Estimating Price Elasticities of Demand for Alcohol and Tobacco In The UK

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 Abstract

UK duties on alcohol and tobacco generated almost £18 billion in exchequer revenues in 2009-10. HM Revenue & Customs use own-price and cross-price elasticities to analyse the effect of duty rate changes upon exchequer revenues. A duty rate increase will have two opposing effects on tax revenues: increase revenues by levying more duty per unit sold, but also reducing consumption through the resulting higher prices as consumers substitute away to other products, and sometimes towards the significant non-duty paid sector. The interplay between these effects is very important for predicting exchequer revenues and informing policy debate.

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# 1 Introduction

Duty on alcohol and tobacco generated £9.0 billion and £8.9 billion respectively in exchequer revenues in 2009-10. This is around 3%-4% of the total raised by HM Revenue & Customs (HMRC).

HMRC uses own-price and cross-price elasticities to analyse the effect of duty rate changes upon exchequer revenues. A duty rate increase will have two opposing effects on tax revenues: increase revenues by levying more duty per unit sold, but also reducing consumption through the resulting higher prices as consumers substitute away to other products. There is also the possibility that consumers may opt to switch to the non-duty paid sector both through legal (cross border shopping) and illegal (smuggling and counterfeit) means. The size of the non-duty paid sector can be significant. The latest estimates for cigarettes, for example, suggest the market share is around 12%. The interplay between these different effects is very important for predicting exchequer revenues and informing policy debate.

HMRC are primarily concerned with the elasticity of duty paid alcohol and tobacco rather than consumption as a whole. This distinction is important because whilst the consumption of these products is typically thought of as inelastic, particularly with regard to their social habit or addiction properties, consumption from the duty paid sector will be more elastic.

As well as overall revenue, HMRC are also interested in the substitutability across different products and what that implies for duty rates. For example, for a number of years in the 1990s, spirits duty was frozen whilst duty rates on beer and wine increased; cider has typically been taxed less heavily than beer. When considering the revenue effects of such policies, it is important to understand in what way changes in the relative prices of different alcohols will affect sales and therefore tax revenues from each type of alcohol.

One of the main objectives in re–estimating the models are to ensure that our elasticity estimates accurately reflect current market conditions. The evidence is that estimated demand elasticities can be relatively unstable and can vary considerably across studies. This variability may reflect actual changes in tastes but probably also includes a stochastic element, particularly with regard to different data sets and non-linearity and so on.

We are estimating elasticities separately for the alcohol and tobacco markets. This paper outlines the different methodologies pursued to estimate demand for alcohol and tobacco. Section 2 summarises some previous studies. Section 3 discusses a cointegration technique using time series data. Sections 4 and 5 are based on the same cross-section household expenditure dataset. The first uses a QUAIDS model whilst the second employs a Tobit estimation.

# 2 Previous Studies

Alcohol

The last time that HMRC modelled alcohol demand was in the paper by Huang (2003). That used a single equation dynamic error-correction model and applied it to data from the Office for National Statistics (ONS). Four different equations were estimated: beer in the off trade, beer in the on trade, spirits and wine.

Although the model has performed well it is clearly time that the estimations were updated. In particular, there are a number of areas that we think need to be re-considered. Firstly, the current model only considers the distinction between the on and off trade for beer. Whilst it is arguable that the beer market is the one where the distinction is most important, we would ideally like to make the separation for all products. Secondly, there have been some significant changes in drinking habits, in particular the growth of the markets for cider and the ready-to-drink category. Neither of these was modelled in the previous study.

Tobacco

The previous tobacco modelling exercise was carried out by Cullum and Pissarides (2004). They used an Almost Ideal Demand System (AIDS) to look at the markets for cigarettes and hand rolled tobacco (HRT). They also explicitly estimated the demand for the duty-paid domestic market, the cross-border market and the illicit market. They used data from ONS, HMRC and tobacco manufacturers.

At the time of this research there was considerable concern that prior models had not captured the rapid rise in the growth of the non duty-paid sector. During the 1990s the size of this sector grew from virtually zero to over 20% of the cigarettes market and over 60% of the HRT market.

Arguably, this model has performed less well than the alcohol estimation. One of the main reasons for this is that the size of the non duty-paid sector has declined in the ensuing years. In 2000 HMRC introduced a new tobacco strategy to counter the growth in the non duty-paid sector and it would appear that this has had a good degree of success, though other factors (exchange rates, inflation only duty rises amongst others) have also likely played a role. The elasticities estimated in the Cullum and Pissarides study are probably on the high side in the current climate, where receipts from tobacco have risen sharply in recent years.

Meta-Analysis

There are a large number of studies looking at alcohol and tobacco but, fortunately, Gallet (2007) and Gallet and List (2003) have conducted extensive meta-analysis to examine the differences across the literature. Gallet (2007) considers results from 132 international studies on alcohol from 1942 to 2002 to see how the price elasticity varies across a range of different factors, including beverage type, functional form, data type and estimation method. Each was compared to a simple baseline regression. He found that:

* Beer was consistently more inelastic than other beverages (wine and spirits).
* Non-linear functional forms (AIDS, Rotterdam, semi-log) tended to produce more inelastic elasticities than linear models.
* However, addiction models were not significantly different.
* There was no significant difference between time series data and panel data.
* Compared to OLS, other estimation methods - two stage least squares (2SLS) and three stage least squares (3SLS) produce more elastic price elasticities.
* However, a single equation maximum likelihood estimation (MLE) tends to result in more inelastic elasticities than OLS.
* Full information maximum likelihood (FIML), generalised least squares (GLS) and generalised method of moments (GMM) were not significantly different to OLS.
* The short run elasticity is more inelastic than the long run.

Gallet and List (2003) looks at tobacco research in a similar way, comparing different studies to a baseline estimation, in this case a single equation, OLS, semi-log regression with smoking consumption as the dependent variable. They look at 86 studies from 1933 to 2001. Again, their selection is not limited to the UK. The main findings were:

* Estimations based on AIDS specifications tend to produce more inelastic elasticities than the baseline.
* The rational addition model tends to generate more inelastic elasticities than the baseline; estimates from the myopic model are not significantly different.
* The linear and double-log specifications are not significantly different to the baseline.
* There is no significant difference between using time series and cross section data.
* Neither 2SLS, 3SLS, FIML were significantly different to the OLS baseline. GLS and MLE studies tended to produce more inelastic elasticities, though the latter result is of marginal significance. GMM estimations tend to result in more elastic elasticities.
* The short run elasticity is more inelastic than the long run.

The results from these two meta-analyses are useful benchmarks when modelling alcohol and tobacco. In particular, they are of value when we compare results across the different approaches we have been exploring.

# 3 Approach 1: Cointegration

## 3.1 Data

Data on consumption is sourced from the ONS publication Consumer Trends. This provides quarterly data on expenditure for each of the following:

* On-trade beer
* Off-trade beer
* On-trade spirits
* Off-trade spirits
* On-trade wine
* Off-trade wine
* Cigarettes
* Hand Rolled Tobacco

Pricing data for alcohol also comes from ONS, who make use of industry data. Tobacco prices are direct from the manufacturers. The prices for smuggled and cross border tobacco are estimated internally in HMRC.

For alcohol we separate on-trade (bought in pubs and restaurants) from off-trade (bought in off-licenses and supermarkets). This is because the markets are distinct from one another. For example, consumers may switch to drinking at home if prices in pubs become too high. Real non-seasonally adjusted quarterly data is used. The volume of sales and the average prices of individual types of beverages for the off trade are obtained from a continuous survey of retail outlets. Volumes are then grossed up to align with clearances data from HMRC. The price data is used to estimate current expenditure. Expenditure on alcohol in the on trade is estimated separately.

In addition, we also have data on household final consumption expenditure, employment ratios, exchange rates and duty rates for each type of alcohol. The household final consumption data is used as a proxy for income in the regressions. It is also possible to use this data to transform our prices into relative prices to control for the positive correlation between price and expenditure on any given good. An alternative way to cope with this problem is to convert expenditures into volumes.

There are some weaknesses in the data set. Data on cider is not available. Wine includes both cider and coolers, which ideally we would like to separate. Whilst the alcohol expenditure data excludes cross-border shopping, it includes smuggled goods. For tobacco, there is a separate data set for smuggled expenditure though cross border shopping is not accounted for. We have internal HMRC data on smuggled and cross border tobacco, spirits and beer. However, there is concern over the reliability of some of this data.

For tobacco, the ONS Consumer Trends data includes consumption expenditure on cigarettes and other tobacco products. Expenditure is split between UK duty paid and smuggled. One of the weaknesses with the data is that the smuggling estimates are probably an overestimate, since they do not fully take into account the recent reduction measured by HMRC.

Pricing data comes from information provided by tobacco manufacturers. Most other data: income, exchange rates, overseas travel numbers is also sourced from the ONS. Tax information is held by HMRC.

For alcohol the dependent is available from 1970q1 up to 2009q4. However, we believe that omitting some of the early data would likely give better results due to changes in the market since the 1970s. For tobacco, the data on the dependent variable is available from 1982q1.

## 3.2 Methodology

The general model is described in the equation below. It is a straightforward specification where consumption or expenditure is a function of own prices (*Pi*), prices of other goods (*Pj*), income (*Y*), and a number of other explanatory variables (*X*). These include the exchange rate, overseas travel numbers duty rates. Important dummies, *D*, such as the 2007 smoking ban have also been included.



As is commonly the case with time series data, many of our variables suffer from non-stationarity. This can cause spurious correlations between variables in our regressions which do not reflect any true economic relationships. We use Augmented Dickey-Fuller tests along with simple data plots and correlograms which confirm our suspicions of non-stationarity in the data. Further testing establishes that the data is integrated of order one and therefore is stationary in first differences.

Modelling in differences overcomes many of the problems associated with non-stationary variables. However, this is done at the sacrifice of the long-term properties of the model. In the long-run, the differences should be zero and hence the differences approach looses the long-run relationship between the variables in the regression. In order to keep both the short and long-run relationships in our model we follow the two step Engel-Granger (EG) procedure for cointegration modelling.

The first step of this method is to model the long-run relationship in levels. We must assume that this is a true long-run relationship to proceed with the EG method. Given the weight of economic theory supporting the relationship between price and quantity demanded of a good; this is a weak assumption. The t-statistics from the first stage procedure should be taken as indicative at best, because the non-stationary variables undermine the standard distributions. The residuals from this regression are then tested for stationarity. If they are stationary, there is a cointegrating relationship and we can proceed to the second stage. The second stage is to estimate the dynamic short-run relationship in differences. We use seasonal differences when there is strong seasonality in the data; otherwise first differences are used. The short-run regression includes the lagged residuals from the first step as the error correction term. Because the variables used in the dynamic relationship are stationary, the results are no longer spurious and the t-statistics can now be interpreted without bias. However the explanatory power of a model on differences is not expected to be great.

The two-stage EG method may be less appropriate for modelling more than two variables. With two variables there is a single long-run relationship which the EG procedure estimates. However, with more than two variables, there are multiple possibilities of the long-run relationship from which the EG procedure implicitly assumes only one is correct. This A more robust alternative when modelling multiple variables is the Johansen Vector Error Correction (VEC) procedure. This follows a similar error correction process to the EG model but relaxes the implicit assumption on the choice of the long-run relationship. As with the EG procedure, the Johansen VEC model is only applicable to cointegrated variables. Although this approach was specifically developed for use with systems of Vector Autoregression equations, it can also be used as an auxiliary tool for the single equation EG procedure. If the Johansen procedure indicates the existence of only one cointegrating vector, it can be regarded as some confirmation of the single equation model to which EG method was applied.

## 3.3 Results

Due to data issues and availability the time series approach proved more appropriate for tobacco rather than alcohol analysis. Therefore initial alcohol results are not reported in this paper. For tobacco, this approach is the only one that has been pursued. The model requires less complexity than alcohol because of the significant difference in size between cigarettes and other tobacco products. In the first instance we have only looked at the demand for cigarettes, which forms 90% of the UK tobacco market. Table 1 below lists the two best long run relationships identified through data mining and cointegration testing. Both models have been estimated for two time periods: 1982q1 to 2009q4 and 1984q1 to 2009q4. Initial observations show much higher levels of cigarettes consumption followed by a sharp decline in 1984. The shorter estimation period was used in order to avoid leverage and preserve the number of degrees of freedom.

*Table 1*



The second step of the Engle-Granger procedure is performed separately for each of the four models and the final long run regression is established based on cointegration results and residuals testing. Dynamic equations are estimated on first differences. In order to prevent the loss of information available in the earlier years, as well as due to the weak data reliability, illicit and cross border shopping variables have been excluded from the final regression. Instead the impact of the non duty paid consumption developments was approximated by other regressors like exchange rate, travel numbers and overseas prices. This choice of variables was dictated by the fact that falling travel numbers during recessions are expected to have negative implications for the levels of cross border shopping and that, as shown by evidence, the tax gap estimates have fallen alongside the exchange rate. Hence we expect declining exchange rate to reduce both the demand for and supply of illicit product, since the price differential between UK duty paid and non duty paid is lowered.

Tables A1 and A2 in the annex shows long run and short run results of the above equations for both linear and semi-log specifications. Cointegration tests give satisfactory results and the error correction terms are successfully identified. High significance and negative sign of the lagged residuals in the short run regressions ensure that the series adjust to the long run equilibriums.

The elasticities that have been estimated are consistently lower than those of Cullum and Pissarides. This supports the view that the demand for cigarettes has become less elastic in the past six years. It also defies one of the main results from the meta analysis that AIDS models tended to produce lower elasticities.

The alcohol model has a bit more complexity since we attempt to estimate all the alcohol cross price elasticities. Given that this approach and data set is broadly similar to that of Huang, it is not surprising that the results are not massively different. Own price elasticities all have the correct sign though that for wine is not significant. As predicted by the meta-analysis, beer is less elastic, spirits are more elastic. However, some of the cross price elasticities are puzzling, particularly one or two instances where the results suggest there is a sizeable complement effect. As this is not our preferred model, the full results are not reported in this paper.

# 4 Approach 2: QUAIDS

The second approach we have pursued uses cross-section data in a quadratic almost ideal demand system (QUAIDS). This approach was only used for alcohol due to insufficient coverage of tobacco in cross-sections. The QUAIDS approach is theoretically very appealing as it is a complete demand system and it is very efficient because of the simultaneous estimation procedure. Another benefit is that the wider data coverage allows us to explicitly model both cider and RTDs, as well as the on and off trade for all beverages. It was also hoped that we might be able to get more plausible cross-price effects,

## 4.1 Data

The data set used in this analysis is from the Expenditure and Food Survey (EFS) which contains data on the price, quantity and value of alcohol bought/consumed across the UK. The variables included in the data set are:

* Alcohol:
* Beer and Lager (off trade)
* Spirits and Liqueurs (off trade)
* Wine from grape of other fruit (off trade)
* Fortified Wine (off trade)
* Ciders and Perry’s (off trade)
* Ready To Drink (off trade)
* Champagne and Sparkling Wine (off trade)
* Beer and Lager (on trade)
* Spirits and Liqueurs (on trade)
* Wine from grape or other fruit (on trade)
* Fortified Wine (on trade)
* Ciders and Perry’s (on trade)
* Ready To Drink (on trade)
* Champagne and Sparkling Wine (on trade)
* Round of Drinks (on trade)

Non-Alcohol:

* Gender
* Ethnicity
* Age
* Education
* Region
* Household composition
* Household size
* Employment status
* Income

The EFS is an annual survey of around 7,000 randomly selected households in the United Kingdom. It records the purchasing of a range of goods, via a diary system for the individual over a two week period. In general, EFS records the amount of a good bought, the price paid by the purchaser and the type of outlet where the purchase was made. In terms of alcohol, it provides detailed information on all the categories we require. In addition, the EFS also contains a substantial set of information on the individuals’ characteristics.

There are two key draw backs to using the EFS data set. Firstly there is a fairly low response rate (53% in 2008) which could lead to bias. Secondly, there is an apparent over reporting of zero consumption of alcohol. Roughly 30% of households report no alcohol consumption, double the usual estimate of 10%-15% of UK households that are teetotal. As can be seen in table 5 in the annex, of those households that do consume some alcohol, most consume only a few types; over half consume only one or two drink types. Dealing with these zeros is a major obstacle to obtaining usable results.

## 4.2 Methodology

The first step is to consider an appropriate framework for specifying individual preferences at the microeconomic level. The aim is to model a narrow set of non-durable commodities that are well recorded in micro data sets. Preferences are characterised such that in each time period *t*, household *h* makes decisions about how much to consume of these commodities subject to various household characteristics and on the consumption levels of other goods.

For each household, we measure the share of expenditure on a given alcohol for each household as

 

Where  is real total expenditure; the,and  parameters are allowed to vary with household characteristics and other conditional characteristics; and ln *P* (*p*) is defined as

 

E.g. the share of expenditure on on-trade beer in a given period will be a function of:

* log of its own prices;
* logs of prices of other alcohols;
* log of total real household expenditure;
* log of total real household expenditure squared.

## 4.3 Results

Gallet’s meta-analysis suggests that both AIDS models and maximum likelihood estimation tended to produce lower elasticities. However, our finding for the QUAIDS approach produces higher elasticities. Also, unusually, the results suggest that wine, rather than beer is more inelastic. For almost all the alcohols, the on trade is more elastic than the off trade, which we would probably expect. All own price elasticities have the expected signs; some cross price elasticities again suggest a degree of complementarity. As this is not our preferred model, the full results are not reported in this paper.

# 5 Approach 3: Tobit

The motivation for pursuing the Tobit model originated with the difficulties in dealing with the large numbers of recorded zero consumption. Once again, this approach has only been used for alcohol. As the QUAIDS methodology suffered considerably from the large degree of zero consumption reporting, and the time series approach did not produce satisfactory results for as many alcohol types as we would like, the Tobit approach for alcohol is the only one for which results are reported in this paper.

## 5.1 Data

The data set is the same household expenditure survey as is used for the QUAIDS approach.

## 5.2 Methodology

With a large number of zeros reported in the data set, it is difficult to analyse the interactions between consumption of different alcohol types when prices change. Fitting a simple OLS regression is likely to yield biased and inconsistent results: the slope being biased downward and the intercept biased upward. Reducing the dataset to remove a number of the zero observations would not fully alleviate this problem and would, in turn, entail a selection bias.

One method to cope with the problem of the zero observations is to employ Tobit analysis (censored regressions). This method is essentially a hybrid of a binary choice model, estimated using maximum likelihood, and a conventional regression. The basic equation is the following:

 Y\* = β1 + β2X + u

 Y = Y\* for Y\* > YL

 Y = YL for Y\* ≤ YL

Where, for example, Y could be expenditure on beer and X the price of beer. The binary choice element investigates why some households consume zero of a given alcohol while others consume a positive amount. The conventional regression element quantifies the relationship between the regressors for those with a positive demand for the alcohol in question. That is, it assesses how much a change in price affects demand amongst households already consuming the alcohol.

Tobit analysis assumes that the error term, u, is homoskedastic and has a normal distribution. If either of these assumptions is violated then the regression yields inconsistent estimates. In the presence of heteroskedasticity, using consumption shares (rather than levels) may be preferable (Amemiya [1984]). Atkinson et al [1990] show that the assumption of normality can be relaxed by using what they term a Gamma-Tobit Model as a generalisation of the standard Tobit approach.

A potential weakness of the Tobit model is that it assumes that the effects of the independent variables are closely linked in both the binary choice decision and the conventional regression. This may not necessarily be the case for alcohols. It is possible to capture heterogeneity between the two elements of the Tobit regression by instead conducting a Two-stage Heckman approach, with the first stage run as a Probit regression. This is largely equivalent to a Tobit model but at the sacrifice of some efficiency by moving to two-stages.

Tobit analysis is simpler to use than the QUAIDS approach, making experimentation with the inclusion of extra variables, or use of sub-samples, more practical.

## 5.3 Results

Within the Tobit framework, it is possible to experiment with different functional forms. For example, should we assume constant elasticities with a log-log function, or is a linear model more realistic? We experiment with various functional forms. We found the lin-log form to be most appealing both in terms of results, and through not having to impose the assumption of constant elasticities.

For our dependent variable we have experimented with the use of volumes of alcohol and expenditure shares, defined as expenditure on a given alcohol product as a proportion of total household consumption expenditure. As shown table A9in the appendix, using volume as the dependant variable yields very high elasticities which appear unrealistic. Using logged volume, the elasticities are somewhat varied with some higher and some lower than expected. Hence we prefer to use expenditure shares as the dependent variable.

For our independent variables, we have the price of each of the ten alcohol categories (lnpi and lnpj), total expenditure on alcohols (lnexp\_alc), total expenditure on non-alcohol goods (lnexp\_notalc), region (gor), socio-economic characteristics (socio) and year (yr) and quarter (qtr) dummies. The time dummies control for time-specific variations and allow the pooled cross-section dataset to be used. Hence our model is:

 wci = lnpi + lnpj + lnexp\_alcs +ln exp\_notalcs + gor + socio +yr +qtr

The standard Tobit estimates will be inconsistent if the distribution of the residuals is not normal or if they suffer from heteroskedasticity. If these problems are severe then it may be necessary to extend the Tobit model to a more generalised form that allows different distributions of the residuals (such as the Gamma-Tobit model discussed previously). However if the violations of the standard Tobit assumptions are moderate, then the Tobit estimates are likely to still be reasonably good. A simple plot is very informative about the distribution of the residuals. Taking the example of on trade beer, we can see below that the residuals appear to be largely normally distributed; supporting the assumptions underlying the standard Tobit model.

*Diagram 1: residuals from on trade beer Tobit regression*



An informal test of the general appropriateness of the model is to estimate a Probit model for the same binary choice element as the Tobit regression and compare the results to those of Tobit. Dividing each coefficient form Tobit by the regression output σ computes a comparable figure to the Probit estimates. The two sets of results will never be identical because of sampling error, but the coefficients should not be significantly different in sign if the model is well specified. Taking the example of on trade beer once again, the results are shown in table 2 below. As can be the seen, the coefficients for logged prices (note elasticities are not reported here for computational convenience) always have the same sign when significant and their magnitudes are always fairly similar. However, the coefficients for expenditure on non-alcoholic products are opposite in sign. This result is slightly concerning however the variable in question is not of primary importance for our analysis.

*Table 2: Tobit and Probit results for on trade beer*



As a further general check, we analyse the robustness of the estimates to the inclusion of extra variables. If the coefficients (and resultant elasticities) change significantly when adding or dropping variables then the model may be misspecified. We find that our results are generally robust to including or dropping variables. For example, table A8 in the appendix shows the results of dropping the expenditure on non-alcohol goods variable, socio-economic characteristics or excluding RTDs from the regressions. As can be seen, the elasticities change only slightly in each case. In particular, the results are almost identical with and without RTDs.

Tobit allows us to compute elasticities for those households starting with positive consumption from the complete population. It is likely that these households will be more responsive to price changes than when considering the population as a whole, which would include those that will not consume at any price. This is supported by our results, given in table A6 of the appendix. The own price elasticities from this approach all seem sensible, though they are, on the whole, slightly lower than the other two approaches.

The results suggest that beer and wine are the least elastic while spirits and cider are more elastic, again fairly sensible results. The relative elasticities of on and off trade products are mixed. Beer and cider own-price elasticities are a bit less elastic in the on trade; wine and spirits are a bit more elastic in the on trade; RTDs are very similar in both. Of the three approaches, the Tobit also produces arguably the most plausible cross-price elasticities. We would generally expect positive cross-price effects, reflecting substitution between alcohols. This is the case for most of our drink types. Where cross-price effects are negative, the complimentarity could plausibly be the result of decisions being made at the household rather than individual level. For example, if one household member likes wine and another likes beer, the household decision to go out could depend on the prices of both alcohols. Where cross-price elasticities are not reported, the results were insignificant at the 5% level.

# 6 Conclusions

We have used various data sources and methodological approaches in order to estimate price elasticities of tobacco and alcohol demand in UK. The two markets differ considerably in structure and underlying characteristics. The split between on-trade and off-trade alcohols is important as are various cross price elasticities for each of the alcohol types. Tobacco market in turn is made up of cigarettes in 90% which makes the cross-price effect less crucial.

Cointegration analysis of the tobacco time series data gave satisfactory and robust results and the Engle-Granger approach has been accepted as the final model. Issues characteristic to the cross-sectional alcohol data motivated the use of Tobit analysis and indeed this model gave the most sensible and stable results.

Estimated cigarettes elasticities are consistently lower than those from the most recent study (Cullum and Pissarides 2004). This supports the view that the demand for cigarettes has become less elastic in the past six years.

The own price alcohol elasticities are sensible, though they tend to be slightly lower than in the other approaches in this paper. Of the three alcohol approaches discussed in this paper, the final Tobit model arguably produces the most plausible cross-price elasticities.

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# Annex















