THE IMPACT OF PRICE PROMOTIONS IN
MARKETS WITH INFORMATION AND
CHOICE OVERLOAD

LUCA A. PANZONE

6th February 2011

Abstract

The UK wine market is characterised by a large amount of product selection, where the heterogeneity of the production is generally due to the high level of product differentiation. There is a general argument in favour of product differentiation, as this can be an useful and effective tool to accommodate the needs of different consumers. This would imply an increase in consumer loyalty towards the product that maximises the utility function. On the other hand, an increasing number of options has been shown to have negative effects on the cognitive ability of consumers, who tend to reduce market participation. This problem is exacerbated when quality is not observable before purchase.

This article tests whether a large portfolio of products is beneficial to consumers. Applying Gupta’s (1988) framework to the wine market, the paper tests what is the main effect of discounting on consumer behaviour. Expectations are that if producers benefit (high fidelisation), discounts would favour a stockpiling behaviour (i.e. purchasing more) in consumers, with a negligible brand-switching effect. On the other hand,
a brand-switching might favour consumers and retailers over producers, particularly when costs of information are high, since consumers could engage a trial-and-error strategy that reduces loyalty toward product and producers.

Results show that discounts do not appear to have an impact on market incidence in the case of wine, while playing a determinant role in directing both the choice of segment and quantity purchased, with brand choice accounting for more than 45% of the total effect. From the results presented in this paper, it would appear that while producers and consumers do not necessarily benefit from discounts, retailers increase their revenues due to an increase in trading volumes.

ACKNOWLEDGMENTS

I am thankful to Lorenza Quintaliani, Giacomo Zanello, Viviana Albani, Ariane Kehlbacher, Noppamas Karoon, Elisabetta Pirodda, and Aurelia Samuel for their support in the data collection process.

1 INTRODUCTION

Provision of information in markets is an important way to overcome barriers to consumption. Limits in the amount of information shared within the market has been often linked to externalities: missing knowledge of the price distribution in the market decreases the efficiency of transactions (Stigler, 1961; Jensen, 2007; Kumbhakar and Parmeter, 2009); missing information on the unobservable characteristics of products create a loss of trust in the market (Akerlof, 1970; Simpson, 2004). On the other hand, providing information or signals to consumers increases the efficiency in the market and protects consumers (Stiglitz, 2000; Spence, 2002).
Provision of information about the quality and the characteristics of the product allow consumers to perceive and understand differences between products, a condition that places them in the condition of demanding such information. In particular, when products differ on the quality level, which determines a hierarchical structure in the market, products are vertically differentiated. Differentiation could also be horizontal to the extent that products within every vertical segment can be further differentiated by a clear set of characteristics, which do not increase quality, but provide variety, a condition requiring further information in the market. This condition is particularly visible in the wine market, where producers started differentiating vertically (Stanziani, 2004), and then each vertical segment started to be differentiated horizontally (figure 1).

Despite the conceptual beneficial effects of differentiation, there is little evidence on the advantages of high levels of segmentations. Albeit consumers benefit from large choice set, increasing evidence supports the unexpected notion that excess choice, also known as “choice overload”, discourages individuals from making a choice (Scheibehenne et al., 2010; Fasolo et al., 2009; Fasolo et al., 2007; Iyengar and Lepper, 2000). This paradox is justified by the increasing proximity of products, which become very close substitutes differing by some small and unclear feature, as well as the difficulty of consumers to process large amount of information in a short time.

The impact of large product availability on consumer behaviour is capturing increasing attention from economists, who have focused on the costs and provision of information, and the cognitive limitations that cause the withdrawal from making the choice. On the other hand, there is limited attention on whether producers benefit from the behaviour of consumers, particularly in the long-run. This is particularly important in heterogeneous markets that are commonly subject to price promotions.
The importance of discounting in the presence of a choice overload hinges on the costs information has in these markets (Kiesel and Villas-Boas, 2010; Diehl et al., 2003). When a product can be characterised by a large number of attributes, consumers need to learn the meaning of each of these in order to increase knowledge and improve inference. Consequently, knowledge becomes very valuable, and market participation requires high fixed costs of information.

While consumer can access information on a variety of sources (see Chaney, 2000 for the case of wine), experience can be extremely effective in filling the informational gap, particularly when the product is accessible. Promotions can be commonly available in certain markets, as they maintain a market dynamic, and consumers can profit from their presence, improving their knowledge trough the trial of different alternatives at a lower cost.

While an advantage to consumers, promotions can have a negative effect on producers in the presence of highly heterogeneous markets. In fact, favouring a brand-switching behaviour, manufacturers lose a crucial component of their marketing strategy: branding. This particularly visible in the UK wine market, where the leading brand (Hardy’s) only share 4% of the value of the market, and the five leading brands reach together a mere 12% in value (Bainbridge, 2009). This would make the market less sustainable over time, since producers would be unable to perfectly targeting their supply, having to face a continuously changing demand, particularly having a relatively limited control over promotions. On the other hand, when discounting has a positive effect on producers, the main impact is expected to be on stockpiling behaviour, which is consistent with the behaviour of a brand-loyal consumer.

To test what are the effects of promotions on a choice overload, the paper proposes the use of Gupta’s (1988) model. Essentially, temporary discounts affect three steps of consumer behaviour: reduces interpurchase time, i.e. consumers
chase more; and directs preference, i.e. they switch brands. As indicated each
time and inventory behaviour would be beneficial for both consumers, who wo-
be able to increase consumption of their favourite product, and producers, w
would increase sales in the short-run. On the other hand, if discounting he-
ily favours brand choice, producers would be negatively affected, to the ex-
that consumers would have low interests in product loyalty, favouring only the
products on offer. Both effects benefit retailers, whilst the second would ha:
a long-term negative effect on producers, because they would fail to capti:
market shares facing “unloyal” consumers.

Figure 1: Product differentiation in the wine sector

Premium wines

AOC wines

Quality wines

Table wines

Brands, colour

Country of origin, area (region) of
origin, colour

Grape variety, country of origin,
colour, technology

Colour, country of origin

Variety

Quality

In this paper, the objective is to observe how discounts affect markets with
large portfolio of products sold, focusing the attention on the UK wine mark
which is a useful case study in terms of choice overload. In particular, the
paper is structured as follows. Section 2 analyses in more detail the theoreti-
background of the paper. This is followed by section 3, which will present

5
econometric model used in the paper. Section 4 reports the dataset used for the analysis. Results will be reported in section 5. Finally, section 6 will highlight the main findings of this work and conclude.

2 PRODUCT HETEROGENEITY, CONSUMERS AND PRODUCERS

Neoclassical economics is generally based on the assumption that more choice is better. Due to the high heterogeneity in consumer preferences, the existence of a large number of unique products representing all possible combinations of characteristics conceivably (and ideally) allows every consumer to find the optimal point on their utility function. This effectively means that providing the full spectrum of possible products in the market, producers cater for all consumers and cover all possible tastes. Consequently, supplying more choice implies the provision of the ideal product for each individual consumer, increasing personal and total welfare in the economy, hence improving the standards of living of the economy that can benefit from such wide choice availability.

2.1 Choice overload and consumer behaviour

Despite the theoretical benefits of a large heterogeneous supply of products, excess levels of product heterogeneity, also referred to as “choice overload”, can have negative effects on consumer behaviour, and can actually lead to a decrease rather than an increase in market participation (Scheibehenne et al., 2010). In fact, the difference between alternatives in markets with highly differentiated products can be perceived and clearly understood only after processing a large amount of information, coming from (costly) search processes (Cronqvist and Thaler, 2004). The higher the costs of information the lower is going to be
the incentive to engage in search in the first instance (Kuksov and Villas-Boas, 2010; Kiesel and Villas-Boas, 2010), and scarce information on the unobserved quality discourages market participation, an argument that has characterised the development of the theory of asymmetric information (see Akerlof, 1970).

Apart from economic incentives, there are physiological barriers: the human brain possess a finite ability to process new and old information and this limits the choice-making performance, a phenomenon called bounded rationality (Gigerenzer and Goldstein, 1996). This physiological limitations effectively make consumers unable to assimilate all the information available, independently on the source, and increase the level of confusion among consumers (Drummond and Rule, 2005). This problem is exacerbated by the finite amount of time available to consumers in making their choices: in a supermarket consumers make dozens of product choices in a limited amount of time (Jabs and Devine, 2006), with estimates of 12 seconds on average to make a brand choice, and a median of around 1 second (Blaylock et al., 1999).

The final result of physiological and economic barriers to information limits the ability to make utility-maximising choices consistently over time. This would result in consumers either dismissing information once they reached their maximum capacity, or abandoning entire areas of the market that are considered irrelevant, unfamiliar, or with a low probability of a satisfaction, leaving their full cognitive ability for relevant choices only.

2.2 Choice overload and producer behaviour

From the perspective of producers, a high level of product differentiation can be beneficial. In a context where each product can be considered unique, substitution is always imperfect, and each good would have its own niche in the market, operating in a monopolistic competition (Spence, 1976). This unique-
ness operates decreasing price sensitivity (Shaked and Sutton, 1982; Lynch and Ariely, 2000), potentially increasing the price elasticity of demand among loyal customers, maintaining the niche sufficiently profitable.

On the other hand, the supply of heterogeneity increases costs to manufacturers: if a producers aims to enlarge its market share, he will need to manufacture different alternatives, alloacting resources to different segments of the market. This entails a reduction in the benefits of an economy of scale and learning curves. While resource rich producers may be able to supply different alternatives, resource scarce enterprises might be unable to do the same, becoming more exposed to the possible instability of the market.

The multiple participation to different segments also presents the side effect of self-competition (Desai, 2001). This entails that whilst a producer invests resources to supply two different products, consumers will inevitably choose either one or the other. This is particularly the case when companies have a portfolio that includes relatively close substitutes, as the purchase of one item crucially will determine the exclusion of the other (e.g. two red wines), a problem that would not affect complementary items instead. While decreasing the risk of no purchase, and potentially increasing revenues, the strategy may limit the profitability of one of the segments, or reducing the benefits of product specialisation. The strategy may remain viable if the market is sufficiently large, i.e. with sufficiently large number of transactions, and loyal, guaranteeing repeated purchases.

2.3 Discounting and product heterogeneity

In a market with high heterogeneity and high costs of information, the middleman (i.e. the retailer) supplies and guarantees quality and heterogeneity, but this comes at the cost of increasing the fixed costs of the category, and taking
the risk of low dynamism. To encourage consumers to engage in the market, retailers often use discounting as a strategy to reduce the risks of market stagnation (Villas-Boas, 1998). A discount changes the relative price of the different alternatives available in the shop, reducing possible barriers to substitutability and directing consumer choices (Gupta, 1988; Guadagni and Little, 1983; Guadagni and Little, 1998). On the other hand, a price reduction increases quantity demanded, both providing an incentive to consumers to enter the market, i.e. purchasing at least one unit in the category (see Gupta, 1991; Gupta, 1988), or stimulating a stockpiling behaviour (Gupta, 1988; Hendel and Nevo, 2006).

The effect of intense price promotions in markets with a large variety to choose from is difficult to determine a priori. The literature has so far focused on oligopolies (e.g. coffee, yogurt, soft drinks), but there is little understanding (namely from a quantitative perspective) on the mechanisms and the behaviour of consumers in highly differentiated markets. As better explained in the next section, Gupta (1988) indicate that discounts can stimulate three alternative strategies: reduce the interpurchase time; stockpile, and purchase more of the favourite product; or switch, and purchase the product on discount. Whilst the first two are consequences of an income effect, the second is a substitution effect of the price change. It is difficult to have prior expectations on what the dominant effect is, as results differ from product type (i.e. durable or non-durable), and the structure of the market.

The objective of this paper is to empirically observe what is the dominant effect of discounts on consumer behaviour, to infer whether the heterogeneity favours brand-loyalty or brand-promiscuity. If the dominant behaviour is brand-switching, producers are expectedly penalised by discounts, to the potential benefit of retailers and consumers. Nevertheless, a continuous brand-switching
behaviour decreases the demand (and the costs) of future information (Nelson, 1970; Villas-Boas, 2006), which is an important benefit for consumers.

On the other hand, a predominant effect on stockpiling would indicate a good level of loyalty, and a profitable market for manufacturers. This would entail that consumers would take advantage of the offer increasing their purchase rate, and consuming more of their favourite wine. Alternatively, consumers could strategically wait for their favourite product (or products) to be on sale before purchasing any item in the category, and then purchasing it. While the overall effect of price promotion refers essentially to demand anticipation, e.g. a stock-up for future consumption (Hendel and Nevo, 2006), the dominant effect of discounts depends on the product in analysis. Homogeneous storable products like coffee appear to be largely dominated by brand choice effects (Gupta, 1988), while differentiated goods with short shelf-life like yogurt are generally subject to a stockpiling behaviour (Chintagunta, 1993). While the literature considers a large variety of products, it seems scarce in the analysis of highly differentiated and storable products, a condition that leads to unclear expectations in the case of wine, as argued in the previous section.

2.4 Product heterogeneity and the UK wine market

To the purpose of this study, the UK wine market is an appropriate field experiment. This context is characterised by a large choice availability: the 2008 wine report (Boggis et al., 2008) groups information on the top 50 brands for white, red, and rosé wines separately, the top 10 countries of origin, and a survey of 50 producers reporting 13 different varieties supplied altogether. The combination of attributes inevitably creates a high level of differentiation, and it is unclear to what extent different wines are actually substitutes or complements. This heterogeneity has been related to a widespread sense of confusion (Drummond
and Rule, 2005) and high perceived risk of dissatisfactory purchases (Mitchell and Greatorex, 1988; 1989).

Despite the difficulties in gaining market shares, the UK wine market is highly sought after. While British wine production is close to zero and the retail market is entirely dependent on imported production (USDA, 2007), the UK is the largest wine trade market in the World. In 2005, the UK imported around $3.5 billions worth of still wine (USDA, 2007), and in 2008 the retail market reached £4.7 billion (Boggis et al., 2008). Due to the reliance on foreign production, the average UK consumer has a low level of knowledge of the market, and depends on the information available in the market (Chaney, 2000). Furthermore, to maintain the market dynamic, retailers often use price mechanisms (i.e. discounts), which may be responsible of the low level of brand loyalty in the market.

3 ECONOMETRIC MODEL

In his original work, Gupta (1988) showed that the unit sales of a product, \( S_i \), can be broken down in three components (see also Van Heerde et al., 2003):

\[
S_i = P(I) \cdot P(C_i|I) \cdot Q_i
\]

(1)

where \( T \) equals the probability of purchasing an item in the specific food category in analysis, \( P(C_i|I) \) corresponds to the probability of choosing the \( i \)th alternative given a purchase, and \( Q_i \) represents the quantity of product \( i \) purchased. The impact of a price promotion can be then calculated observing its impact on all these three components. In detail, the discount elasticity of the sale of product \( i \) can then be calculated applying the chain rule:
\[ \varepsilon^S = \frac{\partial S}{\partial D} \cdot \frac{D}{S} = \frac{\partial T}{\partial D} \cdot \frac{D}{T} + \frac{\partial P(C|T)}{\partial D} \cdot \frac{D}{P(C|T)} + \frac{\partial Q}{\partial D} \cdot \frac{D}{Q} = \varepsilon^T + \varepsilon^C + \varepsilon^Q \] (2)

where \( \varepsilon^T, \varepsilon^C, \varepsilon^Q \) indicate elasticities respectively for category purchase incidence, choice probability and quantity purchased. The variable \( D \) represents the discount, i.e. the amount consumers save on the unit of wine purchased. These three elasticities can be estimated via regression analysis, using an interpurchase model, a brand choice model, and a quantity purchased model. Essentially, the three equations indicate the household/consumer decisions of when, what and how much to purchase of a given item as a response to a promotional offer, i.e. a price discount. The single elasticities can also be aggregated to obtain the Primary Demand Effects (PDE), which refer to inventory decisions, as well as Secondary Demand Effects (SDE), which relate specifically to choice, as

\[ \frac{\varepsilon^T + \varepsilon^C + \varepsilon^Q}{\varepsilon^S} = \left( \frac{\varepsilon^T}{\varepsilon^S} \right) + \left( \frac{\varepsilon^C}{\varepsilon^S} \right) = PDE + SDE \] (3)

Equation (3) holds in the presence of a constant category volume in the presence of brand-switching behaviour (Van Heerde et al., 2003), an assumption that this paper maintains throughout its arguments. The specific structure of the three equations that constitute equation (1) are going to be described in more detail in the next subsections.

### 3.1 Interpurchase time model

The decision on whether to participate into the market (market incidence) is essentially a measure of time between different purchase occasions. Consumers generally consume and purchase items at a fairly regular rate, which is determined by their rate of consumption (their demand), a function of household
size, its income, household tastes, and inter-household economy (e.g. cost of storage). The general interpurchase model can be thought as

\[ T_{ij} = f(X_i, H_j, P_i, D_i) \]  

(4)

where the time between two purchases within the same category, \( T_{ij} \), is a function of the full price of the product bought, \( P_i \), its discount \( D_i \), its observable characteristics of the product, \( X_i \), and household characteristics \( H_j \).

Assuming a simple exponential interpurchase time model (see Gupta, 1991), equation (4) can be specified in the form

\[ T_{ij} = \alpha_0 \cdot \exp(\alpha_1 X_i + \alpha_2 H_j + \alpha_3 P_i + \alpha_4 D_i + \eta_{ij}) \]  

(5)

which can then be linearised as

\[ \ln(T_{ij}) = \ln(\alpha_0) + \alpha_1 X_i + \alpha_2 H_j + \alpha_3 P_i + \alpha_4 D_i + \eta_{ij} \]  

(6)

In the present dataset, a linear measure of time is not available. However, the dataset observed whether the consumer purchased wine in the previous period (no interpurchase time), or not. The econometric problem is the reduced to a binary dependent variable model, where the time variable was identified as a latent construct \( \ln(T^*) = 1 \) if the respondent had not purchased any wine in the previous trip (a positive amount of time), and 0 otherwise, under the assumption of i.i.d. extreme-value distributed residuals \( \eta_{ij} \).

Therefore,

\[ \ln(T_{ij}) = 0 \quad i f \quad -\infty < \ln(T^*_{ij}) \leq 0 \]

\[ \ln(T_{ij}) = 1 \quad i f \quad 0 < \ln(T^*_{ij}) < +\infty \]

The elasticity for each coefficient can be then obtained from equation (6) (Greene
and Hensher, 2009) as

\[ \varepsilon^T = \frac{\partial P[\ln(T_{ij}) = 1]/P[\ln(T_{ij}) = 1]}{\partial D_i/D_i} = \alpha_4 \cdot \frac{P[\ln(T_{ij}) = 1]}{D_i} \cdot \left(1 - P[\ln(T_{ij}) = 1] \right) \cdot \left[1 - P[\ln(T_{ij}) = 1] \right] \]

(7)

and the elasticity is calculated at the mean values of \( D_i \) and \( P[\ln(T_{ij}) = 1] \).

### 3.2 Brand choice model

To estimate a brand choice model, the paper follows Davis et al. (2008), who estimate an utility function for wine following Berry (1994) and Berry et al. (1995). The model derives from a general utility-maximisation problem in the form

\[ U_{ij} = g(X_i, H_j, P_i, D_i) \]

(8)

The utility consumer \( j \) obtains from the purchase of product \( i \) can be assumed to be linear, in the form

\[ U_{ij} = \beta_0 + \beta_1 X_i + \beta_2 P_i + \beta_3 D_i + \xi_i + \nu_{ij} \]

(9)

where \( X_i \), \( \xi_i \), and \( P_i \) indicate respectively the observable and unobservable product characteristics, and the price of the good. The residual \( \nu_{ij} \) can be written as

\[ \nu_{ij} = \gamma_{ig} \sigma_g + (1 - \sigma_g) \cdot \epsilon_{ij} \]

(10)

where the subscript \( g \) indicates the segment where the wine is located, \( \gamma_{ig} \) is individual tastes for the segment, and \( \sigma_g \) represents a correlation coefficient of
consumer taste within each segment, which can go from 1 (homogenous tastes) to 0 (heterogeneous tastes). Both the residual $\epsilon_{ij}$ and the combined unobservable tastes $\nu_{ij}$ are assumed to be i.i.d. extreme value distributed, a logit assumption.

The econometric structure of the problem is a nested logit model, where consumers substitute products within the segment, but not within segments. Compared to simpler logit models, a nested logit can better predict demand, as it releases the restrictive independence of irrelevant alternative (IIA) assumptions (which can also be tested), and allowing the coefficient $\sigma_g$ to vary, the model gains flexibility in the behavioural representation of consumers (Davis et al., 2008). In this case, the elasticity of a discount can be obtained as (Feldman, 2007)

$$
\varepsilon_C = \frac{\partial P(U_{ij} = 1)/P(U_{ij} = 1)}{\partial D/D} = \sum_{g=1}^{G} s_g \beta_g D_i [1 - P(U_{ij} = 1)]
$$

(11)

where $s_g$ corresponds to the market share of segment $g$.

3.3 Quantity purchase model

To observe the quantity decision, the model corresponds to

$$
Q_{ij} = h(X_i, H_j, P_i, D_i)
$$

(12)

This model corresponds to a reduced form demand function with exogenous prices (Sunil Gupta, private communication), which appears in the form

$$
Q_{ij} = \delta_0 + \delta_1 X_i + \delta_2 H_j + \delta_3 P_i + \delta_4 D_i + \nu_{ij}
$$

(13)

An estimation problem associated to this model is the discrete structure of the quantity purchased, where products are sold in 750 ml bottles, which is the most
common format traded in the UK (USDA, 2007)\(^1\).

To treat this problem, earlier approaches proposed to treat quantity purchased as perfectly indivisible (Kalyanam and Putler, 1997; Ehrenberg, 1959; Zhang et al., 2005; Jen et al., 2003), using a Poisson model. However, consumers can be expected to have a continuous preference for quantity, \(Q^*_{ij}\), and the discrete packaging “forces” them to purchase the closest amount \(Q_{ij}\) (Gupta, 1988). The latent variable \(Q^*_{ij}\) can then be defined as

\[
Q_{ij} = \begin{cases} 
0 & if \quad -\infty < Q^*_{ij} < \mu_1 \\
1 & if \quad \mu_1 < Q^*_{ij} \leq \mu_2 \\
2 & if \quad \mu_2 < Q^*_{ij} \leq \mu_3 \\
\vdots & \vdots & \vdots \\
m & if \quad \mu_m < Q^*_{ij} \leq +\infty 
\end{cases}
\]

where \(\mu_m\) indicate the average cutoff points of the quantity purchased corresponding to the change in units purchased. The residuals \(u_{ij}\) are also assumed to be i.i.d. extreme value distributed, and the quantity purchased equation would be estimated as an ordered logit model. The discount elasticity in this case would then be derived as (Gupta, 1988)

\[
\varepsilon^Q = \frac{\partial P(Q_{ij} = k)/P(Q_{ij} = k)}{\partial D_i/D_i} \tag{14}
\]

\[
= \left\{ \sum_{k=1}^{m} k \cdot s_i \cdot \delta_k [P(Q_{ij} \leq k - 1) \cdot P(Q_{ij} > k - 1) - P(Q_{ij} \leq k) \cdot P(Q_{ij} > k)] \right\} \frac{D_i}{\sum_{k=1}^{m} kP(Q = k)}
\]

where \(s_i\) corresponds to the market share of product \(i\).

\(^1\)Wines sold in other different formats were not surveyed in the present work
4 DATA COLLECTION

To test the research hypothesis of this paper, data on wine purchases were collected in a specific study area, the Greater Reading area in Berkshire, a concentrated urban area neighbouring rural and mixed urban and rural contexts, located in the south East of England. This area includes the area belonging to the Borough of Reading itself (accounting for almost 20% of the total population in the whole county), plus neighbouring areas immediately adjacent to the main urban settlement belonging to three other different districts: West Berkshire, Wokingham, and South Oxfordshire.

The interest of the study focuses only on the off-licence retailing, which corresponds to around 66% of the whole UK wine market (Off-licence news, 2008). Needless to say, a survey covering part of a county is not going to give results representative of the whole UK situation, leading to a work which is not going to give a nationwide picture of the problem discussed in this paper. However, results are going to be representative of a consumer population, under the assumption that consumers react to price promotions in a similar way.

Data were collected via a mall intercept\(^2\). All 58 stores located in the area were contacted, and 20 authorised an in-store survey. The final sample included all the biggest retailers in the UK (see table 2), plus the Cooperative Food and the wine specialist Oddbins, covering slightly more than 70% of the UK wine market (see table 1). It also included all the largest points of sale in the study area, as well as several smaller sized shops, giving a fairly representative sample of wine sales.

\(^2\)The survey collected data between the 22nd of November and 5th of December 2008, and from the 16th to the 29 of January 2009, excluding the immediate pre- and post-Christmas period. In each of the two rounds, 10 stores were surveyed.

In the final sample, 52.7% of respondents were interviewed in December, when 55.4% of the wines in the dataset were sold, while 47.3% of buyers bought 44.6% of the sample of wines in January.
Each store was surveyed for a 2-hour period. Individuals who bought at least one bottle of wine in the shopping trip on the day of the interview were stopped and invited to participate in the survey. In order to avoid a bias, the survey covered every day of the week (including weekends), and interviews took place during mornings as well as evenings. Since customers are not selected with *a priori* criteria, the expectation is that the sample of wine is representative of the whole “wine population” in the market, and the sample of consumers is also randomly selected.

The survey registered 160 valid questionnaires reporting the purchases of 260 wines, for a total of 480 units (i.e. 750 ml bottles) of wine traded, an average of 3.0 bottles per person. Since the same wines can be bought by more individuals, some wines appear more than once (no wine appeared more than 3 times), and the sample reduces to 255 unique wines, corresponding to an average of 1.6 single wines bought by each person. Table 2 shows that in the sample used in this survey Morrisons and Tesco are largely underrepresented, whilst retailers with a good wine reputation such as Oddbins and Waitrose seem to be have a larger market share compared to national figures. The remaining retailers are rather close to the national percentages.

<table>
<thead>
<tr>
<th>Type of retailer</th>
<th>Market share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple grocers</td>
<td>69.5%</td>
</tr>
<tr>
<td>Multiple specialists</td>
<td>10.1%</td>
</tr>
<tr>
<td>Cooperatives and independents</td>
<td>20.4%</td>
</tr>
</tbody>
</table>

Source: own calculation based on Boggis *et al.* (2008)

---

3Those individuals who manifested their interested in the survey were informed about the treatment of the data collected, as well as of all privacy norms before the survey started. The interview was carried on exclusively subject to individual consensus.

4In reality, there were 225 unique wines. However, some wines can be sold in different retailers, hence corresponding to essentially different pricing structures. Considering these different wines, the sample would count actually 255 different wines.
Table 2: Market share (value) of wine sales in supermarkets

<table>
<thead>
<tr>
<th></th>
<th>Present sample</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tesco</td>
<td>27.5%</td>
<td>38.0%</td>
</tr>
<tr>
<td>Sainsbury’s</td>
<td>21.5%</td>
<td>21.1%</td>
</tr>
<tr>
<td>Asda</td>
<td>12.2%</td>
<td>13.6%</td>
</tr>
<tr>
<td>Waitrose</td>
<td>15%</td>
<td>5.4%</td>
</tr>
<tr>
<td>Oddbins</td>
<td>12.7%</td>
<td>1.4%</td>
</tr>
<tr>
<td>Cooperative/Somerfield</td>
<td>6.4%</td>
<td>7.5%</td>
</tr>
<tr>
<td>Morrisons</td>
<td>3.9%</td>
<td>12.9%</td>
</tr>
<tr>
<td>Aldi</td>
<td>0.8%</td>
<td>Not available</td>
</tr>
</tbody>
</table>

* Complete wine buyer survey (n = 160)
Sources: For wine shares (2009), own elaboration of Mintel data presented in Bainbridge (2009), based on annual reports and accounts

5 RESULTS

The data on wine purchases collected in the study area has then been analysed using the models presented in section 3. Before the analysis, income and age, which were collected in intervals (e.g. age 18-25), were recoded using the median of the respective band, and then included in a non-linear (i.e. logarithmic) form. Missing income values were replaced with the mean value of those who reported an income, and a dummy variable for the missing observations was included. Finally, the display variable used in the models presented here is a dummy variable equal to 1 if the product was located outside the specific wine aisle, in display to capture the attention of consumers.

5.1 Hedonic model

Before starting the analysis on the impact of discounts on household decision, it is worth analysing the impact of discounts in the market. In fact, it remains possible that although present, discounts are not actually visible to consumers. To test this assumption, the data is analysed using an hedonic regression as
\[ \ln(P_i) = \theta_0 + \theta_1 X_i + \theta_2 D_i + u_i \]  

(15)

The discount variable can be included in percentage point over the original (full) price; as a dummy variable equal to 1 if the product is discounted, and 0 otherwise; and as a continuous linear variable. The impact of discount measured as a dummy variable corresponds to

\[ 1 - \exp(\theta_2) \]  

(16)

where a significantly negative value would indicate a visible discount. For a continuous variable, the same price change for a unit increase in discount is obtained as

\[ (e^{\theta_2})^{(D_i+1)} = (e^{\theta_2})^{D_i} \cdot (e^{\theta_2})^1 = (e^{\theta_2})^{D_i} \cdot e^{\theta_2} \]  

(17)

where \( e^{\theta_2} \) indicates the effect of the marginal increase in the value of the discount.

The results of the hedonic regression are reported in table 3, and it appears evident that discounts negatively impact equilibrium prices, as expected. More precisely, the average discount (the dummy results) reduces price of 12.26%. This corresponds to a 1.06% discount every pound off, and 0.33%\(^5\) for each percentage point in the other equations. This result is far from surprising, but for the purpose of this analysis it clearly indicates that discounts are visible and certainly lower market. Consequently, it is expected that consumers would react to discounts, which are potentially beneficial to them in terms of consumer surplus.

\(^5\)The coefficient of discount in the percentage equation gives the increase for 1 unit, or 100% of the discount. The exponential of the coefficient is therefore divided by 100.
<table>
<thead>
<tr>
<th>Discount as Parameter</th>
<th>Percentage Coefficient</th>
<th>Percentage Standard error</th>
<th>Dummy Coefficient</th>
<th>Dummy Standard error</th>
<th>Linear Coefficient</th>
<th>Linear Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.7332***</td>
<td>0.2610</td>
<td>0.7281***</td>
<td>0.2573</td>
<td>0.6177**</td>
<td>0.2637</td>
</tr>
<tr>
<td>Private label†</td>
<td>-0.1273***</td>
<td>0.0475</td>
<td>-0.1123**</td>
<td>0.0492</td>
<td>-0.0996*</td>
<td>0.0507</td>
</tr>
<tr>
<td>AOC†</td>
<td>0.2427***</td>
<td>0.0569</td>
<td>0.2581***</td>
<td>0.0565</td>
<td>0.2576***</td>
<td>0.0550</td>
</tr>
<tr>
<td>Reserve†</td>
<td>0.0505</td>
<td>0.0683</td>
<td>0.0163</td>
<td>0.0701</td>
<td>-0.0222</td>
<td>0.0780</td>
</tr>
<tr>
<td>Alcohol</td>
<td>0.0554***</td>
<td>0.0192</td>
<td>0.0532***</td>
<td>0.0189</td>
<td>0.0542***</td>
<td>0.0197</td>
</tr>
<tr>
<td>Screwcap†</td>
<td>-0.0606*</td>
<td>0.0334</td>
<td>-0.0517</td>
<td>0.0341</td>
<td>-0.0701**</td>
<td>0.0342</td>
</tr>
<tr>
<td>% Discount</td>
<td>-0.4351***</td>
<td>0.0917</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Discounted product†</td>
<td>-</td>
<td>-</td>
<td>-0.1431***</td>
<td>0.0365</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Discount (£)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.0107</td>
<td>0.0149</td>
</tr>
<tr>
<td>Variety dummies</td>
<td>Yes</td>
<td></td>
<td>Yes</td>
<td></td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Origin dummies</td>
<td>Yes</td>
<td></td>
<td>Yes</td>
<td></td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
<td></td>
<td>Yes</td>
<td></td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Retailer dummies</td>
<td>Yes</td>
<td></td>
<td>Yes</td>
<td></td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>260</td>
<td></td>
<td>260</td>
<td></td>
<td>260</td>
<td></td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.6149</td>
<td></td>
<td>0.6045</td>
<td></td>
<td>0.5799</td>
<td></td>
</tr>
<tr>
<td>Model test: $F[37,222]$</td>
<td>12.18***</td>
<td></td>
<td>11.70***</td>
<td></td>
<td>10.66***</td>
<td></td>
</tr>
</tbody>
</table>

Note: Significance levels are specified as follows: * = 10%; ** = 5%; *** = 1%.
† indicates a dummy variable.
5.2 Interpurchase time model

The first effect of a price change is the reduction in interpurchase time, implying that consumers would make a purchase within the category earlier than initially planned. As mentioned earlier, the data available does not contain the information on waiting time, but only observes whether the respondent has made a purchase in the category the week immediately before the shopping trip of the interview. Consequently, the results of this analysis indicates whether the promotion has an influence on the probability of purchasing twice (or more) consecutive times within the wine category.

Apart from variables observing price and promotions, particularly the original price of the product, the discount, and the display of the product, the model includes a set of variables that capture the characteristic of the respondent, and his household. In particular, the regression included the age of the respondent; yearly household income; the number of wine drinkers within the household; and monthly purchases of wine. The model also captured the size of the inventory in weeks, calculated as \( \text{inventory} = \frac{\text{total stock (bottles)}}{\text{purchase rate (bottles/trip)}} \), which indicates how long the stock can satisfy the purchase rate of the family. Finally, a Christmas variable collected whether the respondent admitted to purchasing more than usual because of the festivities (need to purchase more to prepare for Christmas; or the need to restock after Christmas), which measures the impact of special occasions on demand.

The model, which treats time as a dichotomous variable, was then estimated using a a logistic regression model. Results are reported in table 4. Results clearly indicate that prices and discounts do not have a relevant role in the

---

6While respondents were expressively enquired about their last weekly shopping trip, some of them may have interpreted this as the last time they entered a supermarket, and the interpretation of the results should be interpreted accordingly. While this problem is certainly possible, the number of respondents confusing the question is expectedly negligible, as interviewers were aware of the problem and trained to address it properly.
decision of consumers who purchased wine in the previous shopping trip to
purchase again in a second consecutive occasion. Consumers instead would
rather focus more strictly on consumption needs, which are the economic drivers
of waiting time for wine in the study area.

In particular, inventory is an important determinant in stimulating a wine pur-
chase, which observes a lower time waited among people with longer-lasting
inventory, which presumably have lower stock costs and a higher preference for
wine. Similarly, the number of monthly wine purchases is inversely related to
the waiting time, as expected from marketing theory. More important than the
stocking behaviour is the occurrence of specific occasions, such as Christmas,
where consumption is heavily accelerated, due to the importance of the social
component of wine consumption. Finally, income is positively correlated with
waiting time, where richer consumers tend to have longer waiting time compared
to the average wine buyer.

Table 4: Parameter estimation of a quantity purchase model via binary logistic
regression

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Coefficient</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.4715</td>
<td>2.0388</td>
</tr>
<tr>
<td>Inventory (week)</td>
<td>-0.0381**</td>
<td>0.0193</td>
</tr>
<tr>
<td>Original Price (£)</td>
<td>0.0098</td>
<td>0.0673</td>
</tr>
<tr>
<td>Discount (£)</td>
<td>-0.1648</td>
<td>0.1207</td>
</tr>
<tr>
<td>Display†</td>
<td>0.6254*</td>
<td>0.3666</td>
</tr>
<tr>
<td>Log (Age)</td>
<td>0.0488</td>
<td>0.5213</td>
</tr>
<tr>
<td>Log (Household income)</td>
<td>0.5223**</td>
<td>0.2438</td>
</tr>
<tr>
<td>No income reported†</td>
<td>-0.7389</td>
<td>0.5224</td>
</tr>
<tr>
<td>Household drinkers</td>
<td>-0.3990*</td>
<td>0.2339</td>
</tr>
<tr>
<td>Monthly purchases (number of trips)</td>
<td>-0.1406***</td>
<td>0.0282</td>
</tr>
<tr>
<td>Christmas†</td>
<td>-2.1037***</td>
<td>0.8043</td>
</tr>
<tr>
<td>Log-likelihood function</td>
<td>-126.1534</td>
<td></td>
</tr>
<tr>
<td>Restricted log likelihood</td>
<td>-153.4062</td>
<td></td>
</tr>
</tbody>
</table>

Note: Significance levels are specified as follows: * = 10%; ** = 5%; *** = 1%.
5.3 Brand choice model

As mentioned earlier, the data collected for this analysis contains a large amount of choices: it essentially accounts for almost 255 different wines sold in 260 different choices to 160 different consumers. Consistently with the other regressions shown in this paper, wines are considered independent, and each purchase is seen as a unique observation. To tackle the issue of the overabundance of products, wines have been grouped by colour and origin, a procedure that identifies 26 different segments (figure 2). For each segment, the regression includes the average of the variable used.

This classification was preferred because this is the strategy used by retailers in marketing their selection of wines, hence the most likely way consumers process information during a shopping trip. As a consequence of this strategy, more than a pure brand choice exercise the task is essentially a segment choice. Results are reported in table 5. The IIA hypothesis is rejected using a LR test \( \chi^2(3) = 33.70, p = 0.0000 \), indicating that the segments are significantly different from each other.

From the results, it appears that consumers in the selected sample do not make use of the full price of the wine in their choice of segment. What drives the choice instead is the amount of money saved for the wine, and segments with larger discounts are those capturing higher number of choices. This is an important finding, in the sense that consumers appear not to actually focus on the specific product they aim to, but would rather switch segment to their convenience, favouring in every shopping trip only the segment which provides the highest saving.

More important than price is the role of trust in the producer. In fact, although brand loyalty is not really a feature that consumers value in the wine market, two important brand-like variables are significant: the presence of an AOC label,
and private (retailers') labels. The importance of these indicators rests on the trust consumers place in the retailer and to monitoring institutions to overcome information deficiencies in the presence of a choice overload. Finally, among product characteristics, the average alcohol content of the segment guides the choice of consumers, who favour products with a relatively high alcohol content.

5.4 Quantity purchased model

To explore the impact of discounts on quantity purchased, the dataset contains information on the number of bottles purchased per type of wine for each consumer. The original quantity data was recoded to have a scale starting at zero, and to remove any discontinuity\(^7\), obtaining a latent quantity purchased variable going from 0 to 5. Table 6 presents the results, which highlight several key points.

The full price information, irrelevant in the segment and waiting time decisions,

\(^7\)To achieve this objective, values between 1 and 4 were not modified, 6 units were recoded as latent quantity 5 (which was missing), and the remaining values (8, and 12, appearing in only 4 observations) were recoded as latent quantity 6. After this initial step, the scale was adjusted subtracting 1 unit from each observation, to achieve a starting point of the scale at 0.
Table 5: Parameter estimation of a choice model via nested logit

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Coefficient</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original price (£)</td>
<td>-0.0154</td>
<td>0.0258</td>
</tr>
<tr>
<td>Discount (£)</td>
<td>0.2355***</td>
<td>0.0658</td>
</tr>
<tr>
<td>Alcohol content</td>
<td>0.2177***</td>
<td>0.0774</td>
</tr>
<tr>
<td>Age of the wine</td>
<td>-0.0373</td>
<td>0.0685</td>
</tr>
<tr>
<td>AOC</td>
<td>0.5014**</td>
<td>0.2028</td>
</tr>
<tr>
<td>Display</td>
<td>0.3291</td>
<td>0.2957</td>
</tr>
<tr>
<td>Private label</td>
<td>1.5199***</td>
<td>0.3379</td>
</tr>
<tr>
<td>Dissimilarity parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_{white}$</td>
<td>0.4897</td>
<td>0.0696</td>
</tr>
<tr>
<td>$\sigma_{red}$</td>
<td>0.4972</td>
<td>0.0839</td>
</tr>
<tr>
<td>Wald $\chi^2(7)$</td>
<td>44.41***</td>
<td></td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-786.24</td>
<td></td>
</tr>
</tbody>
</table>

Note: Significance levels are specified as follows: * = 10%; ** = 5%; *** = 1%.
Note: The rosé branch is degenerate (it only has one segment attached to it), and its dissimilarity parameter $\sigma_{rosé}$ is consequently not defined.

becomes crucial in determining how much product for purchase, with consumers purchasing less of more expensive wines, as from general demand theory. Discounts give a positive contribution to the quantity purchased, to support the importance of the cost component of the product in the final decision of the consumer. This in surprisingly more important than other economic and marketing variables, such as income and display, who have no impact on the final quantity decision.

The size of the inventory consumers hold at the moment of purchase has no impact on the amount of product bought, as irrelevant appears to be the inter-purchase time\textsuperscript{8}. More important in the process of determining quantity are the demand for wine in the household and household preferences for this product. In fact, the number of drinkers in the household is a very influential determinant, indicating that choice-makers tend to make sure they cater for their needs as well as for those of the whole family. Similarly, respondents who purchased more units of other wines in the same shopping trip also purchased more units

\textsuperscript{8}This dependent variable is the same as the dependent variable in section 5.2.
of wine $i$, *ceteris paribus*, a result that indicate that other wines are not considered substitutes, but rather as complements. The outside good (the amount spent in all other goods) on the other hand is irrelevant in the quantity decision, suggesting the budget for wine is different from that of all other grocery.

Table 6: Parameter estimation of a quantity purchase model via ordered logistic regression

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Coefficient</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-1.5528***</td>
<td>0.7814</td>
</tr>
<tr>
<td>Discount (£)</td>
<td>0.3307***</td>
<td>0.0959</td>
</tr>
<tr>
<td>Original Price (£)</td>
<td>-0.1487***</td>
<td>0.0524</td>
</tr>
<tr>
<td>Inventory (weeks)</td>
<td>0.0060</td>
<td>0.0046</td>
</tr>
<tr>
<td>Interpurchase time†</td>
<td>-0.4635</td>
<td>0.3083</td>
</tr>
<tr>
<td>Display†</td>
<td>0.3644</td>
<td>0.2889</td>
</tr>
<tr>
<td>Household drinkers</td>
<td>0.4914***</td>
<td>0.1757</td>
</tr>
<tr>
<td>Number of other wines purchased</td>
<td>0.2322***</td>
<td>0.0407</td>
</tr>
<tr>
<td>Outside good (£)</td>
<td>0.0012</td>
<td>0.0036</td>
</tr>
<tr>
<td>Ln (Household income) (£)</td>
<td>0.0104</td>
<td>0.2229</td>
</tr>
<tr>
<td>No income reported†</td>
<td>0.3917</td>
<td>0.4485</td>
</tr>
</tbody>
</table>

Estimated thresholds

| Mu(1)                                  | 1.4101***   | 0.1569         |
| Mu(2)                                  | 2.7786***   | 0.2653         |
| Mu(3)                                  | 3.1464***   | 0.3078         |
| Mu(4)                                  | 4.1962***   | 0.4725         |

Log-likelihood function: -267.0222
Restricted log likelihood: -297.0154

Note: Significance levels are specified as follows: * = 10%; ** = 5%; *** = 1%.

5.5 Price-promotion Elasticities

Having estimated the three equations on time, choice and quantity, the paper can now observe the impact of discounts on them. Accordingly, the three coefficients of the discount variable have been converted in the respective elasticities, to capture the magnitude of price changes on the respective dependent variables. In the analysis of these results, it is worth noticing that a static analysis such as this tends to overestimates the impact of promotions on sales, since it does not account for the dynamic effect of such incentives (Hendel and
Nevo, 2006). Consequently, the estimated elasticities and the percentages can be slightly imperfect.

Results are reported in table 7. It appears evident that the largest effect of price promotions is to make consumers to switch segments, which represents 45.68% of the total impact of discounts. This could even be higher than what reported here if the statistical analysis could observe consumer behaviour at the brand level (i.e. the 255 different wines in the dataset), allowing for switching within the same segment. As a consequence of a large discount elasticity of choice, primary demand effects account for 54.32% of the total response, indicating that inventory decisions constitute a substantial component of the response to prices, almost equally shared by an early purchase (lower interpurchase time) and higher quantities.

These results is in line with previous research that finds price promotions to have a large impact on PDE (Erdem et al. 2003; Ailawadi and Neslin 1998; Chintagunta, 1993), also for durable goods (Pauwels et al., 2002). A dominant effect of brand switching has been a less frequent phenomenon (see e.g. Gupta, 1988), and associated to rather undifferentiated products. However, brand switching appears to increase in importance as heterogeneity increases in the market, suggesting that consumers would rather prefer to switch segment to follow a discount rather than stock up on a product they feel loyal to.

The results in this section indicates that producers might not benefit from price promotions in the presence of a choice overload, because despite accelerating consumption it provides an incentive to consumers to switch the segment they choose, hence maintaining profitable the market, but not necessarily the segment. However, elasticities appear to be very low, and consumer behaviour actually responds weakly to price incentives. These are surprisingly low responses, that the use of a discount might not be as beneficial in terms of demand
generation.

<table>
<thead>
<tr>
<th></th>
<th>Price-promotion coefficient</th>
<th>Price-promotion elasticity</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Waiting time</td>
<td>0.1648$^\dagger$</td>
<td>0.2047</td>
<td>26.73%</td>
</tr>
<tr>
<td>Brand (segment) choice</td>
<td>0.2355</td>
<td>0.3498</td>
<td>45.68%</td>
</tr>
<tr>
<td>Quantity purchased</td>
<td>0.3307</td>
<td>0.2112</td>
<td>27.58%</td>
</tr>
</tbody>
</table>

$^\dagger$Coefficient not significantly different from zero.

5.6 Expenditure model

Having seen that consumers purchase more when prices are lowered, a follow-up research question would be to understand whether consumers actually benefit from discounts, in terms of total expenditures. Research work (OFT, 2010) seems to suggest that consumers lament the fact they are actually unable to quantify whether they are making savings in the presence of reference pricing, as commonly used in the wine market. To understand the effect of discounts on the overall consumer expenditure, the natural logarithm of total expenditures on an individual wine is regressed on household and promotion dependent variables, as

\[
\ln(\text{exp}_{ij}) = \tau_0 + \tau_1 H_j + \tau_2 D_i + e_i \tag{18}
\]

The marginal effects of equation (18) are calculated as in section 5.1.

Apart from price and promotion variables, the model also includes variables that proxy consumption. In particular, the regression included the household preferences for wine (captured by expenditures in other wines, household drinkers, and the quantity of bottles purchased on the last occasion), household standards of living (captured by income, and the size of the outside good), and the size of the inventory. Results are presented in table 8.

Results identify a positive effect of promotions on the overall allocation of re-
sources of the household. In fact, discounts and display appear to be significantly positive in each of the regressions, therefore having an impact on consumer behaviour. In particular, results indicate that on average consumers spend 15% more on a discounted wine, essentially purchasing multiple units. This corresponds to around 3% more for each pound of discount, and 0.34% more for each percentage point of discount. Expenditures further increases by around 13.30%-13.96% if the wine is in display. While their significant is not strong, it is consistent throughout all models.

This is a surprising finding, as promotions are generally thought to be beneficial for consumers, who can ideally “save money” (OFT, 2010). Contrary to this general belief, the results presented here suggest that discounts do not benefit consumers in terms of money saved, but only on the unit costs of consumption. However, it is not clear whether this is a positive outcome, since the analysis is unable to observe a longer time span: discounts increase the speed of consumption (Ailawadi and Neslin, 1998), and as such they might go against consumer interests, who may consume and spend more than they had plan or wish.

The remaining results only confirm that wine expenditures are a function of household wealth and preferences, increasing with the number of more wine drinkers, income, the amount spent on other wines on the same trip, and the amount of wine purchased on the previous occasion. This seems to indicate that consumers who prefer expensive products or enjoys variety spend more than the average consumer on wine. Finally, the monetary size of the outside good is irrelevant in determining the size of the wine budget, suggesting wine complements consumption of other goods.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Percentage</th>
<th></th>
<th>Dummy</th>
<th></th>
<th>Linear</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Standard error</td>
<td>Coefficient</td>
<td>Standard error</td>
<td>Coefficient</td>
<td>Standard error</td>
</tr>
<tr>
<td>Constant</td>
<td>1.0081***</td>
<td>0.1676</td>
<td>0.9900***</td>
<td>0.1661</td>
<td>1.0343***</td>
<td>0.1652</td>
</tr>
<tr>
<td>Expenditures in other wines (£)</td>
<td>0.0134***</td>
<td>0.0019</td>
<td>0.0130***</td>
<td>0.0019</td>
<td>0.0130***</td>
<td>0.0020</td>
</tr>
<tr>
<td>Inventory (weeks)</td>
<td>0.0019</td>
<td>0.0020</td>
<td>0.0019</td>
<td>0.0019</td>
<td>0.0020</td>
<td>0.0020</td>
</tr>
<tr>
<td>Last purchase (bottles)</td>
<td>0.0361***</td>
<td>0.0133</td>
<td>0.0350***</td>
<td>0.0132</td>
<td>0.0365***</td>
<td>0.0133</td>
</tr>
<tr>
<td>Display†</td>
<td>0.1249*</td>
<td>0.0721</td>
<td>0.1278*</td>
<td>0.0712</td>
<td>0.1307*</td>
<td>0.0703</td>
</tr>
<tr>
<td>Household drinkers (persons)</td>
<td>0.1128***</td>
<td>0.0384</td>
<td>0.1066***</td>
<td>0.0389</td>
<td>0.1105***</td>
<td>0.0380</td>
</tr>
<tr>
<td>Outside good (£)</td>
<td>-0.0005</td>
<td>0.0009</td>
<td>-0.0005</td>
<td>0.0009</td>
<td>-0.0004</td>
<td>0.0009</td>
</tr>
<tr>
<td>Ln (Household income) (£)</td>
<td>0.1015**</td>
<td>0.0493</td>
<td>0.1059**</td>
<td>0.0491</td>
<td>0.0963**</td>
<td>0.0493</td>
</tr>
<tr>
<td>No income reported†</td>
<td>0.0520</td>
<td>0.1010</td>
<td>0.0499</td>
<td>0.1033</td>
<td>0.0525</td>
<td>0.1007</td>
</tr>
<tr>
<td>% Discount</td>
<td>0.2898*</td>
<td>0.1697</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Discounted product†</td>
<td>-</td>
<td></td>
<td>0.1403**</td>
<td>0.0672</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Discount (£)</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td>0.0322*</td>
<td>0.0188</td>
</tr>
<tr>
<td>N</td>
<td>260</td>
<td></td>
<td>260</td>
<td></td>
<td>260</td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.3753</td>
<td></td>
<td>0.3781</td>
<td></td>
<td>0.3755</td>
<td></td>
</tr>
<tr>
<td>Model test: F[ 9, 250]</td>
<td>18.29***</td>
<td></td>
<td>18.50***</td>
<td></td>
<td>18.31***</td>
<td></td>
</tr>
</tbody>
</table>

Note: Significance levels are specified as follows: * = 10%; ** = 5%; *** = 1%.
† indicates a dummy variable.
6 CONCLUSIONS

This paper explores the effects of a large choice availability in the market and the response to promotional price stimuli. Essentially, this paper observes whether the existence of price competitions in the wine market provides an advantage or a disadvantage to producers in markets characterised by a choice overload. In particular, the argument follows the idea that if the largest impact of promotions is on the quantity purchased, producers may profit in terms of larger sales. On the other hand, if the largest impact is brand choice, price competition constitutes an incentive to consumers to move across segments or brands, a strategy that in the long run should prove beneficial because wine buyers would have lower search costs in the future, but negative to producers, who lose brand loyalty.

The paper shows that brand (i.e. segment) switching is the largest behavioural component affected by price promotion, accounting for just over 45% of the total response to the change in price. This value probably underestimate the actual effect of brand switching, to the extent that the large variety of products in the dataset does not allow an estimation at brand level. Nevertheless, the significance of the model appears clear, and promotions have a significant impact on purchase patterns, in particular on the amount of product purchased and brand chosen.

Finally, the results clearly indicate that the ultimate effect of price promotions is to increase consumer wine expenditures in the market. The same occurs with product display, which does not play any significant role in the behaviour of wine buyers, apart from stimulating product expenditures. Respondents appear to spend more on average when purchasing discounted product, an effect that is certainly good for consumers in terms of unit cost, but it is also beneficial for retailers, in terms of higher revenues per type of wine sold. Consequently, retailers
appear to are effectively those benefitting from the use of price mechanisms in the wine market\textsuperscript{9}, while consumers and producers seem to be negatively affected by the excessive use of price promotions.

References


\textsuperscript{9}The benefit to retailers in the wine market can be questioned on an empirical basis, since two important dedicated wine businesses have shown financial difficulties in recent years: Unwin’s entered administration in 2005, see http://www.guardian.co.uk/business/2005/dec/16/retail1; Threshers was substantially reduced in 2010, as their holding company, First Quench, went into administration, see http://www.decanter.com/news/wine-news/483899/first-quench-owes-creditors-41m-threshers-and-wine-rack-sold.

However, the business appears profitable for generic grocers such as supermarkets, which use wines as loss-leaders.


36


