What's holding it back?

A study in organic retail coffee purchases.[♣]

by

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Abstract

In several surveys a majority of respondents state that they are willing to buy organic products even if they cost more. Despite this, market shares for such products are typically modest. We explore reasons for this apparent divergence using three years of household panel data on retail coffee purchases in Sweden, combining household's stated and revealed behavior in a discrete-choice model. Households that state they try, to the extent feasible, to buy organic products indeed have higher estimated choice probabilities for organic products. We use supply-side counterfactual exercises to examine contributing factors to why mainly conventional coffee is bought by such households. The results suggest that limited overlap between organic and other highly-valued characteristics is the most important constraint to higher levels of organic coffee purchases. High price of organic coffee and lack of access to organic coffee per se are also contributing factors, but with a smaller impact.

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1. Introduction

Many people claim to be willing to buy environmentally friendly products. For instance, Eurobarometer (2011, p 76) reported that 72 percent of respondents are ready to buy environmentally friendly products even if they cost more (this result was based on face-to-face interviews with more than 26,000 respondents across the 27 EU member states – see Loreiro and Loutade (2005) for another example of high stated willingness to buy organic products in a survey). Despite these stated intentions, the market for products that carry an organic label remains relatively small. The estimated market share of organic coffee in Germany and Italy (Europe's largest and second largest coffee markets) is 3 percent and around 0.5 percent respectively.[1] In the USA, organic coffee had an estimated market share of around 3.5 percent in 2009.[2]

Why are market shares of organic-labeled products not higher given the stated intentions of consumers? There are several potential explanations. Are organic-labeled products only available in a small fraction of stores, such that it is a lack of access that limits purchases? Or are prices for these products simply too high? Or is the breadth of choice too limited? Or is it the consumers themselves who, consciously or not, exaggerate the extent to which they are willing to buy organic products? These questions motivate the present article. We use a consumer scan panel of Swedish households' coffee purchases, and stated behavior of these same households, to examine the propensity to buy organic products. Firstly, we relate the *stated behavior* of a household to the same household's *actual* shopping choices. We observe the coffee varieties that households buy at the bar-code level as well as a number of demographic variables such as area of residence, household income and the number of people in the household. We also observe the age and level of education of the household's primary shopper. The source of data is the market research firm GfK. Once a year participating households fill in a questionnaire and answer whether they, to the extent feasible, try to buy organic products when shopping.[3] We find that even households that say they do their utmost to purchase organic products in fact buy

[1] Tropical Commodity Coalition (2012).
[2] Organic Trade Association (2010).
[3] The subjects surveyed answer the questions by ticking a box that corresponds to one of five responses that vary from "Totally Agree" to "Totally Disagree."

mostly conventional coffee.[4] Over the three years that we examine, for the group that was in total agreement with the statement that "When I buy groceries I try to the extent feasible to buy organic", only 22 percent of the coffee bought was organic.

To systematically investigate coffee choice we combine revealed and stated behavior and apply a discrete-choice, conditional logit, model of demand. We establish that household willingness to pay is in line with their survey responses. *I.e.*, households that said they try buying organic products have – as demonstrated through the shopping choices they made in the market – higher choice probabilities for organic labels. Thus, we establish firstly that stated behavior is informative and secondly that even the most keen organic households buy mostly conventional coffee.[5] This is consistent with the findings of, for example, the referenced Eurobarometer survey.

While a tendency to verbally profess pro-social behavior is well documented,[6] we note several other explanations that could explain why even keen organic households but mostly conventional coffee. We use the demand estimates to examine how the choice probabilities of organic coffee would be affected by changes in availability or prices. We consider three counterfactual scenarios. Firstly, a household might not buy organic products because these products are simply not available in nearby stores, suggesting *lack of access* as an explanation for the discrepancy. When there are fixed costs of supplying a particular product, sufficiently many consumers need to share your preferences if that product is to be offered (for an early formalization of this problem see Spence (1976) and for empirical evidence of this mechanism see for instance George and Waldfogel (2003)). Secondly, for the same reason, there may be a *limited overlap* of organic labeling with other characteristics that consumers value. A household could very well value organic, but also value a particular brand that is not available as an organic coffee. The value associated with a brand may trump the value associated with organic. Again, with fixed costs of retailing a particular product, sufficient numbers of consumers need to demand a combination of characteristics for the product to be offered. Finally we examine the

[4] "Conventional coffee" in this context refers to non-organic labeled coffee.

[5] The last year included in the data set a corresponding question was introduced for Fairtrade products. While the qualitative results of interactions between choice of Fairtrade coffee and stated behavior are similar as for organic coffee, the significance is lower, reflecting less observations. In the paper we therefore focus on the choice of organic coffee.

[6] See for instance Harrison and Rutström (2005). Note that labels are themselves part of a solution to informational problems surrounding goods produced in an environmentally friendly way.

effect of *lowering prices* - a household might sincerely try to buy organic products but find them too expensive relative to the next-best alternative.

To examine the importance of *lack of access* per se, and *limited overlap* between organic labeling and popular product characteristics, we introduce synthetic counterfactual organic products that are made available in all stores. We use the estimates from our discrete choice model to generate market shares for organic products under these counterfactual experiments. In a similar way we examine market shares when the price premium of organic products is halved. We predict that the introduction of an additional organic product and a halving of the organic price premium each is associated with a doubling of organic purchases among the self-professed organic households. Introducing an organic product with highly attractive other characteristics has an even stronger impact however, suggesting limited overlap as the strongest constraint.

These counterfactuals provide insight on why the share of organic products is not higher. In a second step one could examine if, under the status quo, producers and retailers are "leaving money on the table" - calculations such as these are highly relevant to coffee producers contemplating pricing policy or product assortment. If we could observe the cost of developing and distributing additional products, and were willing to make behavioral assumptions on competitor responses, it would be possible to calculate the profitability of changes in strategy.[7] However, absent such information, any suggestion to further increase producer profits would be speculative. We therefore contend ourselves with an examination of consumer responses to a relaxing of potential constraints for organic market penetration.

Let us briefly clarify how our paper relates to the literature. First and foremost we relate to a large number of articles that examine the impact of the introduction of environmentally or ethically-labeled (EE-labeled) products and that try to estimate the willingness to pay for EE-labels. A number of different approaches have been used. One set of studies use market data, similar to ours, but without complementing the data with stated preferences. For example Bjørner et al. (2004) use a discrete choice model to establish that the introduction of an organic label in Denmark had a significant impact on brand choices for toilet paper and washing detergents (but

[7] How straightforward this is of course depends on what one is willing to assume, back-of-the-envelope calculations are easy enough to make under different scenarios by simply using the estimated demand system. If we are to more rigorously model strategic interactions the complexity increases substantially, see for instance Dubé et al. (2005) for an overview.

less so for paper towels). Kiesel and Villas-Boas (2007) find that the appearance of a government sponsored label on organic milk increased consumer valuation of organic milk and Teisl, Roe and Hicks (2002) document substantial consumer responses to the appearance of dolphin-safe labels in the USA. Willingness to pay for environmental and ethical labels has also been estimated using stated preference methods and choice experiments across a range of products. Overall these studies also tend to find positive willingness to pay for such labels. For example, on coffee in particular, Loureiro and Lotade (2005) use face-to-face interviews to study willingness to pay for EE- labeled coffee and find that consumers in the USA were on average willing to pay a premium of 3-4 percent for Fairtrade coffee. Their corresponding estimate for organic coffee was 2.5 percent. Hainmueller, Hiscox and Sequira (2011) conduct labeling experiments in stores and find that sales of two popular brands of coffee increased by almost 10 percent when they were labeled as being Fairtrade products. Likewise a study by De Pelsmacker et al. (2005) found willingness to pay premiums for Fairtrade coffee at 10 percent amongst Belgian test subjects.[8] Thus, a positive willingness to pay for EE-labels is a feature in many studies and serves as a motivation for our examination of why the market share for organic-labeled products is not higher, despite an important fraction of consumers appearing to have a positive willingness to pay for such products.

As noted a part of the above literature relies on stated preferences. Asking about willingness to pay for organic products can be problematic. A desire to conform to social norms can bias responses. Indeed a rather large set of papers analyze the discrepancy between answers to questionnaires (typically involving contingent valuation) and observed actions in a lab or field experiment. Many such studies find evidence of what Harrison and Rutström (2005) refer to as *hypothetical bias*: a systematic difference between values that are elicited in a hypothetical context, such as a questionnaire, and those elicited in a real context, such as a market where decisions are economically binding (see for instance Blumenschein et al. (2008), Cummings and Harrison (1995), Seip and Strand (1992)). Test subjects in many of the studies on hypothetical bias are likely to make the connection between the questions being asked and the behavior being tracked. In these settings, anchoring and other behavioral biases can affect findings. We use responses to a questionnaire that asks whether people, to the extent feasible, purchase organic

[8] Several studies have also found considerably higher willingness to pay estimates. Rotaris and Danielis (2011) survey Italian coffee consumers and Hertel et al. (2009) surveys US consumers. They both find that a majority of test subjects would be willing to pay premiums of around 50 percent.

products when they visit grocery stores but only track one product category. Thus our data cannot yield a precise estimate of hypothetical bias.[9] However, the question that we use is but one of a total of 35 questions asked in the annual survey, and the market data tracks consumer choice across a regular assortment and prices of coffee during a year. Thus anchoring, or the need to keep one's word, is likely to be weak in our setting. In this way the results of our study provide support for the hypothesis that stated behavior is informative of actual behavior regarding organic products – a finding that should prove valuable to works that for instance use survey data such as the Eurobarometer (as in Koos (2011) discussed below).

A final strand in the literature estimate willingness to pay for EE-labels using a combination of detailed data on household purchases (tracked over years or months), and stated preference or choice experiment data performed by the same households. A recent example of such a study is Brooks and Lusk (2010), wherein a multinomial-logit model was used to estimate consumer response to milk from cloned cows in the USA. They gauged the social-welfare benefits of labeling initiatives. Their results indicate that consumers are willing to pay large premiums to avoid milk from cloned cows. They also show that predictive power is improved by combining revealed and stated preferences.[10] In a related study Griffith and Nesheim (2010) deploy revealed preference methods to estimate bounds on the willingness to pay for product characteristics – they extend work by Blow, Browning and Crawford (2008) - to accommodate a basket of goods and examine consumer response to the organic label. The consumer scan panel they use also includes questionnaires that are similar to those included in our data set. They show that the lower bound on willingness to pay for organic products is higher for households that agree strongly/agree to the statement that "I try to buy environmentally friendly products." (Griffith and Nesheim (2010), Table 9).

We are not aware of any previous studies that apply, as we do, supply-side counterfactual exercises to examine the role of product availability and prices as a constraint on expansion of organic purchases.[11][12] An interesting comparison can be made with Koos (2011)

[9] The reason is that a subject could purchase organic varieties of all products apart from coffee, and still be seen as answering truthfully. On the other hand, as we show below, coffee is one of the foremost categories of organic and Fairtrade products.

[10] Other studies that combine revealed and stated preferences include Hensher and Bradley (1993), Adamowicz et al. (1994) and Brownstone et al. (2000).

[11] The application of structural models to predict market shares under various counterfactuals is not new however; see for instance Hausman (1997) or Petrin (2002) for ex-post examinations of the welfare effects of new product introductions (breakfast cereal and the Chrysler minivan, respectively).

who uses responses from the 2007 edition of Eurobarometer (a survey of some 17000 individuals across 18 European countries) to provide a cross-sectional account of the probability that a consumer purchases environmental-labeled products. As explanatory variables he uses individual-level demographic characteristics as well as a number of country-level variables intended to capture supply side factors; such as whether there exist state-backed environmental labels, the number of competing environmental labels, the share of retailers that have less than ten employees and a measure of the supply of environmentally labeled products[13]. Interestingly, the supply of environmentally-labeled products is the only variable, apart from individual-level demographics, that has a robust positive influence on the probability that environmental-labeled products are purchased. A concern that one may have in interpreting this result is that supply and demand should in theory be determined jointly and the significance of supply may be partly reflecting its endogeneity. The result from our counterfactual experiments – that broadening the overlap between organic coffee and brands on offer increases organic market shares - lends support to Koos' findings.

Our use of coffee purchases to investigate the relationship between stated and actual behavior is motivated in part by the importance of coffee as a commodity (by value), and in part because the coffee market is characterized by a large number of differentiated products. These factors taken together, in combination with a transparent production technology, arguably make the coffee market fertile ground for studies pertaining to the field of industrial organization.[14] We were also attracted to the fact that coffee is mainly produced in developing countries. Because environmental and labor regulations are weak in several coffee-producing countries, environmental and ethical labeling may provide particularly useful information.

2. The data and a first look at the links between stated and actual behavior

In our analysis, we use a dataset collected by GfK, a German-based market-research consultant with an affiliate in Sweden. GfK has assembled a consumer scan panel that follows

[12] Other factors, that we are unable to investigate with our data, can also affect the effectiveness of eco-labeling. Teisl and Roe (2005) for instance report results from three experiments on the informational content in eco-labels.
[13] This latter measure was calculated by combining the national share of farm land used for organic production with measures of the number of non-food environmental-labeled products available.
[14] See, for example: Nakamura and Zerom (2009) on cost pass-through and Draganska et al. (2010) on the distribution of profits in the vertical chain.

grocery-shopping choices of 3,000 families across Sweden. We use observations from January 2007 to January 2010. The data was collected with an electronic scanner and web-based diary entries. Not all participating households buy coffee. The data set that we use consists of an unbalanced panel of 2,782 households.

[Table 1 about here]

The participating households are chosen as a representative sample of the Swedish population, but were sampled using non-probabilistic methods typical for this type of market research data.[15] We observe household characteristics such as the age and level of education of the reference shopper, household annual income, and postal code of residence. The top panel in Table 1 compares the household characteristics of the sample with national averages in Sweden. There are only small differences compared to the national averages. The average reference shopper is slightly older than the average age of the population: 50.6 versus 48.9 years, respectively (the average age of those 18 years and older, since the reference persons in the panel were all 18 or older). The share of households with a university education is lower in the sample than the national average: 33 versus 36 percent, respectively. The average size of the sampled household is 2.28,compared to the national average of 1.97. We used the postal area in which the households resided to map households into four types of municipalities[16]: 1) sparsely-inhabited municipalities and other municipalities with less than 25,000 inhabitants; 2) municipalities with more than 25,000 inhabitants but not major centers; 3) major regional centers, and; 4) the largest three municipalities in Sweden and their suburbs. The mean of this measure in our data was 2.88, indicating that our sample reflects Swedish urbanization levels.

On the product side, the data was matched to European Article Numbers (EANs), providing a description of each coffee product bought by the household, including the package size, brand name, whether it was labeled organic, Fairtrade, as well as other product characteristics. We use data on purchases of all ground and bean coffee. Instant coffee was excluded. The data on households and the data on product varieties are linked via a database of market transactions. These market transactions describe the price and quantity purchased for each

[15] Lusk and Brooks (2010) provide a critical evaluation of the representativeness of such samples, finding that participants in two US household scanning surveys were slightly more price sensitive than a random sample.
[16] Swedish Association of Local Authorities and Regions, www.skl.se.

variety of coffee on a particular date at a particular store by a particular household. The combined dataset, therefore, includes household statistics, coffee-product descriptions and a record of market transactions. In the lower panel of Table 1 we report some descriptive statistics on household purchasing behavior. On average, households purchased coffee in retail stores on 7.1 occasions per year, and the average annual household expenditure on retail coffee was 325 Swedish crowns (approximately 36 Euro using July 2008 exchange rates).

The households in our dataset appear to have diligently reported their retail coffee purchases. In 2008, average coffee consumption in Sweden was 9.4 kg/capita/year.[17] Of this, roughly 60 percent was bought through retail channels for household consumption. The remaining 40 percent was consumed at work or in restaurants and cafes. Around 12 percent of the total consumption was instant coffee, which is almost exclusively sold retail. This means that, if our sample was representative and fully diligent in reporting all purchases, we would expect them to consume approximately 4.5 kg/capita/year. As seen on the bottom row of Table 1, our sample of households purchased an average of 3.9 kg/capita/year, which is close to the expected level of consumption. As with any Homescan data, some degree of under reporting is expected. Einav et al. (2010) compared the recorded purchasing behavior of US households in the Homescan data administered by AC Nielsen, with the purchasing behavior reported by stores. Overall, the authors found evidence that households are diligent and that Homescan data are a valuable source of information.[18]

GfK questionnaires are completed by households when they join the consumer panel and then again every January, and cover a range of issues related to household shopping preferences. There are 35 questions in the questionnaire, and many questions have multiple alternative responses. One subset of questions relates to household choices of different types of products. We made use of one question regarding organic labeled products. The questions was: "When I buy groceries I try, to the extent feasible, to buy organic products". The respondent can

[17] This figure includes children. Source of this and the following statistics: http://www.kaffeinformation.se/

[18] One important discrepancy that they found is that around 20 percent of purchases on a given shopping trip are not recorded. As seen, this does not appear to be a significant concern with respect to our data. Secondly, they found that consumers who use loyalty cards to receive discounts often fail to report the discounts. In Sweden, the use of such rebates and coupons to achieve discounts is less prevalent than in the US; we do not expect any such misreporting to have had an important impact on our results.

tick one of six boxes; box 1 indicates "Totally Disagree," box 5 indicates "Totally Agree," and box 6 indicates "Don't Know."[19]

To what extent do households that say that they try to buy organic products actually do so? As a first examination of this question we detail the share of expenditures on organic coffee across survey responses (see Table 2). Households that answered "Totally Agree" or "Agree" had a higher expenditure share of organic coffee products subsequent to answering the questionnaire. However, even among the set of households that answered "Totally Agree," we observe that only 22 percent of actual retail coffee purchases were organic. In other words, these households still primarily purchased conventional coffee.[20]

Table 2 about here

Households sometimes change their answers from one year to another, which explains why the number of observations in Table 2 sums to more than the number of households (2,782). As seen, the largest share of households answered "Neither Agree nor Disagree." However, there is considerable variance across survey responses, with substantial numbers of participants responding more or less affirmatively.

3. Constraints on the sales of organic coffee

Why are even those households that say they try, to the extent feasible, to buy organic products not buying more organic coffee? Let us examine a number of possible explanations which guide the subsequent analysis. A first observation is that we track coffee purchases, whereas the questionnaire asks about grocery purchases.[21] This difference between what is asked and what is tracked precludes the data in Table 2 from providing a direct test of whether people's stated and revealed behaviors coincide. On the other hand, we expect that consumers who really try hard to

[19] These surveys are conducted in Swedish. The Swedish survey question is: "När jag/vi köper daglivsvaror försöker vi i görligaste mån köpa ekologiska produkter". The responses range from "instämmer absolut inte" to "instämmer helt" and "vet ej."

[20] We also calculate shares of organic coffee during the year preceding the survey response, and observe only minor differences with respect to Table 2. We further examine the share of purchases in terms of volume and in terms of the share of shopping trips when coffee was purchased. We find that the patterns observed are not sensitive to the timing of the questionnaire or whether purchases are measured by volume or by the share of shopping trips in which organic coffee was bought.

purchase organic products would do so in the case of coffee as well.[22] Organic coffee is one of the top categories of organic products in Sweden by value, after organic dairy and organic eggs.[23] Thus, we do not see the difference between what was asked and what was tracked as a satisfactory explanation for why the self-professed organic shoppers did not have a higher share of organic coffee purchases.

A second potential explanation for the relatively low share of organic coffee purchases is that buying such products can be seen as a pro-social behavior. Respondents may wish to give the appearance of conforming to such norms and *hypothetical bias* (as defined by Harrison and Rutström (2005)) could be driving results.[24] We cannot rule out hypothetical bias as a contributing factor. However, we are able to examine the extent to which stated preferences provide valuable information as opposed to being uninformative talk. If stated preferences were uninformative, self-reported purchasing habits would have no additional explanatory power once we control for prices, income and other household characteristics.

The data also allows us to investigate other potential constraints to higher sales of organic coffee. Our investigation relies on demand estimated at the household level, and then uses these demand estimates to study consumer response to counterfactual settings. Consider then a third potential explanation where household choices of organic products are constrained by lack of access; a household that responds "Totally Agree" or "Agree" might not buy any organic coffee because such products are simply not available in nearby stores. The potential for bias exerted by a lack of product availability has recently been explored in the literature on estimating demand systems using market-level data (see Bruno and Vilcassim (2008)). In a counterfactual simulation we introduced an organic coffee variety, making it available in all household choice sets. We then studied the impact this had on organic market shares. If limited access *per se* kept

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[21] Or, more precisely, about goods purchased in grocery stores: "daglivsvaror" is the Swedish term used.

[22] An example of another product may clarify our point. Say that we instead used data on a really marginal product in terms of environmental labeling, such as carbonated soft drinks. In such as a case introspection suggests a quite weak link between stated purchasing habits in grocery stores in general and the propensity to purchase organic carbonated soft drinks.

[23] Source: www.krav.se, "Marknadsstatistik 2010." In total, 3.4 percent of grocery expenditures in 2008 were made on organic products. Around 7 percent of milk purchases were made on organic products (total value around 500 million Swedish crowns). The total value of sales of organic eggs was around 300 million Swedish crowns, of fermented milk 280 million and coffee 200 million. The next category was juice, with a total of some 100 million Swedish crowns.

[24] Note however that we are not able to distinguish between an agent having an accurate view of her/his behavior but not reporting it accurately, and an agent having a distorted perception of what s/he does but reporting this distorted view truthfully.

organic shares low, then introducing an additional organic brand should lead to a marked increase in the share of organic coffee purchased by the keener households.

A fourth possibility is the limited overlap of organic products with other coffee characteristics valued by consumers. Consider a household that values organic coffee, but also has a strong preference for a particular brand, a particular roast or East African beans. The household may sincerely try to buy organic coffee but be unable to find an organic product that overlaps with the other product characteristics that they also highly value. To investigate the quantitative effect of this mechanism we introduce a highly valued organic product, letting its price reflect the organic premium, and let it be available in all choice sets.

A fifth potential explanation focuses on price effects. A household might sincerely try to buy organic coffee but find it too expensive relative to the next-best alternative. As seen in Figure 1 below, the price of organic coffee has fluctuated relative to regular coffee. Clearly, large increases in the relative prices of organic coffee could lead consumers to purchase regular coffee even if they would not have done so at the prices that prevailed when they responded to the questionnaire. In a counterfactual scenario we halve the organic price premium and consider the effects on market shares of organic coffee.

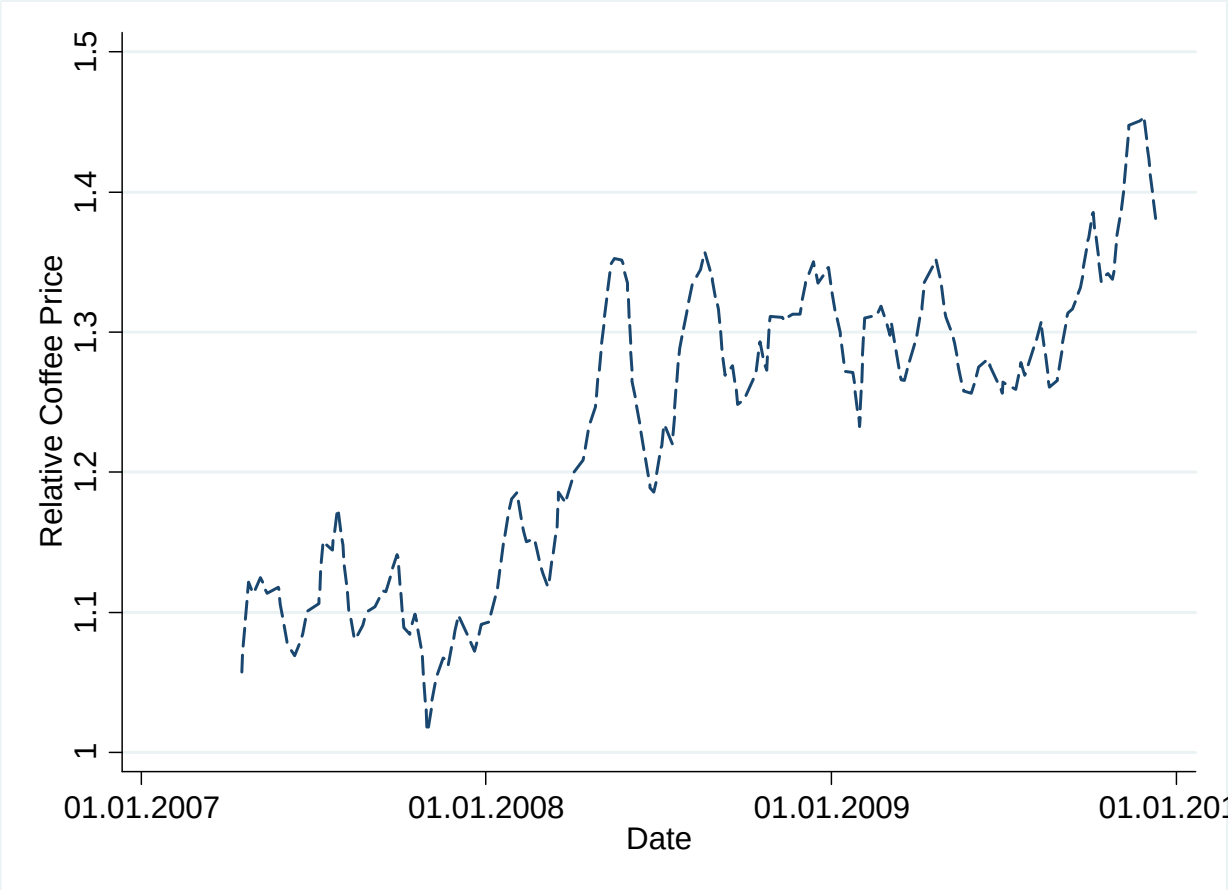

Figure 1 - Price of organic coffee relative to conventional coffee

The extent to which these mechanisms constrain sales of organic coffee is an empirical issue that is discussed in the next sections. But first we describe the determination the dependent variable for the regressions - the choice sets; the choice of coffee varieties facing each household on their shopping trips.

4. Identifying household choice sets

Homescan data provides observations of actual choices, but does not provide observations of choices that are not made. Therefore, we cannot directly observe the choice set facing a household on any given shopping trip. We have derived the choice sets from observations of coffee varieties that were purchased by other households from the same chain and store format (44 combinations in all) for a given type of municipality (4 types) within a three month window.

A manual comparison with the assortment in some selected stores pointed to our generated choice sets as giving a generally accurate representation of the assortment.

A total of 43,252 shopping trips were observed in our data. However, the construction of choice sets expanded the size of the dataset to a total of 1,260,081 observations. Table 3 provides descriptive statistics on the coffees in the expanded sample. Since we only observed the actual price when there was a purchase, we used a hedonic regression to generate prices for all of the products in the choice set. The regression was run on the 43,252 observations on price. We regressed price on bar-code-level fixed effect by product (238 in all), store effects (by chain and store format: 44 in all), monthly fixed effects (1 for each of the 36 months in the data) and municipal-type fixed effects (4 in all). The adjusted R^2 of this regression is 0.58 and the F-statistic for the joint significance of all variables is 184.28.

Table 3 about here

The mean hedonic price is around 52 Swedish crowns per kg, with considerable dispersion between the highest and lowest prices. We also present descriptive statistics for the sample on a number of dummy variables that capture characteristics of the product and the choice set. Around seven percent of the available choices were organic.

As noted, a potential reason for the low share of organic coffee purchases could be the lack of availability of products carrying these labels. If no organic coffees were available in a respondent's store, then there is not much of a puzzle as to why they were not chosen. There are indeed some choice sets in our data that do not include any organic coffee, but the majority do. For example, at the 10^{th} percentile of observations in the sample there was one organic coffee in the choice set. At the median, a household faced 2.5 organic coffee varieties in their choice set. This suggests that, while organic coffee is widely available in Sweden, only a narrow range of these coffees make their way into household choice sets. We return to this issue in the regression work that follows.

5. Empirical specification

We use a discrete-choice model of demand and assume a conditional logit specification (McFadden (1974), Cameron and Trivedi (2009)). Consider household *i* facing the choice of a product *j* among a set of *J* available products on shopping trip *s*. The household derives utility U_{ijs} from its choice *j* and chooses the alternative that provides the greatest utility. The behavioral model is therefore: household *i* chooses alternative *j* if $U_{ijs} > U_{iks} \ \forall \ j \neq k$. We express utility as:

$$U_{ijs} = X_j\beta + HH_{ijs}\gamma + p_{js}\alpha + \varepsilon_{ijs} \quad (1)$$

where X_j is a vector of product attributes and β is a vector of coefficients. HH_{ijs} is a vector of product characteristics that interact with household characteristics and γ is the vector of associated coefficients. p_{js} is the log of the price of coffee *j* on shopping trip *s,* and α is the sensitivity to price. In the main specification we assume that ε_{ijs} is a logit error term: an individual and product specific error term that follows a type II extreme value distribution. We thus estimate the parameters in equation (1) with a conditional logit specification.

$$Prob(choice_{ijs} = 1|X_j, HH_{ijs,}\alpha) = \frac{exp(X_j\beta + HH_{ijs}\gamma + p_{js}\alpha)}{\sum_{k=1}^{J_s} exp(X_k\beta + HH_{ijs}\gamma + p_{js}\alpha)}. \quad (2)$$

In the estimation we group the data by household and use heteroskedasticity-consistent standard errors that are clustered at the level of the household. As a first pass at describing the data we also use a linear probability model which makes for easy interpretation of interaction effects.

Let us now describe the variables in turn. The dependent variable is "choice" which is equal to one if the household chooses variety *j* and equal to zero if the variety is not chosen. To capture the characteristics of the product we use two different specifications. The first specification aims at understanding the effect of an organic label on demand. In the first specification the variables included in X_j are fixed effects defined at the brand level (36 brands), a measure of roast (dark roast and other roast, medium roast is the omitted category), and dummy variables for different national origins of single origin coffee (Columbia, other Latin America, Ethiopia/Kenya and Indonesia). Finally we include dummy variables to capture if good *j* carries an organic or Fairtrade label. While this specification allows us a clear view of the effect of an organic dummy on demand, the predictive ability of what product that consumers choose is

limited with this specification. For the counterfactuals we instead rely on a specification that includes product fixed effects that are defined at the EAN-level (238 products). We also expect consumers to have preferences for certain brands and therefore include a dummy to capture if a particular brand (36 brands) was purchased on the last shopping trip. Thus, while this latter specification provides a good predictive fit, some of the valuation of organic characteristics will be absorbed by product level fixed effects and purchase history.

HH_{ijs} is a vector of household characteristics, interacted with dummy variables that capture organic and Fairtrade labels. "Old" households indicate a primary shopper over the age of 55 years. Likewise "University" for those with a University degree and "high income" for households with a combined annual pre-tax income of at least 500,000 Swedish crowns (SEK) (approximately 53,300 euro in July 2008). These household characteristics are interacted with dummy variables that capture the set of possible household responses to the survey questions. The omitted category is households that answered "neither agree nor disagree".

Our attention focuses particularly on the interaction between the organic label and household survey responses. For example, we are interested in estimating the impact of a household answering "Totally Agree" in the survey on the probability of choosing an organic coffee.[25] By including survey responses one might fear that we are in essence regressing outcome on outcome. Note however that the question asks about whether the households tries to buy organic when shopping for grocery, as opposed to asking if organic coffee was bought on the shopping trip in question. Our preferred interpretation is therefore that this variable should be seen as capturing preferences.

Finally, the natural log of the price for each product, p_{js}, is also included (we use predicted values from the hedonic regression as explained in Section 3). We make two restrictions on the data: Firstly, for clarity of comparison we drop the observations where households had not responded to the question on organic purchasing habits, or answered "don't know", which leads us to drop 65 households, decreasing the number of households from 2785 to 2717. Secondly we exclude shopping trips where we estimate that consumers are faced with three coffee products or less. This mainly excludes a handful of shopping trips to pharmacies.

[25] Recall the survey question is: "When I buy groceries I try, to the extent feasible, to buy organic."

6. Estimation results

In Table 4 we report the coefficients of interest from the estimation of equation (2) in columns (3)-(5). For ease of interpretation we first report the results using a linear probability model in columns (1) and (2).

[Table 4 about here]

We see in column (1) that the estimates for the interaction between survey response and organic provide statistically-significant coefficients and indicate that respondents indeed value organic products when they say they do, and don't value them when they say they don't. The omitted category is households that answered "Neither Agree nor Disagree" to the question on their purchasing habits. The interactions between stated behavior and organic labeling are quantitatively important. For example, answering "Totally Agree" raises the probability that the household purchases an organic coffee by 9.9 percent relative to the indifferent household. The estimates dovetail with the finding presented in Table 2 and provide support for the hypothesis that survey responses do provide useful information on attitudes.

The interactions between observable household characteristics and the choice of organic coffee are small in magnitude and not significant. Income does not significantly explain the choice of organic or Fairtrade coffee. This is in contrast to Kiesel and Villas-Boas (2007), who find that income is a significant predictor of organic milk purchases in the USA, and Griffith and Nesheim (2010), who find a similar result in the UK. The Swedish income distribution is compressed relative to these countries, which may explain part of the reason for the difference. The point estimates indicate that older households are less likely to purchase organic or Fairtrade products, but the effects are small and only in the case of Fairtrade is the coefficient significant. University education raises the probability of purchasing a Fairtrade product but the effect on the choice of organic is low and not significant. In column (2) we report a regression where the stated behavior variables are excluded. As seen, most coefficients are stable across these two specifications but in column (2) the interaction between organic and university implies an increase in the probability of choosing an organic product of about 1 percent, which is significant at the 5 percent level. This points to that the lack of significance for university education on organic choice is in column (1) is partly due to a positive correlation between university

education and the degree to which households say they try to buy organic.[26] The price coefficient is negative and significant in both specifications, as expected.

Column (3) reports the results from an estimation of the specification in column (1) but instead using conditional logit. Signs and significance of variables are similar as in (1) but note that given the nonlinear nature of probabilities the magnitude of coefficients cannot be interpreted without being specific at what point we interpret them. As stressed by Ai and Norton (2003) particular caution is warranted for models with interaction effects and estimates of marginal effects from statistical programs can be misleading. In the next subsection we therefore discuss the interaction between the organic dummy and the stated behavior variables.

Before doing so note that the regressions in columns (1)-(3) are well suited for understanding the qualitative impact of stated behavior on choice probabilities and the pattern that we document is robust to other estimation routines such as probit and mixed logit with a random coefficient on price. However the ability to predict which coffee variety a household will choose is limited, as evidenced by the low (pseudo) R-square in specifications (1)-(3).[27] The counterfactual experiments that we wish to explore require that we are able to predict product choice well. To improve predictive ability we include fixed effects at the product level in columns (4) and (5). This captures product characteristics more fully than we are able to do with the brand level dummies and other observable characteristics.[28] We also know that many households exhibit brand loyalty – and we therefore include a dummy for the products of a particular brand that was purchased on the previous shopping trip. With the full set of behavioral interaction effects, such a specification somewhat over predicts the propensity of the households that answer "totally agree" to purchase organic and somewhat under predicts the propensity of the households that answer "agree" to purchase organic. Extensive specification searches have not come up with an ideal way to treat this and, noting that the effects partly cancel, we pool

[26] Using Kendall's tau, the association is 0.04; statistically significant at the 1 percent level.

[27] Three concerns are often raised in connection with the use of linear probability models: 1) that predictions may be outside the [0,1] interval; 2) that constant marginal effects are assumed, and; 3) that the error term is heteroskedastic. The first issue is a minor concern in our data: only 0.3% of the predicted probability choices in the benchmark regression are outside the unit interval. Constant marginal effects are also a minor concern if we only use dummy variables on the right-hand side of the equation. If, for instance, income were a continuous measure, we could easily predict implausible patterns for very high and very low incomes. Our use of heteroskedasticity consistent standard errors correct for the last concern. In the past, linear probability models have sometimes been discarded because of a perception that they cannot be derived from a random-utility model. However Heckman and Snyder (1997) show that this can indeed be done.

[28] Our motivation is thus similar as in the literature that uses market level data to estimate demand and where product fixed effects are often seen as the preferred way to include product characteristics, see for instance Nevo (2000).

households into three groups – the disagreers (households who answer "totally disagree" or "disagree"), neutrals (answering "neither agree nor disagree") and agreers (answering "agree" or "totally agree"). As seen in columns (4) and (5) the explanatory power of these regressions is considerably higher and we use them for our counterfactual analysis. Before turning to that let us first examine the marginal effects of a product acquiring an organic label. Note that to be able to do this we want a separate estimate of how an organic label affects the probability of purchase rather than have the valuation of organic products absorbed in the product fixed effects. We therefore examine the marginal effects of the specification in column (3).

Marginal effects of organic on coffee choice probabilities

The main coefficients of interest from the regressions are the interactions between the survey responses and the dummy variables for organically-labeled coffee and the associated marginal effects. To illustrate the marginal effect we choose a particular variety and study the impact of changing the organic dummy from 0 to 1. The particular variety chosen for this exercise is a "Zoega Skånerost," 500 gram package; a popular coffee that does not offer organic varieties. A graphical presentation of the effect of said marginal change on choice probabilities is a useful way to illustrate the marginal effect. In Figure 2 we have graphed the change in choice probabilities resulting from the introduction of this counterfactual organic variety against the factual predicted choice probabilities, across the different survey responses.

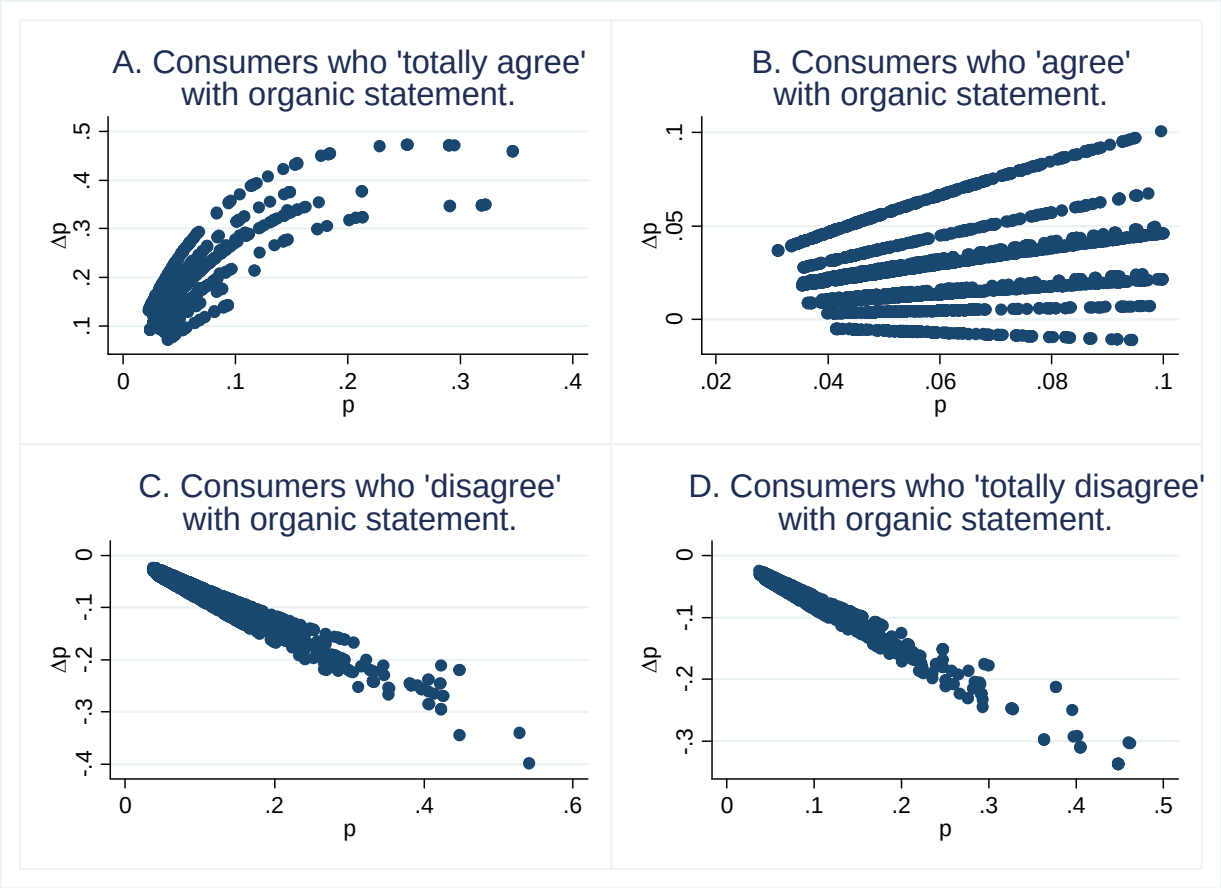

Figure 2 - The marginal effect on choice probabilities for changing "Zoega Skånerost" to a counterfactual organic "Zoega Skånerost" by survey response. The horizontal axes denote the estimated factual choice probabilities "p." The vertical axes denote the change in the choice probability "Δp" under the counterfactual.

Each point in the figure represents an instance in our dataset where "Zoegas Skånerost" appeared in a household choice set. The horizontal axis of each graph denotes the estimated choice probabilities, "p," in the factual data. The vertical axis denotes the change in that probability, "Δp," for the counterfactual organic "Zoega Skånerost." "Totally Agree" and "Agree" households would be more likely to choose "Zoega Skånerost" if it carried an organic label. Likewise, "Totally Disagree" and "Disagree" households would be less likely to choose Zoega if it were organic. The marginal effect of the organic characteristic is, as derived from our regression in Table 4 column (3), with few exceptions positive for households that are keen organic households and negative for households that are not keen organic households. We note that effects are quite strong; the choice probability for positive households frequently doubles when we confront consumers with this counterfactual organic variety. The fan-shaped pattern seen most clearly in Panel B reflects the interaction of the organic dummy with the dummies for

education, age and high income. These differences across household characteristics generate discrete jumps in the choice probability. The qualitative pattern that we see is similar when we repeat this exercise for other coffee varieties.

7. Using the estimates to consider counterfactual choice

Why do self-professed organically-minded households not have a higher share of coffee purchases that carry an organic label? We use our estimated demand model to study counterfactual settings to explore the contribution of the different behavioral responses identified in Section 3. The results from the simulations are presented in Table 5.

[Table 5 about here]

The actual share of organic coffee in our data for the different responses to the stated behavior question is presented in column (1).[29] Taking observed values and combining with our estimates yields a predicted choice probability for each product on each shopping trip. In a discrete choice setting the product with the highest predicted probability will be chosen. Summing over all the choices we present the predicted share of these choices that are organic in column (2). As seen the model predictions are rather close to the actual data but for the counterfactuals column (2) should be seen as the baseline comparison.

In terms of pseudo-R2 or the value of the log-likelihood function there were small differences between the specification where stated preferences were included (Table 4, column (5)) and the one where they were not (Table 4, column (4)). Even so, including stated preferences helps us predict shopping behavior of organically minded households as seen by comparing the predicted values from the specification without stated behavior (column (3)) with actual data and the predictions in column (2). It is also worthwhile noting that the results in column (3) indicate that, also when excluding stated preferences, the observable household characteristics such as university education, age, income are useful in predicting choice of organic coffee. Relating back to our guiding research question, this also indicates that household statements are not just uninformative talk; stated behavior is useful in predicting actual behavior.

[29] These numbers differ from those reported in Table 2. The difference is due to the fact that households that did not respond are omitted from the demand estimates and Table 2 reports means across households, whereas Table 5 reports the aggregate share.

Counterfactual choice settings

We now turn to the analysis of three counterfactual choice settings. In a first counterfactual setting we examined the effect of ensuring access to at least one organic choice on every shopping trip through the sample. Households may not buy organic products because these products are simply not available in nearby stores. Adding one more organic coffee variety to all shopping choice sets would relax this constraint. In order to avoid the confounding effects with other coffee qualities we introduce a "synthetic" average organic coffee variety. We let the fixed effect that captures product attractiveness be equal to the median fixed effect across products (as estimated in Table 4, column (5)). The median fixed effect is associated with a medium roast coffee, sold in a 500 gram package with no specified region of origin sold under the brand name "Gevalia". We generate a price for this synthetic variety is generated using predicted values from the same hedonic regression that we used to generate counterfactual prices in the construction of the choice sets but the organic dummy set to one. We introduce this synthetic variety to *all* choice sets, changing predicted choice probabilities as per equation (2). These new choice probabilities provide the basis for the counterfactual market shares for organic coffee presented in column (4) of Table 5.

If lack of access to organic varieties at nearby stores is an important restriction this counterfactual would generate higher shares of organic for the agreeing households. Indeed, the share of organic products goes up to 19 percent under this counterfactual scenario. This suggests that limited access to organic coffee per se is part of the explanation why not more organic coffee is purchased.

In a second counterfactual setting we examine the effect of relaxing the limited overlap of organic with other coffee characteristics valued by households. To illustrate the quantitative impact of this mechanism we again introduce a synthetic product that is available in all stores, but now let it have a product fixed effect that comes higher in the distribution of fixed effects, from the 75^{th} percentile. This corresponds to a medium roast coffee, sold in a 500 gram package with no specified region of origin sold under the brand name "Löfbergs Lila". The counterfactual setting pursued here assigns an organic label to this coffee and as before uses a hedonic regression to generate the counterfactual price with the organic dummy set to one. Introducing this new variety changes the choice probabilities across households and these new choice probabilities form the basis for the counterfactual market shares for organic presented in

column (5) of Table 6. The introduction of a more attractive organic product has a large effect on the choice probabilities for the self-professed organic-purchasing households and the share of organic coffee approaches 50 percent. While this may seem like an implausibly large effect, let us note that at the median there were only 2.5 organic coffees in the choice set. Adding an attractive organic product thus is an important increase of choice in this dimension and for a consumer that values organic products the interaction between a high product valuation and a valuation of organic makes for this product being ranked number one on many shopping trips. More broadly, this suggests that the limited overlap of the organic label with other valuable coffee characteristics is an important contributing factor to the limited organic expenditures among households that say they try to buy organic. The quantitative impact of this mechanism is clearly dependent on precisely how one specifies the counterfactual.

In a final counterfactual setting we examine the *price effect*; a high price may deter households from purchasing organic coffee. The organic premium from our hedonic regression is 14 percent. In the counterfactual reported in column (6) of Table 5 we discount this premium to seven percent for all coffee carrying the organic label. We see small effects for the households and the households who disagree with the organic statements. This is not surprising – even if the premium is lowered these products are still more expensive than a comparable non-organic product and only in few instances does the lower price push an organic position into the top position for such a household on a shopping trip. In contrast, the lower price has a substantial impact on shopping behavior by households that agree. The market share of organic for the latter group doubles from 11 percent to 22 percent. For these households, with a positive valuation of organic, the lower price is effective in placing an organic product with the highest purchase probability on a given shopping trip. We should note that the price sensitivity of demand was not very precisely estimated in Table 4, column (5). We therefore do not want to overemphasize the quantitative result but rather note that the estimated model points to a potentially important role for the price premium in explaining the low share of organic coffee purchases.

8. Concluding remarks

Our paper presents research that examines why households are not buying more organic labeled coffee despite many surveys that express a wish to do so. We find that even households that say

they try hard to purchase organic coffee products in fact buy mostly conventional coffee. We have identified several behavioral responses that are consistent with the survey question *responses* and the shopping choices *made,* and apply a discrete-choice conditional logit model of demand to study these behavioral responses. We have established that survey responses have important predictive power for the retail coffee purchases made by these households. There is also evidence that the limited overlap between organic and other coffee characteristics is the most important factor limiting organic purchases amongst organic households. Lesser, but still non-trivial roles can be given high organic price premia and limited access to organic products per se. These results are particularly pertinent given recent announcements by the major coffee brands to significantly expand their offering of EE-labeled products. For example, Nestle has announced plans to source all of its Nescafe products from EE-producers within the next 5 years. Likewise Kraft has made a commitment that 100 percent of its European coffee brands will source EE-coffee by 2015.[30]

Let us end with a few observations on external validity. Levitt and List (2007) identify the following factors as important for the external validity of (experimental) results: 1) the potential influence of moral and ethical considerations; 2) the way and extent to which one's actions are scrutinized by others; 3) the context in which the decision is embedded; 4) self-selection of the study subjects into the experiments, and; 5) the stakes of the game. The first factor raised by Levitt and List (2007) – the potential influence of moral and ethical considerations on answers – is a key motivation for our study. It is often suggested that to purchase organic products is a form of pro-social behavior. Thus, there may be an expectation that respondents attempt to conform to such norms.

The other concerns raised by Levitt and List (2007) are unusually minor in our data. The level of scrutiny perceived by subjects participating in the GfK panel are likely to be minimal; we focus on one out of 35 questions answered once a year, but track purchases over the full year. On sample selection, we concede that any group of households that agrees to have their purchases tracked is unlikely to be representative of a true random selection of Swedish households. However, GfK's purpose for tracking these households is not specifically linked to organic consumption. Thus, while sample selection may be an issue, we have no strong prior

[30] Nestlé, 2011. *Nestlé invests CHF 500 million in coffee projects, doubling direct purchases*. Press release, 27 August 2011. See also Kraft, 2011. *Kraft Foods Expands Sustainability Goals to Build on Success*. Press release, 12 May 2011.

belief for what effect, if any, it would have on our results. It is also noteworthy that on observable characteristics, the sample is representative. Finally, the stakes of the game are economically significant and concern consumer choice across a regular assortment and prices of coffee during a year.

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Table 1. Household summary statistics

Variable	Mean	Std. Dev.	National mean
Household characteristics			
Average annual income (thousand Swedish crowns)	371.97	182.23	350.3
Age in years (above 18)	50.60	14.19	48.9
Have university education	0.33	0.47	0.36
Household size	2.28	1.19	1.97
Urbanization (4 most urban)	2.88	0.94	
Purchasing behavior			
Shopping trips per household per year	7.06	6.78	
Purchases per household per year (Swedish crowns)	325.29	329.76	
Purchases per household per year (grams)	7104.40	7206.81	
Purchases per capita per year (grams)	3929.02	4366.96	4500♠

Non-missing observations for income (2678) and for household size (2781). All other variables 2782 observations. Figures on national means from Statistics Sweden, data for 2008. ♠From http://www.kaffeinformation.se/

Table 2. Share of expenditures on organic coffee, by answers to question on purchasing habits.

Q: "When I buy groceries I try, to the extent feasible, to buy organic"	Percent share of organic purchases♦	Standard Deviation	t-stat ♠	Number of survey responses
Don't know/no answer/not available	7.41	21.29		113
Totally disagree	1.14	8.27		436
Disagree	1.82	9.31	1.42	1181
Neither agree nor disagree	3.81**	14.00	4.05	1248
Agree	7.99**	21.94	4.48	678
Totally Agree	21.73**	33.7	5.18	179
Total	4.57	16.51		3835

Notes:

♦ Mean over households giving the respective response

♠ The t-tests are tests of the hypothesis that the mean response for a group is equal to the mean for the response above under the assumption of unequal variances. For example, 5.18 indicates that the t-statistic for the hypothesis that the mean share of Organic purchases for households that respond "Totally Agree" is the same as for households that respond "Agree." This difference is significant from zero at the 1% level, which we denote with **.

Table 3. Summary statistics for the sample

Variable	Mean	SD	Min	Max
Price (Swedish crowns/Kg)	51.66	15.93	15.7	266.0
Organic	0.0702	.2555	0	1
Fairtrade	0.0330	.1786	0	1
Number of products in choice set	35.17	11.48	1	60
Number of organic coffees in choice set	2.50	1.522	0	7
Number of Fairtrade coffees in choice set	1.25	1.269	0	6

Number of observations in sample: 1,260,081.

Table 4. Brand-level demand for coffee, 2,717 Swedish households, 2007-2009

Dependent Variable: Choice	(1)	(2)	(3)	(4)	(5)
Estimation	Linear probability	Linear probability	Conditional logit	Conditional logit	Conditional logit
Coefficient					
Ln(Price)	-0.019	-0.018	-1.854	-2.820	-2.509
	(0.002)**	(0.002)**	(0.239)**	(1.830)	(1.809)
Organic x "totally disagree"	-0.011		-1.033		
	(0.004)*		(0.542)		-0.725♣
Organic x "disagree"	-0.010		-0.908		(0.200)**
	(0.003)**		(0.221)**		
Organic x "agree"	0.023		0.914		
	(0.005)**		(0.177)**		1.238♥
Organic x "totally agree"	0.099		2.149		(0.154)**
	(0.018)**		(0.271)**		
Organic x high income	-0.004	-0.006	-0.232	-0.015	-0.063
	(0.004)	(0.004)	(0.231)	(0.197)	(0.197)
Organic x university	0.007	0.012	0.385	0.700	0.604
	(0.005)	(0.005)*	(0.212)	(0.188)**	(0.181)**
Organic x old	-0.003	-0.003	-0.214	-0.066	-0.098
	(0.004)	(0.004)	(0.197)	(0.173)	(0.165)
Fair trade x high income	0.001	0.001	0.091	0.000	-0.008
	(0.005)	(0.005)	(0.393)	(0.239)	(0.240)
Fair trade x university	0.015	0.015	1.136	0.908	0.916
	(0.006)**	(0.006)**	(0.286)**	(0.204)**	(0.203)**
Fair trade x old	-0.007	-0.007	-0.756	-0.578	-0.547
	(0.003)*	(0.003)*	(0.253)**	(0.201)**	(0.198)**
Organic	-0.021	-0.018	-0.522		
	(0.004)**	(0.004)**	(0.212)*		
Fairtrade	-0.004	-0.004	-0.204		
	(0.003)	(0.003)	(0.210)		
Observations	1225715	1225715	1225715	1225715	1225715
R- squared	0.01	0.01			
Log-likelihood			-128504	-48450	-48244
Pseudo R2			0.05	0.64	0.64

Columns (1) - (3) include product dummy variables for product brand (44), region of origin for single-origin coffees (4) and roast (3). Products (4)-(5) include product fixed effects (238). Number of households: 2,717. In column (5), ♣ indicates that this coefficient captures both households that answer "totally disagree" and "disagree" and ♥ captures both households that answer "agree" amd "totally agree". Heteroskedasticity consistent standard errors clustered by household. ** Denotes significance at 1%, * at 5%.

Table 5 – Counterfactual shares (in percent) of organic coffee purchases by survey response.

Q: "When I buy groceries I try to the extent feasible to buy organic"

Survey response	Factual purchases observed in data	Factual logit predictions using benchmark regression♣	Factual logit predictions without stated behavior♦	*Counterfactuals*♥		
				One more organic coffee of average quality available on all shopping trips ♠	One more organic coffee of high quality available on all shopping trips *	Halved organic price premium
	(1)	(2)	(3)	(4)	(5)	(6)
Totally disagree and disagree	1.43	0.82	0.84	0.86	0.94	0.87
Neutral	3.55	2.27	2.29	2.45	2.75	2.33
Agree and totally agree	12.12	11.15	7.15	19.22	49.02	22.10
Total	4.42	3.50	2.68	5.26	11.63	5.83

♣ Based on estimates reported in Table 4, column (5).
♦ Based on estimates reported in Table 4, column (4).
♠ Predicted market share with organic supply increased by introducing one additional synthetic organic-coffee variety with average quality characteristics (product fixed effect set equal to mean of all brands and hedonic price) to all household choice sets.
* Predicted market share with organic supply increased by introducing one additional synthetic organic-coffee variety with high quality characteristics (product fixed effect set equal to 75th percentile of all brands and hedonic price) to all household choice sets.
♥The counterfactuals below are based on estimates from Table 4, column (5).