Banning Volume Discounts to Curb Excessive Consumption: A Cautionary Tale

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Banning volume discounts to curb excessive consumption: A cautionary tale[†]

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Abstract

Volume discounts encourage consumers to buy more. Banning such discounts should then lead to consumers buying less. This is the thinking behind banning multiple-unit discounts, including multibuy price promotions, to curb harmful excessive consumption of alcohol and high fat, sugar and salt (HFSS) foods. However, our analysis questions the validity of this thinking, which ignores the possible restraining effect of volume discounts. We find that such a ban for retailing alcohol in Scotland increased rather than reduced sales. Retailers switched to using more straight (single unit) discounts, which encouraged high consumption households to increase their shopping frequency and buy more.

Key words: Volume discounts, excessive consumption, multibuy, alcohol
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1. Introduction

Volume discounts are a ubiquitous means to encourage consumers to buy more. They are attractive to firms as a smart means of indirect (second-degree) price discrimination, where customers segment by self-selection when choosing from a menu of price-quantity combinations or nonlinear pricing schedule to obtain more for less cost per unit (Adams and Yellen, 1976, Wilson, 1993). They can also be efficiency enhancing when they boost overall sales, help firms achieve scale economies, and intensify competition (Stole, 2007, Armstrong, 2016). However, governments might not always want consumers to buy more and instead prefer them to buy less when this helps avoid harmful excessive consumption. Such concerns arise with alcohol and unhealthy foods, where moderate consumption may not pose a major health risk, but excessive consumption can seriously harm individuals and impose costs on society. In these circumstances, would banning volume discounts help curb consumption or backfire by driving firms to find alternative means to sell perhaps even more, albeit at lower margins?

This paper considers this question by examining business responses and changes in consumer behavior in the wake of a ban on volume discounts for purchasing alcohol in multiple units. Such bans are advocated by the World Health Organization (WHO, 2010) to remove pricing inducements that encourage consumers to buy and consume more alcohol than they otherwise would do with regular (linear) pricing. Countries with volume discount bans on alcohol sales include Canada, Sweden, Finland, Iceland, Switzerland, and Scotland, where the latter is the focus of this paper.[1] Likewise, there are calls to ban similar volume offers for high fat, sugar, and salt (HFSS) foods and drinks, which are viewed as drivers of excess purchases, resulting in increased consumption fuelling obesity (DHSC, 2021). Accordingly, understanding the consequences of banning volume discounts is an important policy consideration in seeing how well targeted and effective is this intervention in these critical public health contexts.

In examining the consequences of such a ban, we exploit a natural experiment amongst different countries in Great Britain (GB). Scotland used its devolved powers to introduce a ban on volume discounts, in the form of multiple-unit discounts known as multibuys, for retail alcohol sales starting in October 2011, while England and Wales did not adopt such a policy. Yet all three countries share the same British tax system and other policies. We use tobit models to examine weekly household level alcohol purchases (some weeks there are

[1] For a list of countries banning alcohol volume discounts, see https://apps.who.int/gho/data/view.main.54720.

no purchases) over a span of a year and a half. This is within a difference-in-differences (DD) framework where we compare weekly household level purchases before and after the introduction of the ban for households in Scotland with those in England and Wales. We are able to separate household types by the pre-ban volume of alcohol purchased, distinguishing between low, medium and high consumption households, and examine the impact of the ban for each household type on total alcohol sales as well as by segments of the market separately (spirits, beers, and wines). This is because policy impact may differ over both dimensions. Importantly, our analysis also accounts for the fact that as a policy response, equilibrium prices may change and households would react to these changes. Thus, we also control for prices and treat them as endogenous (using a control function) as households would make a joint choice about quantity and price via selection of specific items in the shopping basket based on various discounts.

We find that the ban had the greatest impact on the primary targets of the ban, which were beer and wine sales, where multiple-unit discounts were common, and especially on purchases made by heavy consumption households, who made extensive use of these discounts. However, the effects were the exact opposite of those intended. Sales of beers and wines increased, driven primarily by heavy consumption households buying more, not less. With the top third of consumption households accounting for over three-quarters of alcohol purchases, we find that their extra purchases increased the overall amount of alcohol sold.

We investigate the factors behind this quantity increase and the apparent policy failure. Two key insights emerge. First, retailers responded by replacing multiple-unit discounts, especially in the form of multibuy price promotions (like "buy 6 save 25%" deals), with more straight (single unit) price reductions. Second, while the ban had limited or no impact on the purchasing patterns of low or moderate purchasers, heavy purchasers responded by increasing the number of shopping trips per week, with the more frequent buying resulting in higher overall quantity.

The former finding is perhaps not surprising when retailers can draw on alternative forms of price promotions to counter and circumvent the effects of a volume discount ban, where increasing the use of straight discounts provides an effective counter measure to maintain sales, even if ostensibly giving away more margin on smaller purchases.

The latter finding – heavy drinkers increasing shopping frequency and purchases – is somewhat puzzling. If multiple-unit discounts were serving as effective second-degree price discrimination and the ban released the incentive compatibility constraints, then we might have expected those consumers not previously bulk buying, predominantly low and moderate consumption households, to buy more as retailers increased the use of straight discounts. However, we find little change for these households, and instead the increased quantity is due to high consumption households.

Even so, the intriguing aspect is the increased shopping frequency, since the replacement offers would have allowed high consumption households to continue buying in a single store visit, thereby avoiding the additional shopping costs associated with more frequent shopping trips (e.g., travel, time, and hassle). Budgeting to spread out expenses might be a reason, but we find no relationship based on income differences, and this alone does not explain the additional purchases. Instead, it appears that non-linear pricing was restraining heavy purchasers, committed to buying in bulk to obtain the volume discounts, but once the ban came into effect, then straight discounts removed that constraint, opening up the temptation to make additional store visits for further purchases. Two behavioral economics explanations fit this pattern. First, additional visits and purchases on discounted prices may provide additional transaction utility and segregate perceived gains (Thaler, 1985). Second, multiple unit discounts may facilitate commitment to buying only in bulk as a self-control device to space out purchases and ration consumption, whereas straight discounts allow for top-up purchases anytime, hence undermining that commitment (Thaler and Shefrin, 1981, Schelling, 1984).

Our findings run counter to two early analyses of the aggregate effect of the ban, where Robinson et al. (2014) find a small sales decrease while Nakamura et al. (2014) find no overall effect. However, both studies potentially suffer from aggregation biases, and do not account for price endogeneity as well as have several econometric limitations that we overcome in this paper.

Unlike our household data, Robinson et al. (2014) use Nielsen sales data aggregated at the week-country level and employ interrupted times series analysis to compare sales in Scotland with England and Wales. Thus, they ignore the heterogeneity in policy response by different types of households. As we later show, less than a third of households are responsible for more than three quarters of all alcohol purchases and they differ in how they responded to the policy. They also interpolate for several other covariates that are not available at weekly levels. For instance, they use weekly population estimates for each country to construct per capital weekly measures of alcohol per adult and obtain income measures for England and Wales by constructing differences between UK values and Scotland (yet the sales data is for

GB not UK). By contrast, while Nakamura et al. (2014) keep observations at the household level, they ignore variation in sales over time and collapse all weekly household observations into two single observations, a pre-ban total sales and a post-ban total sales per household (they expand to quarterly observations in a sensitivity analysis). We overcome both these problems and use weekly observations for each household, allowing zero purchases within any given week in our non-linear DD framework. Similarly, while Nakamura et al. (2014) ignore changes in prices by the retailers and have a potential omitted variable bias in their estimates, Robinson et al. (2014) include prices but treat them as exogenous. By contrast, we do not omit the prices and use control functions to account for endogeneity. Thus we believe that a careful reanalysis of the policy is warranted and we provide new estimates in this paper.

Taken together, our findings are novel in showing how a ban on volume discounts can aggravate rather than alleviate the problem of excessive consumption. Our results raise questions about the logic of such a ban in failing to appreciate how the conditional aspect of volume discounts may simultaneously serve as both an inducement and a constraint to buy in bulk, which heavy drinkers could use as a commitment device to avoid the temptation of making more frequent purchases. We put these findings and the salutary lessons they may offer into perspective and seek to contribute to the literatures and ongoing policy debates about alcohol affordability and the wider challenge of curbing excessive consumption of alcohol and unhealthy foods.

First, the paper contributes to the literature on the economic evaluation of alcohol policies seeking to raise prices to curb consumption. This literature predominantly focuses on taxation effects, finding significant variability in pass-through rates across different markets and competitive contexts (Nelson and Moran, 2019, Hindriks and Serse, 2019), with no guarantee that the tax will be fully passed on for cheap alcohol products where excessive consumption is most concerning (Ally et al., 2014, Wilson et al., 2021), and the need for potentially complex rate setting across different product types for optimal tax design (Griffith, O'Connell and Smith, 2019). Alternatively, regulated state control of prices or imposing minimum prices to prevent discounting provides a more assured way of maintaining high prices, but remains highly contentious as an overtly interventionist policy that curtails competition and could promote inefficiency (Miravete, Seim and Thurk, 2018, 2020, Griffith, O'Connell and Smith, 2020, Conlon and Rao, 2019, 2020). Instead, this paper considers a ban on volume discounts as less restrictive partial price regulation in an otherwise openly competitive market, with the intention of curbing bulk buying inducements while still allowing retailers to compete flexibly in their general pricing but without giving quantity discounts.

Second, the paper contributes to the wider literature on policies seeking to curb excessive consumption of products that are harmful to the individual (internalities) or impose costs on others and the state (externalities). This relates to so-called vice or sin products as forms of demerit goods, which offer immediate consumption pleasure but with personal costs (e.g. in the form of adverse health effects) and external costs (e.g., healthcare costs, crime, and reduced work productivity) that are underappreciated or ignored and where self-control is difficult (Wertenbroch, 1998). Policy options to reduce harmful consumption include restricting the availability and marketing of these products, usually with varying degrees of success, especially in respect of alcohol (Marcus and Siedler, 2015, Hinnosaar, 2016, Carpenter and Dobkin, 2017, Kueng and Yakovlev, 2021). Pigouvian style corrective taxes could in principle offset the externalities, but pose challenges in ensuring that they only target harmful consumption, which requires identifying and tagging specific products (e.g. cheap high strength alcohol or sugary drinks), purchasing situations (like discount retailing) and household types most prone to excessive consumption (Griffith, O'Connell and Smith, 2019, Dubois, Griffith and O'Connell, 2020). Corrective sin taxes become even more complex to design if they are to take suitable account of internalities and regressivity when the taxes fall disproportionately on low-income consumers (Allcott, Lockwood and Taubinsky, 2019). In contrast, imposing minimum prices entails direct regulation to reduce affordability as a way to lower consumption, and may be better targeted than standard commodity taxation, but it also proffers an industry profit windfall at the expense of consumers and reduced tax receipts (Calcott, 2019, Griffith, O'Connell and Smith, 2020). Instead, we examine the novelty of volume discount bans that could be widely applied, such as to alcohol and HFSS foods, and yet be politically more palatable than the complexity or regressivity of targeted sin taxes or the inflexibility and inflationary nature of imposing minimum prices. In this regard, following a lengthy consultation process and along with other new measures, the British government is set to ban volume price promotions on HFSS foods and drinks from October 2022, rather than extend sin taxes in the next phase of its national strategy to tackle obesity (DHSC, 2021). Accordingly, our findings may provide useful insights on how well this ban is likely to work, albeit involving different types of vice products.

The rest of the paper proceeds as follows. Section 2 sets out the background to the volume discount ban on alcohol sold in Scotland. Section 3 details the data, methodology and econometric specification. Section 4 reports results of the descriptive and econometric analysis, including robustness checks. Section 5 concludes. Online appendices provide additional information on the variables and the full set of regression coefficients.

2. Background

Scotland has faced a major public health challenge arising from excessive alcohol consumption for many years, with a quarter of the adult population drinking at hazardous or harmful levels, alcohol-related death rates considerably higher than other parts of Britain and amongst the highest in Europe, and with over half of all violent crime involving alcohol (Richardson and Giles, 2021). The Scottish government has responded to the alcohol challenge in several novel ways over the past decade.[2] In 2011, Scotland became the first country within the United Kingdom to ban volume discounts for off-trade retailers selling alcohol (which includes supermarkets, off-licences and convenience stores selling alcohol for consumption off the premises) as part of the Alcohol etc. (Scotland) Act 2010. The wording in the Act specified that the ban relates to "a package containing two or more alcoholic products (whether of the same or different kinds) may only be sold on the premises at a price equal to or greater than the sum of the prices at which each alcoholic product is for sale" (Scottish Parliament Act 2010).[3]

Accordingly, the ban relates to multiple-unit discounts, specifically banning quantity discounts for multipacks and multibuys, where units are purchased as a collection rather than purchased separately. Note that the ban does not cover different product sizes, such as requiring the unit price of a 70cl bottle of spirits not to be less than a 35cl bottle of the same brand. Furthermore, while multipacks are common for beer, they are less relevant to other alcohol categories, and even for beer the effect of the ban is muted because retailers rarely sell individual cans or bottles of beer of the same unit size that also go into multipacks. Instead, the main target of the ban is on multibuys, which feature extensively in sales of beer, cider, wine, and flavored alcoholic beverages (FABs), but less so for spirits.

[2]Notably, Scotland was the first country in the world to introduce comprehensive minimum unit pricing (MUP) in 2018. Our analysis predates the MUP introduction in focusing on the impact of the volume discount ban that commenced in 2011.

[3]The Act also provided for other supporting measures, included restricting the location of drinks promotions to within a single area of the store, the requirement of an age verification policy, powers to introduce a social responsibility levy on license holders, and a requirement for Health Boards to be notified of premises' license applications in their geographical area.

Both of these types of multiple-unit discounts operate as mixed bundling but differ in that multipacks are units physically packaged together, whereas multibuys exist as virtual packages, with the discount applied on individual items bought together. Multipacks are long-established for bulk buying consumer packaged goods, while multibuys have grown in prominence as price promotions, typically framed as 'buy/get' ('X + N free') offers, like 'buy one get one free' and '3 for 2', or deals that state a fixed price ('X for $Y') or saving on multiple units ('buy X and save Y%').

3. Data and Methods

3.1. **Sample and Variables.** Our main data are drawn from Kantar WorldPanel database which contains repeated information of purchases from grocery stores by a representative sample of households from Scotland, England and Wales. These data are increasingly used in research and they offer substantial advantages over other data sources (see e.g. Nakamura et al., 2014, Griffith, O'Connell and Smith, 2019, Dubois, Griffith and O'Connell, 2020). Each participating household uses a handheld scanner to record take-home purchases. For each product purchased in a given transaction, data include the quantity purchased and transaction prices together with information on type of promotion (if any), identity of the store/chain where it was purchased and the date of purchase. For each product, we also know its exact identity (via a unique product number) and manufacturer information along with physical characteristics such as type of package, number of units in the pack, size and strength of each unit (e.g., Carlsberg lager beer, 4 cans pack, 500 ml with 5% ABV), and selected nutrient values associated with each unit (calories, sugar, proteins, carbohydrates, fat, saturated fat, fibers, sodium, and an overall British Food Standard Agency (FSA) nutrient profiling score).[4] With each transaction, we have a household ID which is linked to a companion dataset on household socio-demographics that includes household size, social and economic status and main adult shopper information on age, education, ethnic status. Importantly, the geographic location of the household is also available at 4-digit postcode level (e.g. NR31).

We measured the aggregate volume of ethanol purchased by a household per week by multiplying the aggregate volume of alcohol purchased by its strength (ABV), divided by 1,000. The advantage of this approach is that it standardizes for differences in strength across

[4]Strength is measured as percentage of alcohol-by-volume (ABV, the number of milliliters of pure ethanol present in 100 ml of solution at 20 degree Celsius). For products with missing ABV, we performed online searches to impute their values.

products. Moreover, it is equivalent to the 'units of alcohol' (10ml of pure ethanol) measure used in UK and EU countries for measuring ethanol volume. Units of alcohol purchased per week were further divided by the number of adults in the household and log-transformed to account for the skewness of the data. Thus we have measures of units per adult per week for all alcoholic products combined (S00 - All) and by four alcohol segments: Spirits and Fortified Wines (S01 - Spirits for short: with unweighted mean ABV 30.15%); Ales, Lagers, and Ciders (S02 - Beers for short: unweighted mean ABV 4.83%); Wines and Sparkling Wines (S03 - Wines for short: unweighted mean ABV 12.11%) and Flavored Alcoholic Beverages (S04 FABs for short: unweighted mean ABV 5.68%).

For each transaction, we observe the list price of a given item (pack/bottle etc.), the associated promotion code (if any), and the total amount paid after promotion for the bundle or singleton of alcohol purchased. Thus we compute the price per unit of alcohol as the total expenditure paid after promotions, divided by the total units of alcohol purchased. We also use the information on the list prices to compute the associated discount per unit of ethanol as the difference between the list and transaction prices of the bundle. For each bundle we also compute the values of other characteristics (calories, sugar, etc. mentioned earlier) as the share weighted average of individual items in the bundle.[5] Similarly, we compute overall (S00) and segment-specific (S01-S04) prices per unit and discounts. In a given week, a household might not purchase any alcoholic product, so that the quantity variable is zero and prices are missing. However, rather than discard the observation, we assign a weekly price which corresponds to the average weekly price paid by other households for that segment in the same household group and region of UK (15 regions: 1 for Wales, 9 for England and 5 for Scotland). The same holds true for the discount and other product characteristics listed above.

In our sample, observations are over 83 weeks spanning from Jan/1/2011 to Jul/31/2012 and include only those households that made any purchase of alcohol during this period. The multibuy ban started on Oct/1/2011 which corresponds to week 41. We focused on only those households that were continuously enrolled during this period. We further restricted the analysis to households that purchased at least the equivalent of 5.5 British pints of typical beer (4.5% ABV) or more over weeks 2-12 inclusive (we omitted the first week of January as new year is celebrated later in Scotland). That is equivalent to 2 pints of beer per adult

[5]For instance, if a household purchases four beers and a bottle of wine, we compute share of expense on each item, and then use these weights to compute the mean value of calories per unit of alcohol.

per month.[6] This restriction discards households that purchase alcohol sporadically and are not of concern from a policy viewpoint. (Over the 11-week period excluded households purchased 3.61% of total alcohol.) We also discard households that lived within 35km of the Scottish-English border so as not to contaminate the analysis by those who can easily engage in cross-border purchases.

Table 1. Household consumption patterns (weeks 2-12)

HH-type	England & Wales	Scotland	Total
	Households (#)		
Low	2,565	220	2,785
Medium	2,568	225	2,793
High	2,568	230	2,798
Total	7,701	675	8,376
	Consumption (%)		
Low	7.59	6.82	7.62
Medium	18.8	18.5	18.8
High	73.6	74.7	73.6

Percentage based on total (per adult) purchase.

We grouped the remaining households into country-specific tertiles (HH-type = low, medium or high) of per-adult alcohol purchase over the first 11-week period. The final consumption pattern and the number of households per group and country are given in Table 1. This 11-week period was only used for classifying households in tertiles and was omitted from the main analysis. By construction, each household group has 1/3 of total observations per country. During the first 11 weeks, the HH-type=low were responsible for 7.60% of all alcohol purchases while the HH-type=high purchased about 73.6% of the total. These patterns are somewhat similar in England and Wales (EW) versus Scotland. This skewed pattern, where a third of the households are responsible for almost three quarters of all purchases, is consistent over the entire observational period used in the main analysis (weeks 13-83).

3.2. **Empirical Specification.** We use difference-in-differences (DD) and compare household alcohol purchase patterns before and after the ban was introduced in Scotland to households in England and Wales. We do so in the context of a panel setting where we observe each household for 71 weeks (weeks 13-83 inclusive) and where a household may or may

[6] In details, we required that the total household purchase per adult over weeks 2-12 be more than 14.113 units of alcohol. A British pint is 568ml and a typical beer is 4.5% ABV which is 25.56ml of ethanol. A unit of alcohol is 10ml of ethanol, and so one typical pint of beer is 2.556 units of alcohol.

not purchase any alcoholic product during a given week. Let y^*_{it} be the latent variable that represents (log of) quantity purchased per adult in household i in week t (henceforth we use the terms consumption, purchase and quantity interchangeably and assume no stockpiling) and is given by

$$y^*_{it} = \boldsymbol{x'_{it}}\boldsymbol{\beta} + \epsilon_{it} \quad = \beta_1 S_i + \beta_2 B_{it} + \beta_3(S_i B_{it}) + \boldsymbol{x}'_{4it}\boldsymbol{\beta}_4 + \boldsymbol{x}'_{5it}\boldsymbol{\beta}_5 + \epsilon_{it}. \tag{1}$$

In the equation above, S_i is an indicator variable set to one if the household is located in Scotland and zero otherwise. Similarly, B_{it} is also an indicator variable set to one in the post-ban period (week 41 onwards). We assume that ϵ_{it} is a mean zero standard normal error term (we allow for observations to be correlated over time for a given household), and so the latent variable has the same distribution as ϵ_{it}. We observe the latent variable if the value is greater than zero, so $y_{it} = \max\{0, y^*_{it}\}$. Accordingly, we estimate a random effects tobit model where the dependent variable is the log of quantity purchased per adult in a household (to avoid taking logs of zeros, we added 1 to the rate before logging, but an alternative transformation could be inverse hyperbolic sine, see Burbidge, Magee and Robb (1988)).

The vectors $\boldsymbol{x'_{4it}}$ and $\boldsymbol{x'_{5it}}$ are additional covariates assumed to influence purchase decisions. The vector $\boldsymbol{x'_{4it}}$ includes the group to which the household belongs (HH-type=low, medium or high), household socio-demographics (number of children in the house, social and economic status codes, age, age square, level of education and ethnic status of the main shopper in the house) and dummies for each 4-week period (month) to account for seasonality in purchase patterns. The vector $\boldsymbol{x'_{5it}}$ is included in some specifications and consists of log of price and of information on product characteristics and the discount variable described earlier.

In linear DD models, an identifying assumption is that the time effect is constant across groups and the group effect is constant across time. In turn, the treatment effect is constant across the treated population and allows for the construction of a counterfactual. By contrast, in non-linear models such as the tobit, the treatment effect is not constant across treated population, and hence identification is not straightforward (Athey and Imbens, 2006). Further, as pointed out by Ai and Norton (2003), even if the interaction term coefficient (which is the term of primary interest) is zero, the cross difference/derivative term is generally nonzero. However, as shown by Puhani (2012), in nonlinear but strictly monotonic functions, the interaction term is not equal to a simple cross-difference but rather a difference between cross-differences. Specifically, the interaction term is equal to the cross difference of the conditional expectation of the observed outcome minus the cross difference of the conditional expectation of the potential outcome without treatment (i.e., the counterfactual). Importantly, the treatment effect is equal to the difference in the cross-differences, and hence the sign of the treatment effect in non-linear monotone increasing DD models is equal to the sign of the coefficient of the interaction term.

The tobit specification given above is estimated for all alcohol segments combined ($\ln Y_{s00}$) and then separately by segments: spirits ($\ln Y_{s01}$), beers and ciders ($\ln Y_{s02}$) and wines ($\ln Y_{s03}$). The segment analysis would assess the presence of heterogeneous effects of the ban by alcohol types.[7] In these latter three segment specific estimations, the vector $\boldsymbol{x'_{5it}}$ includes prices of all four segments ($\ln p_{s01}, \ln p_{s02}, \ln p_{s03}$, and $\ln p_{s04}$) rather than just the price of own segment, thereby allowing for substitution or complementary effects.

3.3. **Endogeneity.** If we omit prices from the the tobit specifications (included in the vector $\boldsymbol{x_{5it}}$), the causal effect of the volume discount ban can be identified via the coefficient β_3 as long as the omitted prices are not correlated with any of the included variables. However, it is possible that retailers (or manufacturers) changed other alcohol promotion policies in Scotland in response to the ban on multiple-unit discounts, which in turn affects the price of a purchased bundle or multipack of alcohol. If so, this would imply that prices are correlated with covariates and particularly the interaction term ($S \times B$), causing the estimate of β_3 to be potentially biased due to omitted variable. A simple solution might be to just add the omitted price to the equation.

However, adding prices to the equation does not necessarily overcome the endogeneity problem either. This is because consumers can react to the policy change or the associated price changes of individual items, and adjust the contents of the bundle of alcohol they purchase by, for instance, substituting to cheaper items or those with different product characteristics. In effect then, because the consumers choose the contents of a bundle of alcohol, price may still endogenous due to unobserved bundle characteristics that are correlated with price and the quantity purchased. Since we observe many of these bundle characteristics, we add the vector $\boldsymbol{x_{5it}}$, which includes price and other bundle characteristics (including discount) to the specification. In turn this should attenuate the problem of correlation between price and the error term.

Nonetheless, we cannot rule out the possibility that other omitted demand side variables in the error term are not correlated with prices. For instance, display location within a

[7] As noted earlier, while FABs are expected to be affected by the ban, we omitted estimation of the FABs segment (Y_{s04}) due to very few sales in the observed period.

store may influence choice of items in the bundle and may be correlated with price. Such unobserved (to the econometrician) additional bundle characteristics would cause a bias in the estimated coefficients. To account for these, we include control functions for prices, using instrumental variables that we expect will affect retail prices but not directly the demand for alcohol. Specifically, following Griffith, O'Connell and Smith (2019), our instruments include monthly factory price indexes for beer, cider/fruit wines and an overall all alcoholic beverages index. We also use weekly exchange rates between sterling and US dollar and sterling and euro as these will affect prices of imported alcohols and import duties paid on them. One reason for regional price variation in the UK is the overall coverage by main grocery stores. Thus, we include the market share of chain grocery stores and others by region as additional instruments. Finally, we also use weekly diesel prices, as they would be cost shifters for retailers, and interact them with shares of grocery stores by regions. Variation in these instruments and their construction are described in detail in Appendix A.

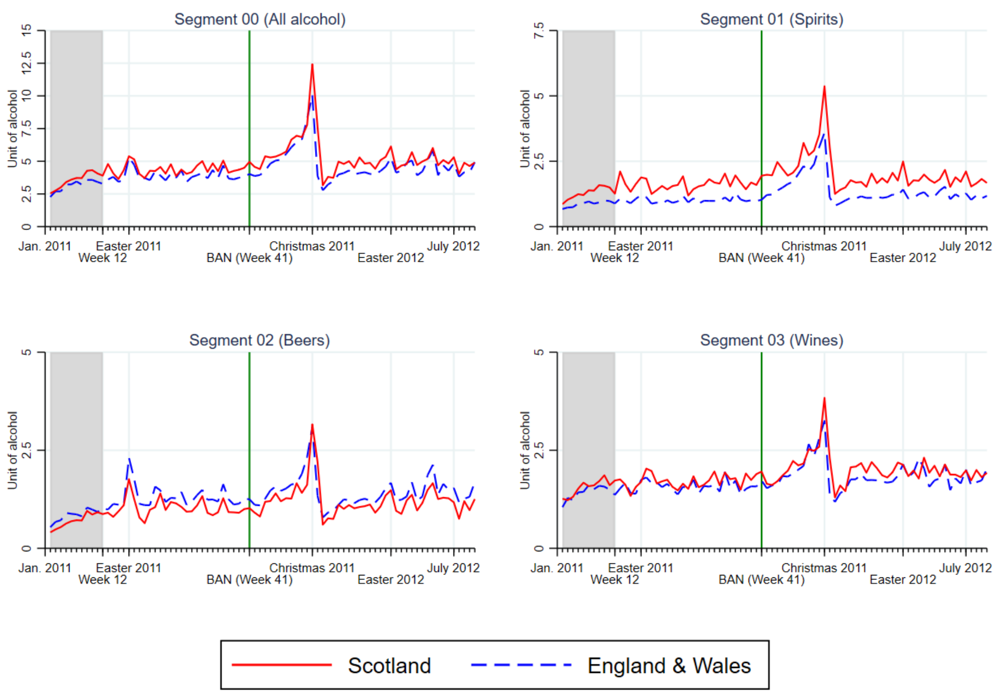
The control functions are constructed as residuals from first-stage regressions of log prices on all the exogenous variables plus the instruments listed above. Additionally, we allow the error terms to be correlated over time and use clustering by households. In order to obtain valid standard errors that account for both of these issues, we used block bootstrap by household and included the first and second stage (random effects) tobit within a draw by household with replacement (100 replications).

4. RESULTS

4.1. **Descriptive Analysis.** Figure 1 shows average consumption per adult by segment and country over the study period including weeks 2-12 (shown in gray) used for classifying households by HH-type. The vertical line marked as 'BAN (Week 41)' corresponds to Monday, Oct/3/2011 (the multiple-unit discount ban came into effect on Oct/1/2011). While alcohol consumption seems to be increasing as Christmas/New Year approaches, there is no real discernable difference in aggregate consumption patterns before and after the implementation of the policy across Scotland vs. England and Wales.

By contrast, Figure 2 shows a very clear drop in multibuy promotions in Scotland after the ban was imposed. The figure shows average household alcohol expenditure by promotion type – in the form of either a temporary price reduction (TPR), which is a straight discount, or a multibuy discount – as a percentage of total alcohol household expenditure by country and week. The top left panel reports trends for all alcoholic products combined (S00). In

FIGURE 1. Weekly (ln) purchase per adult



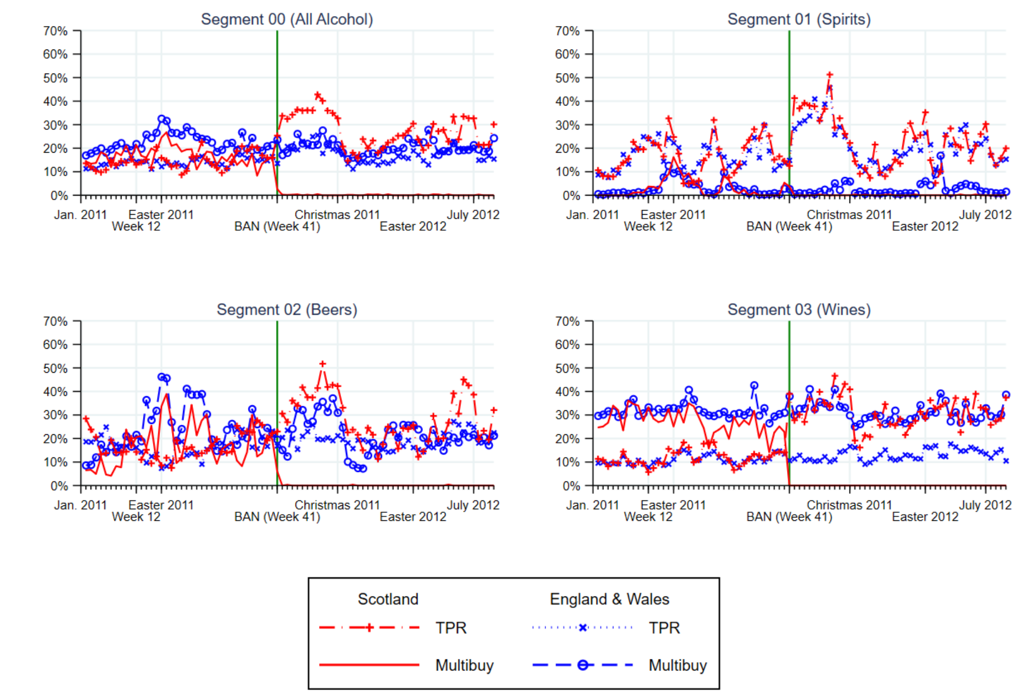
Week 12 (Starts March/14/2011); Week 41 (Starts Oct/03/2011)

week 41, the percentage of expenditure on multibuy promotions dropped to near zero in Scotland, while that on TPR jumped up from about 10% to around 30%. By contrast, there were no similar changes in the shares computed for England and Wales.

Further breakdown by segments shows that this change in promotion types is mostly in beers and wines segments (the lower two panels, S02 and S03). On the other hand, spirits (S01) were minimally affected by the ban. This is because multibuy promotions are not a typical promotion type for spirits; they were not used even before the ban came into effect and no discernible changes were found in the post-ban period.

4.2. **Price regressions.** Figure 2 for expenses by promotion type suggests that effective prices may have changed. To check this, we tested if in fact consumers in Scotland chose bundles with different prices after the ban was introduced. To this end, using household level weekly data, we estimated random effects linear regressions of log price on $S_i, B_{it}, S_i \times B_{it}$, household characteristics in $\boldsymbol{x}_{4it}$ as well as weekly dummies and other product characteristics listed in $\boldsymbol{x}_{5it}$. Selected regression coefficients are reported in Table 2. Except for spirits (S01), we find a small but statistically significant reduction in prices for bundles selected by

FIGURE 2. Percent Expenditures by Promotion Type



Week 12 (Starts March/14/2011); Week 41 (Starts Oct/03/2011)

consumers in Scotland after the ban and is most evident for beers (S02) and wines segments (S03).

TABLE 2. Reduced form regressions for (ln) prices

	(1) $\ln p_{s00}$	(2) $\ln p_{s01}$	(3) $\ln p_{s02}$	(4) $\ln p_{s03}$	(5) $\ln p_{s04}$
B: PostBan	0.020^a	0.051^a	0.021^a	0.010^a	0.004
	(0.002)	(0.001)	(0.001)	(0.001)	(0.005)
S: Scotland	-0.004^c	0.007^a	0.006^a	0.003^c	-0.081^a
	(0.002)	(0.001)	(0.002)	(0.001)	(.003)
$S \times B$: Scotland$\times$PostBan	-0.006^a	-0.001	-0.010^a	-0.013^a	0.031^a
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)

Superscripts a, b, c indicate significance at 1%, 5% and 10%, respectively. Regressions are at household level and include random household effects, observable household characteristics, other product characteristics and time dummies. Standard errors are clustered by household.

4.3. **Tobit Estimates.** The tobit specifications were estimated for all segments and we added in price and bundle characteristics (x_{5it}) sequentially, followed by control functions to further account for endogeneity. This allows us to measure the total effect of the ban, as well as the effect net of any price changes. We further estimated the models by household types. However, since there is a very large number of variables in each regression (vectors $\boldsymbol{x}_{4it}$ and $\boldsymbol{x}_{5it}$ described earlier), for sake of brevity we report and discuss here only the marginal effects of select variables of interest. The full set of all regression coefficients is available in the online Appendix B. Specifically, we report $\beta_k\Phi(\cdot)$ where Φ is the CDF for the normal distribution, and refer to this term as the left censored marginal for the associated variable.[8] The marginal effects are computed at the sample mean values and over 4-weeks immediately following the ban.[9]

TABLE 3. Marginals ($\beta_k\Phi(\cdot)$) for segment S00 (All Alcohol)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
$S \times B$: Scotland×PostBan	0.086^a	0.086^a	0.077^a	-0.004	0.074^a	0.195^a
	(0.014)	(0.013)	(0.018)	(0.023)	(0.030)	(0.035)
$\ln p_{s00}$: ln price ethnol		-0.809^a	-1.384^a	-1.091^a	-1.317^a	-1.793^a
		(0.016)	(0.073)	(0.120)	(0.122)	(0.128)
d_{s00}: segment discount		0.450^a	0.442^a	0.163^a	0.426^a	0.706^a
		(0.015)	(0.032)	(0.049)	(0.054)	(0.063)
Sample	594,696	594,694	594,694	197,735	198,302	198,657
Households	8,376	8,376	8,376	2,785	2,793	2,798
Prices?	✗	✓	✓	✓	✓	✓
Control functions?	na	✗	✓	✓	✓	✓

Superscripts a, b, c indicate significance at 1%, 5% and 10%, respectively. All standard errors are clustered by household. Columns (3-6) show bootstrapped (and clustered) standard errors.

All regressions include household characteristics, a dummy for country, a dummy for pre-post ban and a dummy for each month. Columns (1,2,3) additionally contain dummy variables for type of household (low, medium and high) while columns (4,5,6) provide sub-analysis by HH-type.

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and observable product characteristics. Column (3) adds in control variables as residuals from first-stage regressions where price is regressed on exogenous variables and additional excluded instruments. Columns (4,5,6) are similar to (3) but restrict that sample by household types.

[8]For a non-interactive variable x_k, the left censored marginal is given by $\partial E(\ln y|X_i)/\partial x_k = \beta_k\Phi(\cdot)$ and we provide it here for the interactive term as well. Results from truncated marginal, i.e., $\partial E(\ln y|X_i, y_i > 0)/\partial x_k$ are similar and omitted in interest of space.

[9]Our specifications include dummies for each 4-week period, and the marginal effects are calculated with the dummy for the first 4-week period following the ban equal to one.

4.3.1. *Overall analysis - S00.* Table 3 reports marginals (i.e., $\beta_k\Phi(\cdot)$) for the overall alcohol segment (S00). Following the ban, there is clear evidence of an overall increase in alcohol purchase. Without controlling for prices, discount and product attributes (Column 1), alcohol purchase went up by 8.6% in the post-ban period. This result holds when controlling for prices, discount and product attributes (Column 2). In this same column, the marginal effect for log price is -0.809 and for the discount it is 0.450 (meaning own-price elasticity is -0.809% and a 10p increase in discount changes the quantity purchased by 4.50%).

In column (3) we add the control function. Doing so attenuates the overall effect of the ban as the marginal effect changes from 8.6% to 7.7%. Observe also that the price elasticity increased in magnitude from -0.809 to -1.384. The next three columns report the analysis in column (3) by household types (HH-type: low, medium and high). The impact of the ban is not present in low consumption households, i.e., the marginal on the interaction term is not statistically significant, but in medium and high consumption households it is positive, significant and progressively increases in magnitude (7.4% and 19.5% in columns 5 and 6). Additionally, the sensitivity to price also increases as we move from low to high consumption households.

Columns (3) onwards rely on the use of instruments described earlier. While the exogeneity condition of our instruments is credible (as they are cost shifters and would not directly affect demand except through prices), their relevance in determining prices is largely an empirical issue. Table A-2 provides first-stage F-tests for joint significance of the excluded instruments (weak instruments tests). For the overall alcohol segment (segment S00), this value is 44.2 indicating that we can reject the null hypothesis of no relationship between price and excluded instruments. Similarly, the F-tests associated with the HH-type analysis are 32.6 for low, 20.3 for medium and 14.0 for high.[10] The first-stage residuals from these regressions are added as control functions in the second stage tobit models and were all statistically significant (the regression coefficients are given in the online Appendix B). Further, adding in the control functions results in negative and larger in magnitude own-price coefficients.

4.3.2. *Segment Analysis - S01,S02 and S03.* We repeated the analysis above for each segment separately. Table 4 summarizes marginal effects (i.e., $\beta_k\Phi(\cdot)$). The top panel of the table for the spirits segment shows minimal negative net impact of the ban for all households combined. It becomes significant at the 5% level only for medium level households and their

[10] Table A-2 also provides first-stage F-tests for segment level analysis to follow. In each case, the F-test values are large and hence reject a null hypothesis that there is no relationship between our instruments and prices.

overall purchased quantity declined by about 4.6%. This result is in line with the observation that the multiple-unit discount ban was not a binding constraint, as this type of promotion was hardly used for spirits (see Figure 2). However, there were other supporting measures in the legislation (see footnote (3)) that could have had a marginal effect, such as restricting the in-store display area. For instance, if alcohol can no longer be displayed at checkout counter, this would not act as a potential reminder to medium level drinkers about purchase, while the low and heavy drinkers would not be tempted or reminded by it anyway. Our results show a net decrease among medium level consumers, but neither the high nor low HH-type were affected. Price sensitivity increases by HH-type, and adding in control functions increases the magnitude of the price coefficient relative to when it is omitted. Also, the cross-price effects become positive (and often significant) after adding in the control functions.

TABLE 4. Marginals ($\beta_k\Phi(\cdot)$) by segment

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
			Segment S01 (Spirits)			
$S \times B$: Scotland×PostBan	-0.004	-0.009	-0.016	-0.016	-0.046^b	-0.002
	(0.009)	(0.009)	(0.014)	(0.012)	(0.022)	(0.028)
$\ln p_{s01}$: ln price sprits		-0.214^a	-1.958^a	-0.230^b	-1.726^a	-3.228^a
		(0.012)	(0.186)	(0.100)	(0.279)	(0.325)
$\ln p_{s02}$: ln price beers		-0.030^a	0.225^a	0.071^c	0.324^a	0.263^a
		(0.008)	(0.036)	(0.041)	(0.076)	(0.078)
$\ln p_{s03}$: ln price wines		-0.029^a	0.230^a	0.100	0.256^a	0.340^a
		(0.008)	(0.051)	(0.064)	(0.095)	(0.105)
$\ln p_{s04}$: ln price FABs		-0.003	0.126^a	0.020	0.049	0.274^a
		(0.006)	(0.033)	(0.032)	(0.040)	(0.091)
d_{s01}: segment discount		0.576^a	-0.055	0.032	-0.185	0.886^a
		(0.045)	(0.122)	(0.089)	(0.206)	(0.198)

Superscripts a, b, c indicate significance at 1%, 5% and 10%, respectively. All standard errors are clustered by household. Columns (3-6) show bootstrapped (and clustered) standard errors.

All regressions include household characteristics, a dummy for country, a dummy for pre-post ban and a dummy for each month. Columns (1,2,3) additionally contain dummy variables for type of household (low, medium and high) while columns (4,5,6) provide sub-analysis by HH-type.

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount for the segment and observable product characteristics. Column (3) adds in control variables as residuals from first-stage regressions where each price variable is regressed on exogenous variables and additional excluded instruments. Columns (4,5,6) are similar to (3) but restrict that sample by household types.

Table 4. Marginals ($\beta_k \Phi(\cdot)$) by segment

Sample Households	(1) All	(2) All	(3) All	(4) Low	(5) Medium	(6) High
			Segment S02 (Beers)			
$S \times B$: Scotland×PostBan	0.062^a	0.051^a	0.034^a	-0.011	0.054^a	0.068^a
	(0.008)	(0.008)	(0.009)	(0.012)	(0.019)	(0.024)
$\ln p_{s01}$: ln price sprits		0.014^b	0.169^a	0.079^a	0.182^a	0.276^a
		(0.007)	(0.022)	(0.023)	(0.037)	(0.052)
$\ln p_{s02}$: ln price beers		-0.365^a	-1.138^a	-0.635^a	-0.984^a	-1.824^a
		(0.015)	(0.064)	(0.090)	(0.112)	(0.159)
$\ln p_{s03}$: ln price wines		-0.053^a	0.138^a	0.126^a	0.110^c	0.130^b
		(0.006)	(0.029)	(0.042)	(0.067)	(0.060)
$\ln p_{s04}$: ln price FABs		0.001	0.093^a	0.063^a	0.054^b	0.176^a
		(0.004)	(0.019)	(0.020)	(0.024)	(0.053)
d_{s02}: segment discount		0.111^a	0.091^a	0.022	0.132^a	0.107^c
		(0.011)	(0.023)	(0.031)	(0.042)	(0.056)
			Segment S03 (Wines)			
$S \times B$: Scotland×PostBan	0.033^a	0.028^a	0.005	-0.019	-0.008	0.042
	(0.009)	(0.009)	(0.012)	(0.014)	(0.022)	(0.028)
$\ln p_{s01}$: ln price sprits		0.019^b	0.130^a	0.040	0.225^a	0.224^a
		(0.009)	(0.026)	(0.025)	(0.055)	(0.069)
$\ln p_{s02}$: ln price beers		-0.024^a	0.231^a	0.122^a	0.235^a	0.274^a
		(0.007)	(0.040)	(0.038)	(0.057)	(0.081)
$\ln p_{s03}$: ln price wines		-0.434^a	-1.324^a	-0.594^a	-1.345^a	-2.104^a
		(0.016)	(0.094)	(0.106)	(0.146)	(0.207)
$\ln p_{s04}$: ln price FABs		-0.001	0.067^a	0.016	0.089^a	0.067
		(0.005)	(0.023)	(0.032)	(0.030)	(0.074)
d_{s03}: segment discount		0.192^a	0.113^a	0.073^b	0.097^b	0.175^a
		(0.010)	(0.022)	(0.036)	(0.039)	(0.046)
Sample	594,696	584,067	584,067	193,673	193,088	197,306
Households	8,376	8,376	8,376	2,785	2,793	2,798
Prices?	✗	✓	✓	✓	✓	✓
Control functions?	na	✗	✓	✓	✓	✓

Superscripts a, b, c indicate significance at 1%, 5% and 10%, respectively. All standard errors are clustered by household. Columns (3-6) show bootstrapped (and clustered) standard errors.

All regressions include household characteristics, a dummy for country, a dummy for pre-post ban and a dummy for each month. Columns (1,2,3) additionally contain dummy variables for type of household (low, medium and high) while columns (4,5,6) provide sub-analysis by HH-type.

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount for the segment and observable product characteristics. Column (3) adds in control variables as residuals from first-stage regressions where each price variable is regressed on exogenous variables and additional excluded instruments. Columns (4,5,6) are similar to (3) but restrict that sample by household types.

The second part of Table 4 provides marginals for the beers and ciders segment. The descriptive statistics have documented the relevance of promotions applied in this alcohol segment and the significant changes in prices and discounts occurred in Scotland following the ban. Marginals reflect this: the estimated net impact of the ban is of about 6.2% in column (1) but reduced when controlling for prices to almost halve (3.4%) in column (3). While the low HH-type group was largely unaffected by the ban, an increase of 5.4% and of 6.8% in the purchased quantity was estimated in medium and high HH-types. As before, adding in the control functions results in negative and larger in magnitude own-price coefficients, while the price coefficients of other alcohol segments become almost all positive and significant.

Finally, the third part of Table 4 provides marginals for the wines segment. While the net effect of the ban is positive and significant (+2.8% increase), this seems to be driven mostly by the associated price changes. The effect of the ban is eliminated when we add in the price and control functions (see column (3)). As before, adding in the control functions results in negative and significantly larger in magnitude own-price coefficients, while the price coefficients of other alcohol segments become almost all positive and significant. Further, as columns (4) and (6) reveal, while the effect of the ban is not statistically significant for either group after accounting for endogeneity of prices, the sign is negative for low HH-types and positive for high HH-types. Results not shown here – by HH-type and without adding in prices – also show negative and positive marginal effects for low and high types respectively but were statistically significant in those cases. In turn it shows that the net effect of the ban worked through prices but in opposite direction for the low and high HH-types.

4.4. **Visits per week.** The foregoing analysis indicates that overall alcohol quantity increased, especially for the beer segment, in the post-ban period in Scotland despite controlling for the price decreases observed in most segments. This is the exact opposite of the expected policy outcome, begging the question of why consumers responded this way.

One possibility is that shopping patterns changed. The presence of volume discounts may simultaneously provide both a financial inducement and a constraint to bulk buy. With the ban in place, though, and replacement of multibuys with straight discounts, the constraint is removed even if the incentive and ability to buy on discount still exists, allowing for both buying in bulk and for extra incremental purchases. The implication is that consumers could then spread out their purchases over time, rather than focus their buying on single large shopping trips. Moreover, beyond any budgeting benefit that this may afford, there may be psychological drivers to increase shopping trips, either to gain additional transaction utility and segregate perceived gains from buying on straight discounts, in line with Thaler (1985), or because the absence of multibuys made it harder to commit to spaced out shopping trips and avoid top-up shopping, in line with Thaler and Shefrin (1981) and Schelling (1984).

To illustrate the latter possibility, consider a consumer who makes a fixed number of visits per week to grocery stores to purchase alcohol for the entire week. Prior to the ban, she takes into account the non-linear prices and purchases four packs of her favorite alcohol where the fourth unit is at a lower price per unit. If she runs out of alcohol before the end of the week, she waits until the next week to purchase a similar total amount for the next week, rather than buy a fifth unit at a higher marginal price. However, after the multiple-unit discount ban is imposed, so all units are sold at the same uniform price, the marginal price of the fifth unit of alcohol is the same as that of the earlier four units. In this case she might be willing to make an additional visit to the store during the same week to purchase the extra unit of alcohol, and end up purchasing as much as in any other visit.

Whether it is about better budgeting, segregating perceived transaction utility gains, or weakened ability to commit to limiting store visits, one might expect that higher consumption households with a greater desire for additional alcohol may be more susceptible to increasing the number of store visits after the ban. To test this hypothesis, we computed the total number of alcohol purchase visits per week for each household and used it as the outcome variable in our DD design. Specifically, using the count of number of shop visits per week as the dependent variable, we estimated the random coefficients poisson models with over-dispersion (i.e., negative binomial models to allow the variance of the dependent variable to be larger than its mean).[11] Table 5 shows the results, revealing that the mean number of visits increased for medium and, especially, for high consumption households in line with the hypothesis of increased shopping frequency.

We further investigated whether this pattern was driven by income differences, so essentially about budgeting. Note, though, that the regressions reported above already control for household characteristics including their income level. Nevertheless, we performed two further tests using additional count models by sub-samples of income groups. If the pattern was simply about the desire to smooth spending and better budgeting, then we might expect upon restricting the low drinking households in column (2) to just the lowest-income

[11] Since we allowed for clustering, over-dispersion can be rejected in favor of a simple poisson estimate. In models without clustering, over-dispersion is not rejected and hence the negative binomial is preferred in that case. In fact, the mean and variance of visits per week are not too different (given in the table) and hence the poisson model may be appropriate.

Table 5. Poisson regression (visits per week)

Sample Households	(1) All	(2) Low	(3) Medium	(4) High
Visits (mean)	0.588	0.313	0.491	0.959
Visits (variance)	(0.676)	(0.310)	(0.459)	(1.034)
S: Scotland	0.054^c	0.034	0.068	0.085^c
	(0.032)	(0.069)	(0.050)	(0.051)
B: PostBan	0.035^a	0.058^b	0.019	0.036^a
	(0.009)	(0.023)	(0.017)	(0.013)
$S \times B$: Scotland-PostBan	0.078^a	-0.025	0.073^a	0.112^a
	(0.017)	(0.044)	(0.028)	(0.023)
alpha (log of)	-0.842	-0.653	-0.866	-1.021
(dispersion parameter)	(1.304)	(2.152)	(2.238)	(2.299)
Sample	594,696	197,735	198,303	198,658
Households	8,376	2,758	2,793	2,798

Superscripts a, b, c indicate significance at 1%, 5% and 10%, respectively. All standard errors are clustered by household. All regressions include household characteristics and monthly dummy variables. Column (1) includes observations from all households while columns (2,3,4) restrict by HH-type (low, medium, high).

households in our sample (annual income less than £20K) that the non-significant -0.025 coefficient on the interaction term may become positive and significant. Conversely, if we restrict the highest drinking households in column (4) to the most well-off households among them (annual income above £60K), then the significant and positive coefficient of 0.112 on the interaction term may no longer be significant and possibly even negative (as this group would not be budget constrained and may want to have fewer visits due to higher opportunity costs). Neither of these tests turned out to be true and the results by all the income sub-samples stayed the same as those reported above in Table 5. (These additional results are available upon request).

Similarly, we also computed the average amount of alcohol purchased per trip, rather than per week, for each household both before and after the ban (using just two values for each household computed from all the trips in the pre- and post-ban periods). In a similar DD design as above, the interaction term did not show a decrease in the amount of alcohol purchased per trip in Scotland after the ban relative to England and Wales by any of the household consumption types.

Taken together, the additional analyses point to increased shopping frequency and purchases after the ban being more than simply due to budgeting, lending credence to the aforementioned behavioral arguments as well as leaving open the possibility of other unmodeled factors.

4.5. **Robustness.** We report here the sensitivity of our main results (marginal effects of the interaction terms $S \times B$) to (i) the sample selection criteria, (ii) econometric specifications, and (iii) aggregation of data over time or households.

4.5.1. *Sample selection criteria.* Our sample comprises of households living in Great Britain. We checked the robustness of our finding to (i) the exclusion (from the control group) of respondents living in Wales and, (ii) to the inclusion of households living within 35 km of the Scottish-English border which were excluded from the main analysis. When re-run our main models under these new sample selection criteria, the estimated effects were only marginally influenced, reflecting their residual role in determining our main results.

4.5.2. *Linear models.* Because of the large predominance of zeros in the weekly data, the tobit estimator seems to be a good choice to treat zero purchase as a corner solution problem. Nonetheless, we also estimated all the earlier models by ignoring the problem of zero purchases and using linear specifications including observations when a household did not purchase any alcohol within a week.[12] Thus, we estimated the models as linear random effects models, with and without price and bundle characteristics, and with and without treating price as endogenously determined (i.e., with and without the control function approach). From all these cases, the results in terms of signs and significance were consistent with those reported in the main analysis, albeit the magnitudes of the marginal effects were different. Estimates of the coefficients on the interaction $S \times B$ are summarized in Table 6.

4.5.3. *Aggregation over time.* The raw data are at trip level and we aggregated the observations to weekly levels. If instead we aggregate to the monthly level, then the predominance of households with zero purchases reduces significantly. However, the error in prices increases as now we assign a single price to four weeks of purchases even though stores often change prices at a higher frequency. Nonetheless, the analysis at the monthly level confirms previous findings in terms of the sign and significance of the $S \times B$ parameter, albeit the marginal effects were found to be slightly higher in magnitude and significant at 10% level for the

[12]By restricting the analysis to observations having positive purchases only, we would ignore the possible impact of the ban at the extensive margin, introducing biases in the analysis.

TABLE 6. Marginals for linear model: coefficient on $S \times B$

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
			$\beta_3/(s.e.)$			
Segment S00 (All Alcohol)	0.080^a (0.016)	0.090^a (0.016)	0.082^a (0.017)	0.001 (0.024)	0.075^a (0.027)	0.172^a (0.029)
Segment S01 (Spirits)	0.011 (0.012)	0.004 (0.012)	-0.001 (0.014)	-0.007 (0.011)	-0.025 (0.017)	0.002 (0.028)
Segment S02 (Beers)	0.066^a (0.010)	0.050^a (0.011)	0.032^a (0.012)	-0.019 (0.017)	0.058^a (0.020)	0.052^c (0.028)
Segment S03 (Wines)	0.036^a (0.013)	0.037^a (0.014)	0.015 (0.014)	-0.026 (0.018)	-0.004 (0.024)	0.048^c (0.028)

Superscripts a, b, c indicate significance at 1%, 5% and 10%, respectively. All standard errors are clustered by household. Columns (3-6) show bootstrapped (and clustered) standard errors.

All regressions include household characteristics, a dummy for country, a dummy for pre-post ban and a dummy for each month. Columns (1,2,3) additionally contain dummy variables for type of household (low, medium and high) while columns (4,5,6) provide sub-analysis by HH-type.

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and observable product characteristics. Column (3) adds in control variables as residuals from first-stage regressions where price is regressed on exogenous variables and additional excluded instruments. Columns (4,5,6) are similar to (3) but restrict that sample by household types.

high consumer group in the spirits (S01) and wines (S03) segments. A further problem with monthly analysis is the relatively weaker association between monthly average price and our instruments as the first stage F-stats were quite low and often below a value of 10. Thus, the weekly analysis remains our preferred approach.

4.5.4. *Aggregation over households.* Our main analysis is performed at the household level. An alternative is to aggregate over households by regions and by week (which also removes the predominance of zeros, but then ignores heterogeneity in purchase patterns by household types). We tested the robustness of our findings to a regional level aggregation (recall we have 15 regions). Specifically, we estimated linear regressions overall (S00) and by segments (S01-S03) over a sample collapsed at regional level and weighted by (segment-specific) purchased quantities. For this analysis, we did not account for the endogeneity of weekly (regional) prices. While the signs of the $S \times B$ parameter are in line with those reported in the main analysis, the net effects were found to be statistically significant only for the S00 analysis (p-value≤ 0.001).

4.5.5. *Parallel trends.* The main assumption of the DD model is the 'parallel trends' assumption. That is, without the ban, time trends in the household alcohol purchase patterns would have been parallel in Scotland and England and Wales. The graphical inspection of Figure 1 suggests that treated and control countries had similar trends in the period prior to the ban (weeks 13-39) and that the common trends is a reasonable assumption. We tested whether the trends in alcohol consumption were parallel in the pre-ban period, by estimating the random effects linear regression model for (log) quantities which included a polynomial in time up to the cubic term, and its interaction with the country indicator. We then tested for the joint significance of the interaction terms being zero using an F-test. The p-values of the F-tests are reported in Table 7.

Table 7. Pre-ban parallel trends test (p-values)

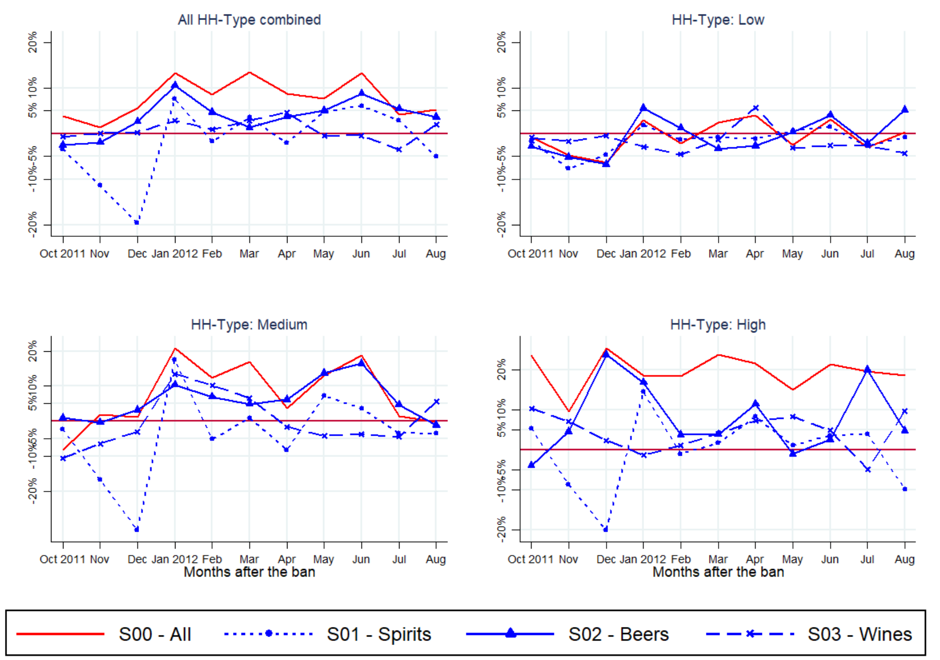
Sample Households	(1) All	(2) Low	(3) Medium	(4) High
Segment S00 (All Alcohol)	0.017	0.117	0.859	0.051
Segment S01 (Spirits)	0.186	0.251	0.570	0.213
Segment S02 (Beers)	0.103	0.713	0.166	0.335
Segment S03 (Wines)	0.205	0.534	0.232	0.369

All reduced form regressions on log quantity (linear random effects model) include household characteristics, product characteristics, time, time square, time cube, a country dummy and interaction of country dummy with time trends. The p-values are reported for the joint F-test with a null that the interaction terms are zero.

At the 5% significance level, we do not reject the parallel trend assumption for any of the individual alcohol segments or by household groups. However, the null of parallel trend is rejected (p-value = .017) for the combined analysis, i.e., all household groups and all alcohol (S00, HH-type = All). We re-tested the pre-ban parallelism with a tobit specification. Conclusions are mostly similar with the exception that we also reject pre-ban trend parallelism in the S00 segment for the HH-type=high group as well (see Table A-3 in the appendix). Overall these results suggest that the DD design method is suitable for identification in this context.

4.5.6. *Persistent Effects.* In the main analysis, the interaction term $S \times B$ enters the equation to capture the overall effect of the ban in Scotland. The coefficient on this interaction term captures the average effect over all postban periods in our dataset (weeks 41-83) and its marginal effect is evaluated at the single 4-week post-ban period. In other words, we assumed that the ban has caused a parallel shift in trends, but that is not necessarily the case if the impact evolved over time. For instance, it is possible that the effect of the ban diminishes over time. Since we do not have clear reasons to assume a particular functional form for the policy response path, we re-estimated the model in two different ways.

Figure 3. Marginals of the interaction terms $S \times B$ over time



First, we re-estimated all the models but replaced the interaction term $S \times B$ with $\sum_j S \times B \times \tau_j$ where τ_j is a 1/0 dummy equal to one if the observation is from the month j. This allow us to estimate a flexible policy response path at the cost of increasing considerably model complexity and overfitting (AIC/BIC goodness-of-fit statistics were higher than the main specification). Figure 3 displays the estimated marginal net effects of the ban across alcohol segments and household types in the post-ban period. To reduce the clutter in the figure we have not drawn confidence intervals on these coefficients, but it is straightforward to infer that lines close to zero are not statistically significant. Nonetheless, we observe that for all types of alcohol combined (S00), and for beers and ciders (S02) in particular, the net impact of the ban on consumption is positive and well above the zero line for most of the post-ban observed time window, notably for high consumption group (see bottom right panel).

Second, rather than using the data for all the post ban periods (weeks 41-83), we included only a 4-weeks post-ban window, restricted to be (i) immediately after the ban (weeks 41-44), (ii) 3 months after the ban (weeks 53-56), (iii) 6 months after the ban (weeks 67-70) and

(iv) last four weeks of our data series (weeks 80-83). Results were overall consistent with our main results and showed significance on the interaction terms for the same products and households. (We have omitted these for brevity but they are available upon request).

5. Summary and Conclusions

Volume discounts are designed to encourage consumers to buy more. In principle, banning these discounts should lead to consumers buying less. Our results do not support this finding. Following the ban on multiple-unit discounts on alcohol sales in Scotland, which commenced in October 2011, we observe retailers complying with the ban but switching to make much greater use of straight (single unit) discounts, which helped maintain sales levels.

Two prior studies, Nakamura et al. (2014) and Robinson et al. (2014), which focus on population-level effects but with different aggregation problems, report mixed results, as either nil or some overall effect in curbing alcohol purchases at the population level. Instead, our focus is on the impact on different household types according to their alcohol consumption levels. We find that the ban had little effect on purchases made by low and moderate consumption households but resulted in a distinct increase for high consumption households, as they increased their shopping frequency and spread their purchases. While not expected in the policy design, these outcomes fit with behavioral economics explanations in respect of segregating transaction utility (Thaler, 1985) and being less able to resist making extra top-up purchases (Thaler and Shefrin, 1981, Schelling, 1984).

We are mindful that our analysis only considers a relatively short period following the introduction of the ban, and it could be that market outcomes changed in subsequent years. Even so, our findings support the UK government decision in July 2013 for England and Wales not to follow Scotland in introducing a similar ban in view of the lack of evidence that a ban on multibuy promotions reduces harmful alcohol consumption.

The original intention of the Scottish government was to initiate the ban on volume discounts alongside introducing minimum unit pricing (MUP), which was delayed until 2018 but early indications point to reduced purchases by high consumption households since then (Griffith, O'Connell and Smith, 2020). In this context, the policy combination could be effective when MUP limits the ability of retailers to offer deep straight discounts or deep volume discounts for large size containers and multipacks. On this basis, a volume discount ban may work well in tandem with other measures affecting alcohol affordability, if not so well on its own.

Finally, in terms of possible lessons for other contexts, a ban on multibuys in the UK for HFSS foods and drinks is due to come into force in October 2022 (DHSC, 2021). Again, this volume discount ban focuses on multibuy offers and does not apply to different container sizes. On this basis, the ban could fail for similar reasons as we find with the multiple-unit discount ban on alcohol in Scotland. In particular, the ban might trigger retailers to switch to using more straight discounts as a way to maintain sales. Indeed, British retailers have already been moving in this direction on their own accord, with at least one major retailer entirely abandoning the use of multibuys on HFSS foods (Kantar Worldpanel UK, 2020). However, there are two subtle but important differences between the contexts to suggest that the multibuys ban on HFSS foods may be more effective than that on alcohol. First, to the extent that consumers are willing to substitute between HFSS and non-HFSS foods, a volume promotion ban on the former may highlight better value on the latter (where multibuys will still be allowed), encouraging consumers to switch to healthier foods. Second, while multibuys on alcohol may help with regular bulk buying that could continue in the absence of the offers, multibuys on HFSS foods are strongly associated with impulse purchases (Kantar Worldpanel UK, 2020). Thus, the absence of such offers may mean fewer HFSS food purchases and potentially thereby less consumption.

References

Adams, William James, and Janet L. Yellen. 1976. "Commodity bundling and the burden of monopoly." *Quarterly Journal of Economics*, 90(3): 475–498.

Ai, Churong, and Edward C. Norton. 2003. "Interaction terms in logit and probit models." *Economics Letters*, 80(1): 123–129.

Allcott, Hunt, Benjamin B. Lockwood, and Dmitry Taubinsky. 2019. "Regressive sin taxes, with an application to the optimal soda tax." *Quarterly Journal of Economics*, 134(3): 1557–1626.

Ally, Abdallah K., Yang Meng, Ratula Chakraborty, Paul W. Dobson, Jonathan S. Seaton, John Holmes, Colin Angus, Yelan Guo, Daniel Hill-McManus, Alan Brennan, and Petra S. Meier. 2014. "Alcohol tax pass-through across the product and price range: do retailers treat cheap alcohol differently?" *Addiction*, 109(12): 1994–2002.

Armstrong, Mark. 2016. "Nonlinear pricing." *Annual Review of Economics*, 8(1): 583–614.

Athey, Susan, and Guido W. Imbens. 2006. "Identification and inference in nonlinear difference-in-differences models." *Econometrica*, 74(2): 431–497.

Burbidge, John B., Lonnie Magee, and A. Leslie Robb. 1988. "Alternative transformations to handle extreme values of the dependent variable." *Journal of the American Statistical Association*, 83(401): 123–127.

Calcott, Paul. 2019. "Minimum unit prices for alcohol." *Journal of Health Economics*, 66: 18–26.

Carpenter, Christopher, and Carlos Dobkin. 2017. "The minimum legal drinking age and morbidity in the united." *The Review of Economics and Statistics*, 99(1): 95–104.

Conlon, Christopher T., and Nirupama L. Rao. 2019. "The price of liquor is too damn high: alcohol taxation and market structure." New York University NYU Wagner Research Paper 2610118.

Conlon, Christopher T., and Nirupama L. Rao. 2020. "Discrete prices and the incidence and efficiency of excise taxes." *American Economic Journal: Economic Policy*, 12(4): 111–43.

DHSC. 2021. "Consultation outcome: Restricting volume promotions for high fat, sugar, and salt (HFSS) products." Department of Health and Social Care, United Kingdom Consultation Outcome (updated July 19, 2021). Reference No: RPC-DHSC-4333(3).

Dubois, Pierre, Rachel Griffith, and Martin O'Connell. 2020. "How well targeted are soda taxes." *American Economic Review*, 110(11): 3661–3704.

Griffith, Rachel, Martin O'Connell, and Kate Smith. 2019. "Tax design in the alcohol market." *Journal of Public Economics*, 172: 20–35.

Griffith, Rachel, Martin O'Connell, and Kate Smith. 2020. "Price floors and externality correction." Institute for Fiscal Studies Working paper series 20/37, London WC1E 7AE, UK.

Hindriks, Jean, and Valerio Serse. 2019. "Heterogeneity in the tax pass-through to spirit retail prices: evidence from Belgium." *Journal of Public Economics*, 176: 142–160.

Hinnosaar, Marit. 2016. "Time inconsistency and alcohol sales restrictions." *European Economic Review*, 87: 108–131.

Kantar Worldpanel UK. 2020. "An analysis of the role of price promotions on the household purchases of food and drinks high in sugar, and purchases of food and drinks for out of home consumption." Public Health England PHE publications, London, UK.

Kueng, Lorenz, and Evgeny Yakovlev. 2021. "The long-run effects of a public policy on alcohol tastes and mortality." *American Economic Journal: Economic Policy*, 13(1): 294–328.

Marcus, Jan, and Thomas Siedler. 2015. "Reducing binge drinking? the effect of a ban on late-night off-premise alcohol sales on alcohol-related hospital stays in Germany." *Journal of Public Economics*, 123: 55–77.

Miravete, Eugenio J., Katja Seim, and Jeff Thurk. 2018. "Market power and the Laffer curve." *Econometrica*, 85(5): 1651–1687.

Miravete, Eugenio J., Katja Seim, and Jeff Thurk. 2020. "One markup to rule them all: taxation by liquor pricing regulation." *American Economic Journal: Microeconomics*, 12(1): 1–41.

Nakamura, Ryota, Marc Suhrcke, Rachel Pechey, Marcello Morciano, Martin Roland, and Theresa M. Marteau. 2014. "Impact on alcohol purchasing of a ban on multi-buy promotions: a quasi-experimental evaluation comparing Scotland with England and Wales." *Addiction*, 109(4): 558–567.

Nelson, Jon P., and John R. Moran. 2019. "Effects of alcohol taxation on prices: a systematic review and meta-analysis of pass-through rates." *The B.E. Journal of Economic Analysis and Policy.*, 20(1): 20190134.

Puhani, Patrick A. 2012. "The treatment effect, the cross difference, and the interaction term in nonlinear "difference-in-differences" models." *Economic Letters*, 115(1): 85–87.

Richardson, Elizabeth, and Lucie Giles. 2021. "Monitoring and Evaluating Scotland's Alcohol Strategy (MESAS): Monitoring Report 2021." Public Health Scotland PHS

MESAS Monitoring Repor, Edinburg.

Robinson, Mark, Claudia Geue, James Lewsey, Daniel Mackay, Gerry McCartney, Esther Curnock, and Clare Beeston. 2014. "Evaluating the impact of the alcohol act on off-trade alcohol sales: a natural experiment in Scotland." *Addiction*, 109(12): 2035–2043.

Schelling, Thomas C. 1984. "Self-command in practice, in policy, and in a theory of rational choice." *The American Economic Review (Papers and Proceedings)*, 74(2): 1–11.

Stole, Lars A. 2007. "Price discrimination and competition." In *Handbook of Industrial Organization.* Vol. 3, , ed. M. Armstrong and R. Porter, Chapter 34, 2221–2299. Amsterdam, North-Holland:Elsevier Science Publishers.

Thaler, Richard. 1985. "Mental accounting and consumer choice." *Marketing Science*, 4(3): 199–214.

Thaler, Richard H., and H. M. Shefrin. 1981. "An economic theory of self-control." *Journal of Political Economy*, 89(2): 392–406.

Wertenbroch, Klaus. 1998. "Consumption self-control by rationing purchase quantities of virtue and vice." *Marketing Science*, 17(4): 297–423.

WHO. 2010. "Global strategy to reduce the harmful use of alcohol." World Health Organization, Geneva, Switzerland. Last accessed on May 17, 2021.

Wilson, Luke B. Robert Pryce, Colin Angus, Rosemary Hiscock, Alan Brennan, and Duncan Gillespie. 2021. "The effect of alcohol tax changes on retail prices: how do on-trade alcohol retailers pass through tax changes to consumers?" *European Journal of Health Econonomics*, 22(3): 381–392.

Wilson, Robert B. 1993. *Nonlinear Pricing.* New York:Oxford University Press.

APPENDIX A. INSTRUMENTS AND FIRST-STAGE REGRESSION STATS

Out instrumenting strategy follows very closely that of Griffith, O'Connell and Smith (2019). To generate exogenous shocks to price, we used several variables that influence costs but are not likely to directly influence demand for alcohol. Some of these variables generate variation over time while others give geographic variation. To this end we used exchange rates for EUR and USD which vary over time and may affect the prices differentially for products that are imported vs home brewed. Similarly, we also used factory gate prices (indexes) for beer, cider and fruit wines, and for overall alcoholic beverages as recorded by the Office of National Statistics. Weekly diesel prices were also used and were interacted with shares of stores by geographic coverage (see Figure A-1). To compute the latter, we used alcohol purchase data from the first 12 weeks and aggregated it up to store and regional level to compute shares by store type (seven type of stores) for each of the 15 regions separately (see Table A-1).

FIGURE A-1. Variation in price instruments over time

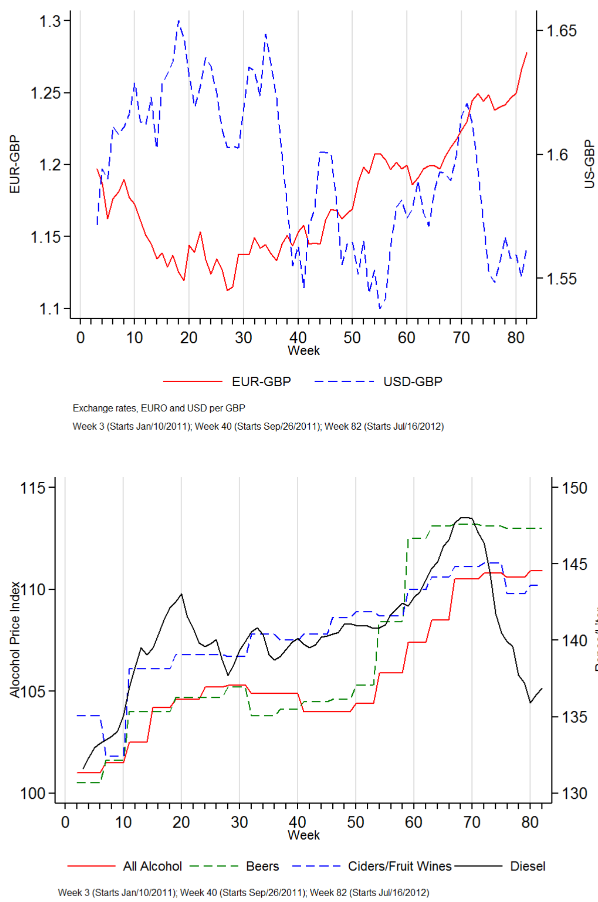


Table A-1. Shares of alcohol sales by stores per region

Region	Tesco	Sainsbury's	Asda	Morrisons	Discounter	Upmarket	Other
North East	0.22	0.13	0.27	0.14	0.07	0.03	0.14
North West	0.27	0.13	0.28	0.12	0.06	0.02	0.12
Yorkshire & The Humber	0.23	0.13	0.20	0.21	0.05	0.02	0.17
East Midlands	0.30	0.15	0.17	0.15	0.07	0.02	0.13
West Midlands	0.25	0.19	0.20	0.14	0.06	0.03	0.13
East of England	0.42	0.19	0.13	0.09	0.05	0.03	0.09
London	0.31	0.30	0.14	0.06	0.03	0.07	0.09
South East	0.36	0.25	0.15	0.07	0.05	0.05	0.07
South West	0.36	0.18	0.16	0.11	0.06	0.04	0.08
North Eastern Scotland	0.43	0.12	0.24	0.06	0.08	0.02	0.06
Highlands and Islands	0.42	0.00	0.26	0.09	0.06	0.01	0.17
Eastern Scotland	0.35	0.11	0.25	0.13	0.05	0.03	0.08
West Central Scotland	0.28	0.10	0.28	0.16	0.07	0.02	0.09
Southern Scotland	0.28	0.06	0.23	0.20	0.08	0.03	0.12
Wales	0.31	0.09	0.26	0.11	0.11	0.02	0.10

Shares based on weeks 1-12 purchases (Jan/1-Mar/20, 2011). Discounters are Aldi and Lidl, upmarket is Waitrose and Marks and Spencers and others are independent stores.

Thus our first stage instruments consisted of exchange rates, alcohol price index, ex-factory prices for beer, and for cider/fruit wines, diesel prices, shares of store types by region, and the interactions of store shares by region with diesel prices. Second stage equations are estimated separately for each segment and by household type and all households combined. Each of these contain four different price variables and slightly different exogenous variables in second stage equations. For example, for the beers segment (S02), the four endogenous variables are prices of spirits, beers, wines and FABs, and there are four such regressions by household type and hence there are a total of 16 first-stage regressions for this segment. In total, control variables were constructed from 52 separate first-stage regressions. Table A-2 provides F-tests from first-stage regression of (log) prices on all exogenous variables in the segment and for the household type, where the test is the restriction test of excluded instruments (i.e., a weak instruments test). In all cases, the test statistic is reasonably high and above the rule-of-thumb value of 10.

Table A-2. First Stage F-Test for Excluded Instruments

Sample Households		(1) All	(2) Low	(3) Medium	(4) High
Segment S00: All Drinks Combined					
ln price	Overall	44.2	32.6	20.3	14.0
Segment S01: Spirits and Fortified Wines					
ln price	Sprits	237.5	479.8	245.1	48.7
	Beers	66.6	53.5	52.4	21.3
	Wines	140.1	139.7	57.4	34.4
	FABS	609.4	5237.3	4132.3	4022.3
Segment S02: Beers and Ales					
ln price	Sprits	232.5	416.1	245.9	47.8
	Beers	67.0	54.0	53.3	21.3
	Wines	136.4	133.8	54.2	35.0
	FABS	607.7	3092.2	1948.7	2463.1
Segment S03: Wines and Bubblies					
ln price	Sprits	234.8	448.3	252.3	47.4
	Beers	66.1	53.0	53.1	21.2
	Wines	131.8	129.7	54.8	32.3
	FABS	606.7	3717.0	4683.2	4515.0

ln price regressed on instruments and exogenous variables. Regressions are by alcohol segment and by household type.

Pre-ban parallel trends test based on a tobit specification.

TABLE A-3. Pre-ban parallel trends test (p-values)

	HH-type			
	(1)	(2)	(3)	(4)
Sample Households	All	Low	Medium	High
Segment S00 (All Alcohol)	0.002	0.066	0.658	0.011
Segment S01 (Spirits)	0.252	0.215	0.610	0.239
Segment S02 (Beers)	0.067	0.746	0.107	0.189
Segment S03 (Wines)	0.073	0.421	0.229	0.158

All reduced form regressions on log quantity (tobit specification) include household characteristics, product characteristics, time, time square, time cube, a country dummy and interaction of country dummy with time trends. The p-values are reported for the joint F-test with a null that the interaction terms are zero.

Appendix B. (For Online Publication)

Banning Volume Discounts to Curb Excessive Consumption: A Cautionary Tale
by Farasat A.S. Bokhari, Paul W. Dobson, Marello Morciano and Marc Suhrcke

This online appendix provides full regressions outputs (Tobits) reported in the main paper. The paper showed only the marginal effects. Here we have all the associated regression coefficients. There are four tables in this appendix (B1-B-4).

Table B-1. Tobits for segment S00 (All Alcohol)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
S: Scotland (1/0 dummy)	0.0306	-0.0269	-0.013	-0.114	0.019	0.033
(1= Scotland)	(0.057)	(0.055)	(0.051)	(0.112)	(0.093)	(0.095)
B: Ban (1/0 dummy)	0.111	0.0473	0.030	0.068	-0.040	0.060
(1 = Post-Ban)	(0.021)	(0.021)	(0.023)	(0.053)	(0.041)	(0.033)
$S \times B$: Scotland-Post Ban	0.168	0.171	0.153	-0.018	0.160	0.257
Interaction	(0.027)	(0.026)	(0.035)	(0.085)	(0.063)	(0.046)
Product characteristics						
$\ln p_{s00}$: log price ethnol		-1.611	-2.771	-4.058	-2.868	-2.364
		(0.017)	(0.142)	(0.410)	(0.239)	(0.159)
d_{s00} : discount		0.896	0.884	0.605	0.927	0.931
		(0.027)	(0.062)	(0.177)	(0.114)	(0.081)
c_1 : ABV		0.0131	-0.001	-0.018	0.006	0.004
		(0.001)	(0.005)	(0.009)	(0.006)	(0.006)
c_2 : calories		0.00385	0.005	0.010	0.007	0.003
		(0.000)	(0.001)	(0.002)	(0.001)	(0.001)
c_3 : protein		1.428	1.474	1.507	1.693	1.517
		(0.073)	(0.252)	(0.441)	(0.438)	(0.405)
c_4 : carbohydrates		-0.0304	-0.045	-0.064	0.005	-0.106
		(0.008)	(0.024)	(0.035)	(0.036)	(0.037)

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

Table B-1. Tobits for segment S00 (All Alcohol)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
c_5 : fat		-1.673	-2.390	-5.408	-6.333	-1.537
		(0.872)	(2.642)	(6.849)	(6.791)	(4.825)
c_6 : saturated fat		4.106	9.726	18.769	-0.253	4.415
		(1.656)	(5.528)	(13.749)	(14.365)	(10.139)
c_7 : sugar		0.0417	0.044	0.083	0.017	0.090
		(0.011)	(0.025)	(0.053)	(0.046)	(0.040)
c_8 : fibre		-0.0806	-1.950	-4.067	12.083	0.863
		(1.644)	(7.588)	(17.651)	(20.936)	(14.397)
c_9 : sodium		-1.209	-4.758	-2.710	-5.052	-7.649
		(1.261)	(3.068)	(7.325)	(4.718)	(5.171)
c_{10} : FSA score		0.00586	0.070	-0.028	-0.021	0.142
		(0.028)	(0.064)	(0.138)	(0.112)	(0.100)
Household/Mainshoper Characteristics						
x_2 : age	0.0993	0.0937	0.091	0.106	0.099	0.087
	(0.008)	(0.007)	(0.008)	(0.014)	(0.014)	(0.015)
x_3 : age square ($\times 10^{-2}$)	-0.0827	-0.0787	-0.075	-0.094	-0.080	-0.070
	(0.007)	(0.007)	(0.007)	(0.013)	(0.013)	(0.013)
x_4 : race	-0.189	-0.200	-0.197	-0.196	-0.183	-0.207
(1/0 dummy, 1= Non-white)	(0.079)	(0.076)	(0.081)	(0.152)	(0.166)	(0.153)
$x_{5.1}$: income (group 1)	-0.206	-0.241	-0.264	-0.396	-0.439	-0.027
	(0.047)	(0.046)	(0.049)	(0.097)	(0.089)	(0.073)
$x_{5.2}$: income (group 2)	0.0426	0.0387	0.042	0.038	-0.099	0.141
	(0.046)	(0.045)	(0.044)	(0.083)	(0.077)	(0.073)
$x_{5.3}$: income (group 3)	0.116	0.148	0.177	0.175	0.129	0.226

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

TABLE B-1. Tobits for segment S00 (All Alcohol)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
	(0.054)	(0.053)	(0.047)	(0.082)	(0.092)	(0.083)
$x_{5.4}$: income (group 4)	-0.0230	0.0707	0.131	0.223	0.125	0.081
	(0.067)	(0.065)	(0.058)	(0.111)	(0.115)	(0.099)
x_8 : education	-0.159	-0.110	-0.088	-0.023	-0.095	-0.133
(age finished education)	(0.033)	(0.032)	(0.035)	(0.060)	(0.057)	(0.052)
x_9 : children	0.00772	0.00389	0.000	-0.049	0.054	-0.009
(total in household)	(0.020)	(0.019)	(0.019)	(0.036)	(0.037)	(0.039)
$x_{1.m}$: Household group 2	0.969	0.859	0.812			
(1/0 dummy, 1 = medium)	(0.037)	(0.036)	(0.033)			
$x_{1.h}$: Household group 3	2.629	2.296	2.149			
(1/0 dummy, 1 = high)	(0.037)	(0.036)	(0.038)			
Monthly dummies						
τ_4 : month 4	0.149	0.0984	0.072	0.001	-0.027	0.193
	(0.021)	(0.021)	(0.026)	(0.068)	(0.046)	(0.033)
τ_5 : month 5	0.291	0.230	0.189	0.226	0.144	0.204
	(0.021)	(0.021)	(0.024)	(0.061)	(0.042)	(0.034)
τ_6 : month 6	0.124	0.0817	0.059	0.014	-0.009	0.136
	(0.021)	(0.021)	(0.023)	(0.055)	(0.044)	(0.037)
τ_7 : month 7	0.0788	0.0716	0.065	0.014	-0.018	0.158
	(0.021)	(0.021)	(0.024)	(0.063)	(0.042)	(0.034)
τ_8 : month 8	0.0522	0.0761	0.089	0.111	-0.011	0.161
	(0.021)	(0.021)	(0.022)	(0.057)	(0.041)	(0.035)
τ_9 : month 9	0.0334	0.0109	0.004	-0.040	-0.037	0.065
	(0.021)	(0.021)	(0.022)	(0.053)	(0.041)	(0.036)

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

TABLE B-1. Tobits for segment S00 (All Alcohol)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
τ_{12} : month 12	0.340	0.320	0.332	0.418	0.342	0.279
	(0.021)	(0.020)	(0.020)	(0.044)	(0.037)	(0.033)
τ_{13} : month 13	0.725	0.700	0.728	1.078	0.771	0.485
	(0.021)	(0.020)	(0.024)	(0.055)	(0.034)	(0.037)
τ_{14} : month 14	-0.645	-0.533	-0.485	-0.534	-0.606	-0.385
	(0.022)	(0.021)	(0.024)	(0.060)	(0.045)	(0.041)
τ_{15} : month 15	-0.112	-0.0343	-0.003	-0.101	-0.040	0.080
	(0.021)	(0.021)	(0.022)	(0.049)	(0.044)	(0.039)
τ_{16} : month 16	-0.107	-0.0441	-0.024	-0.110	0.000	0.010
	(0.021)	(0.021)	(0.024)	(0.052)	(0.039)	(0.036)
τ_{17} : month 17	0.00834	0.0506	0.061	0.043	0.064	0.078
	(0.021)	(0.021)	(0.021)	(0.047)	(0.039)	(0.034)
τ_{18} : month 18	-0.0286	0.0106	0.019	-0.021	0.004	0.054
	(0.021)	(0.021)	(0.023)	(0.057)	(0.038)	(0.038)
τ_{19} : month 19	-0.0151	0.0491	0.069	0.193	0.071	-0.006
	(0.021)	(0.021)	(0.023)	(0.051)	(0.037)	(0.040)
τ_{20} : month 20	-0.131	-0.0689	-0.047	-0.073	-0.034	-0.054
	(0.021)	(0.021)	(0.023)	(0.053)	(0.044)	(0.034)
τ_{21} : month 21	-0.109	-0.0540	-0.046	-0.095	-0.049	-0.015
	(0.023)	(0.023)	(0.024)	(0.058)	(0.044)	(0.041)
$\hat{u0}_{it}$: residuals			1.177	1.887	1.228	1.157
(residuals from first-stage)			(0.154)	(0.408)	(0.264)	(0.189)
Constant	-4.113	-5.742	-6.423	-8.068	-6.191	-3.787
	(0.210)	(0.207)	(0.245)	(0.442)	(0.424)	(0.488)

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

TABLE B-1. Tobits for segment S00 (All Alcohol)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
σ_h	1.322	1.278	1.271	1.386	1.316	1.226
(std of household RE)	(0.011)	(0.011)	(0.011)	(0.022)	(0.020)	(0.017)
σ_e	2.349	2.294	2.294	2.677	2.416	2.060
(std of error term)	(0.004)	(0.004)	(0.004)	(0.010)	(0.007)	(0.005)
Observations	594,696	594,694	594,694	197,735	198,302	198,657
# Households	8,376	8,376	8,376	2,785	2,793	2,798
Left Censored	334,338	334,338	334,338	143,796	117,837	72,705

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

Table B-2. Tobits for segment S01 (Spirits)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
S: Scotland (1/0 dummy)	0.800	0.860	1.107	0.676	1.619	0.945
(1= Scotland)	(0.124)	(0.124)	(0.138)	(0.319)	(0.217)	(0.241)
B: Ban (1/0 dummy)	0.504	0.430	0.532	0.934	0.866	0.231
(1 = Post-Ban)	(0.047)	(0.048)	(0.048)	(0.149)	(0.111)	(0.074)
$S \times B$: Scotland-Post Ban	-0.0247	-0.0527	-0.087	-0.228	-0.272	-0.005
Interaction	(0.054)	(0.055)	(0.079)	(0.168)	(0.134)	(0.089)
Product characteristics						
$\ln p_{s01}$: log price spirits		-1.263	-10.806	-3.286	-10.154	-10.291
		(0.049)	(0.866)	(1.405)	(1.316)	(0.973)
$\ln p_{s02}$: log price beers		-0.179	1.243	1.010	1.910	0.837
		(0.047)	(0.190)	(0.545)	(0.413)	(0.243)
$\ln p_{s03}$: log price wines		-0.169	1.268	1.427	1.500	1.088
		(0.048)	(0.278)	(0.887)	(0.535)	(0.348)
$\ln p_{s04}$: log price FABs		-0.0153	0.696	0.296	0.287	0.870
		(0.035)	(0.178)	(0.448)	(0.238)	(0.278)
d_{s01} : discount		3.405	-0.296	0.464	-1.066	2.824
		(0.228)	(0.671)	(1.254)	(1.165)	(0.625)
c_1 : ABV		-0.0315	-0.152	-0.036	-0.133	-0.171
		(0.002)	(0.015)	(0.025)	(0.022)	(0.017)
c_2 : calories		0.00936	0.030	0.015	0.032	0.023
		(0.001)	(0.003)	(0.008)	(0.006)	(0.004)
c_3 : protein		-5.158	-20.374	-8.032	-16.202	-25.059
		(0.567)	(3.001)	(6.053)	(5.102)	(3.542)
c_4 : carbohydrates		0.0359	0.181	0.026	0.144	0.209
		(0.010)	(0.039)	(0.061)	(0.067)	(0.052)

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

Table B-2. Tobits for segment S01 (Spirits)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
c_5 : fat		0.000	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
c_6 : saturated fat		0.000	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
c_7 : sugar		0.107	0.278	0.238	0.350	0.099
		(0.017)	(0.052)	(0.110)	(0.107)	(0.075)
c_8 : fibre		0.000	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
c_9 : sodium		-4.581	19.127	12.202	13.645	2.019
		(1.782)	(5.709)	(11.442)	(9.236)	(7.086)
c_{10} : FSA score		-0.455	-1.607	-0.989	-1.672	-0.874
		(0.049)	(0.177)	(0.444)	(0.342)	(0.207)
Household/Mainshoper Characteristics						
x_2 : age	0.0492	0.0470	-0.295	-0.243	-0.225	-0.442
	(0.017)	(0.017)	(0.063)	(0.137)	(0.125)	(0.140)
x_3 : age square ($\times 10^{-2}$)	-0.0109	-0.00815	-0.195	-0.208	-0.189	-0.227
	(0.015)	(0.015)	(0.040)	(0.065)	(0.076)	(0.081)
x_4 : race	0.456	0.461	0.043	0.084	0.035	0.064
(1/0 dummy, 1= Non-white)	(0.172)	(0.171)	(0.017)	(0.025)	(0.030)	(0.032)
$x_{5.1}$: income (group 1)	-0.148	-0.163	-0.005	-0.047	0.001	-0.012
	(0.103)	(0.103)	(0.016)	(0.023)	(0.027)	(0.028)
$x_{5.2}$: income (group 2)	-0.0742	-0.0703	0.446	0.638	0.356	0.450
	(0.101)	(0.100)	(0.166)	(0.291)	(0.288)	(0.367)
$x_{5.3}$: income (group 3)	0.0547	0.0616	-0.179	-0.365	-0.422	0.187
	(0.119)	(0.118)	(0.114)	(0.176)	(0.217)	(0.176)

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

Table B-2. Tobits for segment S01 (Spirits)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
$x_{5.4}$: income (group 4)	-0.112	-0.0669	-0.050	-0.125	-0.326	0.236
	(0.147)	(0.146)	(0.102)	(0.185)	(0.188)	(0.173)
x_8 : education	-0.345	-0.320	0.094	-0.073	-0.155	0.405
(age finished education)	(0.072)	(0.072)	(0.094)	(0.179)	(0.196)	(0.201)
x_9 : children	-0.205	-0.208	0.008	0.074	-0.085	-0.101
(total in household)	(0.044)	(0.044)	(0.136)	(0.231)	(0.241)	(0.239)
$x_{1.m}$: Household group 2	0.931	0.939	0.915			
(1/0 dummy, 1 = medium)	(0.082)	(0.081)	(0.070)			
$x_{1.h}$: Household group 3	2.857	2.805	2.330			
(1/0 dummy, 1 = high)	(0.082)	(0.082)	(0.119)			
Monthly dummies						
τ_4 : month 4	0.182	0.0415	-0.148	0.022	0.035	-0.184
	(0.048)	(0.048)	(0.054)	(0.147)	(0.116)	(0.075)
τ_5 : month 5	0.225	0.0986	-0.034	0.318	0.011	-0.053
	(0.048)	(0.048)	(0.053)	(0.161)	(0.111)	(0.073)
τ_6 : month 6	0.0736	0.0573	0.182	0.170	-0.008	0.191
	(0.048)	(0.048)	(0.050)	(0.158)	(0.098)	(0.078)
τ_7 : month 7	0.147	0.0143	-0.159	0.309	-0.243	-0.127
	(0.048)	(0.048)	(0.051)	(0.172)	(0.115)	(0.071)
τ_8 : month 8	0.0123	-0.0240	-0.173	0.058	-0.424	-0.109
	(0.048)	(0.048)	(0.051)	(0.140)	(0.126)	(0.066)
τ_9 : month 9	0.123	0.0474	-0.217	-0.005	-0.045	-0.126
	(0.048)	(0.048)	(0.057)	(0.162)	(0.111)	(0.068)
τ_{12} : month 12	0.877	0.723	0.713	1.151	0.678	0.652
	(0.043)	(0.044)	(0.042)	(0.136)	(0.100)	(0.064)

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

Table B-2. Tobits for segment S01 (Spirits)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
τ_{13} : month 13	1.812	1.849	2.223	2.815	2.317	1.832
	(0.042)	(0.042)	(0.064)	(0.142)	(0.110)	(0.091)
τ_{14} : month 14	-0.865	-0.770	-0.933	-1.125	-1.417	-0.622
	(0.048)	(0.049)	(0.051)	(0.144)	(0.128)	(0.077)
τ_{15} : month 15	-0.432	-0.316	-0.385	-0.757	-1.068	-0.047
	(0.047)	(0.047)	(0.044)	(0.144)	(0.131)	(0.079)
τ_{16} : month 16	-0.391	-0.311	-0.361	-0.932	-0.673	0.027
	(0.046)	(0.047)	(0.050)	(0.140)	(0.122)	(0.069)
τ_{17} : month 17	-0.326	-0.278	-0.328	-0.470	-0.989	0.033
	(0.046)	(0.047)	(0.045)	(0.143)	(0.138)	(0.072)
τ_{18} : month 18	-0.369	-0.292	-0.165	-0.483	-0.526	0.115
	(0.046)	(0.047)	(0.052)	(0.165)	(0.121)	(0.083)
τ_{19} : month 19	-0.278	-0.271	-0.193	-0.347	-0.495	0.067
	(0.046)	(0.046)	(0.050)	(0.150)	(0.106)	(0.082)
τ_{20} : month 20	-0.448	-0.375	-0.176	-0.620	-0.522	0.031
	(0.047)	(0.047)	(0.047)	(0.157)	(0.104)	(0.080)
τ_{21} : month 21	-0.466	-0.375	-0.250	-0.747	-0.794	0.247
	(0.051)	(0.051)	(0.055)	(0.165)	(0.123)	(0.082)
$\widehat{u1}_{it}$: residuals			9.637	0.717	8.054	10.033
(from first-stage for lnp_{01})			(0.807)	(1.369)	(1.207)	(0.900)
$\widehat{u2}_{it}$: residuals			-1.584	-1.948	-2.378	-0.989
(from first-stage for lnp_{02})			(0.197)	(0.598)	(0.450)	(0.229)
$\widehat{u3}_{it}$: residuals			-1.496	-1.783	-1.786	-1.268
(from first-stage for lnp_{03})			(0.276)	(0.910)	(0.570)	(0.349)

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

Table B-2. Tobits for segment S01 (Spirits)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
$\widehat{u4}_{it}$: residuals			-0.742	-0.359	-0.379	-0.853
(from first-stage for lnp_{04})			(0.181)	(0.460)	(0.254)	(0.286)
Constant	-8.764	-10.05	-14.160	-12.831	-13.423	-10.929
	(0.468)	(0.498)	(0.853)	(1.873)	(1.806)	(1.359)
σ_h	2.798	2.773	2.684	2.656	2.721	2.921
(std of household RE)	(0.028)	(0.028)	(0.027)	(0.056)	(0.050)	(0.046)
σ_e	3.377	3.353	3.353	4.400	3.881	2.909
(std of error term)	(0.010)	(0.010)	(0.010)	(0.038)	(0.025)	(0.011)
Observations	594,696	584,067	584,067	193,673	193,088	197,306
# Households	8,376	8,376	8,376	2,785	2,793	2,798
Left Censored	517,372	507,768	507,768	182,928	174,497	150,343

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

Table B-3. Tobits for segment S02 (Beers)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
S: Scotland (1/0 dummy)	-0.466	-0.449	-0.385	-0.229	-0.244	-0.584
(1= Scotland)	(0.095)	(0.091)	(0.089)	(0.170)	(0.151)	(0.179)
B: Ban (1/0 dummy)	-0.00339	-0.0626	-0.212	-0.008	-0.355	-0.227
(1 = Post-Ban)	(0.032)	(0.031)	(0.034)	(0.071)	(0.067)	(0.048)
$S \times B$: Scotland-Post Ban	0.344	0.293	0.205	-0.122	0.323	0.290
Interaction	(0.041)	(0.041)	(0.054)	(0.125)	(0.103)	(0.092)
Product characteristics						
$\ln p_{s01}$: log price spirits		0.0798	1.036	0.827	1.087	1.173
		(0.040)	(0.120)	(0.222)	(0.216)	(0.194)
$\ln p_{s02}$: log price beers		-2.100	-6.992	-6.676	-5.890	-7.764
		(0.025)	(0.298)	(0.920)	(0.543)	(0.409)
$\ln p_{s03}$: log price wines		-0.307	0.848	1.320	0.650	0.552
		(0.032)	(0.173)	(0.435)	(0.384)	(0.251)
$\ln p_{s04}$: log price FABs		0.00345	0.570	0.664	0.323	0.751
		(0.023)	(0.116)	(0.214)	(0.146)	(0.222)
d_{s02} : discount		0.636	0.562	0.223	0.790	0.454
		(0.056)	(0.146)	(0.314)	(0.249)	(0.230)
c_1 : ABV		-0.181	-0.425	-0.630	-0.286	-0.354
		(0.011)	(0.043)	(0.095)	(0.083)	(0.065)
c_2 : calories		0.00210	-0.003	-0.005	0.002	-0.004
		(0.001)	(0.002)	(0.005)	(0.004)	(0.003)
c_3 : protein		3.308	8.540	0.000	0.000	0.000
		(0.109)	(0.536)	(0.000)	(0.000)	(0.000)
c_4 : carbohydrates		1.562	3.305	2.970	3.119	3.487
		(0.062)	(0.257)	(0.444)	(0.382)	(0.406)

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

Table B-3. Tobits for segment S02 (Beers)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
c_5 : fat		-28.16	-55.996	-74.109	-56.341	-57.902
		(1.953)	(7.124)	(31.429)	(14.358)	(10.127)
c_6 : saturated fat		22.82	43.454	50.734	60.845	78.756
		(3.374)	(16.975)	(38.086)	(24.305)	(43.592)
c_7 : sugar		-1.359	-2.233	-1.945	-2.157	-2.466
		(0.066)	(0.246)	(0.379)	(0.342)	(0.386)
c_8 : fibre		7.372	17.140	25.829	-0.647	-15.994
		(3.321)	(15.860)	(31.554)	(22.482)	(43.187)
c_9 : sodium		-37.45	-153.653	-139.738	-174.526	-237.489
		(17.032)	(62.281)	(149.748)	(92.104)	(78.631)
c_{10} : FSA score		-0.519	-2.158	-2.504	-2.250	-1.760
		(0.134)	(0.358)	(0.908)	(0.947)	(0.559)
Household/Mainshoper Characteristics						
x_2 : age	0.119	0.111	0.107	0.107	0.120	0.078
	(0.013)	(0.012)	(0.012)	(0.018)	(0.021)	(0.027)
x_3 : age square ($\times 10^{-2}$)	-0.139	-0.129	-0.123	-0.118	-0.133	-0.102
	(0.012)	(0.011)	(0.011)	(0.017)	(0.019)	(0.024)
x_4 : race	-0.507	-0.471	-0.449	-0.354	-0.255	-0.598
(1/0 dummy, 1= Non-white)	(0.132)	(0.125)	(0.128)	(0.194)	(0.221)	(0.247)
$x_{5.1}$: income (group 1)	-0.187	-0.214	-0.275	-0.238	-0.442	-0.190
	(0.079)	(0.076)	(0.072)	(0.122)	(0.133)	(0.124)
$x_{5.2}$: income (group 2)	0.185	0.168	0.150	0.273	0.012	0.151
	(0.077)	(0.073)	(0.072)	(0.113)	(0.127)	(0.125)
$x_{5.3}$: income (group 3)	0.232	0.254	0.265	0.327	0.263	0.227
	(0.090)	(0.086)	(0.080)	(0.135)	(0.145)	(0.158)

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

TABLE B-3. Tobits for segment S02 (Beers)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
$x_{5.4}$: income (group 4)	-0.128	-0.0479	0.012	0.162	0.008	-0.104
	(0.111)	(0.106)	(0.094)	(0.159)	(0.151)	(0.177)
x_8 : education	-0.346	-0.291	-0.234	-0.102	-0.208	-0.364
(age finished education)	(0.055)	(0.052)	(0.055)	(0.088)	(0.092)	(0.106)
x_9 : children	0.0837	0.0680	0.062	0.009	0.050	0.124
(total in household)	(0.033)	(0.031)	(0.030)	(0.046)	(0.056)	(0.056)
$x_{1.m}$: Household group 2	0.675	0.550	0.355			
(1/0 dummy, 1 = medium)	(0.062)	(0.059)	(0.059)			
$x_{1.h}$: Household group 3	1.734	1.408	0.947			
(1/0 dummy, 1 = high)	(0.062)	(0.059)	(0.076)			
Monthly dummies						
τ_4 : month 4	0.103	0.0178	-0.094	-0.150	-0.193	0.019
	(0.031)	(0.031)	(0.032)	(0.074)	(0.068)	(0.054)
τ_5 : month 5	0.410	0.282	0.100	0.248	0.049	0.073
	(0.031)	(0.030)	(0.039)	(0.081)	(0.070)	(0.054)
τ_6 : month 6	0.236	0.153	0.034	0.128	-0.096	0.146
	(0.031)	(0.031)	(0.035)	(0.078)	(0.071)	(0.057)
τ_7 : month 7	0.177	0.150	0.143	0.053	0.087	0.251
	(0.031)	(0.031)	(0.032)	(0.080)	(0.061)	(0.054)
τ_8 : month 8	0.169	0.155	0.108	0.024	0.062	0.221
	(0.031)	(0.031)	(0.030)	(0.068)	(0.059)	(0.054)
τ_9 : month 9	0.0980	0.111	0.136	0.144	0.022	0.197
	(0.031)	(0.031)	(0.031)	(0.079)	(0.058)	(0.049)
τ_{12} : month 12	0.188	0.175	0.101	0.132	0.156	0.079

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

Table B-3. Tobits for segment S02 (Beers)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
	(0.031)	(0.031)	(0.032)	(0.069)	(0.056)	(0.051)
τ_{13} : month 13	0.669	0.625	0.494	0.735	0.617	0.251
	(0.030)	(0.030)	(0.039)	(0.069)	(0.058)	(0.062)
τ_{14} : month 14	-0.652	-0.574	-0.511	-0.784	-0.541	-0.301
	(0.033)	(0.033)	(0.039)	(0.078)	(0.070)	(0.061)
τ_{15} : month 15	-0.217	-0.160	-0.030	-0.305	0.033	0.061
	(0.032)	(0.031)	(0.038)	(0.070)	(0.066)	(0.052)
τ_{16} : month 16	-0.145	-0.0968	0.034	-0.108	0.016	0.166
	(0.032)	(0.031)	(0.038)	(0.070)	(0.059)	(0.057)
τ_{17} : month 17	0.0775	0.0941	0.205	0.134	0.208	0.306
	(0.031)	(0.031)	(0.034)	(0.072)	(0.062)	(0.055)
τ_{18} : month 18	-0.0378	0.0175	0.250	0.287	0.246	0.234
	(0.032)	(0.031)	(0.041)	(0.091)	(0.060)	(0.057)
τ_{19} : month 19	0.284	0.327	0.493	0.545	0.552	0.415
	(0.031)	(0.030)	(0.038)	(0.083)	(0.058)	(0.059)
τ_{20} : month 20	0.0299	0.0733	0.256	0.260	0.261	0.278
	(0.031)	(0.031)	(0.035)	(0.074)	(0.066)	(0.063)
τ_{21} : month 21	0.0964	0.175	0.433	0.308	0.398	0.582
	(0.034)	(0.033)	(0.042)	(0.072)	(0.070)	(0.072)
$\widehat{u1}_{it}$: residuals			-1.138	-0.766	-1.255	-1.308
(from first-stage for lnp_{01})			(0.125)	(0.236)	(0.230)	(0.209)
$\widehat{u2}_{it}$: residuals			4.947	3.793	3.806	6.103
(from first-stage for lnp_{02})			(0.300)	(0.826)	(0.521)	(0.387)
$\widehat{u3}_{it}$: residuals			-1.193	-1.695	-1.096	-0.818
(from first-stage for lnp_{03})			(0.166)	(0.453)	(0.379)	(0.249)

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

TABLE B-3. Tobits for segment S02 (Beers)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
$\widehat{u4}_{it}$: residuals			-0.590	-0.668	-0.411	-0.703
(from first-stage for lnp_{04})			(0.120)	(0.228)	(0.152)	(0.230)
Constant	-5.855	-7.595	-10.695	-9.327	-10.167	-9.630
	(0.351)	(0.368)	(0.717)	(1.680)	(1.312)	(1.167)
σ_h	2.181	2.069	2.015	1.843	1.999	2.200
(std of household RE)	(0.020)	(0.019)	(0.019)	(0.032)	(0.033)	(0.034)
σ_e	2.646	2.562	2.561	2.875	2.617	2.391
(std of error term)	(0.007)	(0.006)	(0.006)	(0.016)	(0.012)	(0.009)
Observations	594,696	584,067	584,067	193,673	193,088	197,306
# Households	8,376	8,376	8,376	2,785	2,793	2,798
Left Censored	480,591	471,522	471,522	170,309	158,318	142,895

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.

Table B-4. Tobits for segment S03 (Wines)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
S: Scotland (1/0 dummy)	-0.0696	-0.0598	-0.032	-0.093	-0.000	0.038
(1= Scotland)	(0.091)	(0.089)	(0.079)	(0.160)	(0.182)	(0.187)
B: Ban (1/0 dummy)	-0.0180	-0.0356	-0.023	-0.026	-0.007	-0.020
(1 = Post-Ban)	(0.027)	(0.027)	(0.034)	(0.072)	(0.057)	(0.043)
$S \times B$: Scotland-Post Ban	0.124	0.104	0.019	-0.151	-0.037	0.100
Interaction	(0.034)	(0.034)	(0.048)	(0.113)	(0.096)	(0.065)
Product characteristics						
$\ln p_{s01}$: log price spirits		0.0721	0.511	0.308	0.964	0.534
		(0.035)	(0.101)	(0.193)	(0.215)	(0.160)
$\ln p_{s02}$: log price beers		-0.0923	0.904	0.942	1.009	0.651
		(0.027)	(0.151)	(0.284)	(0.238)	(0.186)
$\ln p_{s03}$: log price wines		-1.640	-5.185	-4.597	-5.777	-5.002
		(0.024)	(0.342)	(0.800)	(0.561)	(0.394)
$\ln p_{s04}$: log price FABs		-0.00196	0.262	0.121	0.381	0.160
		(0.020)	(0.091)	(0.251)	(0.125)	(0.178)
d_{s03} : discount		0.725	0.441	0.557	0.417	0.415
		(0.029)	(0.083)	(0.261)	(0.163)	(0.105)
c_1 : ABV		-0.0180	-0.021	-0.071	-0.020	0.019
		(0.006)	(0.020)	(0.045)	(0.040)	(0.031)
c_2 : calories		0.00198	0.003	0.003	0.004	0.003
		(0.001)	(0.001)	(0.003)	(0.002)	(0.001)
c_3 : protein		-12.38	-34.301	-29.244	-36.722	-38.451
		(1.023)	(2.864)	(6.043)	(4.739)	(4.521)
c_4 : carbohydrates		1.770	-14.587	-36.295	10.913	1.509
		(1.438)	(23.519)	(55.567)	(40.825)	(33.427)

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Table B-4. Tobits for segment S03 (Wines)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
c_5 : fat		-76.50	-181.410	-157.446	-198.780	-181.755
		(102.942)	(265.009)	(639.300)	(436.440)	(337.265)
c_6 : saturated fat		-150.5	-609.795	-768.608	-240.000	-543.027
		(226.659)	(632.462)	(1,560.559)	(978.611)	(798.481)
c_7 : sugar		-1.417	15.330	36.859	-10.141	-0.676
		(1.438)	(23.510)	(55.549)	(40.836)	(33.445)
c_8 : fibre		233.6	798.992	954.956	488.105	682.764
		(329.017)	(875.560)	(2,128.122)	(1,366.038)	(1,101.906)
c_9 : sodium		-21.18	-43.273	-68.843	-85.472	-2.946
		(11.376)	(26.400)	(75.510)	(53.632)	(40.996)
c_{10} : FSA score		1.191	3.470	2.561	4.095	4.008
		(0.199)	(0.436)	(0.921)	(0.756)	(0.703)
Household/Mainshoper Characteristics						
x_2 : age	0.108	0.102	0.097	0.111	0.089	0.110
	(0.012)	(0.012)	(0.012)	(0.022)	(0.022)	(0.027)
x_3 : age square ($\times 10^{-2}$)	-0.0841	-0.0784	-0.074	-0.094	-0.061	-0.083
	(0.011)	(0.011)	(0.011)	(0.021)	(0.020)	(0.023)
x_4 : race	-0.278	-0.268	-0.257	-0.269	-0.197	-0.442
(1/0 dummy, 1= Non-white)	(0.126)	(0.124)	(0.120)	(0.202)	(0.236)	(0.279)
$x_{5.1}$: income (group 1)	-0.663	-0.669	-0.683	-0.631	-0.794	-0.654
	(0.076)	(0.075)	(0.072)	(0.142)	(0.140)	(0.122)
$x_{5.2}$: income (group 2)	-0.0708	-0.0703	-0.063	-0.053	-0.214	0.040
	(0.074)	(0.072)	(0.073)	(0.133)	(0.122)	(0.122)
$x_{5.3}$: income (group 3)	0.290	0.310	0.347	0.349	0.308	0.390
	(0.087)	(0.085)	(0.072)	(0.134)	(0.129)	(0.150)

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Table B-4. Tobits for segment S03 (Wines)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
$x_{5.4}$: income (group 4)	0.466	0.528	0.602	0.611	0.560	0.714
	(0.107)	(0.104)	(0.081)	(0.155)	(0.157)	(0.160)
x_8 : education	0.158	0.176	0.188	0.184	0.100	0.302
(age finished education)	(0.053)	(0.051)	(0.049)	(0.081)	(0.081)	(0.092)
x_9 : children	0.0582	0.0480	0.038	-0.041	0.122	0.052
(total in household)	(0.032)	(0.031)	(0.027)	(0.048)	(0.051)	(0.063)
$x_{1.m}$: Household group 2	0.871	0.836	0.845			
(1/0 dummy, 1 = medium)	(0.059)	(0.058)	(0.049)			
$x_{1.h}$: Household group 3	2.199	2.052	1.990			
(1/0 dummy, 1 = high)	(0.060)	(0.059)	(0.066)			
Monthly dummies						
τ_4 : month 4	0.111	0.0698	0.074	0.025	0.003	0.164
	(0.027)	(0.027)	(0.040)	(0.091)	(0.060)	(0.048)
τ_5 : month 5	0.229	0.184	0.224	0.265	0.255	0.177
	(0.027)	(0.027)	(0.035)	(0.079)	(0.061)	(0.045)
τ_6 : month 6	0.0105	-0.0125	0.019	-0.032	-0.009	0.066
	(0.027)	(0.027)	(0.032)	(0.075)	(0.057)	(0.046)
τ_7 : month 7	-0.00922	0.0200	0.100	0.048	0.087	0.152
	(0.027)	(0.027)	(0.038)	(0.083)	(0.056)	(0.046)
τ_8 : month 8	-0.0139	0.0337	0.135	0.036	0.108	0.227
	(0.027)	(0.027)	(0.035)	(0.079)	(0.059)	(0.046)
τ_9 : month 9	-0.0624	-0.0814	-0.111	-0.274	-0.059	-0.036
	(0.027)	(0.027)	(0.031)	(0.073)	(0.053)	(0.047)
τ_{12} : month 12	0.319	0.375	0.500	0.634	0.466	0.439

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Table B-4. Tobits for segment S03 (Wines)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
	(0.027)	(0.026)	(0.031)	(0.083)	(0.050)	(0.047)
τ_{13} : month 13	0.755	0.766	0.856	1.155	0.878	0.683
	(0.026)	(0.026)	(0.034)	(0.078)	(0.052)	(0.048)
τ_{14} : month 14	-0.522	-0.425	-0.272	-0.304	-0.508	-0.124
	(0.028)	(0.028)	(0.037)	(0.083)	(0.054)	(0.052)
τ_{15} : month 15	0.0579	0.123	0.221	0.192	0.200	0.237
	(0.027)	(0.027)	(0.036)	(0.076)	(0.056)	(0.046)
τ_{16} : month 16	0.0145	0.0525	0.048	-0.002	0.068	0.070
	(0.027)	(0.027)	(0.033)	(0.071)	(0.049)	(0.044)
τ_{17} : month 17	0.133	0.139	0.121	0.118	0.137	0.139
	(0.027)	(0.027)	(0.032)	(0.065)	(0.051)	(0.047)
τ_{18} : month 18	0.124	0.100	0.021	0.020	-0.065	0.089
	(0.027)	(0.027)	(0.033)	(0.074)	(0.054)	(0.042)
τ_{19} : month 19	0.0171	0.0329	-0.005	0.033	-0.057	0.026
	(0.027)	(0.027)	(0.036)	(0.069)	(0.048)	(0.047)
τ_{20} : month 20	-0.0429	-0.0203	-0.008	-0.030	-0.049	0.023
	(0.027)	(0.027)	(0.034)	(0.075)	(0.053)	(0.049)
τ_{21} : month 21	0.00251	-0.00743	-0.086	-0.086	-0.145	-0.028
	(0.029)	(0.029)	(0.033)	(0.076)	(0.055)	(0.050)
$\widehat{u1}_{it}$: residuals			-0.528	-0.392	-1.030	-0.457
(from first-stage for lnp_{01})			(0.114)	(0.209)	(0.242)	(0.172)
$\widehat{u2}_{it}$: residuals			-1.102	-1.374	-1.255	-0.717
(from first-stage for lnp_{02})			(0.149)	(0.315)	(0.242)	(0.188)
$\widehat{u3}_{it}$: residuals			3.562	2.386	4.070	3.699
(from first-stage for lnp_{03})			(0.325)	(0.762)	(0.544)	(0.395)

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TABLE B-4. Tobits for segment S03 (Wines)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Households	All	All	All	Low	Medium	High
$\widehat{u4}_{it}$: residuals			-0.277	-0.129	-0.418	-0.164
(from first-stage for lnp_{04})			(0.094)	(0.253)	(0.128)	(0.181)
Constant	-6.251	-6.021	-5.177	-5.257	-3.896	-3.963
	(0.338)	(0.361)	(0.365)	(0.627)	(0.646)	(0.754)
σ_h	2.118	2.073	2.033	1.966	1.981	2.219
(std of household RE)	(0.019)	(0.019)	(0.019)	(0.034)	(0.032)	(0.033)
σ_e	2.501	2.465	2.465	2.871	2.592	2.247
(std of error term)	(0.005)	(0.005)	(0.005)	(0.015)	(0.010)	(0.007)
Observations	594,696	584,067	584,067	193,673	193,088	197,306
# Households	8,376	8,376	8,376	2,785	2,793	2,798
Left Censored	439,556	431,214	431,214	164,618	147,291	119,305

Column (1) does not contain prices, discount or observable product characteristics. Column (2) adds prices, discount and other observable product characteristics. Column (3) adds in control functions as residuals from first-stage regressions for log price variable regressed on exogenous variables and excluded instruments. Columns (4,5,6) are similar to (3), but restrict the sample by household types. Standard errors are clustered by household. Columns (3-6) show boot-strapped (and clustered) standard errors.