Does Shelf-Labeling of Organic Foods Increase Sales? Results from a Natural Experiment*

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Abstract

Can a simple point-of-purchase (POP) shelf-label increase sales of organic foods? We use a random-effects, random-coefficients model, including a time adjustment variable, to test data from a natural experiment in a hypermarket in Gävle, Sweden. Our model incorporates both product specific heterogeneity in the effects of labeling and consumer adjustment to the labels over time. The introduction of POP displays was found to lead to an increase in sales of organic coffee and olive oil, but a reduction in sales of organic flour. All targeted products became less price-sensitive. The results reveal that product specific heterogeneity has to be accounted for, and in some cases consumers adjusted to labeling over time.

Key Words: Product labeling; random coefficient models; ecological products, experimental economics.

JEL classification: M31; M37; L66; L81.

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1 Introduction

The global organic food market has increased dramatically in recent years. Total organic food sales amounted to $23 billion in 2002, and rose with 21% annual growth to $52 billion in 2008 (Datamonitor, 2009). Whole Foods, a chain that only carries organic food, has been highly successful. The decision of the world's largest retailer, Wal-Mart, to introduce organic food in their super-centers has further increased organic food supply.

Many studies have investigated what determines consumers' attitudes towards and preferences for organic food. Perceived health benefits and considerations about taste and food quality seem to be the main drivers of organic food demand (Magnusson et al., 2001; Chinnici et al., 2002; Wier and Calverly, 2002; Vermeir and Verbeke, 2006, Monier et al., 2009). Private benefits thus seem more important in explaining consumption of organic foods than public benefits such as improved biodiversity and reduction of pollution (Caswell and Mojduska, 1996; Conner, 2004; Molyneaux, 2007).[1] However, there are substantial barriers to growth of sales of organic foods (Jolly, 1991; Treager et al., 1994; Hack, 1995; Chinnici et al., 2002; Vermeir and Verbeke, 2006), including, for example, a large price-difference between organic and non-organic food, inadequate supply of organic products, and multiple overlapping organic standards and certificates.

Using data from a natural experiment in a Swedish hypermarket, we tested whether a simple low-cost point-of-purchase (POP) shelf-labeling could increase sales of organic foods. Three product categories were studied: coffee, olive oil, and flour. Introduction of POP displays might be effective since, according to the Point of Purchase Advertising Institute (POPAI, 1997), 74% of all purchase decisions are made in the store. Previous studies have shown that, in most

[1] However, Hack (1995) and Bellows et al. (2008) argue that environmental concerns are a main incentive for purchases of organic food.

cases, POP displays increase sales (Grover and Srinivasan 1992; McKinnon et al., 1981), but the results seem to differ across product categories (Curhan 1974; Wilkinson et al., 1982a; Wilkinson et al., 1982b). In some cases, POP displays have even reduced sales of the targeted brands (Kumar and Leone, 1988; Areni et al., 1999).

However, few studies have explicitly addressed the effects of POP displays on the demand for organic food. An exception is Reicks et al. (1999), who found that they increased sales of organic food in a discount/warehouse store in the Twin Cities metropolitan area of Minnesota, but produced mixed results in a more up-scale shopping environment. However, they used both printed signs and take-home brochures in their experiment, making it impossible to distinguish between the effects of these interventions.

None of the studies mentioned above took into account that the introduction of POP displays could differently affect individual products within a specific category. For example, the impact of the shelf-label could differ depending on where on the shelf the targeted products were placed. We incorporated this possibility into the statistical analysis by using a random-effects, random-coefficient model.

Previous studies have also (implicitly) assumed that consumers adjust instantaneously to the introduction of POP displays. We relaxed that assumption by introducing an adjustment term into the empirical model, which shows whether consumer demand adjusted instantaneously or over time. If there was an adjustment period, our model measures the speed and duration of adjustment. Contrary to previous studies, we also studied how the introduction of POP-labels affected the own-price elasticities of demand for the targeted products.

The "experiment" analyzed here was not designed by the researchers, but

rather introduced exogenously by the store owners. Shelf-labeling for organic foods was introduced simultaneously for all product categories in the store; consumers had no prior information about the experiment.

We find heterogeneity in how POP displays affected demand, not only across product categories, as also shown by Curhan (1974), Wilkinson et al. (1982a) and Wilkinson et al. (1982b), but also across individual products within categories. The introduction of POP displays increased sales for organic coffee and olive oil, but reduced sales for organic flour. But there were also differences within these categories. For example, the estimated size of the variance parameter shows that some targeted olive oils (which, on average, increased sales) instead lost sales due to the introduction of the shelf-label. Thus there was considerable heterogeneity among individual products within each category.

For two categories, flour and coffee, consumers did not change behavior instantaneously, but rather there was an adjustment process. In these cases, if we had assumed that the process was instantaneous, our estimates would have underestimated the effect of the shelf-labels.

The introduction of POP displays also reduced the own-price elasticity of demand for the targeted products, meaning that a profit-maximizing store owner should have increased their price when introducing the shelf-labels.

The experiment and some descriptive statistics are presented in the next section. Section 3 then describes the empirical method, and Section 4 presents the results. The last section summarizes and draws conclusions.

2 The Experiment and the Data

The effect of POP displays on the demand for organic food was examined using daily sales-data from a ICA hypermarket located in the typical medium-sized Swedish municipality of Gävle (93,000 habitants), 180 kilometers north of Stock-

holm. ICA is the biggest chain-store operator in the Swedish retail-food market. Shelf-labels were introduced for all organic commodities in the hypermarket on March 10, 2008. The label was a green circle with white letters, pointing out from the shelves, making the organic choices in each product category more visible for consumers. The effect of this new POP display was tracked for 521 days, from April 18, 2007 through September 22, 2008.

Data were collected from three product categories: olive oil, flour, and coffee. These categories were selected because the individual products in each were relatively homogenous during the period under study, reducing the risk that the results would be affected by some other exogenous factor correlated with the introduction of the shelf-labels. The data include information on the unique EAN-code for product i, the quantity of product i sold ($SALES$), and the price ($PRICE$) of product i, as well as the year, month, and weekday when the data were collected.

We adopted an intervention-control approach to estimating the impact on sales of the new shelf-displays on organic foods. The intervention group consisted of all organic foods for which shelf-labels were introduced, after the introduction. The control group consisted of those same organic foods before the shelf-labels were introduced, as well as other non-organic foods both before and after the introduction.

Means and standard deviations of both quantities sold and their prices (in nominal Swedish crowns, SEK) of organic foods sold before and after shelf-labels were introduced are presented in Table 1. Prices are reported per sold unit, not converted to price per kilogram. When the POP-displays were introduced, sales increased only for one product category, olive oil (22%). Sales of organic flour fell by 33%, while sales of organic coffee fell by 38%. However, due to an increase in world-market prices, prices had increased a lot for both organic flour

(47%) and coffee (18%), making it impossible, simply from these descriptive statistics, to distinguish the effects of these price increases from the effects of the introduction of POP-displays.

Table 1 About Here

Table 2 shows similar descriptive statistics for non-organic olive oil, flour, and coffee before and after shelf-labels were introduced on organic foods. Again, sales increased for olive oil (13%); while sales of non-organic flour fell 6% and coffee fell 17%. Both the increasing sales of non-organic olive oil and the reduction in sales of non-organic flour and coffee were smaller than the corresponding changes for organic products. However, as for organic products of flour and coffee, prices rose after shelf-labels were introduced, though less than for organic products. Thus, again, analysis based simply on the means of sales before and after the introduction of shelf-labels might produce misleading results.

Table 2 About Here

3 The Empirical Model

We would like our model to account for heterogeneity in the effects of shelf-labels on sales of individual organic foods within each product category, as well as the effects of the price changes discussed above. Thus the following equation was estimated:

$$\begin{aligned} \ln SALES_{it} &= \alpha_0 + \alpha_t TREND_t + \alpha_{te} TORG_{jt} + \beta_1 \ln PRICE_{it} \quad (1) \\ &+ \beta_2 \ln \overline{PRICE}_{jt} + \beta_3 DORG_{it} + u_{it}, \end{aligned}$$

where $\ln SALES_{it}$ is the log of the quantity sold of product i at time t, and $TREND_t$ is a time trend variable.[2] In order to address the possibility of time specific heterogeneity between organic and non-organic products, the model includes a separate time-trend for organic products in the period preceding the introduction of the shelf-labels, $TORG_{jt}$[3], while $\ln PRICE_{it}$ is the price for product i in logarithms; and $\ln \overline{PRICE}_{jt}$ is the log of the mean price of all products in category j, included to capture the effects of price changes on substitute products; $DORG_{it}$ is an indicator taking the value one after shelf-label for organic products was introduced for product i, and zero otherwise. Hence, β_3 compares sales for products after the shelf-display had been introduced to sales before, including all non-organic products in the control group. Finally, u_{it} is the residual (or heterogeneity) term, specified as

$$u_{it} = v_i + \gamma_i DORG_{it} + \varepsilon_{it} \tag{2}$$

where $v_i \sim iid\ N(0, \sigma_v^2)$ are product-specific random effects; $\gamma_i \sim iid\ N(0, \sigma_\gamma^2)$ are product-specific random coefficients related to the introduction of shelf labels; and $\varepsilon_{it} \sim iid\ N(0, \sigma_\varepsilon^2)$ are the within-product residual. The product-specific random effects, v_i, are included in order to capture time-invariant heterogeneity between products (i.e., design of the product, location on the shelf, etc., if unchanged during the study period). The product-specific random coefficients, γ_i, are included since there is no reason to believe that all products were affected equally by the introduction of shelf-labels, and such heterogeneity should be controlled for. For example, the shelf-labels could be less effective if the product is placed on a higher or lower shelf instead of at eye-level. The

[2] Ideally, one would have wanted access to data where the shelf-labels had been introduced at different times for different products. This would have allowed a more elaborate model to control for time-specific heterogeneity, for example by using time-specific fixed effects instead of a time trend.

[3] In our most general specification, we also included a time-adjustment variable for the targeted products after introduction of shelf-labels.

product-specific random effects and random coefficients are assumed independent of each other. The model estimated[4] can thus be written[5]

$$\begin{aligned} \ln SALES_{it} &= \alpha_0 + \alpha_t TREND_t + \alpha_{te} TORG_{jt} + \beta_1 \ln PRICE_{it} \\ &\quad + \beta_2 \ln \overline{PRICE}_{jt} + (\beta_3 + \gamma_i) DORG_{it} + v_i + \varepsilon_{it} \end{aligned} \tag{3}$$

There is a possibility of endogeneity bias in the estimation, since $\ln PRICE_{it}$ and $\ln \overline{PRICE}_{jt}$ are potentially endogenous if they correlate with the error-term. However, no changes in mark-ups were made at the individual store during the study period, so the variation in the prices of coffee, flour, and olive oil in our data come from changes in world market prices, and were thus considered as exogenous.

There is also a possibility of missing-variable bias, since consumer income is included as an independent variable in most estimations of consumer demand; whereas we have no data on consumer income. It can be shown (e.g. Studenmund, 2006: Ch. 6) that the effect of such missing-variable bias on β_3 can be written

$$Bias\ \beta_3 = \beta_{Income} * corr(Income,\ DORG_{it}) \tag{4}$$

where β_{Income} is the parameter estimate related to income if it had been available. We assume that coffee, flour and olive oil are normal goods, so β_{Income} is expected to be positive. The correlation between income and the introduction

[4] We used the software STATA in the estimation of Equation (3), using the *xtmixed* command.

[5] In the estimation of Equation (3), we tested for autocorrelation by regressing the residual on lagged values of the residual (5 lags) and on all other independent variables used in the original estimations. In all estimated models, the parameter estimates for the autocorrelation coefficients were below 0.21. Thus we do not consider autocorrelation an important problem in estimation of Equation (3).

of the shelf–labels is also expected to be positive (but small) since income usually increases over time, and $DORG_{it}$ is equal to one at the end of the study period. Thus β_3 is expected to have some positive bias, and the estimated effect of the introduction of the POP-displays should be interpreted as an upper bound of the actual effect. However, the period under study is short, meaning that income has not increased much (if at all). As such, we believe that missing-variable bias due to no data on consumer income being available is of little consequence for estimates of β_3.

As mentioned, consumers might adjust to shelf-labels only after some time. To capture this possibility, we added the variable $DORG_{it}/(t-R)^{\mu}$, where R is the point when shelf-labeling was introduced. The denominator raised to the power of μ measures the curvature of the adjustment process. The model including the adjustment process is then

$$\begin{aligned} \ln SALES_{it} &= \alpha_0 + \alpha_t TREND + \alpha_{te} TEKO_{it} + \beta_1 \ln PRICE_{it} \\ &\quad + \beta_2 \ln \overline{PRICE}_{jt} + (\beta_3 + \gamma_i) DORG_{it} \\ &\quad + \beta_4 [DORG_{it}/(t-R)^{\mu}] + v_i + \varepsilon_{it} \end{aligned} \tag{5}$$

This model is non-linear in the adjustment variable $DORG_{it}/(t-R)$. Since it is nonlinear only due to one parameter, μ, it is convenient to estimate it using a grid-search estimation strategy, which we did setting μ to values ranging from 0 to 4 and then estimating the remaining parameters using the standard *xtmixed* command in STATA. Finally, likelihood values were used to discriminate among the parameter values for μ.

4 Results

The results from the estimation of Equation (3) are presented in Table 3.

Table 3 About Here

On average over all products within the product category, as indicated by $\Delta \ln SALES/\Delta DORG$,[6] simple and low-cost POP-displays significantly increased sales for organic olive oil (43%) and organic coffee (21%). On the other hand, the estimated parameter for flour is negative, though not significantly different from zero. This is a first indication that the effect of POP-displays for organic foods might differ across product categories.

All the estimated price elasticities (β_1) in Table 3 are negative and statistically significant, implying that price increases reduce demand. Coffee was the most price-sensitive, a 1% increase in its price reducing demand by 3.93%; the corresponding reduction for olive oil is 1.18%. Flour was least price sensitive, a 1% increase in its price reducing demand by only 0.7%. All the estimated cross-price elasticities (β_2) were positive and statistically significant, implying that a price increase for substitute products increased demand. Once again, coffee was the most price-sensitive, with a 1.92% sales response.

The random-effects and random-coefficients parameters (γ_i and v_i) are statistically significant for all product categories except coffee (which had convergence problems), indicating that not including these in the estimations would lead to biased estimates. This means that there was considerable heterogeneity of sales-response to POP displays among individual products within each category.

Likelihood-ratio tests favour the model with an adjustment process (Table 4) for flour and coffee, but not for olive oil. The parameter estimates related to

[6] In the basic model, $\ln SALES/\Delta DORG$ corresponds directly to the estimated parameters (β_3). This will not be the case when the adjustment process is added to the estimated model.

the adjustment process (β_4) for flour and coffee are statistically significant at the 5% level. The effects of the introduction of POP-displays on sales are again reported in Table 4 as $\Delta \ln SALES/\Delta DORG$, and also in Figures 1 to 3 below.

Table 4 About Here

The most noticeable difference compared to the results presented in Table 3 is that the estimated parameter for flour now is negative and statistically significant, indicating that the introduction of a POP-display led to a 29% reduction in sales. In addition, sales of organic coffee increased by 48% (rather than 21%, as estimated earlier). Thus a model that did not take into account the adjustment process would have underestimated the effects of POP-displays on the sales of organic flour and coffee. The results for olive oil did not change, which make sense since we detected no statistically significant adjustment process for sales of olive oil.

Consumers quickly adjust to the introduction of POP-displays (Figure 1-3). For olive oil, the adjustment was instantaneous in the sense that we could not detect any statistically-significant adjustment process parameter in the estimation of Equation (5). For flour and coffee there was a statistically-significant adjustment process, but only lasting a few of days. Within three weeks after introduction of POP-displays, most of the adjustment had taken place.

Figures 1 to 3 About Here.

The introduction of POP displays could also affect consumer behavior less directly. For example, more visible marking of organic products could affect the consumer's willingness to pay for the product. Although not the main focus of our paper, we therefore also estimated the own-price elasticities of the organic products before and after the introduction of the POP displays. Own-price elasticities decreased in all three categories: for organic olive oil, from -3.56

to −1.62; for organic coffee, from −2.26 to −1.89: and for organic flour, from −1.99 to −1.82. Thus, a simple POP display that clearly indicated where the consumer could find organic alternatives to conventional foods seemed to make organic products less price-sensitive. This suggests that a profit maximizing firm could combine POP displays for organic products with an increase in the price of these products.

5 Summary and Conclusions

The demand for organic foods has increased rapidly in recent years. However, it is understood that demand for organic products is still associated with substantial barriers to growth. Using sales data from a Swedish hypermarket, we tested whether simple, low-cost, point-of-purchase (POP) shelf-labeling could increase sales of organic products. On March 10, 2008, such displays were introduced for all organic foods in the hypermarket. The effects were tracked for a period of 521 days, from April 18, 2007 through September 22, 2008. Three product categories were studied: olive oil, flour, and coffee.

Very few previous studies have investigated the effects of POP displays on demand for organic food. We find that the introduction of simple low-cost POP displays was associated with a 43% sales-increase for organic olive oil and 48% for organic coffee. On the other hand, sales of organic flour fell by 29%. Thus, POP displays that made the whole assortment of organic products more visible to consumers did seem to influence sales of organic products, but the results differed across product categories. This result has also been reported in previous studies on the effects of POP displays.

A question that remains is whether POP displays have a stronger effect for organic products compared to non-organic products. POP displays might provide information to the organic-friendly consumer that influence cognitive biases

(e.g., attribution bias and optimism bias), and thereby influence sales (Beretti et al., 2009). Thus, integrating the behavioral dimension when analyzing sales of organic foods might enhance our understanding.

We used a random-effects, random-coefficients specification of our empirical model, including an adjustment variable. Thus we took into account both product-specific heterogeneity in the effects of POP displays and consumer adjustment over time. These techniques are not restricted to the analysis of POP displays, but could be useful in the analysis of any marketing effort.

We found considerable heterogeneity in how products within a given category were influenced by the introduction of POP displays, suggesting that the estimations would have been biased if the empirical model had not taken this into account. Moreover, consumers did not respond instantaneously to the introduction of POP displays for organic flour and coffee, though adjustment for organic olive oil was essentially instantaneous. Thus we would have underestimated the effects of the POP displays if the model had not included an adjustment process.

Our choice of empirical model thus received strong support. Future research should use models that explicitly allow for heterogenous responses to market interventions within a given product category, and that allow consumers to adjust to them over time.

Finally, although not our main focus, we also studied how the introduction of POP displays for organic foods affected their own-price elasticities. This information is important for the store owner introducing such displays, since changes in price elasticities should affect pricing. The introduction of POP displays for organic products was associated with a reduction in their own-price elasticities of demand. Consumers of organic foods thus became, on average, less sensitive to price increases after POP displays were introduced. This suggests

that a profit maximizing firm could combine POP displays for organic products with an increase in their price. However, this study was limited to three product categories that constitute a rather small share of the food budget for a typical household. Fruitful areas for further research might be whether this result holds for other product categories and whether price elasticities for organic foods are more affected by POP displays than non-organic foods.

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Table 1: Means and standard deviations of quantities sold and prices of organic foods before and after shelf-labels were introduced

	Before		After		
Product categories	Mean	St. Dev	Mean	St. Dev	Difference (%)
QUANTITIES					
Flour	2.81	2.52	1.87	1.45	-33.45
Olive oil	2.45	2.79	3.17	3.01	22.86
Coffee	16.56	31.49	10.29	17.04	-37.86
PRICES (SEK)					
Flour	15.95	4.16	23.52	5.70	47.46
Olive oil	36.39	9.03	37.32	9.98	2.56
Coffee	21.29	4.53	25.15	4.45	18.13

Table 2: Means and standard deviations of quantities sold and prices of non-organic foods before and after shelf-labels were introduced

	Before		After		
Product categories	Mean	St. Dev	Mean	St. Dev	Difference (%)
QUANTITIES					
Flour	8.42	16.25	7.90	15.97	-6.18
Olive oil	3.11	4.17	2.88	3.51	12.86
Coffee	25.05	73.30	20.69	54.48	-17.41
PRICES					
Flour	13.78	4.60	15.64	4.96	13.50
Olive oil	45.68	19.47	44.95	19.44	-1.60
Coffee	20.00	3.87	22.32	4.41	11.60

Table 3: Estimation results, basic model (Equation 3).

	Olive oil		Flour		Coffee	
Variable (parameter)	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Constant (α_0)	3.39***	0.64	0.56*	0.30	7.58***	0.28
$TREND$ (α_t)	-0.0002***	0.00004	-0.0002***	0.00008	0.0005***	0.00005
$TORG_{it}$(α_{te})	0.001***	0.0003	0.0004**	0.0002	0.001***	0.0002
$\ln PRICE_{it}$ (β_1)	-1.18***	0.15	-0.70***	0.08	-3.93***	0.04
$\ln \overline{PRICE}_{jt}$ (β_2)	0.41***	0.08	0.82***	0.09	1.92***	0.09
$DORG_{it}$ (β_3)	0.43***	0.12	-0.08	0.08	0.39***	0.06
Random-effects/random-coefficients parameters (variable)						
v_i	0.57***	0.07	0.78***	0.10	1.04***	0.10
γ_i	0.22***	0.08	0.13**	0.06	NA[a]	
$\Delta \ln SALES/\Delta DORG$	0.43***	0.11	-0.08	0.08	0.21***	0.03
Log-likelihood		-6283		-7664		-19296
Observations		8298		9411		18453
Products		43		31		57

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level.

[a] Random-coefficients were not obtained for coffee due to convergence problems.

Table 4: Estimation results, model with adjustment process (Equation 5).

	Olive oil		Flour		Coffee	
Variable (parameter)	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Constant (α_0)	3.39***	0.64	0.57*	0.30	7.63***	0.28
$TREND$ (α_t)	-0.0003***	0.00004	-0.0002***	0.00008	0.0005***	0.00004
$TORG_{it}(\alpha_{te})$	0.001***	0.0003	0.0004**	0.00018	0.001***	0.0002
$\ln PRICE_{it}$ (β_1)	-1.18***	0.15	-0.70***	0.08	-3.94***	0.04
$\ln \overline{PRICE}_{jt}$ (β_2)	0.40***	0.08	0.81***	0.09	1.90***	0.09
$DORG_{it}$ (β_3)	0.43***	0.12	-0.31***	0.14	0.48***	0.07
$DORG_{it}/(t-R)(\beta_4)$	-0.20	0.28	0.60**	0.28	-0.58**	0.23
$DORG_{it}/(t-R)(\mu)$	1.55	NA[b]	0.23	NA[b]	0.45	NA[b]
Random effect/random coefficient parameters (variable)						
v_i	0.57***	0.07	0.78***	0.10	1.04***	0.10
γ_i	0.22***	0.08	0.13**	0.06	NA[a]	
$\Delta \ln SALES/\Delta DORG$	0.43***	0.11	-0.29***	0.13	0.48***	0.07
Log-likelihood		-6283		-7661		-19293
Observations		8298		9411		18453
Products		43		31		57

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level.

[a] Random-coefficients were not obtained for coffee due to convergence problems.

[b] Confidence intervals for μ were not directly reported in the estimations.

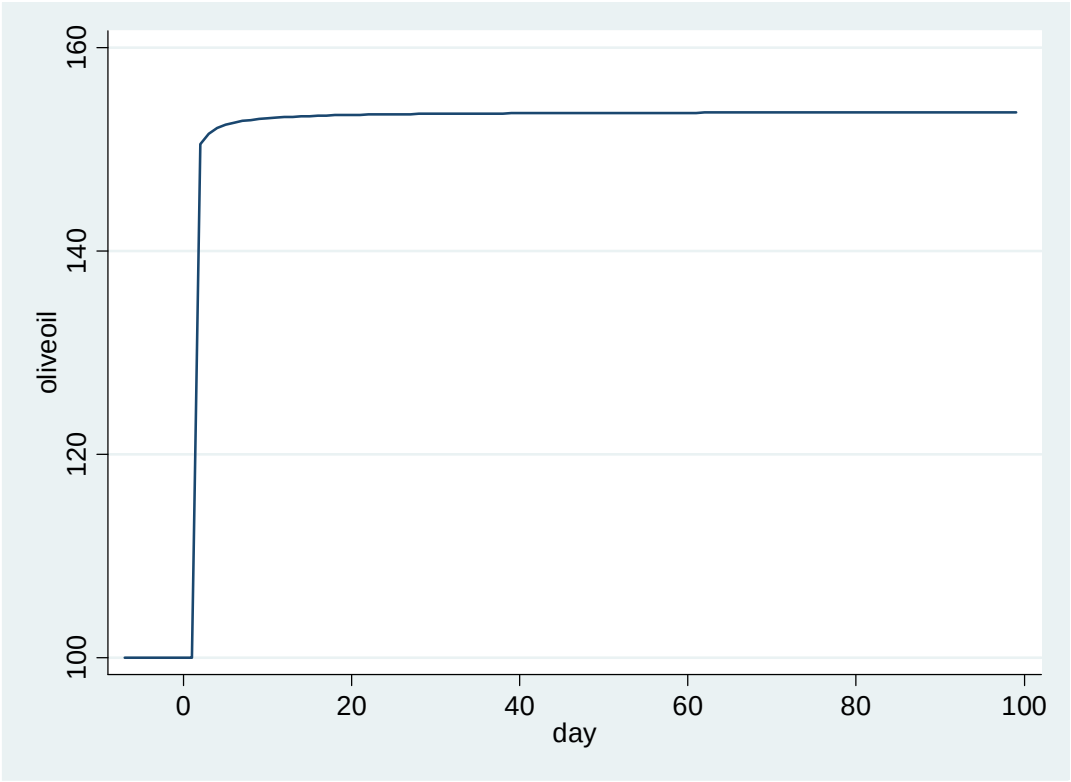

Figure 1: Change in sales of organic olive oil in percent during 100 days after introduction of POP displays.

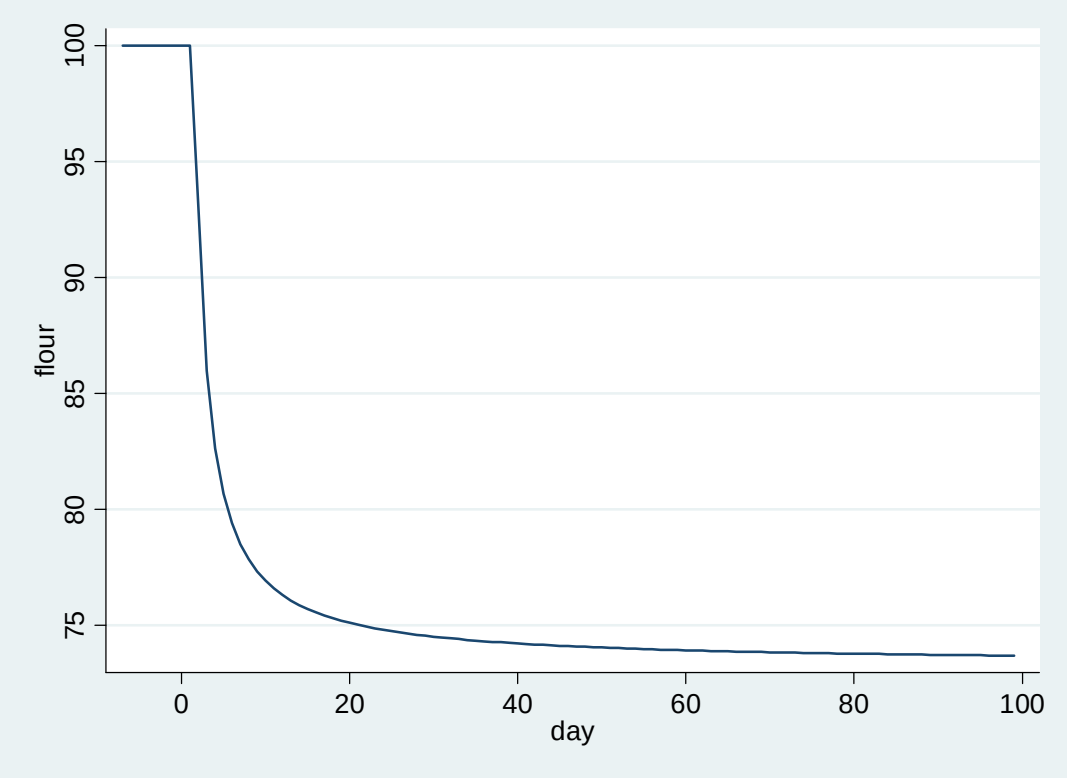

Figure 2: Change in sales of organic flour in percent during 100 days after introduction of POP displays.

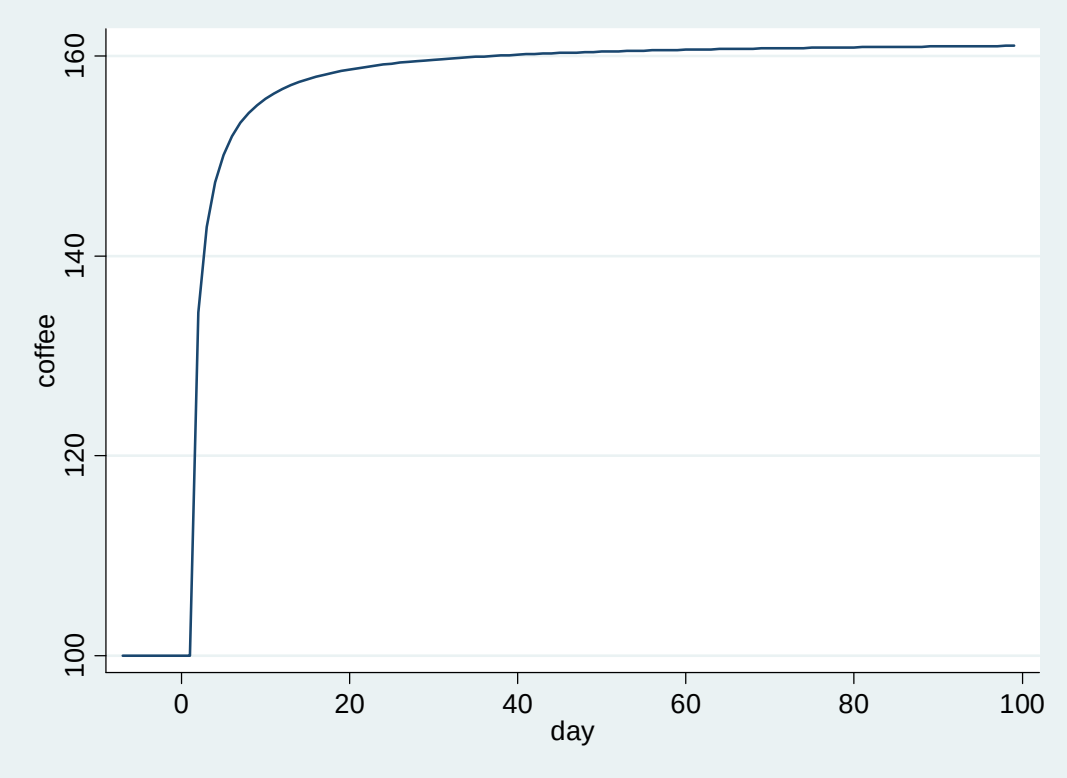

Figure 3: Change in sales of organic coffee in percent during 100 days after introduction of POP displays.