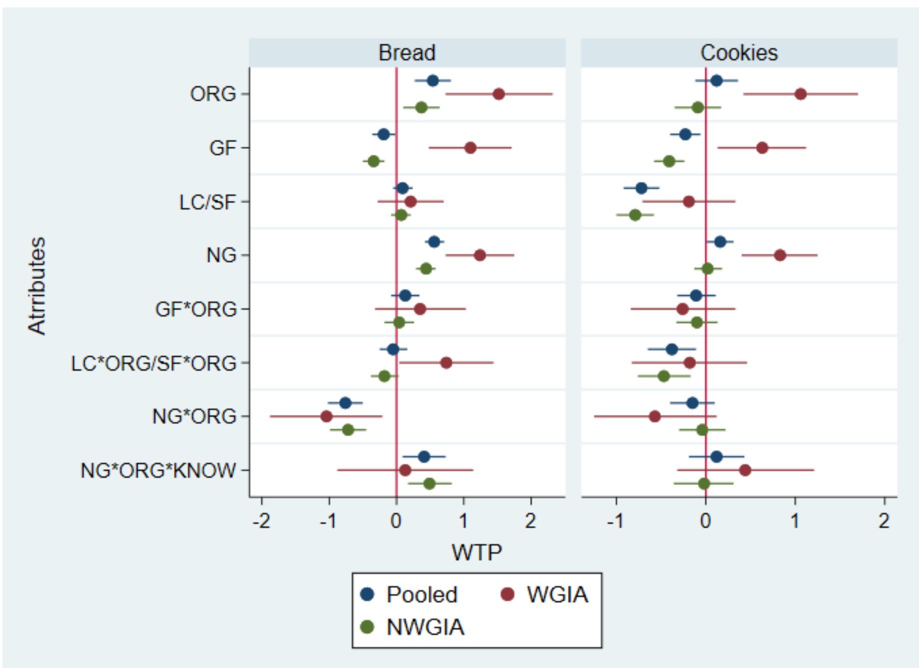


Figure 3-2. Mean WTP values and 95% confidence intervals per consumer subgroup based on wheat/gluten intolerance/avoidance

Note: "ORG" = organic, "GF" = gluten-free, "LC/SF" = low-carb (bread) or sugar-free (cookies), "NG" = non-GMO. Numbers are reported in table B-5 in Appendix B.

Focusing on the individual labels first, mean WTP for organic and non-GMO labels is positive in WGIA group for both products, but in NWGIA group for bread only. Also, the WGIA have significantly higher mean WTP for both labels alone than the NWGIA. As expected, the WGIA are also willing to pay extra for the gluten-free label in both bread and cookies, while the NWGIA require a discount if the label is present on any of the examined products. Similarly, the NWGIA dislike the sugar-free label on cookies, while the mean WTP of the WGIA is not different from zero.

Looking further at the label interactions, the overall mean WTP for organic and low-carb labels in bread increases when these labels are combined for the WGIA (+$0.74), while the effect is zero for the NWGIA. For cookies, the combination of organic and sugar-free labels does not affect overall WTP for the WGIA, but the effect on WTP is negative for the NWGIA (-$0.47).

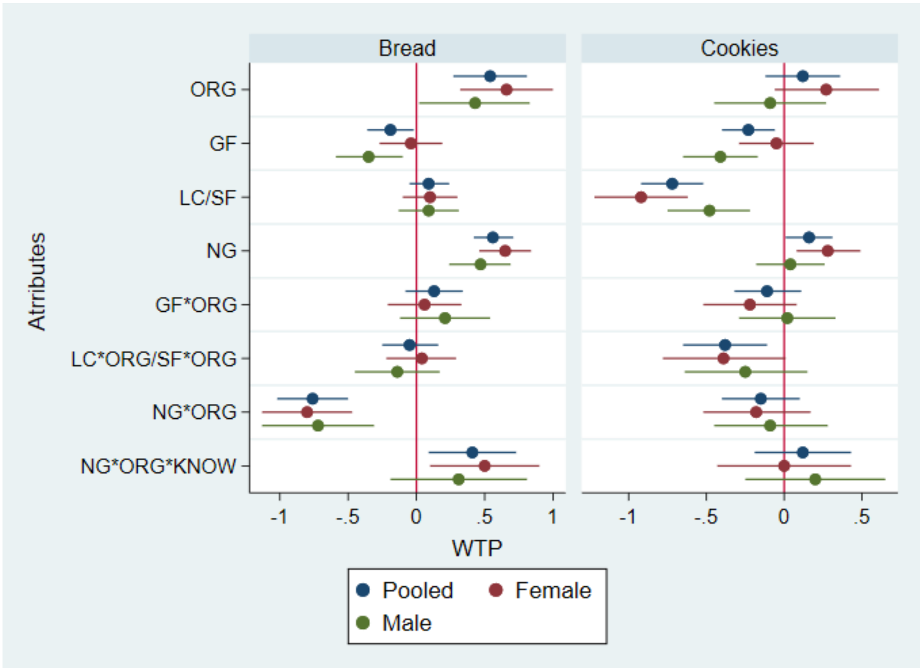
Regarding the interaction of organic and non-GMO labels, for WGIA the effect on overall WTP is negative for bread (-$1.04), but overall mean WTP for the combination of these labels is higher than the mean WTP for each label alone, and the knowledge that organic should be non-GMO does not play any role. For NWGIA, the effect of combining both labels is also negative (-$0.72) but it results in overall mean WTP below their WTP for each of these labels alone; however, not if they have the knowledge that organic is non-GMO (+$0.49 increase in mean WTP). In summary, the WGIA are on average willing to pay more than the NWGIA for the combination of organic and non-GMO on bread ($1.72 vs. $0.09 without knowledge and $0.59 with knowledge).

The interactions of organic and non-GMO labels on cookies, and organic and gluten-free labels on both bread and cookies, are not different from zero for both WGIA and NWGIA. While for WGIA the overall mean WTP for the combination of these labels is greater than WTP for the organic label alone (positive WTP for each label alone), for NWGIA it is either lower or does not change (the WTP values for gluten-free labels are negative and for non-GMO zero).

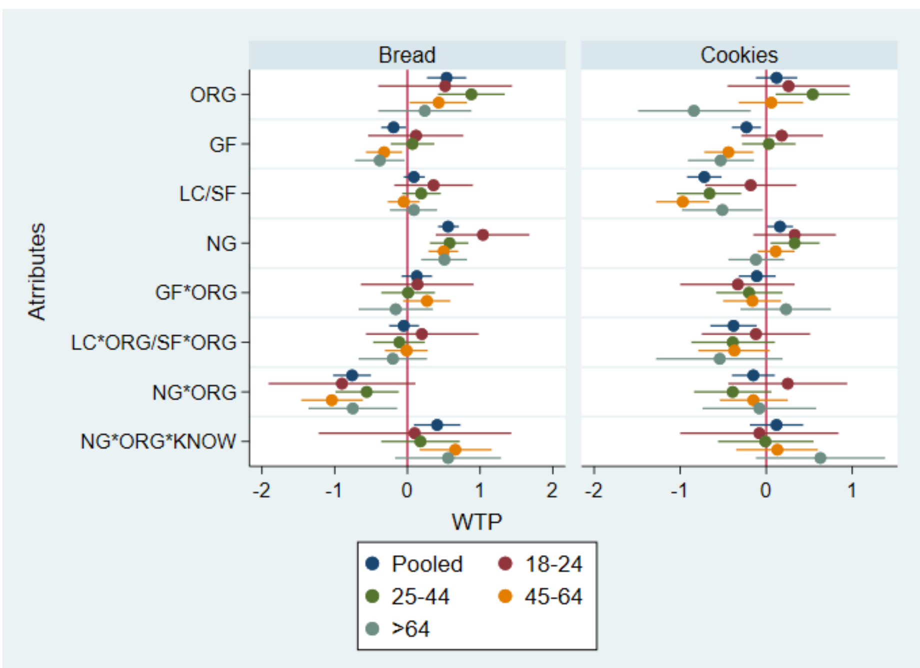
The discussed findings illustrate that there are some major differences in the valuation of individual labels and their combinations between the WGIA and NWGIA. The WGIA have overall higher WTP for examined labels alone including organic and they respond differently to the combinations of labels than the NWGIA. It is also found that 64% and 49% of the WGIA purchased organic bread and cookies in the past month, respectively, while only 33% and 17% of the NWGIA purchased organic versions of these products. This further shows that organic wheat products appeal particularly to the WGIA and based on their estimated WTP values they represent a profitable market segment.

3.6.5 Impact of Socio-Demographic Variables

In this section, mean WTP values are compared across groups created based on selected demographic (gender, age) and socio-economic (income, education, residency in California) variables. The most relevant findings are highlighted with the focus on the differences between the groups in terms of WTP for the organic label alone relative to the non-GMO label, and combinations of labels. Mean WTP values and 95% confidence intervals for demographic and socioeconomic groups are plotted in figures 3-3 and 3-4, respectively.



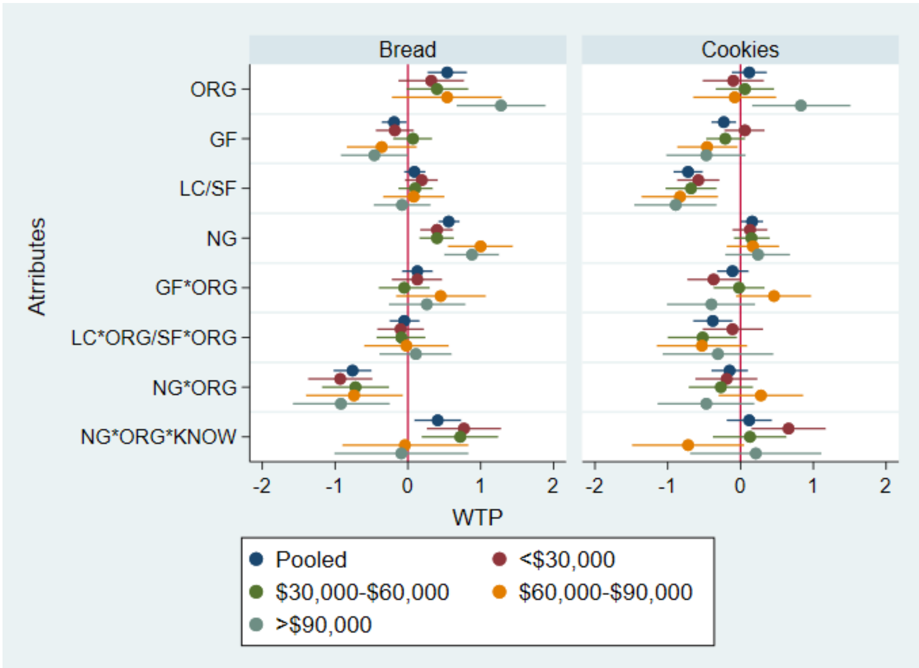
a) Gender



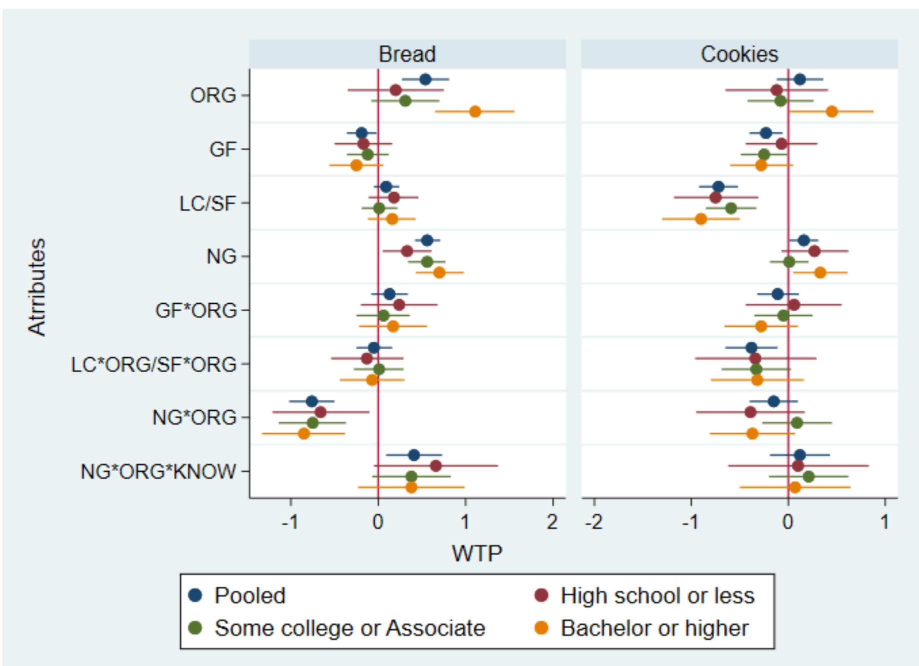
b) Age

Figure 3-3. Mean WTP values and 95% confidence intervals per consumer subgroup based on a) gender and b) age

Note: “ORG” = organic, “GF” = gluten-free, “LC/SF” = low-carb (bread) or sugar-free (cookies), “NG” = non-GMO. Numbers are reported in tables B-6 and B-7 in Appendix B.



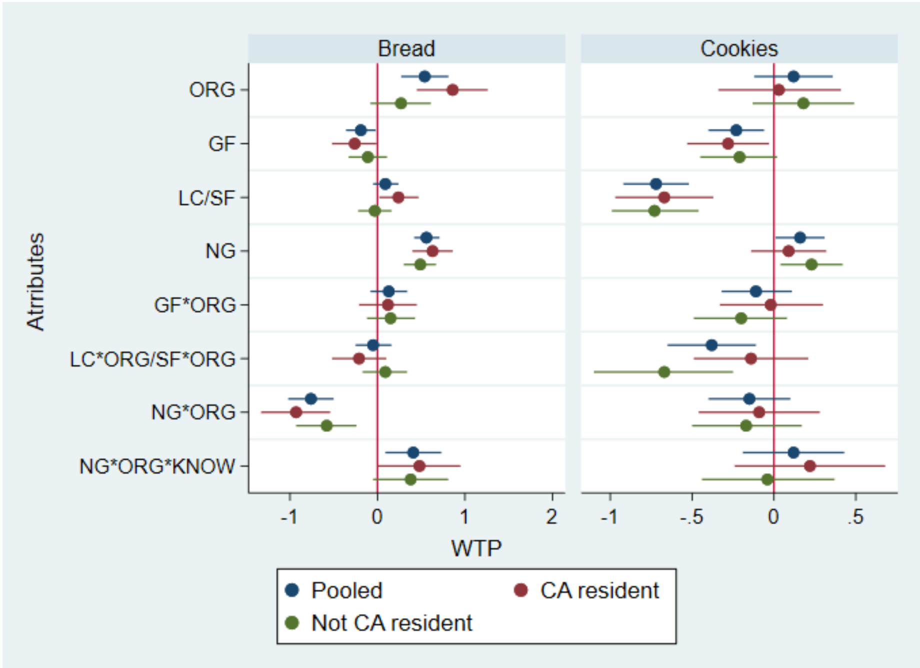
a) Income



b) Education

Figure 3-4. Mean WTP values and 95% confidence intervals per consumer subgroup based on a) income, b) education and c) residency in California

Note: "ORG" = organic, "GF" = gluten-free, "LC/SF" = low-carb (bread) or sugar-free (cookies), "NG" = non-GMO. Numbers are reported in tables B-8, B-9, and B-10 in Appendix B.



c) Residency in California

Figure 3-4 (continued). Mean WTP values and 95% confidence intervals per consumer subgroup based on a) income, b) education and c) residency in California

Note: "ORG" = organic, "GF" = gluten-free, "LC/SF" = low-carb (bread) or sugar-free (cookies), "NG" = non-GMO. Numbers are reported in tables B-8, B-9, and B-10 in Appendix B.

In terms of age, consumers in group 25-44 have the highest mean WTP for the organic label in both bread and cookies, which is consistent with findings in the literature that WTP for organics tends to decrease with age (Hughner et al., 2007), although others suggest that age does not play any role (He and Bernard, 2011). Further, it is found that household income above $90,000 and a bachelor's degree or higher are associated with positive mean WTP for the organic label on bread and cookies. This finding is in line with the findings of previous studies that consumers with higher income and/or education are willing to pay more for organics (Govindasamy and Italia, 1999; Strzok and Huffman, 2015). Also, residents of California are on average willing to pay more than non-residents

for organic bread but not for organic cookies. Thus, California may be an attractive market due to its size and relatively high consumer WTP for some organic products, but not necessarily all.

On the other hand, for bread, less than $90,000 income and less than a bachelor's degree are associated with positive and higher mean WTP for non-GMO relative to WTP for organic, which is insignificant. For cookies, in these groups the mean WTP estimate tends to be higher for non-GMO than organic as well, but the values are not statistically significant. Those who reside outside of California are willing to pay significantly more for non-GMO than organic label on both products. In summary, those with lower income and education and those outside of California tend to prefer non-GMO label over organic.

Among all socio-demographic groups, the interaction of organic and non-GMO labels in bread decreases the overall WTP for these labels together below the mean WTP for organic label alone, except for those in age group 25-44, but even for this group the overall mean WTP is close to the WTP for organic alone. However, if the knowledge that organic is also non-GMO is accounted for, the mean WTP for the combination of labels on bread increases above the WTP value for organic alone for those in age group 45-64, females, California residents, and those with income below $60,000. For cookies, this knowledge increases mean WTP for the combination of organic and non-GMO labels from zero to a positive value only in the group with income under $30,000. In summary, the knowledge that organic should be non-GMO plays a role in overall WTP for these labels together, but it depends on the socio-demographics.

3.7 Conclusions

While many studies have examined consumer WTP for organic labels on a variety of food products, studies that examine the interaction of organic labels with other labels are scarce. In this essay, the impact of additional labels, when combined with an organic label, on overall WTP is investigated. The analysis was conducted using two different wheat product categories, bread and cookies, to note any differences between a staple and a hedonistic food item. The labels selected for the analysis are non-GMO, gluten-free, and low-carb in the case of bread and sugar-free in the case of cookies. Multinomial logit (MNL) and random parameter logit (RPL) models are used to perform the analysis, where RPL model accounts for the possibility of heterogeneous consumer preferences. The data were collected using an online survey, which was administered in the summer of 2017 across 16 U.S. western states. In total, 1,009 valid responses were received.

Results show that, on average, consumers are willing to pay extra for the organic label on bread but not on cookies. It appears that the healthy image of organic label interferes with the hedonistic nature of cookies. This finding suggests that consumers prefer organic labels more on staple food items than on hedonistic food items, which has also been found previously (Van Doorn and Verhoef, 2011). Further, it is found that consumer interest in the organic label alone is more consistently associated with self-reported familiarity with organics rather than tested knowledge, and thus it is in line with the findings of Pieniak, Aertsens, and Verbeke (2010) and Aertsens et al. (2011).

Second, in comparison to mean WTP for organics, consumers are willing to pay a similar amount for the non-GMO label on bread, but a higher amount for cookies. This

suggests that consumers either do not know that organic is also non-GMO, or they confuse the two labels, or they care mostly about the non-GMO component of organics. Similar WTP values for organic and non-GMO labels alone have been observed in previous studies (Bernard, Zhang, and Gifford, 2006; McFadden and Lusk, 2017). But the gap found between WTP for the organic and non-GMO labels in cookies relative to bread further indicates that consumers find the organic label less desirable in a hedonistic food product. Next, considering the overall knowledge of and familiarity with organics, it is found that specifically those with low knowledge and those unfamiliar are in fact willing to pay more for the non-GMO label than the organic, suggesting that both objective and subjective knowledge affect whether organic and non-GMO labels are confused.

Third, the interaction of organic and non-GMO labels on bread decreases mean WTP for these labels in the whole sample as found in McFadden and Lusk (2017) as well. But it depends on the age, WGIA, overall familiarity with and knowledge of organic, and specific knowledge that organic is also non-GMO, whether the overall WTP for these labels together is higher or lower than mean WTP for the organic label alone. Similarly, the interaction of organic and sugar-free labels on cookies decreases overall mean WTP for these labels in the whole sample. However, even the sugar-free label alone in cookies is on average valued negatively by consumers, with an exception of consumers with some WGIA and younger consumers. WGIA is also among factors determining whether the interaction is negative or not, in addition to residency in California, income group, and familiarity with and knowledge of organic. This shows that there are many factors that may influence consumer preferences for the combination of organic with other labels.

Fourth, it is found that the impact of organic and non-GMO labels on WTP depends on product category; for bread this interaction impacts WTP for both labels negatively, but for cookies the individual WTP values are additive. It might be that the organic and non-GMO labels alone are more important on a staple product like bread and thus consumers are willing to pay a high amount for them individually, but they cannot afford to pay the sum of these WTP values when the labels are provided together. On the other hand, in cookies, the WTP for each label alone is much lower, indicating lower importance of these labels to consumers, but when they are combined, consumers can afford to pay the sum of the individual WTP values.

Fifth, the consumer response to a label indicating reduction of sugar content (low-carb in bread and sugar-free in cookies) alone, as well as in combination with organic label, is on average negative for cookies but neutral for bread. This further shows that consumer response to a particular label or combination of labels depends on a product category. Considering the findings for the other labels as well, it appears that many consumers do not prefer “healthy” labels or they prefer them less on hedonistic products than on staple products, but significant standard deviations indicate that there are consumers who would benefit from products with these labels alone or combined with the organic label.

This essay contributes to the existing literature in several aspects. First, it revisits the issue of consumer confusion surrounding the organic and non-GMO labels, which was identified in previous studies, and examines the potential effect of consumer knowledge that organic must be also non-GMO on the WTP, which has not yet been done. It is found that if the combination of the labels decreases overall WTP, the knowledge can increase

overall WTP above the WTP for the organic label alone. Food manufacturers may benefit from marketing strategies aimed at educating consumers about the organic label and how it is related to non-GMO label. This will reduce the confusion between organic and non-GMO labels, and consumers will be able to make more informed decisions and re-evaluate their preferences for the organic label relative to non-GMO.

Second, this essay provides insights regarding the effects of other labels on consumers' WTP for organic products, which is important as the number of claims per product has been increasing in recent years, and thus will be useful for food manufacturers and marketers. Specifically, this essay examines the interactions of the organic label with gluten-free, low-carb, and sugar-free labels, which to our knowledge has not been examined in the literature. It is found that the effect of combining organic and other labels depends on a product category and several consumer factors. Although combining the organic label with health promoting labels such as low-carb, sugar-free and gluten-free does not affect positively the overall utility of consumers on average, there are consumers that would benefit from such label combinations. Food manufacturers and marketers need to carefully examine specific preferences of their target market for a given label combination.

Third, the impact of consumer actual knowledge and self-reported familiarity with organic label on consumer WTP for organic is examined in the context of organic wheat products, which extends the findings of previous studies, as well as the impact of consumer WGIA on WTP for organic, which has not been studied before. While socio-demographic factors can be useful to describe the target market, criteria such as knowledge and

familiarity with organic and WGIA can serve better to detect consumer segments with relatively high mean WTP values. Specifically, those with WGIA are among the consumers with high WTP for the organic label in both bread and cookies, and thus they may represent a profitable target market for organic wheat products.

This essay uses the same data as essay 2 and thus the limitations highlighted in essay 2 apply here as well. First, it is possible that the group of organic consumers is underrepresented in the sample. Further, due to the hypothetical nature of the choice experiment, it is possible that the respondents did not evaluate the product attributes, in particular price, as rigorously as they would in a real shopping scenario. As a result, derived WTP distributions are only approximations of the true WTP distributions.

We found differences in consumer WTP for the labels alone and their combinations on bread and cookies, but we examined two product categories only. Future research might examine consumer WTP for other groups of staple and hedonistic food items to further confirm our findings regarding higher consumer WTP for organic label on staple food products. Another area of research could explore in more detail why consumers prefer the organic label more on staple products. Finally, it would be interesting to investigate the impact of increasing consumer factual knowledge of organic on the WTP for the organic label, as well as what determines consumer perceived familiarity with organic.

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SUMMARY AND CONCLUSIONS

This dissertation has addressed issues related to the supply and demand for organic wheat either as a commodity or as an input in final consumer baking products. It provides insights that are important to wheat growers as they strive to manage the uncertainty in the development of organic wheat prices, which may affect profitability. It also provides insights that will be helpful to food manufacturers and marketers as they strive to make production, labeling and marketing decisions that will match consumer needs with a limited supply of organic wheat available.

In the first essay, organic and conventional wheat prices for a period from 2008 to 2017 were used to simulate organic premiums and examine the risk associated with the profitability of organic wheat production relative to conventional wheat production. Further, since organic premium and organic wheat price are closely related, two possibilities to manage the organic wheat price uncertainty were investigated. This study is the first one to examine (1) the possibility to cross hedge price risk of an organically grown commodity using the futures market for its conventional counterpart, and (2) dynamic price relationships between these two related, but qualitatively differentiated commodities. In this process, vector error correction and vector autoregressive models were employed. Because organic wheat prices were not observed during the entire studied period, we applied three different methods for imputing the missing observations.

The results show that there were occasions when the organic premium did not cover the additional costs of producing organic wheat, but the losses were compensated over time during the period studied. The results further provide limited evidence that cross hedging

using conventional futures can be used to manage the organic wheat price uncertainty, since it is found to depend on the method used to impute missing organic wheat prices and the studied time period. To implement hedging, wheat growers would have to purchase conventional futures contracts as their hedge instead of selling them. It is also found that the organic wheat market is connected to the conventional wheat market, since there is evidence of long-run and short-run dynamic relationships between organic spot and conventional futures prices. The nature of these relationships has been changing over time, but more recently, conventional futures have been found to contain information that can be useful to predict organic wheat prices in the short run. A possible explanation for these findings is that the U.S. organic wheat market has been evolving during the studied period but has become more mature recently.

For the second and third essay, the data were collected using an online consumer survey, which was conducted in the summer of 2017 across 16 U.S. western states. In the second essay, the review of literature suggested that it is more appropriate to identify organic food consumers based on attitudinal and lifestyle factors than socio-demographic factors, which many studies in the past had focused on. Based on this knowledge, we used attitudes toward organic products and production systems in combination with stated and revealed preferences for the organic label on bread and cookies to identify groups of "very likely," "likely" and "unlikely" consumers of organic bread and cookies. This was performed using latent class modeling. Further, differences between the groups were analyzed using the Welch test and Wilcoxon test to contribute to the literature by examining factors that determine consumer interest in organic food products. In addition,

the findings will likely be of great importance to marketers of the examined products. Since the literature review further indicated that the interest in organic products depends on whether the product is virtue or vice, the analysis is performed for bread, as an example of a virtue product, and cookies, as an example of a vice product.

The findings from the second essay show that significant differences exist across the consumer segments, which are not product specific. The importance of product labels and characteristics and willingness to pay (WTP) values differ significantly between groups of “very likely,” “likely” and “unlikely” consumers. Further, significant differences have been found also in terms of motivations and barriers to purchase organic bread and cookies, socio-demographics, lifestyles, and shopping and consumption habits. These findings form basis for recommendations, provided to food manufacturers and marketers.

In the third essay, consumer WTP for the organic label on bread and cookies was examined in more detail. Further, the use of several product labels (non-GMO, gluten-free, and low-carb or sugar-free) in combination with the organic label was investigated to determine whether these combinations are beneficial for consumers or whether they experience information overload. Overall, studies that examine consumer interest in the combination of labels that involve organic label are scarce, and to our knowledge, none of the previous studies have examined the interaction of the organic label with gluten-free and low-carb or sugar-free labels. To accomplish these tasks, multinomial logit and random parameter logit models were used.

The findings show that WTP for organic bread is higher than WTP for organic cookies, and WTP for organic is either similar (bread) or lower (cookies) than WTP for the

non-GMO label, supporting and extending previous findings in the literature. It is also found that the combinations of labels with the organic label on average do not increase overall consumer utility and WTP. However, there are consumers who find some of these label combinations appealing. Specific knowledge that organic is non-GMO by definition, as well as general tested knowledge of organic, self-reported familiarity with organic, wheat or gluten intolerance or avoidance, and several socio-demographic factors are found to affect consumer preferences for the labels alone and/or their combinations. Considering these factors in the analysis of the consumer preferences for the combination of organic and non-GMO labels extends previous findings in the literature. Finally, this study found that organic and gluten-free labels are perceived by consumers as independent, but it also uncovered that a group of consumers, who avoid or have intolerance for wheat or gluten, represents a profitable segment for organic bread and cookies.

Policy Implications

The findings of this dissertation result in several market and policy implications. First, findings of the first essay point to the need of a risk management education for the organic wheat producers, which would discuss the profitability risks of organic wheat production and familiarize the producers with the tools they could use to minimize the risks. Such educational programs may support the growth of the organic wheat production. Improved understanding of the profitability risks associated with the organic wheat production relative to the conventional wheat production and the tools that can be used to reduce organic price uncertainty can help producers gain confidence as they make production decisions.

Second, we confirm that consumer interest in organic products depends on the product category. Organic bread attracts interest of a broader group of consumers compared to organic cookies, but some of these consumers are very price-sensitive. Put differently, if the price is favorable, some consumers are willing to buy organic bread, but not organic cookies. This is likely due to the varying quality (e.g. taste) expectations and preferences associated with these products. However, these may not be necessarily founded on an actual experience, but rather on perception. Thus, consumer education about the organic label should be extended to also include emphasis on how the quality of organic products might be affected. Elimination of misconceptions about the quality of organic foods relative to conventional foods, in particular in case of hedonistic food items, can contribute to the increase of consumer interest in these products.

Third, we find that average consumer knowledge about organic products and production systems is low. At the same time, certain lifestyles and consumer wheat/gluten intolerance/avoidance are associated with the interest in foods containing organic wheat. Thus, education surrounding the organic label and promotion of organic products should be targeted to specific consumer groups who will likely be more responsive to the information related to organic products.

Fourth, we find that many consumers are not aware that organic production does not allow for the use of GMOs. However, we also find that many consumers consider organic and non-GMO labels to be substitutes, which shows that there is a lot of confusion among consumers regarding the relationship between the two labels. This confusion can lead to consumer preference for the non-GMO label and their unwillingness to pay more

for the organic label, which holds especially for the consumers with overall low knowledge of the organic label. This points to the need of consumer educational programs that would focus on explaining the relationship between these two labels. We find that providing both organic and non-GMO labels on products will not be helpful to consumers who are less knowledgeable about the organic label, since it results in their overall WTP below that of the organic label alone.

Mandatory labeling of GMOs, which can be considered an alternative to providing both organic and non-GMO labels, will help assure consumers that organic products are non-GMO, but it will not serve to eliminate confusion of some consumers regarding these two labels. Besides, we find that "likely" and "unlikely" consumers of organic bread and cookies tend to pay less attention to front labels than "very likely" consumers, which implies that they may benefit less from the mandatory GMO labeling than the "very likely" consumers. However, since we find that they are more price-sensitive, they might respond better to promotional campaigns, which could also be used to inform about the differences between labels.

APPENDICES

APPENDIX A: An Example of the Questionnaire Used for Online Data Collection

UtahState University

Consumer Preferences for Wheat Products

Thank you for your interest in this research study. Before you choose to participate in this study, please read the following information carefully.

This research study is being conducted by Dr. Kynda Curtis, Professor in the Department of Applied Economics at Utah State University. The purpose of this research is to explore consumer preferences and attitudes toward wheat products. More specifically, we seek to understand which attributes of bread and cookies are valuable to you as a consumer and how your attitudes towards food related issues influence your preferences. There are no “right” or “wrong” answers and if you choose to participate in this study, it is very important that you provide answers that reflect your true opinions.

Procedures
Your participation will involve filling out the survey that will contain questions about your food shopping and consumption habits, preferences for different food attributes and labels, attitudes towards specific food related issues and lifestyle and demographic questions which will only be used to evaluate how responses vary among different groups of consumers. In addition, you will be shown different product descriptions and asked to choose the ones you would purchase, if you were facing them in a real shopping scenario. It should take you no longer than 20 minutes to complete the survey. You do not need to complete the survey in one sitting. If you initiate the survey and you wish to complete it at a later time, you can save your answers and come back to the survey later.

Risks
This is a minimal risk research study. That means that the risks of participating are no more likely or serious than those you encounter in everyday activities.

Benefits
There is no direct benefit to you in participating in this research study. This study will help the researchers learn more about consumer preferences for specific attributes of wheat products and the results are expected to provide insight to wheat producers, wheat product manufacturers and marketers, and/or researchers interested in related topics in the future.

Confidentiality
The researchers will make every effort to ensure that the information you provide as part of this study remains confidential. Your identity will not be revealed in any publications, presentations, or reports resulting from this research study.

We will collect your information through Qualtrics and it will be stored on the Qualtrics platform. We will not receive information about your name, and thus, we will not be able to identify you or link your responses to you in any way. The demographic data that we will collect will be aggregated and used only to make comparisons across groups of consumers.

It is unlikely, but possible, that Utah State University and state or federal officials may require us to share the information you give us from the study to ensure that the research was conducted

safely and appropriately. We will only share your information if law or policy requires us to do so.

The research team works to ensure confidentiality to the degree permitted by technology. It is possible, although unlikely, that unauthorized individuals could gain access to your responses because you are responding online. However, your participation in this online survey involves risks similar to a person's everyday use of the Internet.

Voluntary Participation and Withdrawal
Your participation in this research study is completely voluntary. If you agree to participate now and change your mind later, you may withdraw at any time by exiting your browser, as long as you have not received the message confirming “your response has been recorded”. You will not be able to withdraw after you have fully completed the survey, as your participation is completely anonymous and we will not be able to track your responses.

Compensation
For your participation in this research study, you will receive the incentive listed in your invitation. You will only receive compensation after you qualify for and complete the survey.

IRB Review
The Institutional Review Board (IRB) for the protection of human research participants at Utah State University has reviewed and approved this study. If you have questions about the research study itself, please contact the Principal Investigator, Dr. Kynda Curtis, at (435) 797-0444 or kynda.curtis@usu.edu. If you have questions about your rights or would simply like to speak with someone other than the research team about questions or concerns, please contact the IRB Director at (435) 797-0567 or irb@usu.edu.

1. What is your gender?
○ Male
○ Female
○ Fluid or other

2. What is your current age in years?
○ Under 18 years
○ 18-24 years
○ 25-44 years
○ 45-64 years
○ 65 years and over

3. What was your 2016 annual household income before taxes?
○ Less than $10,000
○ $10,000 - $19,999
○ $20,000 - $29,999
○ $30,000 - $39,999
○ $40,000 - $49,999
○ $50,000 - $59,999
○ $60,000 - $69,999
○ $70,000 - $79,999
○ $80,000 - $89,999

○ $90,000 - $99,999
○ $100,000 - $149,999
○ More than $150,000

4. What is your marital status?
○ Single
○ Married
○ Other

5. How many people including yourself live in your household per age group?
5 years and younger ______
6-17 years ______
18-60 years ______
61 years and older ______

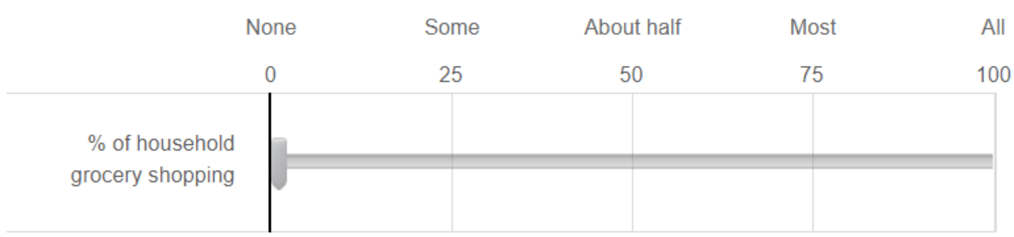
6. Which of the following best represents your completed level of education?
○ Middle school
○ High school
○ Some college
○ 2-year associate's degree
○ 4-year college degree
○ Graduate degree or higher

7. Which of the following best describes your employment status?
○ Full-time employed
○ Part-time employed
○ Unemployed
○ Homemaker
○ Retired
○ Student

8. Which of the following best describes your ethnic background?
○ Black or African American
○ American Indian and Alaska Native
○ Asian
○ Native Hawaiian and Other Pacific Islander
○ White
○ Hispanic or Latino
○ Some other race
○ Two or more races
○ Prefer not to answer

9. In which U.S. state or territory do you reside?
○ Alaska
○ American Samoa
○ Arizona
○ California
○ Colorado
○ Guam
○ Hawaii
○ Idaho
○ Kansas
○ Montana
○ Nebraska
○ Nevada
○ New Mexico
○ North Dakota
○ N. Marianas Islands
○ Oklahoma
○ Oregon
○ South Dakota
○ Utah
○ Washington
○ Wyoming

10. What percentage of your household grocery shopping are you responsible for? (Please slide the bar to the appropriate level)



11. Do you or any member of your household suffer from the following? (Select all that apply)
□ Some degree of wheat intolerance or allergy
□ Some degree of gluten intolerance or allergy
□ Celiac disease
□ None of the above

12. Do you or any member of your household avoid foods containing wheat or gluten for reasons other than intolerance, allergy, or Celiac disease? (Select all that apply)

□ Yes, avoid foods containing wheat

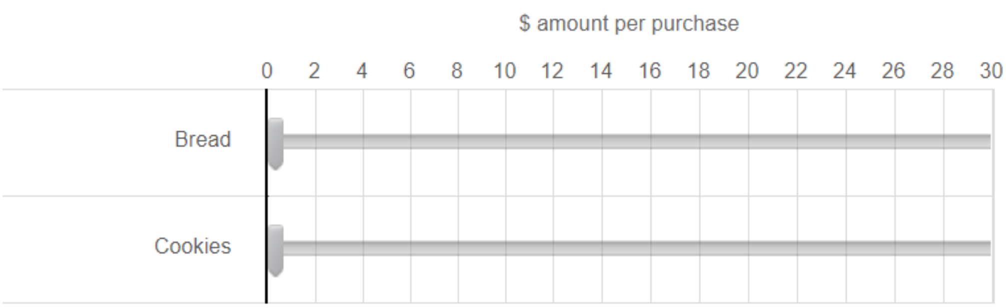
□ Yes, avoid foods containing gluten

□ None of the above

13. How often do you purchase breads or cookies?

	Bread	Cookies
Several times a week	○	○
Once a week	○	○
Several times a month	○	○
Once a month or less	○	○
Never	○	○

14. How much do you spend on average per purchase on bread and cookies? (Please slide the bar to the appropriate level)



15. Where do you typically shop for breads and cookies? (Select all that apply)

	Bread	Cookies
Grocery store (Smith's, Winco, etc.)	□	□
Bulk store (Sam's Club, Costco, etc.)	□	□
Multi-purpose store (Wal-Mart, Kmart, etc.)	□	□
Specialty store (Whole Foods, Trader Joes, etc.)	□	□
Discount store (Savers, etc.)	□	□
Local bakery	□	□
Other	□	□

16. How often do you consume breads and cookies?

	Bread	Cookies
Two servings per day or more	○	○
Several servings per week	○	○
Several servings a month	○	○
One serving a month or less	○	○
I do not consume this food	○	○

17. Please rank the importance of the following when you purchase bread by dragging each up or down until they are in the appropriate order.

Taste	1
Appearance	2
Nutritional value	3
Freshness	4
Price	5
Brand	6
Safety	7
Origin	8

18. Please rank the importance of the following bread labels by dragging and dropping the labels on the left to the box on the right (1=most important, 7=least important).

Items	Ordered labels
Gluten-free	
Non-GMO	
Organic	
Natural	
Locally made	
Whole grain	
Low-carb	

19. Have you purchased organic bread in the past month?

○ Yes

○ No

20a. Why yes? (Select all that apply)

- □ Organic bread is healthier
- □ Organic bread is more visually attractive
- □ Organic bread tastes better
- □ Organic bread does not contain harmful substances
- □ I like to try new food alternatives
- □ My family members like organic bread
- □ Organic food is trendy or in fashion
- □ Organic food production is better for the environment

20b. Why not? (Select all that apply)

- □ I did not think about it
- □ Organic bread is too expensive
- □ Organic bread is not visually attractive
- □ Regular bread tastes better than organic
- □ Organic bread is not available in the store where I shop
- □ It is difficult to find the variety I like
- □ I do not think organic bread is better than regular bread
- □ I do not trust that it is really organic
- □ Organic bread has a shorter shelf life
- □ I am not familiar with organic bread
- □ My family members do not like organic food
- □ I am not familiar with organic foods

21. Please rank the importance of the following when you purchase cookies by dragging each up or down until they are in the appropriate order.

Taste	1
Appearance	2
Nutritional value	3
Freshness	4
Price	5
Brand	6
Safety	7
Origin	8

22. Please rank the importance of the following cookie labels by dragging and dropping the labels on the left to the box on the right (1=most important, 7=least important).

Items	Ordered labels
Gluten-free	
Non-GMO	
Organic	
Natural	
Locally made	
Whole grain	
Sugar-free	

23. Have you purchased organic cookies in the past month?

○ Yes

○ No

24a. Why yes? (Select all that apply)

□ Organic cookies healthier

□ Organic cookies are visually attractive

□ Organic cookies taste better

□ Organic cookies do not contain harmful substances

□ I like to try new food alternatives

□ My family members like organic cookies

□ Organic food is trendy or in fashion

□ Organic food production is better for the environment

24b. Why not? (Select all that apply)

□ I did not think about it

□ Organic cookies are too expensive

□ Organic cookies are not visually attractive

□ Regular cookies taste better

□ Organic cookies are not available in the store where I shop

□ It is difficult to find the variety I like

□ I do not think organic cookies are better than regular cookies

□ I do not trust that they are really organic

□ Organic cookies have a shorter shelf life

□ I am not familiar with organic cookies

□ My family members do not like organic food

□ I am not familiar with organic foods

25. Rank the importance of having a certified organic option for the products below by dragging each up or down until they are in the appropriate order.

Bread (standard white/wheat loaf)	1
Cookies	2
Crackers	3
Pastries	4
Bagels	5
Pies	6
Breadsticks	7
Pasta	8
Bread (specialty loaf - sourdough, rye, etc.)	9

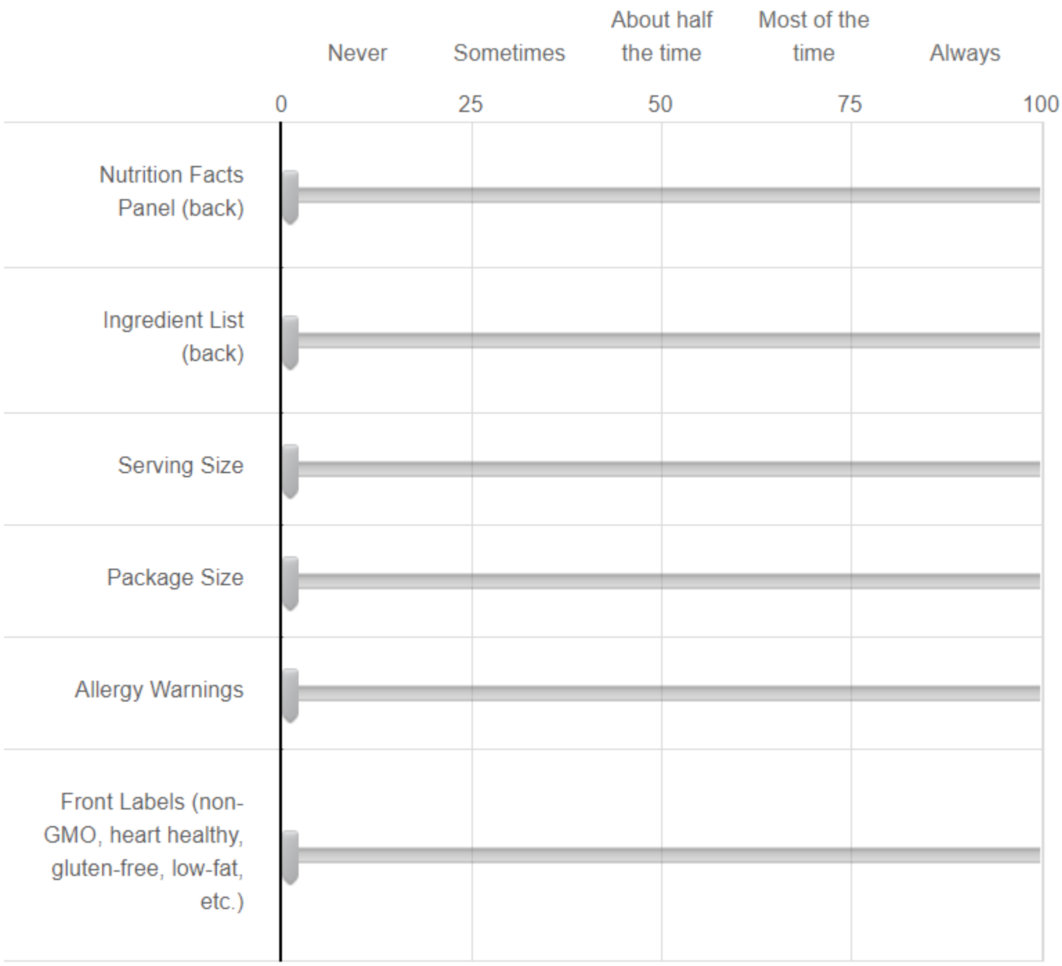
26. In the past month, what other types of bread or cookies did you purchase? (Select all that apply)

	Bread	Cookies
Non-organic	□	□
Non-GMO	□	□
Gluten-free	□	□
Locally made	□	□
Whole grain	□	□
Home baked	□	□
Low-carb or sugar-free	□	□
None of above	□	□

27. How often do you consume foods labelled organic, locally-grown, sustainable, GMO-free, natural, grass-fed, free-range, etc.?

○ Several times a week
○ Once a week
○ Several times a month
○ Once a month or less
○ Never

28. How often do you review the following information when purchasing food? (Please slide the bar to the appropriate level)



29. Please specify if you agree or disagree with each of the following statements about organic food and organic production in general.

	Strongly Disagree	Somewhat Disagree	Unsure	Somewhat Agree	Strongly Agree
Organic products are healthier than conventional products	○	○	○	○	○
Organic products are fresher than conventional products	○	○	○	○	○
Organic products are not safer than conventional products	○	○	○	○	○
Organic products do not taste better than conventional products	○	○	○	○	○
Organic products are too expensive	○	○	○	○	○
The selection of organic products in stores isn't good	○	○	○	○	○
Organic products do not contain harmful substances	○	○	○	○	○
Organic production is better for the environment	○	○	○	○	○
Buying organic food does not benefit local farmers	○	○	○	○	○

30. Are you familiar with "organic" food production standards?

○ Yes

○ No

○ Unsure

31. Please answer True, False or Unsure to the following statements related to organic food production and products.

	True	False	Unsure
Organic production prohibits the use of all synthetic fertilizers	○	○	○
Organic production prohibits the use of sewage sludge as fertilizer	○	○	○
Organic production allows for the use of GMOs	○	○	○
Organic production requires use of locally-sourced inputs	○	○	○
Products with an organic label must be certified by the USDA or third party	○	○	○
All products that are certified organic are 100% organic or contain 100% organic ingredients	○	○	○

32. Please specify if you agree or disagree with each of the following statements.

	Strongly Disagree	Somewhat Disagree	Unsure	Somewhat Agree	Strongly Agree
I control my salt and sugar intake	○	○	○	○	○
I control my fat consumption	○	○	○	○	○
I follow a vegetarian or vegan diet	○	○	○	○	○
I eat fresh produce daily	○	○	○	○	○
I eat grains daily	○	○	○	○	○
I avoid eating processed foods	○	○	○	○	○
I avoid eating food products with additives	○	○	○	○	○
I am concerned about my health	○	○	○	○	○
I am concerned about the safety of my food	○	○	○	○	○
I am concerned about the origin of my food	○	○	○	○	○
I eat out infrequently	○	○	○	○	○
Physical activity or exercise is an important part of my routine	○	○	○	○	○
I buy products with low environmental impact	○	○	○	○	○
Recycling is a priority for me	○	○	○	○	○
Supporting local farmers is important to me	○	○	○	○	○
Agricultural open space is important to me	○	○	○	○	○

You will now be asked several questions regarding your preferences for conventionally and organically produced high quality bread. Please select the option you would choose when shopping and consider your true preferences and budget for the bread types, prices, and labels on each product.

33. Which of the following loaves of bread (approx. 1 pound) would you purchase based upon the listed price in dollars and labels indicated?

	 Conventional White Bread $1.63	 Organic White Bread $2.25	None
I would choose...	○	○	○

34. Which of the following loaves of bread (approx. 1 pound) would you purchase based upon the listed price in dollars and labels indicated?

			
	Conventional White Bread **$2.79** Non-GMO	**Organic White Bread** **$4.71** Non-GMO Gluten-free Low-carb	**None**
I would choose...	○	○	○

35. Which of the following loaves of bread (approx. 1 pound) would you purchase based upon the listed price in dollars and labels indicated?

			
	Conventional White Bread **$1.63** Non-GMO Low-carb	**Organic White Bread** **$3.20** Non-GMO Gluten-free	**None**
I would choose...	○	○	○

36. Which of the following loaves of bread (approx. 1 pound) would you purchase based upon the listed price in dollars and labels indicated?

			
	Conventional White Bread **$3.15** Gluten-free	**Organic White Bread** **$3.33** Gluten-free Low-carb	**None**
I would choose...	○	○	○

37. Which of the following loaves of bread (approx. 1 pound) would you purchase based upon the listed price in dollars and labels indicated?

	Conventional White Bread **$1.76** Gluten-free Low-carb	**Organic White Bread** **$4.40** Non-GMO Low-carb	**None**
I would choose...	○	○	○

38. Which of the following loaves of bread (approx. 1 pound) would you purchase based upon the listed price in dollars and labels indicated?

	Conventional White Bread **$4.36** Non-GMO Gluten-free	**Organic White Bread** **$4.49** Non-GMO	**None**
I would choose...	○	○	○

39. Which of the following loaves of bread (approx. 1 pound) would you purchase based upon the listed price in dollars and labels indicated?

	Conventional White Bread **$4.08** Low-carb Non-GMO Gluten-free	**Organic White Bread** **$4.23** Low-carb	**None**
I would choose...	○	○	○

40. Which of the following loaves of bread (approx. 1 pound) would you purchase based upon the listed price in dollars and labels indicated?

	Conventional White Bread $4.83 Low-carb	Organic White Bread $2.03 Gluten-free	None
I would choose...	○	○	○

You will now be asked several questions regarding your preferences for conventionally and organically produced high quality cookies. Please select the option you would choose when shopping and consider your true preferences and budget for the cookie types, prices, and labels on each product.

41. Which of the following 1 pound bags of cookies would you purchase based upon the listed price in dollars and labels indicated?

	Conventional Choc Chip Cookies $6.24	Organic Choc Chip Cookies $6.14	None
I would choose...	○	○	○

42. Which of the following 1 pound bags of cookies would you purchase based upon the listed price in dollars and labels indicated?

			
	Conventional Choc Chip Cookies **$5.07** Non-GMO	**Organic Choc Chip Cookies** **$5.54** Non-GMO Gluten-free Sugar-free	**None**
I would choose...	○	○	○

43. Which of the following 1 pound bags of cookies would you purchase based upon the listed price in dollars and labels indicated?

			
	Conventional Choc Chip Cookies **$5.53** Non-GMO Sugar-free	**Organic Choc Chip Cookies** **$5.11** Non-GMO Gluten-free	**None**
I would choose...	○	○	○

44. Which of the following 1 pound bags of cookies would you purchase based upon the listed price in dollars and labels indicated?

			
	Conventional Choc Chip Cookies **$2.72** Gluten-free	**Organic Choc Chip Cookies** **$4.78** Gluten-free Sugar-free	**None**
I would choose...	○	○	○

45. Which of the following 1 pound bags of cookies would you purchase based upon the listed price in dollars and labels indicated?

	Conventional Choc Chip Cookies **$4.67** Gluten-free Sugar-free	Organic Choc Chip Cookies **$5.81** Non-GMO Sugar-free	None
I would choose...	○	○	○

46. Which of the following 1 pound bags of cookies would you purchase based upon the listed price in dollars and labels indicated?

	Conventional Choc Chip Cookies **$3.88** Non-GMO Gluten-free	Organic Choc Chip Cookies **$7.58** Non-GMO	None
I would choose...	○	○	○

47. Which of the following 1 pound bags of cookies would you purchase based upon the listed price in dollars and labels indicated?

	Conventional Choc Chip Cookies **$6.54** Sugar-free Non-GMO Gluten-free	Organic Choc Chip Cookies **$4.07** Sugar-free	None
I would choose...	○	○	○

48. Which of the following 1 pound bags of cookies would you purchase based upon the listed price in dollars and labels indicated?

	Conventional Choc Chip Cookies $4.91 Sugar-free	Organic Choc Chip Cookies $7.93 Gluten-free	None
I would choose...	○	○	○

We thank you for your time spent taking this survey.
Your response has been recorded.

APPENDIX B: Tables

Table B-1. RPL2 and RPL3 Models, Bread

	RPL2a	RPL2b	RPL2c	**RPL2d**	RPL3a	**RPL3b**
Price (Mean)	-1.03***	-1.03***	-1.03***	**-1.03*** **	-1.03***	**-1.03*** **
	(0.04)	(0.04)	(0.04)	**(0.04)**	(0.04)	**(0.04)**
None (Mean)	-4.97***	-5.00***	-5.01***	**-4.90*** **	-4.89***	**-4.89*** **
	(0.23)	(0.23)	(0.23)	**(0.23)**	(0.23)	**(0.23)**
Organic (Mean)	0.57***	0.58***	0.58***	**0.55*** **	0.56***	**0.55*** **
	(0.14)	(0.15)	(0.14)	**(0.14)**	(0.14)	**(0.14)**
Gluten-free (Mean)	-0.19**	-0.19**	-0.19**	**-0.20** **	-0.20**	**-0.20** **
	(0.09)	(0.09)	(0.09)	**(0.09)**	(0.09)	**(0.09)**
Low-carb (Mean)	0.10	0.10	0.10	**0.10**	0.09	**0.09**
	(0.08)	(0.08)	(0.08)	**(0.08)**	(0.08)	**(0.08)**
Non-GMO (Mean)	0.58***	0.58***	0.59***	**0.58*** **	0.58***	**0.58*** **
	(0.08)	(0.08)	(0.08)	**(0.08)**	(0.08)	**(0.08)**
Gluten-free×Organic (Mean)	0.13	0.13	0.13	**0.13**	0.13	**0.13**
	(0.11)	(0.11)	(0.11)	**(0.11)**	(0.11)	**(0.11)**
Low-carb×Organic (Mean)	-0.05	-0.05	-0.05	**-0.05**	-0.05	**-0.05**
	(0.11)	(0.11)	(0.11)	**(0.11)**	(0.11)	**(0.10)**
Non-GMO×Organic (Mean)	-0.61***	-0.60***	-0.60***	**-0.60*** **	-0.78***	**-0.78*** **
	(0.12)	(0.12)	(0.12)	**(0.12)**	(0.14)	**(0.14)**
Non-GMO×Organic× Knowledge (Mean)	-	-	-	**-**	0.42**	**0.42** **
					(0.17)	**(0.17)**
None (SD)	4.58***	4.54***	4.59***	**4.54*** **	4.54***	**4.54*** **
	(0.22)	(0.22)	(0.22)	**(0.22)**	(0.22)	**(0.23)**
Organic (SD)	2.55***	2.60***	2.59***	**2.57*** **	2.55***	**2.55*** **
	(0.12)	(0.12)	(0.12)	**(0.12)**	(0.12)	**(0.12)**
Gluten-free (SD)	1.39***	1.40***	1.40***	**1.40*** **	1.40***	**1.40*** **
	(0.10)	(0.10)	(0.10)	**(0.10)**	(0.10)	**(0.10)**
Low-carb (SD)	0.75***	0.75***	0.76***	**0.75*** **	0.74***	**0.74*** **
	(0.11)	(0.11)	(0.11)	**(0.11)**	(0.11)	**(0.11)**
Non-GMO (SD)	0.69***	0.72***	0.73***	**0.66*** **	0.65***	**0.65*** **
	(0.12)	(0.12)	(0.11)	**(0.13)**	(0.13)	**(0.13)**
Gluten-free×Organic (SD)	0.25	0.23	-	**-**	-	**-**
	(0.50)	(0.33)				
Low-carb×Organic (SD)	0.05	-	0.04	**-**	-	**-**
	(0.29)		(0.26)			
Non-GMO×Organic (SD)	0.75***	0.68***	0.68***	**0.75*** **	0.76***	**0.76*** **
	(0.22)	(0.26)	(0.22)	**(0.24)**	(0.23)	**(0.24)**
Non-GMO×Organic× Knowledge (SD)	-	-	-	**-**	0.21	**-**
					(0.44)	
Log-Likelihood	-5,589.5	-5,584.1	-5,583.8	**-5,588.5**	-5,585.2	**-5,585.3**
AIC	11,213.0	11,200.3	11,199.5	**11,206.9**	11,204.4	**11,202.6**
BIC	11,350.6	11,329.8	11,329.1	**11,328.4**	11,342.0	**11,332.1**

Note: *, **, *** denote significance of the coefficients at 10%, 5% and 1% level, respectively. Standard errors are in the parentheses. Only parameters with significant standard deviations are specified as random and remaining parameters are fixed. The number of observations used in the estimation of each model is 24,216. Final selected models are in bold.

Table B-2. RPL2 and RPL3 Models, Cookies

	RPL2a	RPL2b	RPL2c	**RPL2d**	RPL3a	**RPL3b**
Price (Mean)	-1.10***	-1.09***	-1.09***	**-1.08*** **	-1.08***	**-1.08*** **
	(0.04)	(0.04)	(0.04)	**(0.04)**	(0.04)	**(0.04)**
None (Mean)	-6.24***	-6.27***	-6.23***	**-6.21*** **	-6.21***	**-6.22*** **
	(0.27)	(0.27)	(0.26)	**(0.27)**	(0.27)	**(0.27)**
Organic (Mean)	0.14	0.14	0.12	**0.11**	0.10	**0.10**
	(0.14)	(0.13)	(0.14)	**(0.13)**	(0.13)	**(0.13)**
Gluten-free (Mean)	-0.24**	-0.25***	-0.25***	**-0.25*** **	-0.25***	**-0.25*** **
	(0.10)	(0.10)	(0.10)	**(0.10)**	(0.10)	**(0.10)**
Sugar-free (Mean)	-0.80***	-0.76***	-0.75***	**-0.77*** **	-0.77***	**-0.77*** **
	(0.11)	(0.11)	(0.11)	**(0.11)**	(0.11)	**(0.11)**
Non-GMO (Mean)	0.18**	0.19**	0.18**	**0.18** **	0.18**	**0.18** **
	(0.08)	(0.08)	(0.08)	**(0.08)**	(0.08)	**(0.08)**
Gluten-free×Organic (Mean)	-0.14	-0.11	-0.14	**-0.12**	-0.12	**-0.12**
	(0.12)	(0.12)	(0.12)	**(0.12)**	(0.12)	**(0.12)**
Sugar-free×Organic (Mean)	-0.38**	-0.40***	-0.42***	**-0.41*** **	-0.41***	**-0.41*** **
	(0.15)	(0.15)	(0.15)	**(0.15)**	(0.15)	**(0.15)**
Non-GMO×Organic (Mean)	-0.11	-0.13	-0.10	**-0.10**	-0.15	**-0.15**
	(0.12)	(0.12)	(0.12)	**(0.12)**	(0.14)	**(0.14)**
Non-GMO×Organic× Knowledge (Mean)	-	-	-	**-**	0.11	**0.12**
					(0.17)	**(0.17)**
None (SD)	4.72***	4.74***	4.78***	**4.69*** **	4.69***	**4.69*** **
	(0.21)	(0.22)	(0.22)	**(0.21)**	(0.22)	**(0.21)**
Organic (SD)	2.30***	2.29***	2.27***	**2.24*** **	2.24***	**2.24*** **
	(0.12)	(0.12)	(0.12)	**(0.12)**	(0.12)	**(0.12)**
Gluten-free (SD)	1.53***	1.48***	1.49***	**1.49*** **	1.49***	**1.49*** **
	(0.12)	(0.11)	(0.11)	**(0.11)**	(0.11)	**(0.11)**
Sugar-free (SD)	2.05***	1.98***	1.95***	**1.98*** **	1.98***	**1.98*** **
	(0.13)	(0.12)	(0.12)	**(0.12)**	(0.12)	**(0.12)**
Non-GMO (SD)	0.74***	0.65***	0.69***	**0.67*** **	0.68***	**0.68*** **
	(0.12)	(0.12)	(0.12)	**(0.12)**	(0.12)	**(0.12)**
Gluten-free×Organic (SD)	0.46*	-	0.43	**-**	-	**-**
	(0.27)		(0.31)			
Sugar-free×Organic (SD)	1.29***	1.42***	1.42***	**1.36*** **	1.36***	**1.37*** **
	(0.24)	(0.22)	(0.21)	**(0.24)**	(0.24)	**(0.24)**
Non-GMO×Organic (SD)	0.10	0.41	-	**-**	-	**-**
	(0.32)	(0.28)				
Non-GMO×Organic× Knowledge (SD)	-	-	-	**-**	-0.14	**-**
					(0.44)	
Log-Likelihood	-5,479.6	-5,480.1	-5,478.7	**-5,482.3**	-5,482.0	**-5,482.0**
AIC	10,993.1	10,992.1	10,989.4	**10,994.5**	10,997.9	**10,996.0**
BIC	11,130.7	11,121.7	11,118.9	**11,115.9**	11,135.5	**11,125.6**

Note: *, **, *** denote significance of the coefficients at 10%, 5% and 1% level, respectively. Standard errors are in the parentheses. Only parameters with significant standard deviations are specified as random and remaining parameters are fixed. The number of observations used in the estimation of each model is 24,216. Final selected models are in bold.

Table B-3. Mean WTP Values and 95% Confidence Intervals per Consumer Subgroup Based on Objective Knowledge of Organic

	Bread			Cookies		
	Mean WTP	Lower bound	Upper bound	Mean WTP	Lower bound	Upper bound
High knowledge of organic						
Organic	1.28*	0.62	1.95	0.19	-0.40	0.77
Gluten-free	-0.09	-0.52	0.35	-0.57*	-1.00	-0.14
Low-carb/Sugar-free	0.24	-0.13	0.62	-0.71*	-1.13	-0.29
Non-GMO	0.74*	0.34	1.15	-0.08	-0.44	0.27
Gluten-free×Organic	-0.15	-0.68	0.39	0.22	-0.29	0.73
Low-carb×Organic/ Sugar-free×Organic	-0.14	-0.66	0.38	-0.14	-0.77	0.49
Non-GMO×Organic	-0.12	-1.06	0.82	0.45	-0.32	1.22
Non-GMO×Organic×Knowledge	-0.58	-1.55	0.39	-0.58	-1.37	0.21
Medium knowledge of organic						
Organic	0.91*	0.53	1.30	0.41*	0.04	0.78
Gluten-free	-0.20	-0.47	0.07	0.03	-0.24	0.30
Low-carb/Sugar-free	0.27*	0.05	0.49	-0.73*	-1.05	-0.42
Non-GMO	0.70*	0.47	0.92	0.34*	0.11	0.58
Gluten-free×Organic	0.22	-0.10	0.54	-0.30	-0.63	0.02
Low-carb×Organic/ Sugar-free×Organic	-0.08	-0.38	0.22	-0.32	-0.70	0.07
Non-GMO×Organic	-0.96*	-1.37	-0.54	-0.17	-0.57	0.23
Non-GMO×Organic×Knowledge	0.48*	0.02	0.94	0.01	-0.44	0.47
Low knowledge of organic						
Organic	-0.15	-0.58	0.28	-0.28	-0.65	0.10
Gluten-free	-0.17	-0.41	0.06	-0.38*	-0.64	-0.13
Low-carb/Sugar-free	-0.15	-0.38	0.08	-0.73*	-1.05	-0.41
Non-GMO	0.35*	0.14	0.56	0.07	-0.15	0.29
Gluten-free×Organic	0.11	-0.22	0.45	-0.01	-0.35	0.32
Low-carb×Organic/ Sugar-free×Organic	-0.01	-0.33	0.30	-0.54*	-1.02	-0.07
Non-GMO×Organic	-0.48*	-0.84	-0.12	-0.07	-0.41	0.28
Non-GMO×Organic×Knowledge	-0.38	-1.35	0.58	-0.14	-1.07	0.79

Note: * denotes significance of the mean WTP at 5% level.

Table B-4. Mean WTP Values and 95% Confidence Intervals per Consumer Subgroup Based on Subjective Knowledge of Organic

	Bread			Cookies		
	Mean WTP	Lower bound	Upper bound	Mean WTP	Lower bound	Upper bound
Familiar with organic						
Organic	2.13*	1.47	2.79	1.03*	0.44	1.62
Gluten-free	-0.03	-0.47	0.42	-0.09	-0.51	0.34
Low-carb/Sugar-free	0.41*	0.02	0.79	-0.77*	-1.26	-0.28
Non-GMO	1.10*	0.68	1.53	0.48*	0.07	0.88
Gluten-free×Organic	-0.02	-0.56	0.52	-0.37	-0.90	0.16
Low-carb×Organic/ Sugar-free×Organic	-0.20	-0.73	0.34	0.16	-0.39	0.71
Non-GMO×Organic	-0.81*	-1.48	-0.14	-0.09	-0.70	0.53
Non-GMO×Organic×Knowledge	0.03	-0.75	0.81	-0.16	-0.89	0.57
Not familiar with organic						
Organic	-0.29	-0.61	0.03	-0.26	-0.55	0.04
Gluten-free	-0.31*	-0.50	-0.12	-0.25*	-0.46	-0.03
Low-carb/Sugar-free	0.03	-0.14	0.20	-0.71*	-0.95	-0.46
Non-GMO	0.35*	0.18	0.51	-0.02	-0.19	0.16
Gluten-free×Organic	0.33*	0.07	0.60	-0.05	-0.33	0.22
Low-carb×Organic/ Sugar-free×Organic	0.00	-0.24	0.24	-0.51*	-0.88	-0.14
Non-GMO×Organic	-0.46*	-0.76	-0.16	-0.16	-0.48	0.16
Non-GMO×Organic×Knowledge	0.28	-0.09	0.65	0.10	-0.30	0.50
Unsure						
Organic	1.23*	0.72	1.74	0.23	-0.23	0.68
Gluten-free	0.16	-0.22	0.53	-0.24	-0.58	0.09
Low-carb/Sugar-free	0.05	-0.26	0.37	-0.66*	-1.07	-0.26
Non-GMO	0.63*	0.31	0.95	0.27	-0.01	0.55
Gluten-free×Organic	-0.19	-0.62	0.23	-0.02	-0.42	0.38
Low-carb×Organic/ Sugar-free×Organic	-0.09	-0.51	0.32	-0.56*	-1.08	-0.03
Non-GMO×Organic	-1.06*	-1.63	-0.49	0.09	-0.39	0.57
Non-GMO×Organic×Knowledge	0.72*	0.04	1.40	-0.05	-0.61	0.51

Note: * denotes significance of the mean WTP at 5% level.

Table B-5. Mean WTP Values and 95% Confidence Intervals per Consumer Subgroup Based on Wheat/Gluten Intolerance/Avoidance

	Bread			Cookies		
	Mean WTP	Lower bound	Upper bound	Mean WTP	Lower bound	Upper bound
WGIA						
Organic	1.52*	0.73	2.32	1.06*	0.42	1.70
Gluten-free	1.10*	0.48	1.71	0.63*	0.13	1.12
Low-carb/Sugar-free	0.21	-0.28	0.70	-0.19	-0.71	0.33
Non-GMO	1.24*	0.73	1.75	0.83*	0.40	1.25
Gluten-free×Organic	0.35	-0.32	1.03	-0.26	-0.84	0.33
Low-carb×Organic/ Sugar-free×Organic	0.74*	0.04	1.44	-0.18	-0.83	0.46
Non-GMO×Organic	-1.04*	-1.88	-0.21	-0.57	-1.25	0.12
Non-GMO×Organic×Knowledge	0.13	-0.88	1.14	0.44	-0.32	1.21
NWGIA						
Organic	0.37*	0.10	0.64	-0.09	-0.35	0.17
Gluten-free	-0.34*	-0.50	-0.18	-0.41*	-0.58	-0.24
Low-carb/Sugar-free	0.07	-0.08	0.21	-0.79*	-1.00	-0.58
Non-GMO	0.44*	0.29	0.58	0.02	-0.13	0.18
Gluten-free×Organic	0.04	-0.18	0.26	-0.10	-0.33	0.13
Low-carb×Organic/ Sugar-free×Organic	-0.18	-0.38	0.03	-0.47*	-0.76	-0.17
Non-GMO×Organic	-0.72*	-0.99	-0.45	-0.04	-0.30	0.22
Non-GMO×Organic×Knowledge	0.49*	0.17	0.82	-0.02	-0.36	0.31

Note: * denotes significance of the mean WTP at 5% level.

Table B-6. Mean WTP Values and 95% Confidence Intervals per Consumer Subgroup Based on Gender

	Bread			Cookies		
	Mean WTP	Lower bound	Upper bound	Mean WTP	Lower bound	Upper bound
Female						
Organic	0.66*	0.32	1.00	0.27	-0.06	0.61
Gluten-free	-0.04	-0.27	0.19	-0.05	-0.29	0.19
Low-carb/Sugar-free	0.10	-0.10	0.30	-0.92*	-1.22	-0.62
Non-GMO	0.65*	0.46	0.84	0.28*	0.08	0.49
Gluten-free×Organic	0.06	-0.21	0.33	-0.22	-0.52	0.08
Low-carb×Organic/ Sugar-free×Organic	0.04	-0.22	0.29	-0.39	-0.78	0.01
Non-GMO×Organic	-0.80*	-1.13	-0.47	-0.18	-0.52	0.17
Non-GMO×Organic×Knowledge	0.50*	0.10	0.90	0.00	-0.43	0.43
Male						
Organic	0.43*	0.02	0.83	-0.09	-0.45	0.27
Gluten-free	-0.35*	-0.59	-0.10	-0.41*	-0.65	-0.17
Low-carb/Sugar-free	0.09	-0.13	0.31	-0.48*	-0.75	-0.22
Non-GMO	0.47*	0.24	0.69	0.04	-0.18	0.26
Gluten-free×Organic	0.21	-0.12	0.54	0.02	-0.29	0.33
Low-carb×Organic/ Sugar-free×Organic	-0.14	-0.45	0.17	-0.25	-0.64	0.15
Non-GMO×Organic	-0.72*	-1.13	-0.31	-0.09	-0.45	0.28
Non-GMO×Organic×Knowledge	0.31	-0.19	0.81	0.20	-0.25	0.65

Note: * denotes significance of the mean WTP at 5% level.

Table B-7. Mean WTP Values and 95% Confidence Intervals per Consumer Subgroup Based on Age

	Bread			Cookies		
	Mean WTP	Lower bound	Upper bound	Mean WTP	Lower bound	Upper bound
18-24						
Organic	0.52	-0.40	1.44	0.26	-0.45	0.97
Gluten-free	0.12	-0.54	0.77	0.18	-0.29	0.66
Low-carb/Sugar-free	0.36	-0.18	0.90	-0.18	-0.71	0.35
Non-GMO	1.04*	0.39	1.68	0.33	-0.15	0.81
Gluten-free×Organic	0.14	-0.64	0.91	-0.33	-1.00	0.33
Low-carb×Organic/ Sugar-free×Organic	0.20	-0.57	0.98	-0.12	-0.75	0.51
Non-GMO×Organic	-0.90	-1.91	0.11	0.25	-0.44	0.94
Non-GMO×Organic×Knowledge	0.10	-1.22	1.43	-0.08	-1.00	0.84
25-44						
Organic	0.88*	0.42	1.34	0.54*	0.11	0.97
Gluten-free	0.07	-0.23	0.37	0.03	-0.28	0.34
Low-carb/Sugar-free	0.19	-0.07	0.46	-0.66*	-1.04	-0.29
Non-GMO	0.58*	0.31	0.84	0.33*	0.05	0.62
Gluten-free×Organic	0.01	-0.36	0.38	-0.20	-0.58	0.19
Low-carb×Organic/ Sugar-free×Organic	-0.11	-0.47	0.24	-0.39	-0.87	0.10
Non-GMO×Organic	-0.56*	-0.99	-0.12	-0.39	-0.84	0.06
Non-GMO×Organic×Knowledge	0.18	-0.36	0.72	-0.01	-0.56	0.55
45-64						
Organic	0.43*	0.03	0.82	0.06	-0.32	0.43
Gluten-free	-0.32*	-0.57	-0.07	-0.44*	-0.72	-0.15
Low-carb/Sugar-free	-0.05	-0.27	0.17	-0.97*	-1.28	-0.66
Non-GMO	0.50*	0.29	0.70	0.11	-0.10	0.33
Gluten-free×Organic	0.27	-0.06	0.59	-0.16	-0.50	0.17
Low-carb×Organic/ Sugar-free×Organic	-0.01	-0.31	0.28	-0.37	-0.79	0.04
Non-GMO×Organic	-1.04*	-1.46	-0.61	-0.15	-0.54	0.25
Non-GMO×Organic×Knowledge	0.66*	0.17	1.16	0.13	-0.35	0.60
>64						
Organic	0.24	-0.40	0.88	-0.84*	-1.49	-0.18
Gluten-free	-0.38*	-0.72	-0.04	-0.53*	-0.91	-0.14
Low-carb/Sugar-free	0.09	-0.24	0.41	-0.51*	-0.98	-0.04
Non-GMO	0.51*	0.19	0.82	-0.12	-0.44	0.21
Gluten-free×Organic	-0.16	-0.67	0.35	0.23	-0.30	0.75
Low-carb×Organic/ Sugar-free×Organic	-0.20	-0.67	0.27	-0.54	-1.28	0.19
Non-GMO×Organic	-0.75*	-1.36	-0.14	-0.08	-0.74	0.58
Non-GMO×Organic×Knowledge	0.56	-0.17	1.29	0.63	-0.12	1.38

Note: * denotes significance of the mean WTP at 5% level.

Table B-8. Mean WTP Values and 95% Confidence Intervals per Consumer Subgroup Based on Income

	Bread			Cookies		
	Mean WTP	Lower bound	Upper bound	Mean WTP	Lower bound	Upper bound
<$30,000						
Organic	0.32	-0.13	0.77	-0.10	-0.52	0.32
Gluten-free	-0.18	-0.44	0.08	0.06	-0.22	0.33
Low-carb/Sugar-free	0.19	-0.04	0.41	-0.58*	-0.87	-0.29
Non-GMO	0.40*	0.17	0.62	0.13	-0.11	0.37
Gluten-free×Organic	0.13	-0.22	0.47	-0.37*	-0.73	-0.01
Low-carb×Organic/ Sugar-free×Organic	-0.10	-0.42	0.22	-0.11	-0.52	0.31
Non-GMO×Organic	-0.93*	-1.37	-0.49	-0.19	-0.62	0.23
Non-GMO×Organic×Knowledge	0.77*	0.26	1.28	0.66*	0.15	1.17
$30,000-$60,000						
Organic	0.40	-0.02	0.83	0.06	-0.34	0.46
Gluten-free	0.07	-0.20	0.33	-0.21	-0.47	0.06
Low-carb/Sugar-free	0.10	-0.13	0.34	-0.68*	-1.03	-0.33
Non-GMO	0.40*	0.16	0.63	0.15	-0.09	0.40
Gluten-free×Organic	-0.05	-0.40	0.30	-0.02	-0.37	0.33
Low-carb×Organic/ Sugar-free×Organic	-0.09	-0.43	0.24	-0.52*	-1.00	-0.05
Non-GMO×Organic	-0.72*	-1.18	-0.26	-0.27	-0.71	0.17
Non-GMO×Organic×Knowledge	0.72*	0.19	1.24	0.13	-0.38	0.63
$60,000-$90,000						
Organic	0.54	-0.22	1.29	-0.08	-0.65	0.49
Gluten-free	-0.36	-0.84	0.12	-0.46*	-0.87	-0.04
Low-carb/Sugar-free	0.08	-0.34	0.50	-0.83*	-1.36	-0.31
Non-GMO	1.00*	0.55	1.44	0.17	-0.19	0.53
Gluten-free×Organic	0.45	-0.16	1.07	0.46	-0.06	0.97
Low-carb×Organic/ Sugar-free×Organic	-0.02	-0.60	0.56	-0.53	-1.15	0.09
Non-GMO×Organic	-0.74*	-1.40	-0.07	0.28	-0.30	0.86
Non-GMO×Organic×Knowledge	-0.04	-0.90	0.83	-0.72	-1.49	0.05
>$90,000						
Organic	1.28*	0.67	1.89	0.83*	0.16	1.51
Gluten-free	-0.46	-0.92	0.00	-0.47	-1.02	0.07
Low-carb/Sugar-free	-0.08	-0.47	0.31	-0.89*	-1.46	-0.33
Non-GMO	0.88*	0.50	1.25	0.24	-0.21	0.68
Gluten-free×Organic	0.26	-0.26	0.79	-0.40	-1.01	0.20
Low-carb×Organic/ Sugar-free×Organic	0.11	-0.39	0.60	-0.31	-1.07	0.45
Non-GMO×Organic	-0.92*	-1.58	-0.25	-0.47	-1.14	0.19
Non-GMO×Organic×Knowledge	-0.09	-1.01	0.83	0.21	-0.69	1.11

Note: * denotes significance of the mean WTP at 5% level.

Table B-9. Mean WTP Values and 95% Confidence Intervals per Consumer Subgroup Based on Education

	Bread			Cookies		
	Mean WTP	Lower bound	Upper bound	Mean WTP	Lower bound	Upper bound
High school or less						
Organic	0.20	-0.35	0.75	-0.12	-0.65	0.41
Gluten-free	-0.17	-0.50	0.16	-0.07	-0.44	0.30
Low-carb/Sugar-free	0.18	-0.11	0.46	-0.75*	-1.18	-0.31
Non-GMO	0.33*	0.05	0.61	0.27	-0.07	0.62
Gluten-free×Organic	0.24	-0.20	0.68	0.06	-0.44	0.55
Low-carb×Organic/ Sugar-free×Organic	-0.13	-0.54	0.29	-0.34	-0.96	0.29
Non-GMO×Organic	-0.66*	-1.21	-0.10	-0.39	-0.95	0.17
Non-GMO×Organic×Knowledge	0.66	-0.05	1.37	0.10	-0.62	0.83
Some college or Associate						
Organic	0.31	-0.08	0.70	-0.08	-0.42	0.26
Gluten-free	-0.12	-0.36	0.12	-0.25*	-0.49	-0.01
Low-carb/Sugar-free	0.01	-0.19	0.22	-0.59*	-0.85	-0.33
Non-GMO	0.56*	0.34	0.77	0.01	-0.19	0.21
Gluten-free×Organic	0.06	-0.25	0.36	-0.05	-0.35	0.25
Low-carb×Organic/ Sugar-free×Organic	0.01	-0.28	0.29	-0.33	-0.69	0.03
Non-GMO×Organic	-0.75*	-1.14	-0.37	0.09	-0.27	0.45
Non-GMO×Organic×Knowledge	0.38	-0.07	0.83	0.21	-0.20	0.62
Bachelor or higher						
Organic	1.11*	0.65	1.56	0.45*	0.01	0.88
Gluten-free	-0.25	-0.56	0.06	-0.28	-0.60	0.05
Low-carb/Sugar-free	0.16	-0.12	0.43	-0.90*	-1.30	-0.50
Non-GMO	0.70*	0.43	0.98	0.33*	0.05	0.61
Gluten-free×Organic	0.17	-0.22	0.56	-0.28	-0.66	0.10
Low-carb×Organic/ Sugar-free×Organic	-0.07	-0.44	0.30	-0.32	-0.80	0.16
Non-GMO×Organic	-0.85*	-1.33	-0.38	-0.37	-0.81	0.07
Non-GMO×Organic×Knowledge	0.38	-0.23	0.99	0.07	-0.50	0.64

Note: * denotes significance of the mean WTP at 5% level.

Table B-10. Mean WTP Values and 95% Confidence Intervals per Consumer Subgroup Based on Residency in California

	Bread			Cookies		
	Mean WTP	Lower bound	Upper bound	Mean WTP	Lower bound	Upper bound
CA resident						
Organic	0.86*	0.45	1.26	0.03	-0.34	0.41
Gluten-free	-0.26*	-0.52	-0.01	-0.28*	-0.53	-0.03
Low-carb/Sugar-free	0.24*	0.02	0.47	-0.67*	-0.97	-0.37
Non-GMO	0.63*	0.40	0.86	0.09	-0.14	0.32
Gluten-free×Organic	0.12	-0.21	0.45	-0.02	-0.33	0.30
Low-carb×Organic/ Sugar-free×Organic	-0.21	-0.52	0.10	-0.14	-0.49	0.21
Non-GMO×Organic	-0.93*	-1.33	-0.54	-0.09	-0.46	0.28
Non-GMO×Organic×Knowledge	0.48*	0.00	0.95	0.22	-0.24	0.68
Not CA resident						
Organic	0.27	-0.08	0.61	0.18	-0.13	0.49
Gluten-free	-0.11	-0.33	0.11	-0.21	-0.45	0.02
Low-carb/Sugar-free	-0.03	-0.22	0.16	-0.73*	-0.99	-0.46
Non-GMO	0.49*	0.30	0.67	0.23*	0.04	0.42
Gluten-free×Organic	0.15	-0.12	0.43	-0.20	-0.49	0.08
Low-carb×Organic/ Sugar-free×Organic	0.09	-0.17	0.34	-0.67*	-1.10	-0.25
Non-GMO×Organic	-0.58*	-0.93	-0.24	-0.17	-0.50	0.17
Non-GMO×Organic×Knowledge	0.38	-0.05	0.81	-0.04	-0.44	0.37

Note: * denotes significance of the mean WTP at 5% level.

CURRICULUM VITAE

Tatiana Drugova
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EDUCATION

- **Ph.D. in Economics, August 2015 – May 2019**

Utah State University, Logan, UT, USA: Supervised by Dr. Kynda Curtis
Dissertation Title: "The Organic Wheat Market: Three Essays on Pricing, Consumer Segments, and the Importance of Labels"

- **B.S. in Tourism Management, September 2003 – May 2008**

University of Economics, Bratislava, Slovakia: Supervised by Dr. Valeria Michalova
Thesis Title: "Trends in the Development of International Trade in Services"

HONORS AND AWARDS

- Presidential Doctoral Research Fellowship, Utah State University, Logan, UT, USA, August 2015 – May 2019
- B.S. Diploma with honors, University of Economics, Bratislava, Slovakia, May 2008
- Studentship for excellent academic record, University of Economics, Bratislava, Slovakia, 2005 – 2007

RESEARCH EXPERIENCE

Graduate Research Fellow, August 2015 – May 2019
Department of Applied Economics, Utah State University

- Analyzed relationships between prices of agricultural commodities using time series analysis (vector autoregressive and vector error correction models)
- Designed and administered a large-scale online consumer survey with choice experiment
- Analyzed consumer behavior, preferences and willingness to pay for food labels and attributes applying discrete choice models (multinomial logit, random parameter logit and latent class models)
- Applied synthetic control methods in a comparative case study

TEACHING AND MENTORING EXPERIENCE

Instructor, Strategic Firm Management (APEC 5020), Spring 2017 and Spring 2018
Department of Applied Economics, Utah State University
- Primary instructor (campus course) – Spring 2018
- Primary instructor (online course) – Spring 2017
- Course covers the economics of food and agricultural product development and marketing for senior undergraduates

Undergraduate Mentor, 2017 – 2019
Undergraduate Research & Creative Opportunities, Utah State University
- Reviewed and evaluated research proposals, submitted for funding by undergraduate students

Student Research Symposium (Fall & Spring), Utah State University
- Provided feedback on presentations and posters showcasing research of undergraduate students

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PROFESSIONAL ARTICLES, REFEREED—UNDER REVIEW

- Drugova, T., V.F. Pozo, K.R. Curtis and T.R. Fortenbery, "Organic Wheat Prices and Premium Uncertainty: Can Cross Hedging and Forecasting Play a Role?." Under Review at the *Journal of Agricultural and Resource Economics*.
- Drugova, T., M.-K. Kim, and P.M. Jakus, "Visitor Congestion and Marketing of National Parks." Under review at the *Ecological Economics*.

PROFESSIONAL ARTICLES, REFEREED/PEER-REVIEWED PROCEEDINGS ISSUES

- Drugova, T., V.F. Pozo, K.R. Curtis and T.R. Fortenbery, 2018. "Organic Wheat Prices and Premium Uncertainty: Can Cross Hedging and Forecasting Play a Role?." Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, Minneapolis, MN. [http://www.farmdoc.illinois.edu/nccc134].
- Drugova, T., V.F. Pozo, and K.R. Curtis, 2018. "Forecasting Organic Wheat Prices: Do Conventional Wheat Prices Play a Role?." *Journal of Food Distribution Research*, 49(1), 48-55.

FACT SHEETS

- Curtis, K., T. Drugova, and H. Thomason, 2018. "Who Are Organic Wheat Consumers?" Utah State University Fact Sheet, Applied Economics/2018-05pr.

- Curtis, K., T. Drugova, and H. Thomason, 2018. “Labeling and Product Characteristic Preferences of Organic Food Buyers.” Utah State University Fact Sheet, Applied Economics/2018-03pr.
- Curtis, K., T. Drugova, and H. Thomason, 2018. “Premium Potential for Organic Wheat Products.” Utah State University Fact Sheet, Applied Economics/2018-06pr.

PEER-REVIEWED CONFERENCE/DEPARTMENTAL PRESENTATIONS

- Curtis, K., and T. Drugova, “Do Multi-labeled Food Products Inform or Confuse Consumers?.” Invited paper presented at the 2019 Annual Meeting of the Australian Agricultural and Resource Economics Society (AARES), Melbourne, Australia, February 2019.
- Kim, M-K., T. Drugova, and P.M. Jakus, “Selling Utah: How Much the Mighty 5 Helps Boost Tourism and Utah Economy?” Selected paper presented at the 2019 Annual Meeting of the Western Regional Science Association (WRSA), Napa CA, February 2019.
- Drugova, T., and K. Curtis, “Do Extra Labels Pay? The Impact of Non-GMO and Health Labels on Consumer WTP for Organics.” Presented at the 2018 Annual Meeting of the Agricultural & Applied Economics Association (AAEA), Washington DC, August 2018.
- Drugova, T., and K. Curtis, “How Do Consumers of Organic Wheat Products Differ from Non-Consumers? Analysis of Market Segments.” Selected paper presented at the 2018 Annual Meeting of the Western Agricultural Economics Association (WAEA), Anchorage AK, June 2018.
- Drugova, T., K. Curtis, V. Pozo, and R. Fortenbery, “Organic Wheat Prices and Premium Uncertainty: Can Cross Hedging and Forecasting Play a Role?” Selected paper presented at the 2018 NCCC-134 Conference, Minneapolis MN, April 2018.
- Drugova, T., K. Curtis, V. Pozo, and R. Fortenbery, “Organic Wheat Prices and Premium Uncertainty: Can Cross Hedging and Forecasting Play a Role?.” Presented at the Applied Economics Seminar, Logan UT, April 2018.
- Drugova, T., K. Curtis, and V. Pozo, “Forecasting Organic Wheat Prices: Do Conventional Wheat Prices Play a Role?” Selected paper presented at the 2017 Annual Meeting of the Food Distribution Research Society (FDRS), Honolulu HI, October 2017.

RESEARCH AND EXTENSION GRANTS, REFEREED

- USDA-NIFA Organic Agriculture Research and Extension Initiative (OREI), 2014-2020. $1.6 million. Compost Carryover and Cover Crop Effects on Soil Quality, Profitability, and Cultivar Selection in Organic Dryland Wheat. Role: Research Fellow.

PROFESSIONAL MEMBERSHIPS

- Agricultural & Applied Economics Association (AAEA) – 2018 to present
- Western Agricultural Economics Association (WAEA) – 2018 to present
- American Economic Association (AEA) – 2019

BUSINESS EXPERIENCE

Billing Analyst, March 2015 – June 2015
AT&T Global Network Services, Bratislava, Slovakia

- Processed monthly billings for business clients

Financial Analyst, November 2008 – June 2012
IBM International Service Center, Bratislava, Slovakia

- Tracked costs and expenses on assigned departments; prepared monthly and quarterly financial forecasts; analyzed discrepancies between actual, forecast and past results; initiated booking corrections; presented monthly and quarterly financial results to business and financial managers
- Prepared revenue and signings reports

SKILLS

Technical skills
Programming and statistical languages and software packages: R, Stata, Nlogit, @Risk
Other: MS Office, Qualtrics

Language skills
Slovak, Czech, English, German, and Spanish