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Consumers Balance Time and Money in Purchasing Convenience Foods

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Abstract

Demand for ready-to-eat foods from restaurants and grocery stores has been growing in the United States. These foods save households time in meal preparation, but they have also been associated with inferior dietary quality and, consequently, poor health for Americans. The demand for such "convenience foods" varies significantly from person to person, and the factors that influence these individual choices are not clear. This study considers four broad groups of factors: consumers' financial resources, prices, consumers' time constraints, and the food environment consumers face. We find that higher income is associated with increased demand for restaurant food, while participation in food assistance programs is associated with increased demand for ready-to-eat and non-ready-to-eat supermarket food. Consumers facing tight time constraints from employment tend to purchase more food from full-service restaurants and less from supermarkets. On the other hand, consumers whose time constraints stem from child-care responsibilities tend to purchase more fast food. The location of restaurants and stores has little effect on demand for convenience foods after controlling for financial resources, time constraints, and relative prices.

Keywords: convenience food, food expenditure, meal preparation, fast food, restaurant, demand, SNAP, food access, time constraint, price

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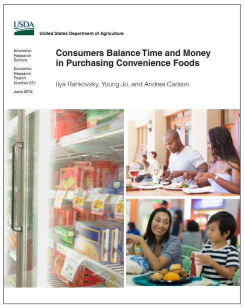

Consumers Balance Time and Money in Purchasing Convenience Foods

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What Is the Issue?

Ready-to-eat foods from restaurants and grocery stores save meal preparation time, but these "convenience foods" tend to have lower nutritional value and can be more expensive than their less convenient counterparts—food that requires extensive preparation. Consumers facing increasingly greater time constraints from work, childcare, and commuting often have to make a tradeoff between time and money when deciding how much convenience food to buy. This raises a number of questions: How do consumers choose how much and what type of convenience food to purchase? What roles do time and financial constraints play? Do consumers with easy access to less healthy convenience foods purchase more of them than consumers without easy access? Does demand for convenience foods differ across sociodemographic groups? The answers to such questions can guide policymakers in promoting public health.

What Did the Study Find?

Descriptive statistics from USDA's 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS) show that, compared to the household average in the sample:

- Primary survey respondents in households that spent more of their food budget on *fast food* tend to be younger, employed, and have children. The primary respondents have a less nutritious diet and slightly higher body mass index.
- Primary respondents in households that spent more on *full-service restaurant meals* tend to be employed, married, and have high education levels and incomes. These households also have fewer children and are less likely to participate in USDA's Supplemental Nutrition Assistance Program (SNAP) or USDA's Special Supplemental Nutrition Program for Women, Infants, and Children (WIC).
- Primary respondents in households that spent more on *ready-to-eat foods* from stores tend to be older, have lower incomes, and are more likely to be SNAP participants. These households tend to live in sparse food environments with few supermarkets and restaurants.
- Primary respondents in households that spent more on *non-ready-to-eat foods* tend to be older, not employed, and participate in SNAP. These households have lower incomes and fewer children than the sample average.

ERS is a primary source of economic research and analysis from the U.S. Department of Agriculture, providing timely information on economic and policy issues related to agriculture, food, the environment, and rural America.

The report uses a consumer demand model, which allows researchers to estimate the relative importance of each factor, enabling factors to be correlated. For example, employed people are more likely to eat at restaurants, but so are those with higher income. Then, which factor matters more? The demand model assesses the effects of a change in a given factor (e.g., being employed), while all other factors are held constant at the average. Such analysis produced the following results:

- Higher income is associated with more purchases from full-service restaurants and fewer purchases from fast-food restaurants. Consumers with monthly gross income over $5,000 purchase 29.3 percent fewer fast-food restaurant meals and 27.8 percent more full-service restaurant meals than middle-income consumers (monthly income between $2,000 and $5,000). Low-income consumers (income less than $2,000 per month) purchase 29.3 percent more fast-food meals, 32.7 percent fewer full-service restaurant meals, and 11.2 percent more ready-to-eat foods than middle-income consumers.

- Participants in a food assistance program purchase more ready-to-eat and non-ready-to-eat food from stores and less food from full-service restaurants. Participation in SNAP is associated with a 26-percent increase in the purchase of ready-to-eat foods, a 22-percent increase in the purchase of non-ready-to-eat foods, and a 102-percent decrease in the purchase of full-service restaurant meals. The relationship between SNAP and fast-food purchases was insignificant.

- When consumers increase their food spending, they tend to spend disproportionately more at restaurants and less at grocery stores.

- Demand for full-service restaurant meals is sensitive to full-service restaurant prices, while demand for non-ready-to-eat foods is not sensitive to price.

- Time constraints from employment shift demand from food at home to food away from home. Employment of all adults in a household lowers purchases of ready-to-eat food by 12 percent and increases purchases in full-service restaurants by 72 percent relative to households where not all adults are employed. Employment of a household head increases spending in fast-food restaurants by 13 percent.

- The presence of children in a household increases demand for convenience foods. Households with children purchase 19 percent more fast food and 38 percent less full-service restaurant food than households without children. However, as the number of children increases, the household increases its food-at-home purchases and reduces its restaurant food purchases. Single-parent households that are particularly time constrained purchase 14 percent more ready-to-eat food than the average household.

- Proximity to and density of restaurants do not have a consistent effect on food purchases.

- Commute time has little effect on demand for convenience foods.

- We find little evidence that consumers easily substitute among fast food, full-service restaurant meals, and ready-to-eat foods. Even as the price of one type of convenience food increases, consumers are reluctant to switch to another type of convenience food.

How Was the Study Conducted?

The study uses food-purchase and demographic information from USDA's 2012-13 FoodAPS, a nationally representative sample of 4,826 households. We construct price indexes based on purchases of consumers who live in the same county. We estimate a censored incomplete Exact Affine Store Index demand system for fast food, full-service restaurant meals, ready-to-eat foods, non-ready-to-eat foods, and nonfood expenditures. Finally, we use estimated price, household characteristics, and food-environment elasticities to assess the factors influencing the demand for convenience foods.

Consumers Balance Time and Money in Purchasing Convenience Foods

Introduction

Demand for "convenience foods," including restaurant meals and ready-to-eat food from grocery stores, has been steadily increasing in the United States. In 2014, U.S. households spent 50.1 percent of their total food expenditures on food away from home, up from 39 percent in 1980 (USDA, ERS, 2017). Between 1999 and 2010, the share of food expenditures spent on fast food (FF) increased from 24 to 27 percent, while the shares spent on ready-to-eat/ready-to-heat (RTE) foods from grocery stores have been more stable, and the share spent on full-service restaurants (FS) decreased from 25 to 23 percent (Okrent and Kumcu, 2016). (For definitions of convenience foods, food away from home, and other terms, see box, "Convenience Foods.")

Because convenience foods are less nutritious and more expensive but save time, consumers often make a tradeoff between time and money when deciding how much convenience food to purchase. Restaurant meals generally contain more calories, are higher in fat and sodium, and have larger portion sizes compared to home-prepared meals (Guthrie et al., 2002; Nielsen and Popkin, 2003; Mancino et al., 2009; Lin and Guthrie, 2012). In purchasing restaurant meals, consumers outsource the tasks of shopping, cooking, and cleaning up. Therefore, the least convenient foods are those that require time and effort to shop for, prepare, and clean up—what we call non-ready-to-eat/heat (NRTE) foods. These foods tend to be healthier than other types of food because households can control both the ingredients and the portion size. Additionally, the less convenient foods, such as NRTE foods, are generally cheaper. Because consumption of convenience foods may lead to poor diet and health, an increasing demand for them raises important public health challenges.

Prior research has identified a number of factors that can affect demand for convenience foods. The desire to save meal preparation time is associated with greater demand for restaurant meals (Park and Capps, 1997; Rydell et al., 2008; Hamrick and Okrent, 2014). The cost of time is determined by employment status (Yen, 1993; Jensen and Yen, 1996; Nayga, 1996; Stewart et al., 2004; Fuzhong et al., 2009; Zan and Fan, 2010; Okrent and Kumcu, 2016) and household income (Yen, 1993; Jensen and Yen, 1996; Zan and Fan, 2010; Davis, 2014). Mancino and Newman (2007) find that a household's time resources have a greater impact on time spent preparing meals than household income. Other factors that are linked to demand for restaurant meals are a dislike for cooking (Dave et al., 2009), taste and price (Rydell et al., 2008), higher restaurant density (Jekanowski et al., 2001; Gordon-Larsen et al., 2011), not participating in the Supplemental Nutrition Assistance Program (SNAP) (Fuzhong et al., 2009; Jilcott et al., 2011), absence of children (Prochaska and Schrimper, 1973; Soberon-Ferrer and Dardis, 1991; Stewart et al., 2004), and small household size (Byrne et al., 1996; Byrne et al., 1998).

Convenience Foods

The term "convenience foods" was first used in the 1950s by Charles Mortimer, president and chief executive officer of General Foods, to refer to foods that were "easy to buy, store, open, prepare, and eat" (Moss, 2013). Some researchers define the term by the amount of preparation outsourced to the food processor (Harrison, 1979), while others focus on the method of preparation (Park and Capps, 1997; Costa et al., 2001).

This report classifies convenience foods by the degree to which they save time in the process of food acquisition and consumption, or effort in preparation and cleanup. Accordingly, we categorize foods into four groups, with non-ready-to-eat foods being the least convenient, full-service restaurant meals being a little more convenient, but not as convenient as ready-to-eat or fast food.

We define ready-to-eat (RTE) foods purchased in stores as foods that can be consumed cold, at room temperature, or heated in a microwave. Examples include frozen cooked foods, bread, snack foods, frozen vegetables, fresh-cut produce, peanut butter and other spreads, milk, juice and drinks, and vegetables such as potatoes that can be cooked in a microwave and are not sold with inedible parts. RTE does not include foods that would require a sharp knife to prepare, or foods that are sold with inedible parts such as shells, skins, or seeds. Note that this definition combines the Okrent and Kumcu (2016) ready-to-eat (e.g., canned fruit, yogurt, soda, and candy) and ready-to-cook (e.g., frozen meals) categories.

Non-ready-to-eat (NRTE) foods are ingredients that are not consumed raw (e.g., meat, poultry, or seafood; flour; oil; sugar) or foods that require more extensive preparation than heating in a microwave (e.g., pilaf mixes, cake mixes, vegetables with refuse, raw pasta, and rice). Our definition of NRTE combines Okrent and Kumcu's (see above paragraph) basic and complex ingredients groups.

Another set of convenience foods is the type purchased from either fast-food (FF) or full-service (FS) restaurants. Data from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), on which we base this study, include the place where the household purchased the food, including fast-food or full-service restaurants. We define FF restaurants as eating places where consumers pay before they eat (e.g., bakery, burger restaurant, and sandwich or coffee shop) and FS restaurants as places where consumers eat before they pay—that is, the consumer sits down at a table and orders food from a server (or selects food from a buffet). The server also brings the ordered food or beverages to the table, and the customer pays at the end of the meal.

Food-at-home (FAH) refers to food that is prepared at home and includes RTE and NRTE foods that are bought from grocery stores, food pantries, super centers, mass merchandisers, convenience stores, drugstores, farmers markets, and food co-ops. Food-away-from-home (FAFH) refers to food prepared outside of home and includes food from FS restaurants and FF restaurants. In this study, we model demand for food purchased only in stores and restaurants. We do not include food from schools, relatives, food pantries, and other sources where the respondent likely did not pay the market price for the food.

Using USDA's 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS), this study groups the potential factors influencing the demand for convenience foods into four categories: financial resources (income, food assistance programs), prices, time constraints (number of children, commute time, employment status), and food environment (distance to and density of restaurants and supermarkets, car access). Taking advantage of the extensive information available in FoodAPS, we assess the relative importance of these factors using a consumer demand model. Specifically, this study addresses two key questions:

1. Do households that spend a large share of their budget on convenience foods differ in demographic characteristics, health indicators, financial resources, time constraints, and expenditure patterns from households that spend only a small share?
2. Which of the four factors—financial resources, prices, time constraints, or food environment—has the largest influence on consumers' decision to acquire convenience foods?

The report's contribution to the existing literature is twofold. First, we add to the growing body of research that examines the determinants of food demand more rigorously. In contrast to earlier studies that find a relationship between food access and food demand (Fuzhong et al., 2009; Jilcott et al., 2011), more recent studies find no effect when controlling for prices (Lin et al., 2014; Ghosh-Dastidar et al., 2014). We find that the distance to or density of restaurants does not have a consistent effect on food purchases. In addition, the commute time to work has little effect on convenience food purchases. These findings are in contrast to a belief that a lack of stores in an area or long travel time contributes to poor diet quality of purchased food. A better understanding of the relationship between food environment and food purchases in this report provides important evidence for future policy design.

Second, this is the first study to show how consumers solve time-money tradeoffs via demand for convenience foods. The rich demographic and food-purchase information available in FoodAPS made this possible. We investigate how time constraints from employment and childcare differ in influencing demand for convenience foods. Constraints from employment tend to increase demand for full-service restaurant meals, while constraints from childcare tend to increase demand for fast food. Consumers with high income purchase more full-service restaurant meals (the most expensive convenience foods) and less fast-food restaurant meals and ready-to-eat supermarket foods (the cheaper convenience alternatives) than those with lower income. Consumers with extra financial resources from SNAP tend to purchase more supermarket foods and less food from restaurants than those with similar income but who are not participating in the program.

This report complements another by Okrent and Kumcu (2016). Okrent and Kumcu estimate a demand model for convenience foods using temporal variations in prices, work hours, income, and food-advertising spending in the four U.S. Census regions (Northeast, Midwest, South, and West) between 1999 and 2010. The authors find that the demand for convenience foods is generally determined by price and income-led changes in total food expenditures. Advertising expenditures have little effect on demand for convenience foods, with the exception of fast food. Okrent and Kumcu also find that an increase in the average number of hours worked reduces the demand for store-bought foods that require an extensive amount of preparation but has little effect on the demand for convenience foods such as restaurant meals.

This report builds on the work of Okrent and Kumcu in three ways. First, with the data available at the time, Okrent and Kumcu used large heterogeneous regions as units of analysis, assuming that people living within the same region display the same work patterns and other characteristics. The more recent FoodAPS data enable us to use actual information reported by individual households. Second, our data also enable us to construct price indexes that vary by household location and that are likely to be closer to the actual prices households face. Third, we examine a larger number of determinants for food demand. FoodAPS data contain detailed information on demographics, socioeconomic characteristics, food prices, and food environment, which allows us to more directly answer policy-relevant questions.

Data

Our main source of data is the National Household Food Acquisition and Purchase Survey (FoodAPS), collected by USDA's Economic Research Service. FoodAPS surveyed 4,826 nationally representative households, each for a 1-week period, between April 2012 and January 2013 across the contiguous United States.[1]

From each sampled household, the primary respondent, who was the main food shopper, provided information on household demographics and general food acquisition.[2] Additionally, food acquisition information was supplied by all household members ages 11 and above. Each household member was instructed to fill out food acquisition diaries for all the food he or she acquired during the survey week, including a description of the food item, the price (if he or she paid for it), and where he or she acquired it. Food acquisition was divided into two broad categories: food at home (FAH) and food away from home (FAFH).

FoodAPS respondents reported only a week of food acquisitions, which may not be representative of typical food purchases. Some households may have purchased most of their food before or after the observed week, while others may have hosted a very large party or purchased food for several weeks ahead. Some households may have underreported their food purchases. To reduce the noise from these outliers, we dropped households with very large and very small reported food purchases. We also excluded 936 households that purchased less than 500 kilocalories (kcal)[3] or more than 10,000 kcal per day for every standard adult equivalent with a recommended caloric intake of 2,000 kcal per day; these households are more likely to represent erroneous or atypical food purchases. And we dropped households that spent less than $10 on food in the observed week, as well as the 87 households with missing census tract information. For the remaining households, we imputed missing demographic information based on nonmissing demographic variables, if necessary. We did not use information on food purchases and price in the imputation. The final sample consists of 3,895 households.[4]

The survey links the household food purchases with the food environment, providing a unique opportunity to test the hypothesis that low access to healthy foods, measured either as a shortage of supermarkets or an abundance of fast-food restaurants, has an adverse effect on the healthfulness of consumers' diets.[5] Studies of restaurant locations often rely on datasets with limited information on a respondent's food purchases and/or food environment. FoodAPS not only includes information on the food acquired, but also the distance to the nearest food retailer and FF and FS restaurants and the density of FF and FS restaurants around the residence (i.e., the number of restaurants within a 5-mile radius).

[1]For more information on FoodAPS, see Clay et al. (2016).

[2]The survey response rate was 42 percent. Less than 4 percent of the households reported any changes in their food acquisition behaviors due to participation in the survey. Since the change in food acquisition behavior does not follow any particular pattern, the bias is likely to be small (USDA, ERS, 2016).

[3]A kilocalorie is equivalent to what is more commonly referred to in food terms as a "calorie."

[4]We checked the robustness of our findings using different exclusion criteria, including not restricting the sample by the amount of food purchased by households. Our findings are quite robust. However, some price effects are imprecisely estimated with the full sample, probably due to the presence of the outliers in food expenditures. Hence, we present the results using the restricted sample.

[5]FoodAPS matches household locations, identified as a population-weighted census block centroid, to a database of restaurant and supermarket locations. The locations of food retailers come from a merge of the proprietary Nielsen TDLinx database and USDA's Food and Nutrition Service (FNS) Store Tracking and Redemption System database. The data on restaurant locations are from a proprietary NPD Group database.

Nonfood Expenditures

In addition to food purchases, we also need to account for nonfood expenditures, even though we do not estimate demand for them directly in the incomplete food demand model we use, following LaFrance and Hanemann (1989). Unfortunately, FoodAPS did not collect data on all nonfood expenditures, so we have to develop a proxy for nonfood expenditures. One way to proxy for nonfood expenditures is to deduct food expenditures from total income, assuming a zero savings rate (Zhen et al., 2014). While this is a simple proxy to construct, it has some drawbacks. First, the unobserved savings rate can bias the results, especially because the savings rate is likely correlated with income and food expenditures. Second, any respondents reporting zero or very small incomes would have implausible negative nonfood expenditures and, thus, would have to be dropped from the sample. This is a serious problem in FoodAPS because it was designed to oversample low-income respondents. Finally, income data are likely to be misreported, as some respondents reporting their expenditures could be reluctant to reveal their true income (Hurst et al., 2014).

Our preferred method is to proxy nonfood expenditures using the respondent's reported expenditures on several nonfood categories—rent or mortgage, rental or homeowners insurance, property taxes, public transportation, health insurance, health insurance copays, doctor and hospital bills, prescription drugs, electricity, heating fuel, sewer and garbage removal, childcare, child support, and adult care. While these categories are not exhaustive, the combined food and nonfood expenditures amount to 34.5 percent of reported income in FoodAPS (the nonfood expenditures amount to 22 percent of income). In this report, we use the reported nonfood expenditures as a proxy for actual nonfood expenditures. We compared our results including and excluding the nonfood expenditures from the demand system and found that the inclusion provides a better prediction of food expenditures.

Prices

For food purchased in stores, FoodAPS respondents reported the prices they paid for individual items. Where the Universal Product Code (UPC) is available, we use it as a food product identifier; for other store products, we use product name as an identifier. For each food product, we calculate both price paid by consumer i and a national average price, which we later use to calculate a price index.

The prices consumers face in restaurants are more challenging to identify because some consumers reported only the total bill, not the price of each individual item ordered. Since the model needs information for individual food items, we imputed the missing prices. First, we calculated the average national price of each food item using the prices respondents reported when they ordered only one thing or reported individual items. This allowed us to construct a national average price for individual meals and then calculate the expenditure share. Finally, we applied the national average expenditure share to the total reported bill at local prices and recovered the local prices of individual food items.

For example, suppose a respondent went to a specific fast-food chain and purchased a cheeseburger and a soda but only reported the total expenditure. We would impute the prices paid by the consumer for the cheeseburger and the soda by first calculating the average national price for cheeseburgers and soda, using the prices recorded by other respondents who reported the individual prices for a cheeseburger and a soda at the chain. By adding the two prices together, we develop a national average price of the cheeseburger and soda combination. The expenditure share of the cheeseburger in this combination is the national average share of a cheeseburger in the combination meal. Then, we imputed the local prices of cheeseburgers by multiplying the total bill (the amount the consumer paid for the bundle) by the expenditure share of cheeseburgers, constructed using the national average prices. With this imputation, we have a complete set of prices for all of the food consumers purchased.

For each household, we constructed a Fisher price index—an aggregate, price-level measure that allows us to compare the prices faced by a consumer to the national average (the national average price index is equal to 1). The aggregation of prices for multiple products requires a decision whether to use a national average basket of goods or a basket of goods specific to a consumer. The consumer-specific basket may better reflect consumer tastes, but it does not reflect the universe of products, so it does not capture all potential options faced by consumers. Conversely, the national goods basket includes all the products, but it does not reflect consumer tastes. The Fisher price index uses both measures in a compromise solution. The index has also been shown to reduce bias from missing quality information and has other desirable properties (Diewert, 1976). For a more detailed discussion of the price index, please see the appendix.

In demand models, it is crucial to observe the prices that consumers face. If we observe only the prices consumers paid, it can bias our estimates because consumers purchase only a small fraction of the products that are available in the market. Some consumers would just go to the nearest stores, while others may not mind spending more time looking for the lowest price. Some consumers may prefer high-priced stores with a large number of helpful staff, while others do not mind less customer service. Deriving prices from actual purchases would lead to an erroneous conclusion that the former face high prices and the latter face lower prices. Finally, as consumers purchase only a small fraction of products available, especially if they are only observed for 1 week, the prices they paid are not likely to be a reliable estimate of prices in their food environment.

We construct local price indexes to measure the food prices faced by consumers. Unfortunately, FoodAPS does not have information on the range of prices consumers faced, since the respondents reported only the prices they paid for the foods they chose and their total food expenditures. Some consumers may spend a lot of time trying to find the lowest price and would seem to face lower prices. Others purchase only a small fraction of available products, which makes it impossible to measure the price of the large consumer basket. Finally, some consumers just did not make any purchases of a particular food type (FF or RTE), and we do not observe any prices for these consumers. To alleviate this problem, we construct a price index based on the prices paid by consumers in the same county.

For each household i, we construct a distance d_{ij} between household i and household j in FoodAPS that reside in the same county. We observe only the census tract of each household, which serves as a location identifier.[6] Then we construct a price index faced by household i in the following way:

$$P_i = \sum_{j=1}^{H} \frac{P_j}{\ln d_{ij}}$$

where H is the number of households in the county that participated in FoodAPS. Household i and other households in the same tract have zero distance to household i, which we cannot use. Instead,

[6]Census tracts are small, relatively permanent statistical subdivisions of a county or equivalent entity established by the U.S. Census Bureau. They generally encompass between 2,500 and 8,000 people.

for these households, we assign $d_{ij} = 0.52 * tract\ area$, which is the approximate distance between two random points in the census tract.

In the demand model, we need to assume the exogeneity of prices. First, the preferences of one individual cannot change the market prices, so the danger lies in the correlation between market-level prices and preferences common among the consumers in the market area. We cannot refute it directly in the absence of exogenous changes to the food supply. However, we have indirect evidence against this hypothesis. When we try to estimate the model using the prices paid by individual consumers, instrumented using market-level prices, we reject the hypothesis of price endogeneity, and we generally find that this model has a poor fit. This indirect evidence leads us to assume that we are likely to have exogenous spatial price variation. Therefore, we use a weighted average of price indexes calculated for each household in the county. As the purchases of nearby households provide a better estimate of local prices than those of households from the other side of a county, we weigh the price indexes by the log of distance between the two households.

In addition to a food price index, the model requires a price index for the nonfood items. FoodAPS respondents reported only expenditures and not quantities for some nonfood categories. Hence, it is impossible to estimate the prices of nonfood items from the FoodAPS data, as we did for the food items. Therefore, we use the Regional Price Parities (RPP) database collected by the Bureau of Economic Analysis (BEA). The database is based on the Bureau of Labor Statistics consumer price index price surveys and the Census Bureau's American Community Survey of housing (BEA, 2016). The price data span 381 Metropolitan Statistical Areas (MSA). For each MSA, the database reports an aggregate price index relative to the national average. We match the RPP data to each FoodAPS household using the MSA identifier. Even though the 381 MSAs offer considerable spatial variations, we assume, due to data limitations, that respondents faced identical prices for the nonfood items within each MSA.

Empirical Method

We can use descriptive statistics to address this study's first question: Do households that spend a large share of their budget on convenience foods differ in demographic characteristics, health indicators, financial resources, time constraints, and expenditure patterns from those households that spend only a small share? However, since the factors are likely to be interlinked, we require the use of an economic demand model to answer the study's second question: Which of the four factors—financial resources, prices, time constraints, or food environment—have the largest influence on consumers' decisions to acquire convenience foods? In this case, we use an Exact Affine Stone Index (EASI) implicit Marshallian demand model to estimate how various determinants affect the demand for convenience foods.

Economic theory assumes that consumers are trying to be as satisfied as possible while staying within their budget. Unfortunately, it is difficult to measure the level of satisfaction (which economists call utility) because each individual consumer has his or her own set of preferences that influence decision making. Instead, economists try to understand utility by first observing how much money consumers save, what they purchase, and what they pay for the products they buy, and then estimating a demand system. For a single product, the quantity purchased is a function of the price and the consumer's preferences. For multiple products, we add the prices of the other products in a set or system of demand equations—one for each product or a group of products.

There is a wide variety of demand models to choose from, depending on the purpose and available data. In this study, we chose the censored EASI model (Lewbel and Pendakur, 2009; Zhen et al., 2014). The EASI model is an improvement over traditional demand models, such as the Almost Ideal Demand System, because it allows for highly nonlinear Engel curves, which describe how the proportion of income spent on a category of a good, such as convenience foods, changes as income changes. When an Engel curve is nonlinear, it means that the proportion of the food budget spent on a particular food may change faster for low-income households than high-income households, even though the amount of increase is the same. We find that a fourth-degree polynomial of real expenditures best predicts expenditure share, so our Engel curves have a rank 4.

We use the EASI model modified by Zhen et al. (2014) to allow for censoring of households with zero consumption of some products via Tobit estimation. We imposed homogeneity and symmetry constraints on the model to connect the demand model with prevailing consumer theory. We follow LaFrance and Hanemann (1989) to model food demand in an incomplete demand system. The incomplete demand system is a better fit for a case where we do not observe all consumer expenditures. In FoodAPS, information available for total expenditures accounts for only 35 percent of reported income, leaving many important expenditures unaccounted for. Also, this method is a better fit for the censored regression used to estimate the model. The Tobit model used to estimate censored regression can produce negative predicted expenditure shares. Then the omitted equation is estimated to make the sum of all total expenditure shares equal to 1. However, as demand cannot be negative, the negative predicted shares are replaced with zeros, which can potentially create the predicted sum of all expenditure shares greater than 1. An incomplete demand system does not have this problem, as there is no omitted equation to make all shares equal to 1.

We estimate four equations for FF, FS, RTE, and NRTE foods using total expenditure shares (including nonfood expenditures). Hence, the budget shares do not add to 1. There is no separate equation for nonfood items, but the price of nonfood items enters the estimation as a demand shifter, and expenditures on nonfood items are included in the total expenditures.

The demand model above estimates the effect of prices, financial resources, time constraints, and the food environment on quantity demanded. While estimating the effect in terms of dollars has economic significance, public health researchers may be more interested in understanding how to translate this result into food energy. Thus, we also present the effects in terms of the amount of calories purchased. From the demand model, we obtain estimates of how consumers would change the quantity of food purchased ($\Delta\%Q$) if prices or other factors change (Z). We multiply this change by the average number of calories from this food reported in FoodAPS ($\overline{Kcal}$) and divide by the number of standard adult equivalents (SAE) in the household.

$$Kcal_{\mathrm{ij}}\left(Z\right) = \Delta\%Q_{ij}\left(Z\right) * \frac{\overline{Kcal_{\mathrm{ij}}}}{SAE}$$

In this method, we use average share of calories from each food type. We have to use this approach as some consumers have no consumption of some food types, thus making relative change calculations impossible. This approach requires an assumption that a household's share of calories coming from each food type $\frac{\overline{Kcal_{\mathrm{ij}}}}{SAE}$ is not correlated with individual demand elasticity $\Delta\%Q_{ij}$ (Z).

Results

Household Characteristics of Above-Average Food Purchasers

Convenience foods are likely to be less healthy and may cause long-term health issues. Therefore, understanding the factors affecting demand for convenience foods has important implications for public health. We begin by examining the relationship between a household's expenditure share for each of the four types of foods (FF, FS, RTE, and NRTE) and the healthfulness of the acquired food, and then we look at the relationship between expenditure share and body mass index (BMI) of the primary survey respondent. The first relationship reflects a current behavior—what the consumer is purchasing (and likely eating) now—while the relationship with BMI likely represents the result of past behavior.

We then produce a bar plot of the expenditure share of each type of food and the Healthy Eating Index (HEI). The HEI was created by the USDA Center for Nutrition Policy and Promotion (CNPP) to measure the healthfulness of a diet (see box, "Healthy Eating Index"). The index represents how closely a diet adheres to the recommendations of the *2010 Dietary Guidelines for Americans*. We use the methodology from Mancino et al. (2018) to estimate HEI using FoodAPS data. The index varies from 0 (the least nutritious diet) to 100 (the most nutritious diet).

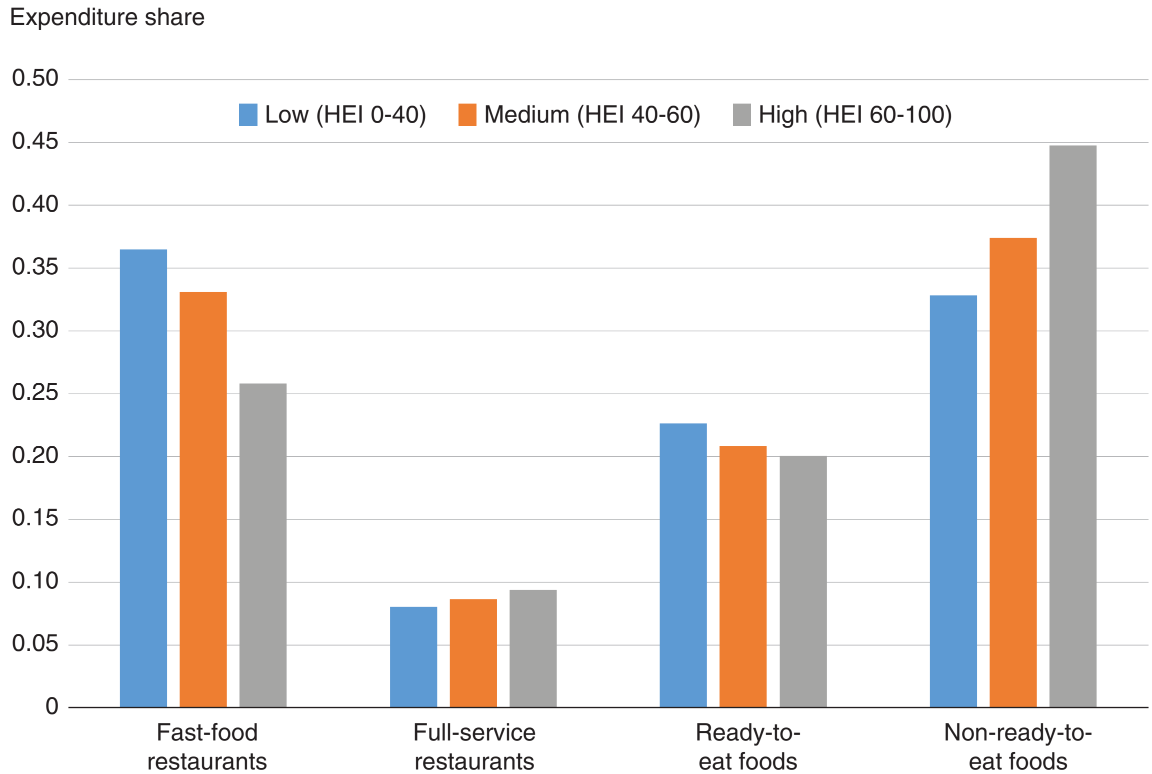
We find that consumers with more nutritious diets (high HEI) spend a larger portion of their total expenditures on NRTE and FS foods and a smaller portion on FF and RTE foods compared to those with less nutritious diets (fig. 1). We also find that higher spending on NRTE and FS foods is associated with a lower BMI for a primary respondent, whereas higher spending on FF is associated with a higher BMI (fig. 2).

Healthy Eating Index (HEI)

We present food purchases aggregated by households because we do not have information on how food was distributed among household members. To compare households of different sizes, we normalize the food purchases by the expected food consumption based on the number of standard adult equivalent (SAE) individuals with 2,000 kcal-recommended intake. We assign weights to each individual in the household according to the recommended caloric intake for sedentary individuals by gender and age from the *2010 Dietary Guidelines for Americans* (USDA and HHS, 2010). For instance, if a household consists of a 35-year-old male (2,400 kcal), a 35-year-old female (1,800 kcal), and 5- and 10-year-old girls (1,200 and 1,400 kcal), then the recommended daily caloric intake for the household is 6,800 calories, which is represented as a household with 3.4 SAEs.

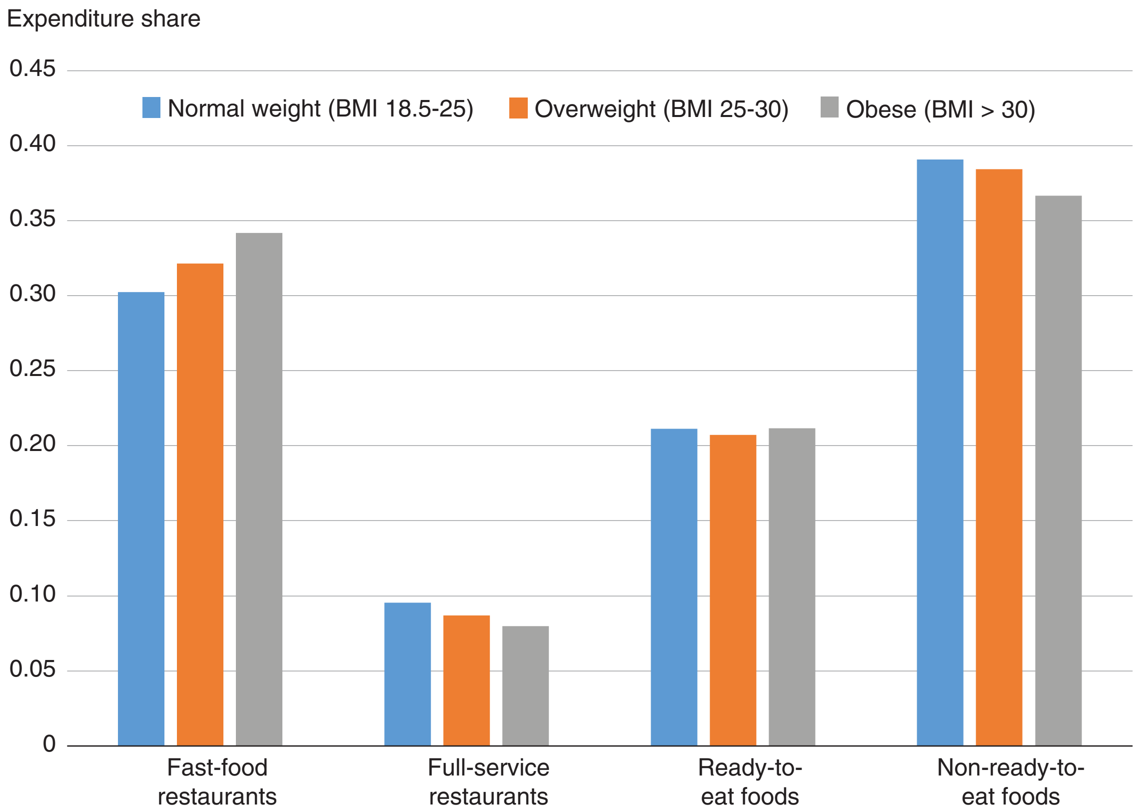
Our primary measure of diet quality is the 2010 Healthy Eating Index (HEI-2010) (Guenther et al., 2013). This index is based on nine recommended food groups and three other food groups that should be consumed in moderation. It is calculated per 1,000 calories consumed and measures the quality of food acquired, rather than the quantity. Each component has a maximum and a minimum score. For example, the recommended consumption amount of fruits is 0.8 cup equivalents per 1,000 kcal. Any consumption higher than the recommended amount will result in a maximum score of 5, and any consumption lower than the recommended amount will result in a lower score. The total composite HEI has a minimum score of 0 and a maximum score of 100. The average HEI for Americans older than age 2 was 49.9 in 2003-04 (Guenther et al., 2014).

Figure 1
Relationship between household purchases' Healthy Eating Index-2010 (HEI-2010) scores and food expenditure share by food category



Note: The higher the HEI score, the healthier a diet is deemed to be.
Source: USDA, Economic Research Service calculations based on data from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), 2012.

Figure 2
Relationship of body mass index (BMI) and food expenditure shares by food category



Source: USDA, Economic Research Service calculations based on data from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), 2012.

While the healthfulness of the food purchases and the BMI of a primary respondent appear to vary as the expenditure shares of the four types of food change, this variation might be explained by other factors such as household demographics, financial resources, and the food environment, including local prices. One way to study these factors is to examine the differences between households that allocate more of their food budget to one type of food versus another.

To explore the differences in budget allocation, we divide the households into four overlapping categories: high FF consumers, high FS consumers, high RTE consumers, and high NRTE consumers. To be classified as a high consumer of a particular food type, a household must have spent more than the average share of its food budget on the food type. The average expenditure shares of our FoodAPS sample are 15 percent for FF, 5 percent for FS, 9 percent for RTE, and 17 percent for NRTE (table 1). Therefore, a household that has expenditure shares of 20 percent for FF, 20 percent for FS, 5 percent for RTE, and 10 percent for NRTE would be classified as both a high consumer of FF and a high consumer of FS.

In the construction of sample means, we account for the complex sampling design in FoodAPS (through probability weights and strata). The ratio of the price index to the national average, which is normalized to 1, is presented in table 1. Despite some statistically significant differences, the size of most of the differences is small, at less than 5 percent. Since consumers faced similar prices, the difference in expenditures was likely driven by the differences in quantity and quality of food purchased.

We do not see much evidence of clustering of consumer purchases. Consumers who purchase a lot of FF do not purchase more FS meals. Similarly, there is no clustering of in-store purchases (RTE and NRTE) or clustering of other convenience food types (RTE and FF).

High-FAFH households spend more on food than high-FAH consumers. High-RTE households spend the least amount on food, at $86 per standard adult equivalent (SAE) per week, followed by high-NRTE consumers, at $93 per week. High-FF households spend the most on food, with $127 of weekly spending per SAE. However, the higher expenditures do not translate into higher amounts of calories purchased. High-RTE and NRTE households purchase more calories than high-FAFH households per SAE. High-RTE and NRTE households purchase 3,109 and 3,112 kcal per SAE per day, respectively. High-FF households, on the other hand, purchase the least number of calories, at just 2,198 kcal per SAE per day. Consumers purchasing FAFH likely purchase only foods they plan to eat at that meal or over the next day or 2, while FAH purchases may be stored for much longer. The cost per calorie is higher for FS and FF relative to NRTE and RTE foods. For example, despite the average spending on FS of 5 percent of total expenditures (14 percent for high-FS households), consumers purchased only 6 percent of their calories from FS (14 percent for high-FS households).

Table 2 presents the relationship between the healthfulness of food purchases and individual weight status. HEI scores are highest for the high-NRTE group and lowest for the high-FF group. The BMI of respondents from high-FF households is slightly higher than the average BMI, while the BMI of respondents in the high-NRTE group is lower. The difference in both cases is small—less than 1 point of BMI. The BMI of children is not significantly different among the four groups. The obesity rate (BMI > 30) of high-NRTE consumers is slightly lower than average (29 vs. 32 percent), while other differences are statistically insignificant.

BMI and diet quality can also be tied to demographic characteristics (table 3). Primary respondents of high-FF households tend to be younger and are more likely to be Black and to have larger household sizes, while primary respondents of high-FS households are the least likely to be Black and the most likely to be married and to have smaller household sizes. Primary respondents of high-RTE households are older and are the least likely to be Asian or Hispanic. Primary respondents of high-NRTE households are older than average and have smaller household sizes. These demographic characteristics have been linked to higher diet quality (Carlson et al., 2014).

Table 1

Food expenditure shares, calorie acquisition, and prices by high purchasers of four food categories

	All households	High-FF households	High-FS households	High-RTE households	High-NRTE households
Total expenditure shares					
Share of FF expenditures	0.15	0.3*	0.12*	0.08*	0.05*
SE	(0.19)	(0.18)	(0.15)	(0.11)	(0.09)
Share of FS expenditures	0.05	0.05*	0.14*	0.03*	0.03*
SE	(0.08)	(0.06)	(0.10)	(0.05)	(0.05)
Share of RTE expenditures	0.09	0.06*	0.07*	0.17*	0.09*
SE	(0.11)	(0.07)	(0.08)	(0.12)	(0.11)
Share of NRTE expenditures	0.17	0.1*	0.12*	0.17	0.28*
SE	(0.17)	(0.10)	(0.11)	(0.13)	(0.18)
Food energy shares					
Share of FF calories	0.14	0.25*	0.14	0.06*	0.05*
SE	(0.19)	(0.22)	(0.19)	(0.08)	(0.08)
Share of FS calories	0.06	0.06*	0.14*	0.03*	0.02*
SE	(0.09)	(0.10)	(0.14)	(0.05)	(0.05)
Share of RTE calories	0.33	0.29*	0.3*	0.5*	0.28*
SE	(0.23)	(0.22)	(0.21)	(0.17)	(0.21)
Share of NRTE calories	0.48	0.39*	0.41*	0.42*	0.65*
SE	(0.26)	(0.24)	(0.23)	(0.19)	(0.20)
Expenditures per week ($)					
Total expenditures	227	291*	231	178*	185*
SE	(497)	(222)	(164)	(185)	(675)
Food expenditures	107.76	126.83*	115.82*	86.05*	93.29*
SE	(93.76)	(90.15)	(75.28)	(56.78)	(219.52)
Food energy					
All kcal per SAE	2,664	2,198*	2,505*	3,109*	3,112*
SE	(1,712)	(1,414)	(1,542)	(1,798)	(1,894)
Price index					
Price FF	0.99	0.97	0.98	0.96*	1.01*
SE	(0.27)	(0.28)	(0.27)	(0.25)	(0.26)
Price FS	1.00	0.99	1.01	1.00	1.00
SE	(0.22)	(0.23)	(0.32)	(0.21)	(0.20)
Price RTE	1.03	1.03	1.05	1.05	1.03
SE	(0.28)	(0.27)	(0.29)	(0.31)	(0.28)
Price NRTE	1.01	0.98*	1.03	0.98*	1.05*
SE	(0.35)	(0.34)	(0.36)	(0.32)	(0.37)
N	3,985	1,756	1,032	1,770	1,898

FF = fast-food restaurants, FS = full-service restaurants, RTE = ready-to-eat foods, NRTE = non-ready-to-eat foods, kcal = kilocalories (1 kcal = 1 "calorie" referred to in food), SAE = standard adult equivalent. SE = standard error (in parentheses). N = sample size.

Note: An asterisk (*) indicates a 5-percent statistically significant difference from the sample average. The FF and FS classifications are refined using the reported number of transactions that included tips. If a restaurant (or a chain) was initially classified as FF but more than 30 percent of reported transactions included tips, we reclassified it as FS. Conversely, if a restaurant that was initially classified as FS had less than 30 percent of reported transactions that included tips, we reclassified it as FF.

Source: USDA, Economic Research Service using data from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), 2012.

Table 2

Relationship of diet quality and weight status to high food purchasers of four food categories

	All households	High-FF households	High-FS households	High-RTE households	High-NRTE households
Total HEI-2010 score	53.89	52.63*	54.36	53.87	55.81*
SE	(13.31)	(12.59)	(13.22)	(13.35)	(13.61)
Primary respondent BMI	27.83	28.16	27.94	27.71	27.39*
SE	(6.20)	(6.35)	(5.99)	(6.19)	(6.08)
Primary respondent, share obese	0.32	0.34	0.33	0.31	0.29*
SE	(0.48)	(0.48)	(0.47)	(0.47)	(0.47)
Household adult BMI (average)	27.74	28.14*	27.88	27.59	27.35*
SE	(5.68)	(5.90)	(5.93)	(5.66)	(5.45)
Household children BMI (average)	20.47	20.78	20.69	20.07	20.12
SE	(5.63)	(6.06)	(5.05)	(5.30)	(5.36)
N	3,985	1,756	1,032	1,770	1,898

HEI-2010 = Healthy Eating Index-2010, BMI = body mass index, FF = fast-food restaurants, FS = full-service restaurants, RTE = ready-to-eat foods, NRTE = non-ready-to-eat foods. SE = standard error (in parentheses). N = number of observations. An asterisk (*) indicates a 5-percent statistically significant difference from the average.

Note: BMI categories: Underweight = <18.5; normal weight = 18.5-24.9; overweight = 25-29.9; obesity = BMI of 30 or greater for adults only.

Source: USDA, Economic Research Service using data from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), 2012.

Table 3

Demographic characteristics of high food purchasers of four food categories

	All households	High-FF households	High-FS households	High-RTE households	High-NRTE households
Primary respondent age	50	46*	51	52*	54*
SE	(16)	(15)	(16)	(16)	(17)
Primary respondent, female (share)	0.68	0.68	0.67	0.68	0.71
SE	(0.44)	(0.43)	(0.44)	(0.43)	(0.43)
Primary respondent, Hispanic (share)	0.13	0.14	0.11	0.08*	0.13
SE	(0.39)	(0.41)	(0.38)	(0.34)	(0.41)
Primary respondent, Black (share)	0.11	0.13*	0.07*	0.09	0.1
SE	(0.34)	(0.36)	(0.29)	(0.32)	(0.33)
Primary respondent, Asian (share)	0.04	0.04	0.05	0.02*	0.04
SE	(0.20)	(0.20)	(0.22)	(0.16)	(0.23)
Primary respondent, married (share)	0.46	0.49*	0.51*	0.44	0.45
SE	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Household size	2.44	2.73*	2.32*	2.4	2.32*
SE	(1.71)	(1.66)	(1.47)	(1.73)	(1.78)
N	3,985	1,756	1,032	1,770	1,898

FF = fast-food restaurants, FS = full-service restaurants, RTE = ready-to-eat foods, NRTE = non-ready-to-eat foods. SE = standard error (in parentheses). N = sample size. Note: An asterisk (*) indicates a 5-percent statistically significant difference from the sample average.

Source: USDA, Economic Research Service using data from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), 2012.

Next, we examine how the four groups differ in factors that potentially affect demand for convenience foods: financial resources (income, food assistance), time constraints (employment, number of children, commute time), and the food environment. High-FS households have fewer financial resource constraints, whereas high-RTE and NRTE households face tighter resource constraints (table 4). High-FS households also have the highest income and education and are the least likely to be eligible for or currently on food assistance programs. On the other hand, households that heavily consume RTE and NRTE foods have lower incomes, and are likely to be eligible for or already participating in food assistance programs.[7]

Table 4

Education level, income, and food assistance participation of high purchasers of four food categories

	All households	High-FF households	High-FS households	High-RTE households	High-NRTE households
Primary respondent education (years)	15.9	16.2	16.4*	15.7*	15.5*
SE	(4.2)	(4.2)	(4.2)	(4.1)	(4.3)
Household monthly income ($)	5,329	5,552	6,424*	4,878*	5,112*
SE	(4,229)	(3,828)	(5,009)	(4,219)	(4,658)
Currently on SNAP (share)	0.12	0.11*	0.05*	0.14*	0.16*
SE	(0.46)	(0.45)	(0.37)	(0.48)	(0.48)
Eligible for SNAP (share)	0.28	0.22*	0.2*	0.31*	0.34*
SE.	(0.50)	(0.49)	(0.47)	(0.50)	(0.50)
Currently on WIC (share)	0.04	0.05*	0.02*	0.03*	0.03*
SE	(0.29)	(0.31)	(0.21)	(0.30)	(0.29)
Likely eligible for WIC (share)	0.44	0.55*	0.42	0.4*	0.37*
SE	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)
N	3,985	1,756	1,032	1,770	1,898

SNAP = Supplemental Nutrition Assistance Program, WIC = Special Supplemental Nutrition Program for Women, Infants, and Children, FF = fast-food restaurants, FS = full-service restaurants, RTE = ready-to-eat foods, NRTE = non-ready-to-eat foods. SE = standard error (in parentheses). N = sample size.

Note: An asterisk (*) indicates a 5-percent statistically significant difference from the average.

Source: USDA, Economic Research Service using data from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), 2012.

Time constraints also vary by the type of group (table 5). Time constraints are the time demands from employment, childcare, and commute time. High-FF households seem to be the most time constrained. They are the most likely to have all adults employed, have a large number of children, and also have the highest rate of single-parent households. On the other hand, the least time-constrained group is the high-NRTE households, where adults are the least likely to be employed and have few children. Like the FF households, FS household are time constrained by work, but the presence of children and the number of children are similar to those of the NRTE households. The employment and childcare time constraints faced by RTE households are similar to the average.

[7]Households eligible for SNAP and WIC include both participants and nonparticipants.

Table 5

Time-constraint characteristics of high purchasers of four food categories

	All households	High-FF households	High-FS households	High-RTE households	High-NRTE households
Primary respondent employed (share)	0.55	0.64*	0.60*	0.53	0.48*
SE	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)
Primary respondent commute time, minutes	9.70	10.60	9.70	9.90	8.80
SE	(16.9)	(14.3)	(22.6)	(19.6)	(13.8)
Household with children (share)	0.33	0.42*	0.29*	0.32	0.30*
SE	(0.50)	(0.50)	(0.48)	(0.50)	(0.50)
Number of children	0.60	0.77*	0.48*	0.62	0.54*
SE.	(1.27)	(1.21)	(1.04)	(1.36)	(1.34)
Single parent (share)	0.04	0.06*	0.04	0.04	0.03
SE	(0.26)	(0.27)	(0.22)	(0.27)	(0.25)
All adults are employed (share)	0.45	0.52*	0.51*	0.42	0.36*
SE	(0.48)	(0.49)	(0.50)	(0.47)	(0.45)
N	3,985	1,756	1,032	1,770	1,898

FF = fast-food restaurants, FS = full-service restaurants, RTE = ready-to-eat foods, NRTE = non-ready-to-eat foods.
SE = standard error (in parentheses). N = sample size.
Note: An asterisk (*) indicates a 5-percent statistically significant difference from the average.

Source: USDA, Economic Research Service using data from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), 2012.

In addition to the demands on a household's time from childcare, employment, and commuting, the food environment can also influence time constraints (table 6). The food environment includes the proximity to restaurants and stores and the density of the stores and restaurants surrounding the residence. Access to a car may mitigate the impact of the food environment. High-NRTE consumers are also the least likely to have car access, but the absolute numbers are small, with only 4 percent of high-NRTE household lacking car access. The farther away a restaurant or a store is, the longer it takes for a consumer to acquire food. A high density of restaurants allows consumers to find a specific restaurant in less time. There is some evidence that proximity to a restaurant can encourage households to eat out more frequently (Davis and Carpenter, 2009; Laska et al., 2010; Carroll-Scott et al., 2013).

High-FF households live closest to the nearest FF restaurant (1.8 miles), but they live even closer to the nearest FS restaurant (0.93 mile). On the other hand, the density of FF and FS restaurants surrounding high-FF households is similar to the average density. High-RTE households are the most likely to live in areas with low density of stores and to live farthest from the nearest supermarket and FS restaurant. High-RTE households are also more likely to live in rural areas and have the smallest number of restaurants in a 5-mile radius. The magnitude of these differences is small; the largest difference in restaurant density does not exceed 30 percent of one standard deviation. The food environment of high-NRTE households is close to the average. Overall, there is little difference in the density of restaurants across all household types.

Table 6
Food environment of high purchasers of four food categories

	All households	High-FF households	High-FS households	High-RTE households	High-NRTE households
No car access (share)	0.03	0.02*	0.01*	0.02	0.04*
SE	(0.19)	(0.16)	(0.15)	(0.17)	(0.23)
Rural (share)	0.34	0.31	0.33	0.39*	0.33
SE	(0.45)	(0.44)	(0.44)	(0.46)	(0.44)
Distance to SNAP-authorized store, miles	2.21	1.8*	*2.15	2.73*	2.35*
SE	(2.86)	(2.29)	(2.65)	(3.21)	(3.14)
Standard deviation of the number of FF restaurants in 5-mile radius[1]	-0.13	-0.09	-0.14	-0.28*	-0.08
SE	(1.00)	(1.03)	(0.98)	(0.83)	(1.05)
Standard deviation of the number of FS restaurants in 5-mile radius[1]	-0.07	-0.05	-0.07	-0.21*	-0.01*
SE	(1.00)	(1.00)	(1.02)	(0.74)	(1.09)
Distance to the nearest FF restaurant, miles	2.49	1.82*	2.28	2.91	2.99*
SE	(3.49)	(2.62)	(3.33)	(3.76)	(4.01)
Distance to the nearest FS restaurant, miles	1.02	0.93	1.07	1.19*	0.99
SE	(1.34)	(1.31)	(1.34)	(1.44)	(1.31)
Population density (number of people per square mile)	1,313	1,250	1,339	989*	1,440
SE	(3,209)	(2,743)	(3,187)	(2,509)	(3,661)
N	3,985	1,756	1,032	1,770	1,898

FF = fast-food restaurants, FS = full-service restaurants, RTE = ready-to-eat foods, NRTE = non-ready-to-eat foods. SE = standard error (in parentheses). N = sample size.

Note: An asterisk (*) indicates a 5-percent statistically significant difference from the average. [1]Standard deviation of the number of restaurants relative to the mean of the sample.

Source: USDA, Economic Research Service using data from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), 2012.

Demand Model Results

While these summary statistics show the differences between households that allocate a higher share of their food budget to one type of foods than the average household, they cannot identify the relative importance of each factor in a consumer's decision to purchase different levels of convenience. In this section, we describe the results obtained from the demand model. We show how food prices, financial resources, time constraints, and the food environment affect consumer demand for convenience food. As discussed in the model section, we can produce estimates of quantity changes and changes in caloric purchases. We present both measures to provide evidence for members of the economics audience, who are likely to be interested in the changes in quantity purchased, and for members of the public health audience, who may care more about the changes in calories. The estimates account for the sampling probability weights provided by FoodAPS.

The demand model includes household financial resources, time constraints, and the food environment, which enter the model as demand shifter variables. More convenient foods save time, so we expect time-constrained consumers to have a stronger demand for them. These consumers are likely to work more, have longer commutes, and have children. They may live closer to restaurants or stores, which enables them to acquire food more easily. On the other hand, convenience foods are often more expensive. Thus, frequent FF, FS, or RTE consumers likely have greater financial resources.

Prices

Table 7 presents estimated price elasticities. Not surprisingly, all own-price elasticities are negative, meaning that as the price of food increases, the demand for that food falls. For example, the estimated price elasticity for FF is -0.92, which means if the price of food at FF restaurants increases by 1 percent, consumers will reduce the quantity of food purchased in FF restaurants by 0.92 percent. Demand for FS restaurant meals is the most price elastic (-1.15), and demand for NRTE is the least price elastic (-0.33). In other words, consumers will reduce purchases of FS as prices rise more than they would for NRTE with a similar price increase. We find no evidence that relative price change leads to a large substitution between food groups. In other words, if the price of FS increases, consumers do not substitute FS with RTE foods (cross-price elasticities are small and/or insignificant). We find evidence of weak substitutability between FF and FS foods—their cross-price elasticity is 0.05 to 0.13—meaning that if we increase the price of either of the two products by 1 percent, the demand for the other will increase by 0.05 to 0.13 percent. We find weak evidence of complementarity of FF and NRTE purchases, which have cross-price elasticities of -0.22 to -0.24. In other words, an increase in the price of one will decrease demand for the other by 0.22 to 0.24 percent.

The expenditure elasticity of a product is greater than 1 if the expenditures on a product grow faster than the growth in total expenditures. Predictably, FS and FF restaurant meals, which tend to be more expensive, have expenditure elasticities greater than one (1.11 and 1.14, respectively). The demand for cheaper RTE and NRTE foods is less expenditure elastic, with estimated expenditure elasticities of 0.97 and 0.94, respectively.

Table 7
Price and expenditure elasticities by food category

	Price elasticity				Expenditure elasticity
	FF	FS	RTE	NRTE	
FF	-0.92*	0.05	-0.14*	-0.24*	1.14*
	(0.05)	(0.03)	(0.02)	(0.03)	(0.01)
FS	0.13*	-1.15*	-0.02	-0.06	1.11
	(0.06)	(0.07)	(0.04)	(0.04)	(0.03)
RTE	-0.15*	0.02	-0.57*	-0.01	0.97
	(0.04)	(0.03)	(0.02)	(0.04)	(0.00)
NRTE	-0.22*	-0.03	-0.02	-0.33*	0.94
	(0.04)	(0.04)	(0.04)	(0.03)	(0.01)

FF = fast-food restaurants, FS = full-service restaurants, RTE = ready-to-eat foods, NRTE = non-ready-to-eat foods.
Standard errors are in parentheses.
Note: * $p<0.05$.

Source: USDA, Economic Research Service using data from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), 2012.

Financial Resources

We expect high-income consumers to demand more convenience foods because, while they save time, those foods tend to be more expensive. High-income consumers (with gross income above $5,000 per month) increase spending on FS foods by 27.8 percent and decrease their purchases of FF foods by 29.3 percent (table 8), relative to middle-income consumers ($2,000-$5,000 monthly income). However, the effect of this change on calories is small. High-income consumers purchase just 22 more calories per day from FS restaurants and just 68 fewer calories per day from FF restaurants. Relative to middle-income consumers, low-income consumers (income less than $2,000 per month), increase their purchases of FF by 29.3 percent and RTE foods by 11.2 percent and decrease their purchases of FS foods by 32.7 percent.

Consumers with higher levels of education tend to increase FS purchases, although the magnitude is small. We estimate that an additional year of education of the primary respondent increases FS purchases by 4.41 percent (table 8). Income and education are correlated, so we can interpret the extra year's education as a general increase in socioeconomic status or an increase in permanent income.[8]

Both USDA's Supplemental Nutrition Assistance Program (SNAP) and Special Nutrition Assistance Program for Women, Infants, and Children (WIC) affect food demand through increasing financial resources. SNAP relaxes a consumer's budget constraints for FAH products. WIC provides certain FAH products at no cost, which frees up income for other types of food or nonfood items. SNAP participation is associated with a reduction in FAFH purchases and an increase in FAH purchases. SNAP participation is associated with a decrease in FS purchases by 102 percent (-82 kcal/day), an increase in RTE food purchases by 25.5 percent (221 kcal/day), and an increase in NRTE purchases by 21.7 percent (284 kcal/day).[9] The effect of WIC participation is statistically insignificant.

There is a certain discrepancy between the expenditure elasticity of demand (table 7) and the effect of high- and low-income indicators (table 8). Both FF and FS food have an expenditure elasticity greater than 1, which implies that we expect a household with larger food expenditures to spend more on FF and FS foods. The effect of income indicators is less clear. High income is associated with more FS purchases, which is consistent with expenditure elasticity, and with fewer FF purchases, which is not.

There are two sources of this inconsistency. First, expenditure elasticity (table 7) measures the changes to the food budget. An indicator variable (table 8) captures preferences common for high-income people, who may have a different share of total budget devoted to food. Second, the indicator variable does not measure the exact change to the household income; it is an average for the preferences common among high-income households with very different income levels. The estimated Engel curves do not change their slope. The RTE and NRTE Engel curves have negative slope, whereas FF has a positive slope, which is consistent with an expenditure elasticity for RTE and NRTE foods of less than 1 and an expenditure elasticity for FF greater than 1. The Engel curve of FS food is relatively flat.

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[8]Education may be a proxy for unobserved preferences since consumers with higher education tend to purchase healthier foods (Handbury et al., 2015). It may also proxy for an individual's willingness to forgo benefits (such as consuming a large amount of calorie-dense foods) in the present time period in order to experience more benefits (such as increased health) in the future. By attending school (including college), the consumer forgoes current earnings to have higher earnings in the future.

[9]The estimates for SNAP participation are obtained by comparing SNAP-participating households to nonparticipating eligible households. Out of all eligible households, those that frequently shop for FAH may be more likely to participate in SNAP. Hence, a selection bias potentially exists.

Table 8

Change in food expenditures and calorie acquisition by education level, income, food assistance participation, and prices of nonfood items by food category

	FF	FS	RTE	NRTE
	Percentage change in expenditures			
Primary respondent education (additional year)	-0.74	4.41*	0.23	-0.19
SE	(0.47)	(1.20)	(0.28)	(0.31)
Low income	29.3*	-32.7*	11.2*	7.2
SE	(5.99)	(16.24)	(3.39)	(4.53)
High income	-29.3*	27.8*	-10.8*	-1.2
SE	(4.81)	(13.22)	(2.65)	(3.86)
Currently on SNAP	-3.5	-102.1*	25.5*	21.7*
SE	(5.36)	(15.12)	(2.90)	(4.44)
Eligible for SNAP	-21.07*	-6.89	0.46	7.59*
SE	(5.86)	(14.26)	(2.87)	(3.63)
Currently on WIC	5.7	-20.9	-1.6	11
SE	(10.24)	(22.69)	(5.48)	(7.68)
Likely eligible for WIC	-5.2	-5.9	2.3	11.7*
SE	(6.03)	(15.26)	(3.35)	(4.46)
	Changes in daily calories purchased per standard adult equivalent			
Primary respondent education (additional year)	-1.71	3.52	1.99	-2.49
Low income	67.76	-26.11	97.02	94.38
High income	-67.76	22.2	-93.55	-15.73
Currently on SNAP	-8.09	-81.53	220.89	284.46
Eligible for SNAP	-48.73	-5.5	3.98	99.49
Currently on WIC	13.18	-16.69	-13.86	144.19
Likely eligible for WIC	-12.03	-4.71	19.92	153.37
Prices of nonfood items	-284.93	78.5	-382.02	220.22
N	3,985	3,985	3,985	3,985

SNAP = Supplemental Nutrition Assistance Program, WIC = Special Supplemental Nutrition Program for Women, Infants, and Children, FF = fast-food restaurants, FS = full-service restaurants, RTE = ready-to-eat foods, NRTE = non-ready-to-eat foods. SE = standard error (in parentheses). N = sample size. 1 calorie = 1 kcal.

Note: * $p<0.05$.

Source: USDA, Economic Research Service using data from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), 2012.

Time Constraints

We consider employment status, commute time, and the presence of children as potential factors affecting food demand through time constraints (table 9). Commute time has little effect on food demand. For example, a 1-minute increase in the primary respondent's commute time is associated with a decrease of 2.27 percent in FF purchases. Employment of all adults is associated with a 12.1-percent (-105 kcal/ day) decrease in RTE purchases and a 72.1-percent (58 kcal/ day) increase in full-service restaurants purchases.

Table 9
Change in food purchases and calories acquired for households by employment status, commute time, and presence of children by food category

	FF	FS	RTE	NRTE
	Change in purchases (percent)			
Primary respondent commute time (additional minute)	-2.27	-3.45	-0.58	-1.42
SE	(1.50)	(5.60)	(0.85)	(0.77)
Primary respondent employed	13.4	-24.8	5.3	-3.1
SE	(7.01)	(16.58)	(3.46)	(5.73)
All adults are employed	-2	72.1*	-12.1*	-5.7
SE	(6.30)	(16.23)	(3.27)	(5.08)
Single parent	4	13.6	13.9*	-0.7
SE	(9.71)	(24.54)	(5.82)	(6.65)
Household with children	18.7*	-38.1*	-2.2	-6.1
SE	(6.03)	(16.73)	(4.22)	(4.69)
Number of children (additional child)	-8.7*	-15*	10.3*	8.8*
SE	(2.26)	(6.17)	(1.53)	(1.65)
	Change in daily calories purchased per standard adult equivalent			
Primary respondent commute time (additional minute)	-5.2	-2.8	-5.0	-18.6
Primary respondent employed	31.0	-19.8	45.9	-40.6
All adults are employed	-4.6	57.6	-104.8	-74.7
Single parent	9.3	10.9	120.4	-9.2
Household with children	43.2	-30.4	-19.1	-80.0
Number of children (additional child)	-20.1	-12.0	89.2	115.4

FF = fast-food restaurants, FS = full-service restaurants, RTE = ready-to-eat foods, NRTE = non-ready-to-eat foods. SE = standard error (in parentheses). 1 calorie = 1 kcal.
Note: * $p<0.05$.

Source: USDA, Economic Research Service using data from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), 2012.

The presence of children increases households' FF purchases by 18.7 percent (43 kcal/day) and decreases FS purchases by 38.1 percent (-30.4 kcal/day). Each additional child tends to increase purchases of RTE by 10.3 percent (89 kcal/day) and NRTE by 8.8 percent (115 kcal/day) and to decrease purchase of FF by 8.7 percent (-20 kcal/day) and FS by 15 percent (-12 kcal/day).

Lack of car access usually increases the time cost of travel outside the most densely populated areas. Only 3 percent of households in the sample do not have access to a car. Lack of car access is associated with a 16.1-percent (211 kcal/day) increase in NRTE purchases (table 10). We find a large but statistically insignificant decline in restaurant purchases, consistent with Ver Ploeg et al. (2017). Some of the sampled households that lack car access are not poor, explaining some of the insignificance.

Food Environment

Greater distance to the nearest supermarket slightly increases purchases of NRTE foods. If the distance to the nearest supermarket is 1 mile farther, consumers spend 1.7 percent (22 kcal/day) more on NRTE foods. Greater distance to the nearest FS restaurant is associated with higher FF and

FS purchases, by 5.3 and 10.9 percent respectively. This is not consistent with the economic theory that easier access should lower the cost of purchases and be associated with increased purchases. Most likely, distance to the nearest store and restaurant is less relevant to consumers, the vast majority of whom have easy access to a vehicle. We know that consumers often choose not to shop in the nearest store as stores farther away may offer more attractive prices and/or varieties of products. Ver Ploeg and colleagues (2015) find that, on average, consumers' primary supermarket is 3.8 miles away, even though their nearest store is just 2.1 miles away.

Distance to the nearest FF restaurant also has little effect on either FF purchases or calories. The findings on densities of restaurants within a 5-mile radius of a residence indicate that consumers potentially substitute among RTE and restaurant meals. A greater density of FF restaurants lowers RTE purchases. One standard deviation of increase in the density of FF restaurants is associated with a 7.8-percent decrease in RTE purchases (-68 kcal per day).

Table 10

Change in food purchases and calories acquired for households by access to a car, distance to nearest foodstore and restaurants, and restaurant density by food category

	FF	FS	RTE	NRTE
	Change in purchases (percent)			
No car access	-19.3	-71.3	-14.2	16.1*
SE	(11.26)	(40.05)	(7.29)	(6.30)
Distance to SNAP-authorized store (1 mile farther)	-2.8	-4.4	1.4	1.7*
SE	(1.51)	(3.40)	(1.44)	(0.72)
Distance to the nearest FS restaurant (1 mile farther)	5.3*	10.9*	1.7	-1.1
SE	(2.22)	(5.40)	(1.25)	(1.42)
Distance to the nearest FF restaurant (1 mile farther)	-0.9	-0.4	0.1	0.6
SE	(1.11)	(3.06)	(0.88)	(0.65)
Standard deviation of the number of FF restaurants in 5-mile radius[1]	-6.7	-6.3	-7.8*	2.5
SE	(4.34)	(11.13)	(2.48)	(2.93)
Standard deviation of the number of FS restaurants in 5-mile radius[1]	1.27	9.94	-3.71	-0.04
SE	(4.00)	(10.42)	(2.28)	(2.59)
	Change in daily calories purchased per standard adult equivalent			
No car access	-44.6	-56.9	-123.0	211.0
Distance to SNAP-authorized store (1 mile father)	-6.5	-3.5	12.1	22.3
Distance to the nearest FS restaurant (1 mile farther)	12.3	8.70	14.7	-14.4
Distance to the nearest FF restaurant (1 mile farther)	-2.1	-0.3	0.9	7.9
Number of FF restaurants in 5-mile radius	-15.5	-5.0	-67.6	32.8
Number of FS restaurants in 5-mile radius	2.9	7.9	-32.1	-0.5

Notes: FF = fast-food restaurants, FS = full-service restaurants, RTE = ready-to-eat foods, NRTE = non-ready-to-eat foods. SE = standard error (in parentheses). 1 calorie = 1kcal. [1]Standard deviation of the number of restaurants relative to the mean of the sample.

Sources: USDA, Economic Research Service calculations based on data from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), 2012.

Comparison With Okrent and Kumcu (2016)

Although the main conclusions are the same, there are a number of differences between our study and that of Okrent and Kumcu (2016). First, Okrent and Kumcu's study is a time-series study that uses temporal changes in prices and advertising in the four census regions to identify demand model parameters.[10] Their study assumes that all consumers in each of the four large regions face the same prices, are exposed to the same advertisements, and work the same number of hours. Our study is cross-sectional and uses local price variations along with detailed household information. Second, Okrent and Kumcu investigated fewer factors affecting food demand. The authors focused on four determinants: hours worked, prices, income, and advertising. We examine financial resources (income, participation in food assistance programs), time constraints (employment, presence and number of children, commute time), food environment, and prices.

The study by Okrent and Kumcu has many strengths. Its time-series demand model allows the authors to control for unobserved heterogeneity of consumers and is potentially more robust in the selection of consumers with particular pricing patterns. The authors also use more comprehensive disaggregation of foods by level of convenience, which provides more detailed findings. They use higher quality consumer price indexes, have a larger sample size, and analyze the effect of advertising. However, their use of the U.S. Bureau of Labor Statistics' Consumer Expenditure Survey brings a number of limitations. The dataset has limited information on demographics and the food environment, and the unit of analysis is large.

One of the key advantages of our study is that the price measures we use likely better reflect the prices that consumers actually face. The assumption of an average regional price in Okrent and Kumcu requires an assumption that the Consumer Expenditure Survey fully represents the census area population. Such an assumption may be true in general, but it conceals important heterogeneities within very large U.S. regions. The issue of heterogeneities can be overcome if the Consumer Expenditure Survey is representative of the populations that face different prices, but it would still not enable us to estimate Engel curves with a rank higher than 3 (Gorman, 1961; Lewbel, 1987), which we found to be significant.

Our price measures improve upon Okrent and Kumcu. By using more localized price variations, our price measures are likely to be closer to true prices that consumers face. Within a particular geographic region, households from different areas can face very different food prices. This difference can come from two sources: the variation in actual prices of individual products and the difference in consumer-basket composition of different localities. For example, the difference between the highest and the lowest FAH price in 2006 was 49 percent among 34 Nielsen market regions, compared with just 7.5 percent among the four census regions (Todd et al., 2010). While this price index based on unit values may overestimate the actual differences in price, the bias from unobserved product heterogeneity may also be large. For example, Handbury and Weinstein (2014) estimate that 97 percent of variance in the prices of food products across cities is due to differences in the product composition. Our price and expenditure measures take into account the basket composition of products locally at a county level as well as nationally.

[10]The U.S. Census Bureau groups 50 States and the District of Columbia into four census regions (Northeast, Midwest, South, and West) for the presentation of census data.

Related to that point, our dataset has more detailed information on demographic characteristics and the food environment. We can investigate more determinants of food demand, allowing us to answer policy-relevant questions more directly. Furthermore, Okrent and Kumcu assume that people living in the same region exhibit the same work patterns and face the same food environment. Finally, the use of regional prices requires an assumption that households are representative agents of a region, and Gorman's law does not allow an estimate of an Engel curve with a rank above 3 (quadratic function). In our model, we find that a fourth-degree polynomial fits data the best, which is an additional justification for our approach.

We replicate the results of Okrent and Kumcu using our data and model in panel 2 of table 11. We cannot estimate the demand model in Okrent and Kumcu because we do not have information on hours worked and advertising expenditures.[11] Okrent and Kumcu use a more disaggregated definition of food, where ready-to-cook (RTC) is broken into ready-to-eat and ready-to-heat foods, and non-ready-to-eat (NRTE) is broken into complex and simple ingredients. For the purpose of comparison, we aggregate the results from Okrent and Kumcu into four groups—FF, FS, RTE, and NRTE—using expenditure weights from 2010.[12]

Table 11

Comparison of elasticities between this study and Okrent and Kumcu (2016)

Panel 1 Elasticities in Okrent and Kumcu (2016)	FF	FS	RTC/E	Basic/ complex ingredients	Expenditure
FF	-0.38	0.32	0.04	-0.01	1.93
FS	0.35	-0.64	0.1	0.08	1.44
Ready-to-cook/eat (RTC/E)	0.08	0.16	-0.96	0.21	0.26
Basic/complex ingredients	-0.02	0.13	0.14	-0.54	0.25
Panel 2 Replicated elasticities using FoodAPS	**FF**	**FS**	**RTE**	**NRTE**	**Expenditure**
FF	-0.81	0.01	-0.11	1.17	1.26
FS	-0.02	-1.78	0.19	1.18	1.19
RTE	0.08	0.26	-1.15	0.94	0.94
NRTE	-0.1	0.19	0.1	0.71	0.61

FF = fast-food restaurants, FS = full-service restaurants, RTC/E = ready-to-cook/eat foods; RTE = ready-to-eat foods, NRTE = non-ready-to-eat foods.

Note: * p<0.05. Panel 1 is a replicate of table 7 in Okrent and Kumcu (2016).

Source: USDA, Economic Research Service using data from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), 2012; and Okrent and Kumcu (2016).

[11] We include indicators on whether the head of the household is employed and whether all adults in the household are employed, instead of hours worked.

[12] In addition, there may be discrepancies between the two datasets in the distinction of fast-food and full-service restaurants.

Household expenditure elasticities tend to be smaller than market elasticities. On the other hand, cross-sectional variation measures longrun elasticities, while a time series captures shortrun elasticities, with longrun elasticities generally larger (Wold and Jureen, 1955). We have lower own-price elasticities for FS and FF foods, and higher own-price elasticities for RTE and NRTE foods, than found in Okrent and Kumcu.

Our expenditure elasticities are generally closer to 1 than those found in Okrent and Kumcu. However, the elasticities show a very similar pattern, albeit at different levels. Both reports find relatively price-elastic demand for FS and RTE foods, and inelastic demand for FF and NRTE foods. In addition, both reports find the expenditure elasticity for more expensive restaurant foods to be greater than 1 and that for cheaper supermarket foods to be less than 1. In short, although the two studies use distinct data and models, the findings are consistent.

Conclusion

When consumers decide what and where to eat, their decision reflects four factors: financial resources, prices, time constraints, and the food environment. In this report, we examine how each of these factors influence consumers' decisions to purchase convenience foods.

We find that additional financial resources are associated with greater spending on restaurant meals. This is not surprising, given that this type of food is the most expensive. Food assistance programs affect demand for food by (1) making store-bought foods cheaper relative to restaurant meals, which results in increased consumption of food at home (FAH) (substitution effect), and (2) increasing income, which can lead to greater purchases of more expensive restaurant foods (income effect). We find that the substitution effect is strong, but we find no evidence for the income effect. For example, our results show that participation in SNAP is associated with increased purchases of store-bought foods and decreased purchases of restaurant meals. Therefore, a policy aimed at increasing SNAP participation rates among eligible households may shift demand from restaurant meals to store-bought foods, eventually leading to more nutritious diets and better health outcomes.

We find that consumers are most sensitive to the price of restaurant foods and less sensitive to the price of store foods. However, despite this relative difference, the purchasers of less healthful fast-food (FF) meals are not very sensitive to their prices. Thus, an increase in the price of these meals is not likely to bring a drastic reduction in FF purchases.

The amount of time available to consumers is another important factor when they choose convenience foods. Consumers who are pressed for time because of work or childcare likely exhibit different behavioral patterns than those who are not. A greater time constraint due to work tends to increase demand for full-service (FS) restaurant meals. On the other hand, a greater time constraint due to children increases demand for FF. The presence of children tends to increase the demand for FF, as convenience outweighs the monetary cost. However, when the number of children in a household exceeds two, the benefit of the lower cost of food at home outweighs the convenience of fast food, leading households to purchase more FAH. FAH is less convenient but cheaper than FF, and thus can easily be scaled up to feed a larger household without much increase in cost.

We find that the demand for convenience foods is not sensitive to travel time. Neither commuting time nor traveling time to a restaurant or a store seems to affect demand for convenience foods. Consistent with the existing studies on food deserts (Handbury et al., 2015; Rahkovsky and Snyder, 2015), consumers living closer to a restaurant do not eat out more often than those who live farther away, potentially because the time cost associated with traveling is negligible. However, we find some evidence that a higher density of FF restaurants is associated with lower purchases of ready-to-eat foods. The demand for relatively unhealthy FF was also insensitive to the location of restaurants. These findings imply that simply reducing the number of FF restaurants is unlikely to affect consumers' purchasing behaviors or diet quality.

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Appendix: Price Index Calculations

Using household surveys for demand estimation poses several challenges. First, many household surveys (e.g., Nielsen Homescan, the Centers for Disease Control and Prevention (CDC) National Health and Nutrition Examination Survey (NHANES), the Consumer Expenditure Survey, and FoodAPS) have no information on the prices the participants face; at best, we have the prices paid. This problem is particularly acute if a participant did not purchase a particular product. Second, conventional demand models can accommodate a limited number of options (at most, few dozen), which requires correct aggregation of foods.

This aggregation can hide substantial quality differences between purchases of different consumers. Some consumers may buy higher quality products for higher prices. Using unit values for these consumers would measure only the high prices consumers paid, not the average prices the consumers faced. Furthermore, some consumers may be better at finding lower prices, and this ability may be correlated with their preferences for particular food products. To address this problem, we used the superlative Fisher ideal price index based on food-item-level prices and quantities, which alleviates the missing quality information, as suggested by Diewert (1976):

$$p_{hkt} = \sqrt{\frac{\sum p_{kht} q_{k0} \sum p_{kht} q_{kht}}{\sum p_{k0} q_{k0} \sum p_{k0} q_{kht}}}$$

Where p_{kht} and q_{kht} are prices and quantities in household h in time t for food item k, q_{k0} is the national average for the quantity of food item k, p_{k0} is the average price of food item k. For products with a Universal Product Code (UPC), we used the UPC as a food item identifier; for other products, we used the food item name. We deleted price index outliers where the price index was less than 30 percent and more than 300 percent of the national average.

Some consumers reported only the total restaurant bill, so the prices of individual food items were unknown. We calculated them using the following procedure: First, we calculated the average national price of each food item using nonmissing prices in the sample. Then, we calculated the price of a total meal at a national price and calculated the expected expenditure share of each item. Finally, we applied the expected expenditure share to the total reported bill at local prices and recovered the local prices of individual food items. We calculated the individual expenditure-based price in the following way:

$\widetilde{C}_j = \sum_i^K \overline{P_{ij}}$ is the expected cost of the meal j, K is the number of food items in a meal, and $\overline{P}_{ij}$ is the average price of each food item.

$s_{ij} = \frac{\overline{P}_{ij}}{\widetilde{C}_j}$ is the expected expenditure share of item i in meal j. Then the expected price of each item is

$\widetilde{p_{ij}} = s_{ij} * C_j$, where C_j is the actual expenditures for the restaurant meal j.

As consumers cannot purchase all food products, and the prices they paid may be affected by their individual store preferences or propensity to seek lower prices, we constructed the expected prices they faced based on the prices paid by other consumers in the same county: $P_i = \sum_{j=1}^{N} \frac{P_j}{w_{ij}}$, where

w_{ij} is the weight of the distance between census tract centroids i and j. $w_{ij} = \frac{\ln\left(d_{ij}\right)}{\sum_{j=1}^{N} \ln\left(d_{ij}\right)}$, where

d_{ij} is the distance in miles between census tract centroids of households i and j. For consumers in the same census tract, we assume the distance between them is equal to the expected distance between two random points in the census tract.[13]

We also estimate an alternative price specification using the average county prices, rather than price indexes weighted by distances, assuming that all households in a primary sampling unit (PSU) (county) face the same prices. This minimizes the measurement error of price indexes from individual food preferences and creates a price index reflecting a larger variety of food products. The approach produces similar results but is not presented here since it offers an inferior explanation for the variation of prices and food purchases.

[13]This distance is 0.52 * census tract area. The formula assumes a round census tract, but it a reasonable approximation. We use log-distance to avoid the domination of the index by the few closest neighbors that share the same census tract. This is undesirable, given that each household reported purchasing just a few available items and that broad expenditure data were needed.