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The Analysis of the Tobacco Product Bans Using a Random Coefficients Logit Model

Bartosz Olesiński*

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Abstract

The studies of tobacco demand accounting for product diversity have attracted much attention in the literature, but the *ex ante* measurements of the effects of product bans are relatively scarce. This paper aims to fill this gap and considers the 2020 EU-induced ban on menthol cigarettes as an example, focusing on the Polish market. In the proposed approach, a 2004-2017 product-level dataset for Poland is used to estimate a random coefficients logit model and simulate the effects of the menthol ban and, for comparison, a cigarette excise hike. The dataset is unique as it encompassess substantial changes in the tobacco tax level and structure that took place in Poland over the sample period. The simulations suggest that the ban, despite switching of consumers towards non-menthol cigarettes, results in relatively strong reduction in demand for duty-paid cigarettes, stronger than in the case of the excise hike.

Keywords: tobacco policy analyses, discrete choice models, substitution effects, BLP

JEL Classification: C25, C26, H22, I18

*Warsaw School of Economics and EY Economic Analysis Team; e-mail: bolesi@sgh.waw.pl; ORCID: 0000-0003-4535-6783

1 Introduction

A well-informed tobacco policy should be based on an economic impact assessment of the considered regulations, taking into account different goals such as raising revenue, reducing tobacco consumption or minimising the illicit trade. Some regulations affect one products more strongly than other. The quantitative assessment of the effects of those targeted policy measures requires developing such models that explicitly account for the product-specific demand effects.

The product-level models of tobacco demand have already attracted much attention in the literature. In an early contribution, Barzel (1976) hypothesized that in reaction to an increased unit-tax on differentiated product category, consumers might try to compensate for increased retail price by choosing products with better non-taxed attributes, leading to higher average product quality. More recently, Evans and Farrelly (1998) and Farrelly et al. (2004) noticed that in reaction to excise hikes, consumers tend to switch to products with higher tar and nicotine content. Adda and Cornaglia (2006), in turn, analyse the cotinine (the metabolite of nicotine) concentration in blood and provide evidence that consumers in reaction to tax increases not only switch towards cigarettes with higher tar and nicotine content, but also avert their smoking style in order to extract more nicotine out of each single cigarette. On the other hand, Ciliberto and Kuminoff (2010) provide results for a product-level demand model and find little evidence in support of the hypothesis of Barzel (1976) in the case of cigarettes.

An important strand of the product-level literature is related to discrete choice models, with the most notable example of the multinomial logit model, popularized by McFadden (1973). The model allows for joint explanation of demand for all the products in the system and overcomes the dimensionality problem, typical for standard demand models, by focusing on product characteristics rather than products themselves. The available literature provides hints that discrete choice logit models indeed are versatile enough to become a standard basis of diverse economic impact assessments. Tan (2006) in a theoretical analysis and Tan (2013) in an empirical analysis focus on the impact of tax policy and advertising restrictions in the US cigarette market, while Tuchman (2017) discusses the impact of advertising bans on the US traditional and electronic cigarette markets. Another interesting example of empirical study related to the public policy is the work of Ciliberto and Kuminoff (2010), who analyse the impact of the so called Master Settlement Agreement in 1997 in the US (signed with the attorneys general of all the 50 states and releasing the cigarette industry from lawsuits in exchange for annual payments) on the competition in the cigarette industry. When it comes to other countries, Min (2011) considers the effects of privatisation, price deregulation and entry of international competitors in the South Korean cigarette market, while Liu et al. (2015) focus on the impact of excise policy on cigarette demand level and structure in China. The product-level analyses of the cigarette market not always focus on public policy. For example, Pham and Prentice (2013) analyse the impact of merger of two cigarette companies on the

Australian cigarette market while Park (2010) studies the possibility of shaping the consumer preferences through introduction of new cigarette products (in the South Korean market context) and suggests applications in marketing.

While the scope of product-specific tobacco analyses is quite diverse, there is a gap in the literature as regards the *ex ante* impact of bans of particular product on the tobacco market. An interesting example of such a targeted policy is included in the Tobacco Products Directive (2014/40/EU), mandating a withdrawal of menthol cigarettes (also those with capsules that change the taste) from the EU market in 2020. The previous studies analyzing the impact of menthol ban on tobacco consumption are based on surveys in which the declared intention to quit or switch to alternative products is analysed (see WHO, 2016 for a review of those surveys). An important drawback of the survey approach is that while the intentions of smokers might provide valuable insights for policy, they are not always consistent with the actual behaviour. For instance, Levy et al. (2011) cite such declarations collected as a part of the 2010 Tobacco Use Supplement to the Current Population Survey in the US, but the actual impact of menthol ban on smoking prevalence is simulated in this paper, basing on additional assumptions (with different scenarios considered). In addition, the coverage of such surveys can sometimes be limited. For instance, O'Connor et al. (2012) admits that the results of his survey might not be broadly generalizable because it was based on an internet panel not focusing specifically to recruit menthol and non-menthol smokers.

This paper aims to fill this gap in the literature by applying a well-known random coefficient logit model proposed by Berry, Levinsohn and Pakes (1995) and developed, i.a., by Nevo (2000a, 2001) to the Polish tobacco market data. The model is referred to as "BLP" thereafter. The estimation in this paper is based on Nielsen data (Nielsen Retail Index for Cigarettes and Tobacco categories, including sales value, sales volume, average price, covering Total Poland monitored channels for 2004-2017), representative for the Polish retail market (purchases done by the final customers). The Polish data provides an interesting basis for policy impact analyses, because the tobacco market in Poland has been strongly influenced by the regulations initiated at the level of the European Union. For instance, a 2011 Directive (2011/64/EU) increased the minimum level of excise per 1000 cigarettes, regulated the structure of cigarette excise tax and obliged Poland to implement the new standards by the end of 2017. These requirements were met by Poland three years ahead of time, following a series of excise hikes that put the local tobacco prices more in line with the prices elsewhere in the EU. The excise hikes and changes in the taxation structure have produced unique patterns of retail price variation, making it possible to identify the product-specific effects for a very rich product portfolio.

Because the discrete choice modeling framework can accommodate various policy measures, in this study the impact of the excise tax hike is calculated for comparison. Such tax policy analyses that account for the product-level diversity are not available in the literature for Poland (especially with such level of representativeness that is

assured by the Nielsen data). In addition, this paper provides the results that fill the gap in relatively limited literature when it comes to up-to-date price elasticities of demand for tobacco products in Poland (the published or forthcoming examples include Florkowski and McNamara, 1992; Ross et al., 2014 and Olesiński et al., 2020). Essentially, the BLP approach can be applied in any other country in which product-level data on the tobacco market is available and the government considers diverse policies towards tobacco.
The remainder of the paper is structured as follows. Section 2 contains the description of the dataset used in this study, Section 3 provides the details of the methodology, Section 4 describes the empirical results and the final Section concludes. Additional technical details are provided in the Supplementary Material.

2 The data

In this section, the dataset is described along with the main descriptive statistics and trends. Much attention is paid to the unique features of the dataset that make it useful for the purposes of the BLP estimation.
This paper uses a product-level dataset on retail sales volumes and values of factory-made cigarettes (FMC) and an aggregate-level dataset on fine-cut tobacco retail sales provided by Nielsen and British-American Tobacco Poland (BAT) for the retail market in Poland. The data is representative of the entire Polish duty-paid retail market when it comes to the market structure and prices. However, it must be stressed that the sum of all the product-level market volumes is not equivalent to the total cigarette market volume in Poland. Firstly, the dataset is sourced only on Nielsen-covered channels for duty-paid cigarettes market in Poland. Secondly, the data does not include illicit trade in tobacco products. Some shadow market segments are more than likely to be subject to, e.g., different pricing strategies of retailers (related to tax evasion) than the mainstream (duty-paid) cigarettes. To include those issues in the modeling strategy, the market shares are calculated while accounting for the existence of the so called outside good. In addition, the calculation of the outside good is based on the Nielsen data on duty-paid fine-cut tobacco retail sales for the Polish retail market (see the Supplementary Material for a more detailed discussion).
Another issue with the dataset used in this study is the fact that it contains the average prices for the Polish cigarette market as a whole, rather than the prices on the shelves encountered by particular consumers. The solution is part of the identification strategy described below. The final issue with the dataset is lack of information about electronic cigarettes and heated tobacco products that have been developing in recent years in Poland, which might potentially result in omitted variable problem in the BLP estimation. However, this problem plays a relatively limited role in the econometric estimation because the shares of adults using those products in Poland remained very low in the sample period (CBOS, 2018). Due to lack of precise quantitative information, the dataset is not adjusted in that respect.

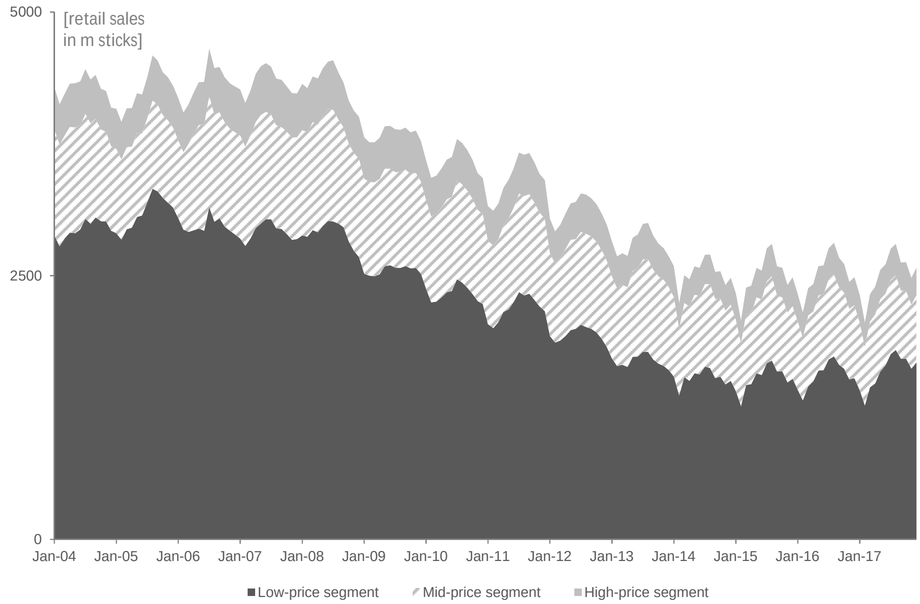
Table 1: Summary statistics for selected characteristics of factory-made cigarettes (FMC)

	The number of products*	Market volume (bn. sticks)	Average length (mm)	The number of sticks in a pack	Shares in retail sales value	
					Menthol	Flavour capsules
2004	424	51.5	80.4	21.2	12.3%	0.0%
2005	466	51.3	81.7	21.0	13.2%	0.0%
2006	436	51.9	82.6	20.9	14.3%	0.0%
2007	415	52.0	83.4	20.9	15.4%	0.0%
2008	403	51.9	84.0	20.9	16.6%	0.0%
2009	396	46.2	84.7	20.9	16.9%	0.0%
2010	357	43.0	85.6	20.8	17.6%	0.0%
2011	370	41.1	86.8	20.8	19.1%	1.0%
2012	382	37.4	87.7	20.8	20.7%	2.4%
2013	366	33.8	88.3	20.7	21.4%	3.2%
2014	389	30.3	89.0	20.5	22.8%	4.7%
2015	414	29.9	89.6	20.4	24.0%	6.8%
2016	411	30.3	90.0	20.3	25.1%	9.8%
2017	392	30.1	90.4	20.3	25.5%	11.1%

*Groups of products identical in terms of their characteristics (including brands) are aggregated and treated as a single product.
Note: the analysed market volume represents the Nielsen-covered channels for duty-paid cigarettes market in Poland.
Source: own calculations basing on Nielsen and BAT data.

The FMC data includes the details for 865 products (groups of products identical in terms of their characteristics, including brands, are aggregated and treated as a single product), while the fine-cut tobacco data includes the Polish market-level information. The monthly sample spans over the 2004-2017 period and the total number of the FMC products available ranges from 357 to 466 (in each year). Such a variation of the product space, resulting from market entry of some products and withdrawal of other, makes the standard demand estimation quite complicated. However, in contrast to the traditional approach, the BLP estimation takes advantage of the changes in the product range throughout the sample period. Those changes imply additional variance of individual product market shares which is crucial for the purposes of estimation of random parameters of market demand. Further, the data on FMC includes the following product characteristics: brand, taste, the number of cigarettes in a single pack, type of pack, thickness, length, declared strength, inclusion of capsules that change the taste, manufacturer and the market segment (with three segments: low-price, mid-price and high-price segment, defined by author based on the information obtained from BAT about price positioning of particular brands on the Polish market). The summary statistics for the selected characteristics of FMC are presented in Table 1.

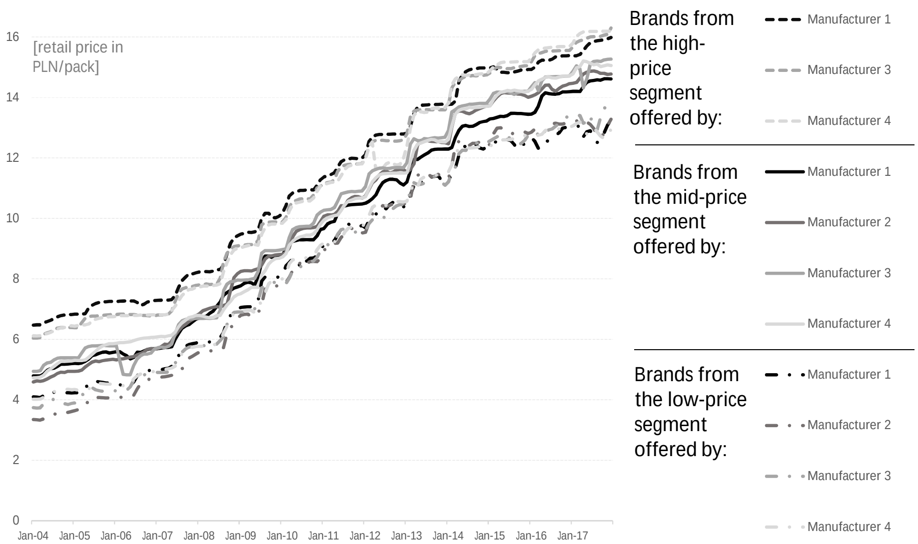
Figure 1: Trends in the level and structure of retail sales volumes



Source: own calculations basing on Nielsen and BAT data.

The following trends in terms of market structure are visible: an increase of the average length, as well as an expansion of the market shares of cigarettes with menthol flavour and with capsules that change the flavour. A shift in the market structure can also be observed in Figure 1 that includes a breakdown of the retail sales volume into particular market segments. Those market developments took place in an environment of continued growth of the market prices, but at different rates for various segments (see Figure 2), which was related to the already mentioned excise hikes and changes in the taxation structure in Poland. In parallel, the overall market volume contracted over the years 2008-2015, with somewhat more stable periods of 2005-2008 and 2015-2017. One can hypothesize that the changes in the market level and structure have been a result of excise-driven price hikes, but also some more general shift of consumer preferences could have taken place, e.g. towards flavoured cigarettes.

Figure 2: Trends in retail sales prices [PLN per 20 cigarettes]



Note: Only the main 4 manufacturers are included in calculations of the average prices in the figure, but in the BLP estimation the products offered by the minor manufacturers are included as well.
Source: own calculations basing on Nielsen and BAT data.

3 Methodology

In this section the methodology applied in this paper is outlined, starting with is a short exposition of the discrete choice modelling approach. Secondly, the specification issues are discussed, followed by the description of the approach to the post-estimation simulations.

3.1 The discrete choice models

The dataset considered in this paper includes information about differentiated cigarette products, which under the standard econometric approach could be analysed using a system of product-specific demand equations. However, the number of parameters to estimate increases considerably with the number of products included in the analysis. For instance, unrestricted substitution matrix (including all the own- and cross-price elasticities of demand) in a system containing 100 products requires estimation of 10 000 price-related coefficients. This dimensionality problem could be assuaged using multi-level budgeting, e.g., under the Almost Ideal Demand System framework, yet it often requires unrealistic or arbitrary assumptions that make it difficult to obtain results comparable across studies (see Ackerberg et al., 2007). There are more general restrictions such as symmetry restriction on the substitution matrix, but in the case of the considered dataset, they do not allow for sparing enough degrees of freedom to make the estimation feasible.

As a solution to the dimensionality problem, this paper embraces a discrete choice model in which each product is treated as a bundle of its characteristics, with the utilities drawn by consumers from particular characteristics explained with a well-designed regression. The utility of the consumer i from product j in period t is defined as u_{ijt}. In a discrete choice model, consumer i chooses the good j when:

$$u_{ijt} \geq u_{irt} \text{ for } r = 0, 1, ...J, \tag{1}$$

in which $r = 0, 1, ..., J$ provide index for all the products offered in the market in period t with 0 denoting the outside good.

In the dataset considered in this study, for each period t only the aggregate market data for each product j is observed. Discrete choice model can explain the related market shares, depending on specification of the consumer utility u_{ijt} and consumer heterogeneity. The simplest case of the aggregate discrete choice model is the conditional logit model (as developed by McFadden, 1973), in which the market share function takes the analytical form:

$$s_{jt} = \frac{\exp(\boldsymbol{x}_{jt}\boldsymbol{\beta} - \alpha p_{jt} + \xi_{jt})}{1 + \sum_{r=1}^{J} \exp(\boldsymbol{x}_{rt}\boldsymbol{\beta} - \alpha p_{rt} + \xi_{rt})}, \tag{2}$$

wherein $\boldsymbol{x}_{jt}$ is an M-element horizontal vector of observable, non-price product characteristics, ξ_{jt} – a scalar conglomerate of unobservable product characteristics, p_{jt} – a scalar product price. After accounting for the existence of the outside good, a linear model can be obtained:

$$ln(s_{jt}) - ln(s_{0t}) = \boldsymbol{x}_{jt}\boldsymbol{\beta} - \alpha p_{jt} + \xi_{jt}, \tag{3}$$

that can be estimated using OLS or instrumental variables methods to account for the endogeneity issues (the related identification strategy is discussed below).

One of the fundamental issues that renders model defined in the equation (3) inadequate to the analysis of the substitution patterns is the independence of irrelevant alternatives (*IIA*) property. In a model that has that property, any price change of good 1 leads to an expansion (or reduction) of the market shares of the remaining goods, yet with relative shares unchanged. In consequence, all the cross-price elasticities of demand with respect to price of good 1 are equal. This is unrealistic because in reaction to an increase in price of good 1, demand for *similar* products should increase by a larger percentage than the demand for products that differ from good 1 to a larger extent (see Nevo, 2000b for a further discussion).

A well-known way to overcome the *IIA* property, embraced in this paper, is to estimate a special case of the random coefficients logit model – the BLP model

(Berry et al., 1995). It has the following market share function:

$$s_{jt} = \int\int \frac{\exp(\boldsymbol{x}_{jt}\boldsymbol{\beta_i} - \alpha_i p_{jt} + \xi_{jt})}{1 + \sum_{r=1}^{J} \exp(\boldsymbol{x}_{rt}\boldsymbol{\beta_i} - \alpha_i p_{rt} + \xi_{rt})} dP_{d_{it}} dP_{\boldsymbol{\nu}_{it}} \tag{4}$$

in which distribution $P_{d_{it}}$ summarises the observable consumer characteristics (from the point of view of the external observer), distribution $P_{\boldsymbol{\nu}_{it}}$ summarises non-observable consumer characteristics and $\boldsymbol{\beta_i}$ and α_i are the random coefficients. The observable consumer characteristics are also referred to as demographic variables. The elements of vector $\boldsymbol{\gamma}_i = [\boldsymbol{\beta}_{\boldsymbol{i}}', \alpha_i]$ in this study are specified as follows (more general formulas are provided in Nevo, 2000b):

$$\gamma_{si} = \gamma_s + \pi_s d_{it} + \sigma_s \nu_{sit} \tag{5}$$

in which γ_s is the sth element of the constant coefficient vector $\boldsymbol{\gamma} = [\boldsymbol{\beta}', \alpha]$, d_{it} is a (demographic) variable summarizing observable consumer characteristic with distribution $P_{d_{it}}$, ν_{sit} is a product-characteristic-specific random variable summarizing non-observable information about consumers (standard normal distribution is assumed), π_s is a parameter describing the impact of the demographic variable on the marginal utility and σ_s is a parameter describing the impact of non-observable consumer characteristics on the marginal utility.

The market shares given by the equation (4) are calculated by simulation and the parameters are estimated with Generalized Method of Moments (GMM). The formula for product-specific price elasticities of demand is provided in Nevo (2000b), but a BLP model can also be assessed in terms of the overall price elasticity that it implies. To assure comparability of the results of this study to the prevalent aggregate-level literature, the total elasticity is calculated according to the following formula (see Olesiński et al., 2020 for a derivation):

$$\bar{\eta}^t = \sum_{j=1}^{J} \left[w_j^t \sum_{k=1}^{J} \eta_{jk}^t \right] \tag{6}$$

in which w_j is the market (value) share of product j and η_{jk}^t is the elasticity of demand for product j with respect to price of product k in period t.

Additional details of the BLP approach and the description of related estimation engine can be found in, e.g., Nevo (2000b). The estimation in this paper is based on an R package `BLPestimatoR` (Brunner et al., 2019).

3.2 Model specification

In this section, the approach to econometric specification is discussed, starting with the issues that are common both to the simple conditional logit model and the BLP model. After that, additional issues specific to the BLP model are discussed.

Common issues

Because the volumes in the Polish tobacco market were in a downward trend and retail prices were in an upward trend (see Figures 1 and 2), it is all too easy to explain the drop in market demand only with price hikes. In particular, there seems to be a negative trend related to increasingly negative attitude of the society towards smoking (as demonstrated by Pękała and Torój, 2017). In such circumstances, simply explaining demand with prices and not including the trend would lead to substantial overestimation of price elasticities. This is avoided in this paper by including both the prices and the non-price-related factors in the considered econometric specifications. In order to mitigate the negative impact of high (negative) correlation of prices and trend on the estimation results, the *real price* is calculated as a % share of retail price of pack of 20 cigarettes in the daily disposable income of households, expressed per adult (15+) resident. The disposable income data comes from the OECD and the adult resident data comes from the Labour force Survey and National Bank of Poland data (Saczuk, 2014).

Further exploration of the correlation patterns in the analysed dataset revealed that the *length* variable is highly correlated with *slim* variable, which is an intuitive result as usually slims tend to be longer cigarettes. In the estimations that follow, the *length* variable is dropped for two reasons. Firstly, it conveys similar, if somewhat more limited, information about particular products as the *slim* variable. Secondly, it seems that only more substantial differences in cigarette length should be visible to the consumers, e.g., between 84mm and 100mm cigarettes, while cigarettes of similar length, e.g., 84mm, 90mm, would be indistinguishable, *ceteris paribus*. Proper treatment of such nonlinearities would require introduction of many variables that after all convey similar information as a more parsimonious *slim* variable.

The explanatory variables also include the brand-specific dummies. Those binary variables can be included because the product category used in this study is a more specific category than brand (some brands can have multiple product varieties). This in turn makes it possible to estimate the fixed brand effects along with the marginal effects of the observable product characteristics. Finally, among the explanatory variables the *temperature* variable is included to account for the seasonal patterns in the Polish tobacco market (necessary to be accounted for due to the monthly frequency of the dataset).

Another issue related to the econometric specification, relevant both to the simple conditional logit and the BLP model is the identification strategy. Non-price product characteristics are used to construct instruments in a way proposed by Berry et al. (1995). It is assumed that those characteristics are exogenous towards prices because they are not set simultaneously with prices in the dataset used in this paper. In particular, the non-price characteristics are set once and for all throughout all the product's lifecycle, while the prices are set by manufacturers *ex post*, most likely basing on the non-price product characteristics (and not the other way round). In addition, in order for the non-price product characteristics (and their functions) to be proper instruments, the orthogonality of the observable and the non-observable non-price characteristics needs to be assumed.

BLP-specific issues

The key difference between BLP and the simple conditional logit model discussed above is the fact that the former includes random coefficients of the utility function, whereas the latter includes constant coefficients. The specification of the random coefficients in this study includes two types of consumer-specific parameters that affect the marginal utilities (see equation (5)):

- the σ_s parameters which describe the impact of the non-observable consumer characteristics ν_{sit} on the marginal utility,

- the π_s parameters which describe the impact of the demographic variable d_{it} on the marginal utility. In this study, the *log income* (log disposable income per adult, corrected by CPI) is the only demographic variable used. It is sampled G times from a parametric normal distribution with period-specific means corresponding to the log mean disposable income based on the OECD data and period-specific standard deviations based on the Polish Central Statistical Office (GUS) data. The resulting variable has been demeaned so the interpretation of average random coefficients corresponds to the average *log income*.

The approach to specifying the equation (5) outlined above implies that for 13 marginal utilities in the logit model, the maximum number of parameters related to deviations of the random coefficients from their respective averages (governed by the π_s and σ_s parameters) equals 26. However, precise estimation of such a full model is infeasible and the standard approach in the literature is to limit the number of those additional parameters. This paper seeks to strike the right balance between precise estimation of utility parameters and realistic substitution matrix which has (i) negative diagonal elements, (ii) positive non-diagonal elements and (iii) cross-price elasticities in each column that differ across products, demonstrating that the model does not have the *IIA* property. This last criterion is important because even a full BLP model can have the undesirable *IIA* property – the estimation algorithm might fail to find any such consumer-specific parameters to be different from zero.
This is related to the overall difficulty of precise estimation of the random components of utility coefficients – many estimation issues need to be accounted for while specifying the BLP model. In this study, the number of analysed products is close to 400 for some months, which is a huge number. As Berry et al. (2004) point out, in order to assure asymptotic normality of the BLP estimator, the ratio of the number of simulation draws (G) needs to grow with the square of the number of products. This issue is explored empirically by Brunner et al. (2017) who demonstrate that many issues of the BLP estimation reported by the previous literature (e.g., Knittel and Metaxoglou, 2014), including instability and bias of the estimates, can be mitigated

by using appropriately high G. The authors even stress that that it is better to run relatively few estimations with large G rather than many more estimations with relatively low G. In order to account for this issue, in this study $G = 5000$ is used, for which the estimation is already a computationally intensive process, taking many hours to complete. Calculating a model with G fully following the recommendations put forward by the literature would be computationally prohibitive due to large number of products considered in this paper. Of course, provided that enough computational power is available to the researcher, using G as close as possible to the square of the number of products should be encouraged as a general rule.

Potential consequences of high number of products in the BLP estimation are also discussed by Armstrong (2016) - those issues might be mitigated with high number of markets (the dimension of data other than product space). In other words, either the highest possible frequency or local level data (e.g., regions, particular shops) should be used. This paper embraces the former approach by using monthly frequency, which has an additional advantage of reducing the maximum number of products in a single period (as some products can be observed only during some months and not over the full year).

3.3 The post-estimation simulations based on the BLP model

The level of detail offered by the BLP model makes it possible to carry out various simulation analyses. The first post-estimation simulation considered in this paper focuses on a counterfactual withdrawal of the menthol cigarettes (including the cigarettes with capsules that change the taste) from the duty-paid market in December 2017 in order to demonstrate the impact of a ban on menthol cigarettes from the EU market in 2020 under the Tobacco Products Directive. In the simulation, the theoretical market shares based on the equations (4) are calculated, with the banned products being omitted.

The second post-estimation simulation considers a tobacco tax policy change. The cigarette excise tax in Poland includes three rates: (i) the specific rate, which is calculated per cigarette, (ii) the *ad valorem* rate that is calculated as a % of gross retail price and (iii) the minimum rate which applies to each cigarette as long as the taxation implied by (i) the specific and (ii) the *ad valorem* rates is too low.

The simulation of change in tax policy considers a scenario of a counterfactual 5% increase in specific excise rate in December 2017. The total tax level per 20 cigarettes is given by:

$$T = \max\left(\alpha P + \beta, \gamma\right), \tag{7}$$

in which P is the retail price of 20 cigarettes, while α, β and γ are the *ad valorem* rate, specific rate (per 20 cigarettes) and minimum rate (per 20 cigarettes) of the tobacco excise tax, respectively. The minimum rate γ itself is calculated automatically according to the following formula:

$$\gamma = \alpha WAP + \beta, \tag{8}$$

in which WAP stands for the weighted average retail price of cigarettes that is calculated by the Polish Ministry of Finance basing on the market data from the preceding year and announced before the beginning of the year in which a given level of γ applies. The γ parameter might change even under constant α and β because WAP transfers the retail price changes into the level of γ with a one year lag. Equation (8) implies that the minimum rate would increase automatically by 2.46%, as a result of a 5% increase in β.
The prices in the simulation are set in such a way that the net consumer price $\bar{P}$ (the retail price minus all the taxes) remains unchanged irrespective of changes in particular tax rates (with the exception of few low-volume products for which $\bar{P}$ is negative – in such cases, the retail price after tax change is calculated with $\bar{P}$ set to 0). The retail price formula of 20 cigarettes is thus:

$$P = \begin{cases} \frac{\bar{P}+\beta}{1-\alpha-\nu/(1+\nu)} & \text{for} \quad \alpha P + \beta \geq \gamma, \\ (\bar{P}+\gamma)(1+\nu) & \text{for} \quad \alpha P + \beta < \gamma. \end{cases} \tag{9}$$

in which ν is the VAT rate (equal to 23%) expressed as % of net price and γ is the minimum rate. The latter parameter not only determines the pricing formula used in the simulation (either first or second line of the formula (9)), but also the price level itself (see line two).

4 The results

In this section, the results are discussed, starting with the simple conditional logit model, followed by the discussion of the BLP and then, by the related post-estimation simulations.

4.1 Conditional logit results

The description of the econometric results starts with the simplified conditional logit model with constant coefficients (in a linear specification, see equation (3)). Although it produces unrealistic substitution patterns, as discussed above, it is useful to explore the validity of the selected instrument set. Table 2 contains the results of the OLS estimation, 2SLS estimation of the linear model as well as the first stage model (explaining the *real price* variable).
As expected, the OLS specification suffers from the endogeneity issues as indicated by the positive *real price* coefficient. Indeed, 'better' products (in terms of utility) are sold for higher prices as the supply side agents seek to cash in the unobservable attractiveness of particular products. The identification issue arises in spite of the inclusion of brand dummies that control for the time-invariant component of the unobserved quality. Gladly, the 2SLS estimation with the instruments as proposed by Berry et al. (1995) solves this issue and produces the price coefficient that is

Table 2: Results of the conditional logit estimation

	OLS	**2SLS**	**First stage (explaining the real price)**		
	Conditional logit	*Conditional logit*	*Linear model*	*Instruments - the same firm*	*Instruments - other firms*
Real price	61.196*** (0.000)	−18.558*** (0.000)			
Menthol	−0.563*** (0.000)	−0.646*** (0.000)	−0.00085*** (0.000)	0.00032*** (0.000)	0.00007*** (0.003)
Slim	0.105*** (0.002)	0.310*** (0.000)	0.00251*** (0.000)	0.00003 (0.199)	0.00018*** (0.000)
The number of sticks in pack	0.004 (0.381)	−0.036*** (0.000)	−0.00050*** (0.000)	0.000005*** (0.000)	0.000005*** (0.000)
Flavour capsules	0.931*** (0.000)	0.956*** (0.000)	0.00025 (0.452)	−0.00091*** (0.000)	−0.00135*** (0.000)
Soft pack	−0.813*** (0.000)	−0.739*** (0.000)	0.00164*** (0.000)	0.00041*** (0.000)	0.00017*** (0.000)
Light	0.038 (0.135)	−0.014 (0.617)	−0.00065*** (0.000)	−0.00005 (0.203)	0.00024*** (0.000)
Super Light	−0.676*** (0.000)	−0.742*** (0.000)	−0.00131*** (0.000)	−0.00044*** (0.000)	−0.00031*** (0.000)
Mid-price segment	−1.846*** (0.000)	−1.760*** (0.000)	0.00003 (0.930)	−0.00057*** (0.000)	−0.00057*** (0.000)
High-price segment	−1.684*** (0.000)	−0.593*** (0.000)	0.01407*** (0.000)	0.00033*** (0.000)	−0.00007*** (0.000)
Temperature	0.022*** (0.000)	0.023*** (0.000)	0.00003*** (0.000)		
Trend	−0.061*** (0.000)	−0.034*** (0.000)	0.00048*** (0.000)		
Intercept	−14.222*** (0.000)	−9.284*** (0.000)	0.01416*** (0.000)		
Sargan statistic for overidentifying restrictions		1 107.52			
F statistic for excluded instruments			680.85		
p-value		(0.000)	(0.000)		

Note: p-values in parentheses (* p<0.10, ** p<0.05, ***p<0.01). The number of observations: 57622 (unbalanced panel of 865 products over 168 months). 210 brand dummies are omitted for clarity.

significant and in the negative range. Further, high correlation between the *real price* and *time period* (trend) seems not to be too much of a problem as both variables exhibit negative, statistically significant marginal utility, which is an intuitive result (the negative impact on the market volumes of (i) the increasing prices and (ii) the

consumer sentiment against smoking coexisted in the Polish cigarette market).
The 2SLS model is controversial when it comes to the substitution patterns that it produces, yet it allows for some interesting conclusions with respect to the marginal utility of product characteristics. Namely, the consumers tend to draw lower utility, *ceteris paribus*, from menthol cigarettes, super lights, bigger packs of cigarettes, soft packs and, quite surprisingly, the mid- and high-price segments (as compared to the low-price segment, which is the reference segment to avoid full collinearity). On the the other hand, consumers tend to prefer slim cigarettes and cigarettes with capsules that change the taste.
The consumer preferences seem to be reflected in the pricing policy of firms – the lower-utility characteristics tend to reduce the prices, *ceteris paribus* (see the third column of Table 2), while the preferred characteristics provide firms with the opportunity to charge higher prices. There are two exceptions. First is the *soft pack* variable which seems to be related to lower utility and higher price. This result might be explained by the fact that cigarettes with soft packs have become increasingly niché products. The second exception is the *high-price segment* variable, which is related to higher price (as the reference segment is the low-price segment) and lower utility.
The overall consistency of signs of the first and the second stage of 2SLS estimation helps explain why IV method succeeds in reducing the upward bias of the price coefficient. Namely, the pricing strategy of firms accounts for the utility that consumers assign to particular products (supposedly, this holds for the characteristics non-observable to the external observer), so accounting for this pricing strategy leads to bias reduction. The remaining two columns of Table 2 contain the first-stage coefficients for the excluded instruments that are usually not interpreted, but the F statistic suggests that, altogether, they significantly affect the retail price of cigarettes.

4.2 The BLP results

In the case of BLP, various specifications can be considered for the same set of product characteristics included in the logit model. The broader set of models estimated as a part of this study focused on rather parsimonious specifications that included random coefficients only for the *real price*, *menthol*, *slim*, *light*, *super light*, *mid-price segment* and *high-price segment* variables (a maximum of 4 random coefficients in a single specification). The decisions with respect to which coefficients are allowed to be random were clearly influential for the results. A single baseline specification was chosen basing on that it produces realistic substitution patterns (see below) and that it exhibits coefficient estimates with reasonable economic interpretation (see the Supplementary Material for more details of the alternative specifications). The results for the mean utility parameters ($\boldsymbol{\beta}$ and α) are demonstrated in Table 3 and the related consumer-specific components (π_s and σ_s) are demonstrated in Table 4.
The marginal utilities can be compared (in average terms) with the conditional logit coefficients estimated using 2SLS. The signs of the estimated marginal utilities are

Table 3: Results of the BLP estimation - mean utility parameters as compared to the conditional logit (2SLS) results

	Conditional Logit (2SLS)	BLP Model (GMM)
	Mean utility parameters	
Real price	-18.558^{***} (0.000)	-12.098^{***} (0.002)
Menthol	-0.646^{***} (0.000)	-0.769^{***} (0.000)
Slims	0.310^{***} (0.000)	0.430^{***} (0.000)
The number of sticks in pack	-0.036^{***} (0.000)	-0.035^{***} (0.000)
Flavour capsules	0.956^{***} (0.000)	1.463^{***} (0.000)
Soft pack	-0.739^{***} (0.000)	-0.719^{***} (0.000)
Light	-0.014 (0.617)	0.038 (0.228)
Super Light	-0.742^{***} (0.000)	-0.637^{***} (0.000)
Mid-price segment	-1.760^{***} (0.000)	-11.412^{***} (0.000)
High-price segment	-0.593^{***} (0.000)	-18.959^{***} (0.000)
Temperature	0.023^{***} (0.000)	0.034^{***} (0.000)
Trend	-0.034^{***} (0.000)	-0.040^{***} (0.000)
Intercept	-9.284^{***} (0.000)	-9.738^{***} (0.000)
Random coefficients for:	(-)	real price, mid-price segment, high-price segment

Note: p-values in parentheses (* p<0.10, ** p<0.05, ***p<0.01). The number of observations: 57622 (unbalanced panel of 865 products over 168 months). The number of simulations of consumer characteristics $G = 5000$. 210 brand dummies are omitted for clarity. In the first column, the conditional logit results (2SLS) are additionally reported (see Table 2 for more details).

largely consistent between 2SLS and GMM model, but the magnitude of coefficients differ, for example for the *real price* variable.

Important results of the BLP modeling are related to the consumer-specific parameters (π_s and σ_s, see Table 4). According to the Wald test, those parameters are jointly significant (under all standard significance levels) in the baseline BLP model, which means that it should include consumer-specific parameters to better describe the data. However, when individual parameters are considered, the estimation results are not straightforward to interpret. The σ_s parameters do not differ statistically from zero in any of the cases which suggests that unobservable consumer characteristics might be hard to capture with the normal distribution with fixed mean and standard

Table 4: Results of the BLP estimation - the random components of the utility coefficients and the additional results

Standard errors of the random coefficients	
σ for real price	-0.024 (1.000)
σ for mid-price segment	-1.467 (0.914)
σ for high-price segment	1.505 (0.892)
Interaction of the random coefficient with log income	
π for real price	-2.262 (0.754)
π for mid-price segment	18.861^{***} (0.000)
π for high-price segment	-23.326^{***} (0.000)
Additional results	
Wald p for joint significance of the random coefficients	0.000
Total elasticity in December 2017	-0.59
The value of GMM objective in the BLP estimation	4 980.2

Note: p-values in parentheses (* p<0.10, ** p<0.05, ***p<0.01). The number of observations: 57622 (unbalanced panel of 865 products over 168 months). The number of simulations of consumer characteristics $G = 5000$.

deviation parameters. The significant results appear in the case of the π_s parameters which might be related to the fact that the mean of the distribution of the *log income* variable (which is also assumed to be normal) increases over time. Interestingly, the π_s parameter for the *real price* variable has a negative sign and for some specifications this parameter is statistically significant, suggesting that consumers with higher income are more price sensitive (see the Supplementary Material for those remaining specifications). One of the explanations of such a result might be the fact that more affluent consumers consider smoking a less attractive habit and are more inclined to quit smoking as a result of price increases as compared to less affluent consumers. However, this result does not hold in the baseline BLP model (due to statistical insignificance). Generally, the mixed results suggest that BLP models might not be a very useful device to verify hypotheses about individual parameters driving the consumer behaviour in the tobacco market. Those results illustrate the practical problems with the BLP estimation that have already been discussed in the literature (see, e.g., Knittel and Metaxoglou, 2014; Brunner et al., 2017).

The total elasticity for the baseline BLP model for December 2017 equals -0.59 which is close to the results of the meta-analysis of Gallet and List (2003), in which the average elasticity of demand for cigarettes in 86 studies equaled -0.48

(the results ranged from -3.12 to 1.41). It must be noted, however, that the estimates in the literature often concern the total cigarette consumption, whereas the total elasticities as reported in Table 4 include only the duty-paid cigarettes (i.e., not the shadow economy). In other words, the price elasticity equal to -0.59 includes the flows between the duty-paid and illicit markets, which are absent in the price elasticity estimates if total cigarette consumption is considered. However, the

Table 5: The substitution matrix for 10 products with the highest market value in the BLP model (the selected month: December 2017)

Total elasticity: -0.59	Brand 1 (84mm, light, mid-price segment)	Brand 2 (84mm, light, low-price segment)	Brand 3 (84mm, light, high-price segment)	Brand 1 (100mm, slim, light, mid-price segment)	Brand 2 (84mm, "full flavour", low-price segment)
Brand 1 (84mm, light, mid-price segment)	-1.687	0.007	0.000	0.222	0.005
Brand 2 (84mm, light, low-price segment)	0.010	-1.453	0.006	0.005	0.030
Brand 3 (84mm, light, high-price segment)	0.000	0.007	-1.055	0.000	0.004
Brand 1 (100mm, slim, light, mid-price segment)	0.403	0.007	0.000	-1.869	0.005
Brand 2 (84mm, "full flavour", low-price segment)	0.010	0.045	0.006	0.005	-1.469
Brand 4 (100mm, slim, super light, low-price segment)	0.010	0.045	0.006	0.005	0.030
Brand 5 (84mm, light, low-price segment)	0.010	0.045	0.007	0.005	0.030
Brand 1 (84mm, light, menthol, mid-price segment)	0.403	0.007	0.000	0.221	0.005
Brand 6 (100mm, "full flavour", low-price segment)	0.010	0.045	0.006	0.005	0.030
Brand 1 (100mm, slim, light, menthol, mid-price segment)	0.403	0.007	0.000	0.221	0.005

Source: own calculations basing on Nielsen and BAT data.

BLP models considered in this study are not subject to the omitted variable problem because the illicit market is included in the outside good (see the Supplementary Material for more details).

The estimated price elasticities of demand (from the BLP model, as of December 2017) for 10 products with the highest market values are presented in Table 5 along with some basic product characteristics. As mentioned above, the preferred BLP model produces substitution matrix in which (i) the diagonal elements are negative, (ii) non-diagonal elements are positive and (iii) the cross-price elasticities in each

Table 5 (cont.): The substitution matrix for 10 products with the highest market value in the BLP model (the selected month: December 2017)

Total elasticity: −0.59	Brand 4 (100mm, slim, super light, low-price segment)	Brand 5 (84mm, light, low-price segment)	Brand 1 (84mm, light, menthol, mid-price segment)	Brand 6 (100mm, "full flavour", low-price segment)	Brand 1 (100mm, slim, light, menthol, mid-price segment)
Brand 1 (84mm, light, mid-price segment)	0.004	0.004	0.158	0.004	0.146
Brand 2 (84mm, light, low-price segment)	0.029	0.028	0.004	0.024	0.004
Brand 3 (84mm, light, high-price segment)	0.004	0.004	0.000	0.003	0.000
Brand 1 (100mm, slim, light, mid-price segment)	0.004	0.004	0.158	0.004	0.146
Brand 2 (84mm, "full flavour", low-price segment)	0.029	0.028	0.004	0.024	0.004
Brand 4 (100mm, slim, super light, low-price segment)	−1.566	0.028	0.004	0.024	0.004
Brand 5 (84mm, light, low-price segment)	0.029	−1.613	0.004	0.024	0.003
Brand 1 (84mm, light, menthol, mid-price segment)	0.004	0.004	−1.967	0.004	0.146
Brand 6 (100mm, "full flavour", low-price segment)	0.029	0.028	0.004	−1.445	0.004
Brand 1 (100mm, slim, light, menthol, mid-price segment)	0.004	0.004	0.158	0.004	−1.981

Source: own calculations basing on Nielsen and BAT data.

columns differ across products, confirming that the model does not have the *IIA* property. Importantly, the cross-price elasticities for products belonging to the same segments are generally stronger than in the remaining cases - indeed, after an increase in price, consumers are more likely to shift to products that are relatively similar. Although a formal test of groups of cross-price elasticities being different from each other is not carried out, such an interpretation is valid because the π_s and σ_s parameters are jointly statistically significant.

The magnitude of individual elasticities seems large and in particular, product-specific own-price elasticities are much larger (in absolute terms) than the total elasticity. This is because both parameters include different scope of the *ceteris paribus* assumption. For instance, the own-price elasticity describes the % change of demand for particular product in reaction to a 1% price increase for that product, with the prices of substitute cigarettes unchanged. The total price elasticity, in turn, describes the % change of market demand in reaction to 1% price increase for all the considered products (so the prices of substitutes change as well).

There is one important caveat to the substitution matrix presented in Table 5. The baseline BLP model excludes consumer-specific parameters for such product characteristics as *slim*, *menthol* or *light*. Inclusion of those additional parameters would result in cross-price elasticities reflecting stronger substitution patterns within the *slim*, *menthol* or *light* category of cigarettes. However, inclusion of all the important consumer-specific parameters is not feasible in a single BLP specification – large number of such parameters aggravates the estimation problems and leads to

Table 6: Simulation result for a hypothetical withdrawal of menthol cigarettes (including those with capsules that change the flavour) from the market in December 2017

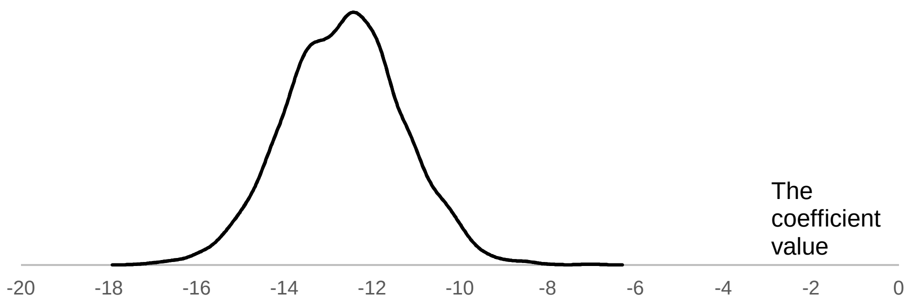
Category	% change in demand
Brand 1 (84mm, light, mid-price segment)	42.60%
Brand 2 (84mm, light, low-price segment)	11.63%
Brand 3 (84mm, light, high-price segment)	29.63%
Brand 1 (100mm, slim, light, mid-price segment)	42.60%
Brand 2 (84mm, “full flavour”, low-price segment)	11.63%
Brand 4 (100mm, slim, super light, low-price segment)	11.63%
Brand 5 (84mm, light, low-price segment)	11.63%
Brand 6 (100mm, “full flavour”, low-price segment)	11.63%
Brand 7 (100mm, slim, light, low-price segment)	11.63%
Brand 8 (84mm, light, low-price segment)	11.63%
Duty-paid market	−10.02%
Outside good	11.66%

Source: own calculations basing on Nielsen and BAT data.

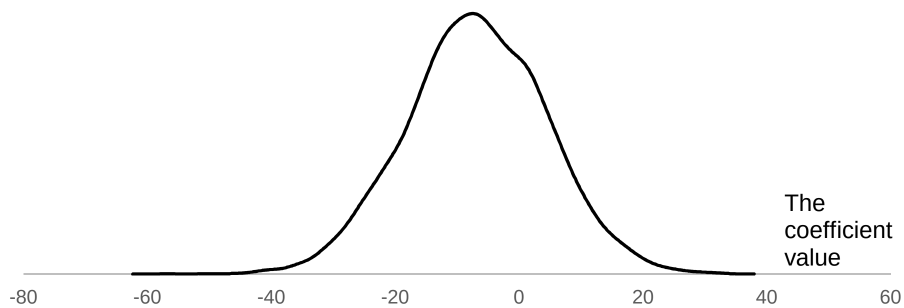
more unstable results.

Finally, the marginal distributions of consumers' preferences towards particular product characteristics can be analysed in order to better understand the consumer diversity (Figure 3). In the case of *mid-price segment* and *high-price segment* variables, there are some groups of consumers whose marginal utilities have different signs than for the majority of the consumer base. From that perspective, the negative (average) marginal utility of a given product characteristic does not mean that products with that particular characteristic should be eradicated by the market forces. It only suggests that on average, products with a given characteristic are chosen more rarely, *ceteris paribus*, but essentially there should be a non-negligible share of consumers that choose products with this characteristic.

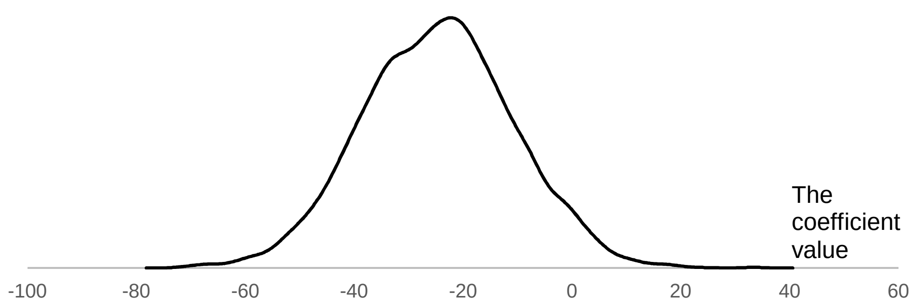
Figure 3: The empirical densities of random coefficients of the utility function in the BLP model in December 2017



3(a) The *real price* coefficient



3(b) The *mid-price segment* coefficient



3(c) The *high-price segment* coefficient

Table 7: Simulation result of a hypothetical 5% increase in specific excise rate in December 2017

	Baseline scenario	Alternative scenario	Change
Excise: specific rate (PLN/20 sticks)	4.14	4.34	5.00%
Excise: *ad valorem* rate (% of retail price)	31.41%	31.41%	0.00pp.
Excise: minimum rate (PLN/20 sticks)	8.41	8.61	2.46%
VAT rate (% of net price)	23%	23%	0.00pp.
Average retail price (PLN/20 sticks)	14.06	14.42	2.56%
Retail sales volume (m sticks)	2576.7	2538.1	−1.50%
Government revenues: excise (PLN m)	1113.4	1133.6	1.82%
Government revenue: VAT (PLN m)	338.7	342.2	1.02%
Government revenues: overall (PLN m)	1452.1	1475.7	1.63%

Source: own calculations basing on Nielsen and BAT data.

4.3 The simulation results

The impact of the withdrawal of menthol cigarettes (including the cigarettes with capsules that change the taste) from the market on (i) the simulated market volumes of 10 products with the highest market value (excluding menthols), (ii) the duty-paid market and (iii) the outside good is demonstrated in Table 6.

According to the simulation results, the ban on menthol cigarettes leads to a reduction of the duty-paid market volume by 10.02% as the consumers to a large extent switch to other brands of cigarettes in the duty-paid market (the volume expansion rates for 10 individual products range from 11.63 to even 42.60%). It is not clear whether expansion of the outside good ‘market volume’, equal to 11.66%, means an expansion of the shadow economy, fine-cut tobacco market or quitting. More precise data on the shadow economy would be required to draw any conclusions in that respect.

The simulation results for the 5% increase in specific excise rate are presented in Table 7. As a result of the tax hike, the average retail price grows by 2.56%, which is related to a drop in retail sales volume by 1.50%. The excise- and VAT-related government revenues are higher by 1.82% as compared to the *status quo* scenario. The results for the volume show that the menthol ban is a relatively strong measure, as compared to the excise hike, despite considerable switching towards non-menthol cigarettes, as demonstrated by the BLP model.

5 Conclusions

This paper considers a well-known BLP model as tool to carry out *ex ante* measurement of the effects of the tobacco product bans, addressing a literature gap in that area. As an example, the impact of a EU-induced menthol cigarettes ban on the Polish cigarettes market is measured, in comparison to a 5% hike of specific excise rate for cigarettes. The simulations suggests that the menthol ban (including the cigarettes with capsules that change the taste), despite switching of tobacco consumers towards non-menthol cigarettes, has a considerable impact on the reduction of the cigarettes duty-paid retail sales volume, as compared to the cigarette excise hike. Also, the simulation exercises demonstrate that BLP is a versatile framework that allows for diverse policy simulations that can help inform future policy decisions. In particular, the BLP model includes different market segments and accounts for different levels of income of particular consumers, making it a natural framework to analyse changes in the level and structure of excise taxation, possibly in combination with other kinds of policies.

For the purposes of estimation in this paper, a product-specific dataset for Poland is used, taking advantage of complex developments in cigarettes retail prices in Poland over the 2004-2017 period. The related price variability made it possible to estimate product-specific demand effects for a very large product portfolio (including up to 466 products marketed in a single year). The results presented in this paper are based on the Polish data, but the approach can essentially be applied in any other country in which product-level data for the tobacco market is available and the government considers diverse policies towards tobacco.

Some of estimation issues reported in the earlier literature are not avoided in this study. In particular, inclusion of all the important consumer-specific parameters is not feasible in a single BLP specification – large number of such parameters aggravates the estimation problems and leads to more unstable results. Such problems with estimation suggest that BLP models might not be a very useful device to verify hypotheses about individual parameters driving the consumer behaviour in the tobacco market.

In the end, it must be noted that the actual impact of the considered policies on the tobacco market and the government revenues could be different from the results presented above because the dataset used in this study ends in December 2017. A more up-to-date policy analysis should use a dataset covering periods closer to the actual policy change.

Taking into account the fact that the final BLP model specification is relatively parsimonious and some results are not very easy to interpret, further BLP estimations in the context of the Polish tobacco market (e.g., using longer time span) are warranted, including additional sensitivity analyses. Such sensitivity analyses could focus on verifying the ability of the BLP model to accurately predict market shares in out-of-sample exercises. This could not only provide additional criteria for the purposes of specifying the BLP model, but could also allow for a verification whether the BLP model is indeed superior to more simplistic models. In addition, further research could benefit from including information about electronic cigarettes and heated tobacco products that could be potential substitutes for the banned menthol cigarettes. Finally, the stability and precision of the econometric estimates could be increased by including the regional split of the product-level data and by including additional variables describing the availability of the analysed products across the retail points.

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Supplementary Material[1]

The Supplementary Material includes two Sections, in which the details of the specification of the outside good and the BLP model sensitivity analysis are provided.

A Specification of the outside good

In this Supplementary Section, specification of the outside good is discussed. In the discrete choice models of demand, the market share of the outside good is typically unobservable and is calculated by using a total market concept, with a definition depending on the actual research context (see, e.g., Nevo, 2000b for a popular set of guidelines). The market shares of the inside goods (as opposed to the outside good) in the core paper are calculated as follows:

$$s_{jt} = \frac{q_{jt}}{M_t} \tag{10}$$

in which s_{jt} is the market share of good j in period t, M_t is the total market volume in period t and the respective market share of the ouside good equals:

$$s_{0t} = 1 - \sum_{j=1}^{J} s_{jt} \tag{11}$$

in which J is the total number of individual cigarette products included in the analysed month. The market share of the outside good essentially depends on the definition of the total market, which is usually based on some auxiliary information. In the discrete-choice literature for the cigarettes market (Ciliberto and Kuminoff, 2010; Min, 2011; Pham and Prentice, 2013), M_t is often proportional to the adult population multiplied by the number of cigarettes each adult could potentially smoke. For instance, Pham and Prentice (2013) use the concept of the number of 'opportunities to smoke' equal to 25 (or 20) cigarettes per day while Min (2011) assumes that each adult can potentially smoke a pack of cigarettes per day. In addition, Min (2011) tests an alternative approach in which the share of the outside good equals the share of non-smokers in the adult population. However, if we took one of those approaches, the market share of the outside good would be overestimated in the context of the Polish tobacco market because it unlikely that the 'non-smokers' would start smoking even if prices dropped substantially, especially taking into account the overall trend

[1] The R appendix is available under the permanent link: `https://doi.org/10.6084/m9.figshare.12434987`.

to quit smoking in Poland (Pękała and Torój, 2017). Therefore, a majority of the adult population should not be considered as a potential market base for the tobacco consumption. A more conservative approach is taken by Ciliberto and Kuminoff (2010) who adjust the adult population (in the analysed local markets) by using, i.a., the information on the share of people who smoked at some point in their lives (equal to 20% of the target population) and on the number of cigarettes smoked par day (equal to 15 sticks, i.e., 75% of a pack on average). However, such kind of information that covers the entire analysed sample period for Poland is unavailable.
Therefore, in the core paper, a more agnostic approach is used. Firstly, the total combustible tobacco market size is calculated for each month basing on the Nielsen data on (i) duty-paid cigarette retail sales volume and (ii) duty-paid fine-cut tobacco retail sales volume (see Section 2 for the description of the Nielsen data). Secondly, M_t is kept constant over time and equal to the maximum market volume observed over the 2004-2017 sample period. Such an approach assumes that the potential market base for the cigarettes retail sales in Poland is relatively limited and under no scenario would produce the market volumes that exceeded the largest market volumes (including both cigarettes and fine-cut tobacco) already observed in Poland over the 2004-2017 sample period. Such an assumption is warranted, firstly, by the overall trend to quit smoking in Poland and secondly, by the EU regulations that in practice prevent considerable retail price reductions in Poland. In sum, the approximation of the total market M_t used in this study includes the following market segments:

- duty-paid cigarettes market,
- duty-paid fine-cut tobacco market,
- the ‘segment’ of ‘recent quitters’,
- partly, the shadow economy and
- partly, the ‘segment’ of ‘potential smokers’.

Note that the data on the adult population is not used (contrary to other literature), which is because high-quality monthly estimates of the actually resident adult population that account for immigration flows from and into Poland remain unavailable.

B Sensitivity analysis of the BLP results

In this Section of the Supplementary Material, the alternative BLP specifications are demonstrated, with the baseline specification, as discussed in the core paper, indicated as BLP Model 1 (see the Tables 8 and 9). The signs of the estimated marginal utilities are largely consistent among the specifications with most notable exceptions for the BLP Model 4 (see the *light*, *mid-price segment* and *high-price segment* variables in

Table 8: Results of the BLP estimation - mean utility parameters as compared to the conditional logit (2SLS) results

	Conditional Logit (2SLS)	BLP Model 1 (Baseline)	BLP Model 2	BLP Model 3	BLP Model 4	BLP Model 5
			Mean utility parameters			
Real price	-18.558^{***} (0.000)	-12.098^{***} (0.002)	-19.110^{***} (0.000)	-26.280^{***} (0.000)	-33.199^{***} (0.002)	-27.768^{***} (0.000)
Menthol	-0.646^{***} (0.000)	-0.769^{***} (0.000)	-0.647^{***} (0.000)	-0.859^{***} (0.000)	-6.185^{**} (0.012)	-0.969^{**} (0.021)
Slims	0.310^{***} (0.000)	0.430^{***} (0.000)	0.312^{***} (0.000)	0.576^{***} (0.000)	1.452^{***} (0.000)	0.553^{***} (0.001)
The number of sticks in pack	-0.036^{***} (0.000)	-0.035^{***} (0.000)	-0.036^{***} (0.000)	-0.063^{***} (0.000)	-0.046^{***} (0.000)	-0.070^{***} (0.000)
Flavour capsules	0.956^{***} (0.000)	1.463^{***} (0.000)	0.961^{***} (0.000)	1.521^{***} (0.000)	1.095^{**} (0.048)	1.509^{***} (0.000)
Soft pack	-0.739^{***} (0.000)	-0.719^{***} (0.000)	-0.738^{***} (0.000)	-0.884^{***} (0.000)	$-0.229*$ (0.096)	-0.905^{***} (0.000)
Light	-0.014 (0.617)	0.038 (0.228)	-0.014 (0.611)	1.968^{***} (0.000)	-1.261^{***} (0.000)	1.980^{***} (0.000)
Super Light	-0.742^{***} (0.000)	-0.637^{***} (0.000)	-0.743^{***} (0.000)	-0.904^{***} (0.000)	-25.928^{***} (0.000)	-1.158^{***} (0.002)
Mid-price segment	-1.760^{***} (0.000)	-11.412^{***} (0.000)	-1.761^{***} (0.000)	-1.830^{***} (0.000)	0.747 (0.107)	-1.690^{***} (0.000)
High-price segment	-0.593^{***} (0.000)	-18.959^{***} (0.000)	-0.588^{***} (0.000)	-1.175^{***} (0.000)	1.825^{***} (0.001)	-1.118^{***} (0.000)
Temperature	0.023^{***} (0.000)	0.034^{***} (0.000)	0.023^{***} (0.000)	0.032^{***} (0.000)	0.036^{***} (0.000)	0.033^{***} (0.000)
Trend	-0.034^{***} (0.000)	-0.040^{***} (0.000)	-0.034^{***} (0.000)	-0.029^{***} (0.000)	-0.039^{***} (0.000)	-0.029^{***} (0.000)
Intercept	-9.284^{***} (0.000)	-9.738^{***} (0.000)	-9.281^{***} (0.000)	-9.661^{***} (0.000)	-8.719^{***} (0.000)	-9.439^{***} (0.000)
Random coefficients for:	(-)	real price, mid-price and high-price segment	real price	real price, menthol, lights	real price, menthol, lights, super lights	real price, menthol, slims, lights

Note: p-values in parentheses (* p<0.10, ** p<0.05, ***p<0.01). The number of observations: 57622 (unbalanced panel of 865 products over 168 months). The number of simulations of consumer characteristics - 5000. 210 brand dummies are omitted for clarity. In the first column, the conditional logit results (2SLS) are additionally reported (see Table 2 for more details).

Table 9: Results of the BLP estimation - the random components of the utility coefficients and the additional results

	BLP Model 1 (Baseline)	BLP Model 2	BLP Model 3	BLP Model 4	BLP Model 5
Standard errors of the random coefficients					
σ for real price	-0.024 (1.000)	0.005 (1.000)	-0.056 (0.999)	-0.003 (1.000)	0.129 (0.998)
σ for menthol			0.001 (1.000)	-0.723 (0.940)	-0.017 (1.000)
σ for slim					-0.006 (1.000)
σ for light			0.001 (1.000)	0.022 (0.999)	-0.017 (0.999)
σ for super lights				4.146 (0.758)	
σ for mid-price segment	-1.467 (0.914)				
σ for high-price segment	1.505 (0.892)				
Interaction of the random coefficient with log income					
π for real price	-2.262 (0.754)	-2.335 (0.811)	-95.666^{***} (0.000)	5.307 (0.714)	-96.647^{***} (0.000)
π for menthol			0.805 (0.446)	-14.205^{***} (0.000)	1.192 (0.414)
π for slim					-1.371 (0.407)
π for light			11.746^{***} (0.000)	-0.762 (0.638)	12.155^{***} (0.000)
π for super lights				33.522^{***} (0.000)	
π for mid-price segment	18.861^{***} (0.000)				
π for high-price segment	-23.326^{***} (0.000)				

Note: p-values in parentheses (* p<0.10, ** p<0.05, ***p<0.01). The number of observations: 57622 (unbalanced panel of 865 products over 168 months). The number of simulations of consumer characteristics - 5000.

Table 9 (cont.): Results of the BLP estimation - the random components of the utility coefficients and the additional results

	BLP Model 1 (Baseline)	BLP Model 2	BLP Model 3	BLP Model 4	BLP Model 5
	Additional results				
Wald p for joint significance of the random coefficients	0.000	0.972	0.000	0.000	0.000
Total elasticity in December 2017	−0.59	−1.20	−3.11	−1.65	−3.21
Positives among own-price elasticities	0.0%	0.0%	43.3%	0.0%	43.3%
Negatives among cross-price elasticities	0.0%	0.0%	33.8%	0.0%	30.3%
The value of GMM objective in the BLP estimation	4 980.2	7 051.5	6 478.0	5 167.3	6 444.7

Note: p-values in parentheses (* p<0.10, ** p<0.05, ***p<0.01). The number of observations: 57622 (unbalanced panel of 865 products over 168 months). The number of simulations of consumer characteristics - 5000.

particular). Apart from that, the magnitude of coefficients differ, for example, for the *real price* variable. Important results of the BLP modeling are related to the random components of the utility coefficients (Table 9). According to the Wald test, the random components are jointly significant (under all standard significance levels) in all the BLP models with the exception of the BLP Model 2, which means that most models should include consumer-specific parameters to better describe the data. However, when particular parameters are considered, the estimation results are not straightforward to interpret. The σ_s parameters do not differ statistically from zero in any of the cases which suggests that unobservable consumer characteristics might be hard to capture with the normal distribution with fixed mean and standard deviation parameters. The significant results appear in the case of the π_s parameters.
As mentioned in the core paper, the preferred BLP model should produce substitution matrix that has (i) negative diagonal elements, (ii) positive non-diagonal elements and (iii) demonstrates that the underlying model does not have the *IIA* property. The requirements (i) and (ii) are satisfied only in the case of BLP Model 1, 2 and 4 (see the Additional Results section of the Table 9). When it comes to the requirement (iii), BLP Model 2 is the only specification in which the random components do not differ statistically from zero even jointly and thus should be rejected. When it comes to the mean utility parameters of BLP Model 4, the signs of some coefficients differ from the remaining specifications which means that the related results might be non-typical. Taking all those factors into account, the BLP Model 1 is selected

as the most suitable for the purposes of post-estimation simulations among all the considered specifications.
The total elasticity for the BLP Model 1 for December 2017 equals -0.59 which is line with the results of the meta-analysis of Gallet and List (2003), in which the average elasticity of demand for cigarettes in 86 studies equaled -0.48 (the results ranged from -3.12 to 1.41). The remaining BLP models imply much larger total price elasticities of demand (in absolute terms), with the largest result for the BLP Model 5 (-3.21).
The key takeaway point from the sensitivity analysis of the BLP model is that the decisions with respect to which coefficients are allowed to be dependent on the consumer characteristics are clearly influential for the results.