Price Responsiveness and Brand Switching in Montenegro's Cigarette Market

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Abstract

Background

Tobacco taxation is recognized as one of the most effective policy tools for reducing cigarette consumption and improving public health outcomes. Understanding the responsiveness of consumers to price changes, particularly across different market segments, is critical for designing effective and equitable tax policies. This study aims to provide robust empirical evidence on both own-price and cross-price elasticities across economy, middle, and premium market segments in Montenegro, which can support the development of more effective fiscal strategies to reduce the prevalence and intensity of smoking.

Methodology

This research utilizes a comprehensive monthly dataset on brand-level sales and prices per pack of cigarettes in Montenegro spanning from 2010 to 2024 to estimate own- and cross-price elasticities of demand. To approximate substitute prices across segments, we apply nearest-neighbor matching based on Mahalanobis distance, using observable product characteristics such as pack color (representing nicotine and tar levels as proxies for perceived harm), cigarette stick length, flavor, and price.

The primary estimation strategy includes fixed-effects panel regression, instrumental variable (IV) regression to account for potential price endogeneity, and a dynamic generalized method of moments (GMM) model that controls for serial correlation and consumption persistence. Robustness checks are conducted using segment-level weighted average prices within the quadratic almost-ideal demand system (QUAIDS) framework. Additionally, we estimate brand-level elasticities using a





random coefficients logit model to capture heterogeneity in consumer preferences and substitution patterns more precisely.

Results

Results show that the overall own-price elasticity of cigarette demand ranges from -0.61 to -0.66 depending on the precise estimation method, meaning that a 10-percent price increase is associated with a 6.1-percent to 6.6-percent reduction in total cigarette consumption. Segment-level estimates indicate the highest price sensitivity in the mid-price segment (-0.819), followed by the economy (-0.711) and premium (-0.632) segments. Cross-price elasticities confirm the presence of downwards tier substitution: a price increase in the mid-price segment leads to greater demand for economy brands (0.210), while a premium segment price increase shifts consumption towards mid-priced brands (0.421). Estimates from the random coefficients logit model further reveal both between and within-segment substitution, with within-segment cross-price elasticities being strongest in the economy segment.

Conclusions

The findings confirm that price increases significantly reduce cigarette consumption in Montenegro, with the strongest effects observed among smokers of mid-priced and economy brands. The results show that consumers of lower-priced brands—who are more likely to have lower incomes—are more price-sensitive, supporting the pro-poor effects of tobacco taxation on public health outcomes. The presence of cross-price elasticities, particularly down-trading towards cheaper brands, highlights the importance of designing excise increases that are sufficiently strong and frequent to curb strategic price changes by the industry. This should minimize brand switching while maximizing the public health impact of tobacco taxation. A clear understanding of how consumers shift their





purchases across price segments in response to tax-driven price changes is, therefore, crucial for designing fiscal policies that not only reduce overall consumption, but also protect more economically vulnerable groups.

JEL Codes: H31, L11, L66, D12, D40

Keywords: own-price elasticity, cross-price elasticity, cigarette demand, tobacco taxation

Introduction





Montenegro has made significant progress in enhancing tobacco control through fiscal measures, particularly by increasing excise taxes on cigarettes consistently since implementing a mixed excise system in 2005. Between 2010 and 2025, the specific excise tax has increased more than tenfold, rising from €5 to €53.50 per 1,000 cigarettes. Combined with the ad valorem excise of 24.5 percent of the retail price, this level meets the minimum required by the EU Tobacco Products Directive (Tobacco Products Directive, 2014). The total tax share of the retail price has already met the World Health Organization's (WHO) recommended minimum, as well. In recent years, the frequency of tax adjustments has accelerated, with biannual increases initiated since 2022. Furthermore, the government has effectively reduced illicit trade while augmenting revenue from tobacco excise taxes. The proportion of the illicit cigarette market declined significantly, from 51 percent in 2019 to between 22.1 percent and 26 percent by 2022 (Tobacconomics, 2023). These fiscal reforms have produced significant public and economic benefits, as excise revenue has increased from €45.6 million in 2020 to €119.15 million in 2024.

All of these policy initiatives contributed to decreasing smoking prevalence from 40.7 percent in 2019 (Mugoša et al., 2023) to 38 percent in 2022 (Tobacconomics, 2023). Nevertheless, smoking still remains a socially acceptable practice in Montenegro. Smoking begins early in Montenegro, with one in five smokers starting before the age of 15 (STC-SEE, 2020). Daily intensity of consumption is also high, averaging nearly 20 cigarettes per smoker.

While cigarette prices have increased, they still remain low by European standards (WHO, 2023). At the same time, rapid income growth, such as the near doubling of the minimum wage in 2022, has made cigarettes more affordable. According to the *Tobacconomics Tax Scorecard* (Drope et al., 2024), Montenegro's affordability score declined from 5 in 2018 (indicating





the highest benchmark in reduction in affordability) to 0 in 2022, which in this case indicates the highest possible relative increase in affordability. This decline contributed to a drop in the overall tax policy score from 3.88 to 3 over the same period. Further evidence from the Institute for Socio-Economic Analysis (ISEA) shows that from 2020 to 2023 cigarette affordability increased annually by 13 percent, 14 percent, and 7 percent, respectively (Čizmović et al., 2024).

These trends threaten to undermine the long-term impact of tax policy in reducing tobacco use, especially among low-income populations, where smoking comprises a significant portion of household expenditures (Mugoša et al., 2024). To support even stronger fiscal and other tobacco control measures and protect public health, more detailed evidence is needed on how consumers respond to price changes.

Montenegro's cigarette market operates as a product-differentiated oligopoly, dominated by a small number of importers that import brands produced by a limited number of companies. In 2024, the market comprised of 83 cigarette brands segmented into low, middle, and premium price tiers. In this setting, the tobacco industry adopts a strategic pricing approach, absorbing part of the tax on cheaper brands to keep them affordable (under-shifting), while increasing prices beyond the tax on premium brands (over-shifting) (Mugoša et al., 2023). This pricing manipulation can potentially undermine the intended impact of excise taxes by encouraging consumers, particularly those with lower incomes, to switch to less expensive products rather than reducing their consumption or quitting. To fully understand how such strategies influence smoking behavior and market outcomes, it is important to capture differences in consumer price sensitivity within and across brand categories.





In previous research, the ISEA team estimated the overall price elasticity of cigarette use in Montenegro, both conditional and unconditional, as well as elasticities by income groups (Cizmovic et al., 2022). Although aggregate price elasticity contributes to the understanding of general effects, it is insufficient in explaining the influence of tax and price changes on consumption patterns associated with specific cigarette brands and market segments. Increases in taxation often lead to brand substitution, particularly towards lower-priced alternatives, which can undermine the intended effects of a price increase, especially in the presence of price differentials among various market segments.

To address this, estimating segment-specific own- and cross-price elasticities is important. Cross-price elasticity will allow us to measure demand shifts between segments as the price of one segment changes, capturing substitution patterns that affect both government revenue and the reduction of overall cigarette consumption. By analyzing the influence of price fluctuations within one segment on the demand in other segments, this research aims to reveal substitution patterns that significantly impact both the efficacy of tobacco taxation and overall consumption levels. This empirical evidence will facilitate the formulation of more targeted and effective fiscal policies. Considering the limited empirical data on these dynamics in Montenegro and the Western Balkan region, this study will significantly contribute to literature by dealing with the issue of cross-price elasticities within tobacco market segments.

Literature review





Tobacco taxation is one of the most effective measures to reduce smoking, especially among low-income groups (Chaloupka et al., 2012, 2011; Colman & Remler, 2008) and youth (Chaloupka et al., 2012; Nikaj & Chaloupka, 2014; Sweis & Chaloupka, 2014). Several studies analyzing the link between tax and price changes and tobacco consumption indicate that demand in low- and middle-income countries (LMICs) is more sensitive to price increases compared to high-income countries. In LMICs, the total price elasticity of demand generally falls between -0.4 and -0.9, suggesting that tobacco use declines more significantly in response to price hikes in these regions than in wealthier nations, reflecting a strong consumption response to higher prices (Sweis & Chaloupka, 2014; Kostova et al., 2015; Onder & Yürekli, 2014; Kostova et al., 2014; Nargis et al., 2014; Mugosa et al., 2020; Vladisavljevic et al., 2020; Mijovic Spasova et al., 2023). In contrast, estimates for high-income countries are generally lower, ranging from -0.2 to -0.6 (Kostova et al., 2014; Guindon et al., 2015), indicating less sensitivity to price changes. ISEA's research (Cizmovic et al., 2022) reveals that in Montenegro, price elasticity for different income groups varies from -1.02 to -0.60, and the demand for cigarettes is more sensitive to price changes among low- and middleincome households than among wealthier ones.

While the overall price elasticity of cigarette consumption has been well researched in numerous studies, research that estimates own-price and cross-price elasticity within different market segments is very limited. Most studies utilize individual-level data for panel or cross-sectional estimation, whereas estimates of market tier or segment elasticities based on aggregate market data are less prevalent. In this review, we highlight recent studies using individual-level data from Bangladesh, Pakistan, and Brazil that offer important insights into price responsiveness across cigarette market tiers, as well as research based on aggregate sales data





from United States of America's (USA) market, which complements this evidence from a different methodological perspective.

In Bangladesh, Shimul et al. (2024) analyzed data from four waves of the International Tobacco Control (ITC) cohort survey, utilizing a three-stage econometric framework to model smoking participation, brand choice, and consumption intensity through probit models and seemingly unrelated regression (SUR). Their research revealed that consumers in both observed tiers respond to price changes, with estimated total price elasticities of -0.17 for low-price and -0.25 for high-price cigarettes. The positive cross-price elasticity of daily cigarette consumption indicates a value of 0.26 for the low-price tier relative to the high-price brands, suggesting downwards tier substitution.

In a study conducted in 2021 by Social Policy and Development Centre (SPDC) in Pakistan (Sabir & Iqbal, 2024), a similar methodology was employed to analyze tier-specific elasticities using logit, probit, and seemingly unrelated regression (SUR) models based on individual smoker data. The cigarette market was categorized into premium, economy, and illicit market segments. The findings revealed that illicit cigarette consumers exhibited the highest price sensitivity (−1.96), along with a substitution pattern where a 10-percent increase in illicit cigarette prices resulted in an 11.5-percent increase in the consumption of economy cigarettes. In the legal market, the estimated own-price elasticities were notably lower, at −0.57 for the premium segment and −0.24 for the economy segment.

In Brazil (Divino et al., 2022), researchers analyzed pooled cross-sectional data from the 2013 and 2019 National Health Surveys (PNS), applying propensity score matching (PSM) to impute prices for illicit cigarettes and control for selection bias. For licit cigarettes the estimated own-price





elasticity ranged between -0.32 and -0.42, depending on the sample used, while for illicit cigarettes it ranged from -0.14 to -0.36, indicating a lower degree of price sensitivity. A statistically significant cross-price elasticity was found only in one direction: a 10-percent increase in illicit cigarette prices led to a 0.7-percent increase in licit cigarette consumption in the pooled sample, suggesting upwards substitution when illicit products become more expensive.

Research conducted by Tauras et al. (2006) in the USA employed quarterly time-series data concerning sales and prices of various brands, along with the characteristics of product types, sourced from Nielsen Retail Scanner Data. The researchers employed a system of demand equations and a seemingly unrelated regression (SUR) model to estimate the market segment's own- and cross-price elasticities, with a focus on premium, discount, and deep discount brands. The results indicated a clear gradient in price responsiveness, with the highest own-price elasticity observed for deep discount brands (-0.63), followed by discount brands (-0.57), and the lowest for premium brands (-0.19). Additionally, significant substitution effects were also observed. A 10-percent increase in the price of discount cigarettes was estimated to raise the market share of premium brands by about 1.5 percent. Also, a 10-percent price increase for premium cigarettes was anticipated to result in a 6-percent increase in the market share of discount brands and a 0.6-percent increase in the market share of deep discount brands.

Data

This research utilizes monthly data on cigarette brand-level retail prices and quantities sold from 2010 to 2024. The data, sourced from the Tobacco Agency (Directorate for Issuing Permits for the Production,





Processing, and Trade of Tobacco Products), cover only imported brands sold in standard packs of 20 cigarettes, as there is no domestic production.

The Montenegrin cigarette market is highly diversified, with a broad range of brand variants. Over the study period, a total of 55 generic brands and 281 product variants were recorded, with a declining trend from 164 variants in 2012 to 83 in 2024 (Figure 1). The average duration of a cigarette brand's presence on the Montenegrin market during the observed period was 6.3 years. The highest level of market turnover—measured by brand entries and exits—was recorded between 2014 and 2019. ¹ In subsequent years, the number of active brands stabilized, with entries and exits occurring at a more balanced pace (Figure A1.1 in Appendix 1). As of 2024, three importers were active in the market, sourcing products from seven different international producers.²

Figure 1. Number of cigarette brands by month (January 2010 – December 2024)

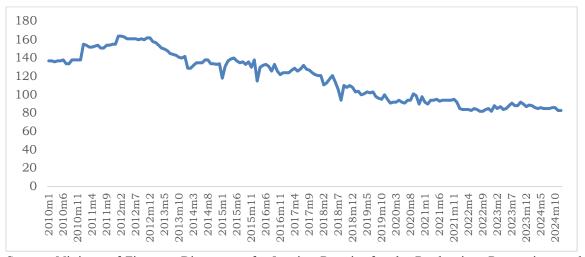
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¹ Possible explanations include intensified illicit trade in that period, leading companies to withdraw underperforming brand variants, or strategic consolidation to focus on the most popular brands and maximize profit margins. However, these remain potential explanations and cannot be empirically verified with available data.

² The largest share of the market in 2024 was held by Philip Morris International brands (28 percent), followed by Japan Tobacco International (24 percent) and Karelia Tobacco Company (21 percent), with British American Tobacco ranking next (20 percent).







Source: Ministry of Finance, Directorate for Issuing Permits for the Production, Processing, and Trade of Tobacco Products

The highest relative price increase occurred among the cheapest brands, rising more than sixfold—from 0.40 in 2010 to 0.40 in 2024. Prices of the most-sold brands more than quadrupled, rising from 0.70 to 0.7

Cigarette market segments are defined using external sources, including importer information, industry publications, and retail price listings,³ following the approach given in Mugoša et al. (2023), which is consistent with methods used in earlier research (Tauras et al., 2006). The mid-price category includes brands priced within a range of €0.25 above or below the most popular brand. For products not explicitly classified in these

³ Philip Morris International, 2023; Japan Tobacco International, 2023





sources, price positioning was used to assign them to the appropriate segment.

Monthly cigarette sales data indicate potential seasonal patterns, with noticeable peaks in June, July, August, and December (Figure 2). To capture this seasonality within the monthly dataset, a seasonal dummy variable is included in the analysis, allowing the model to adjust for systematic fluctuations in consumption throughout the year.

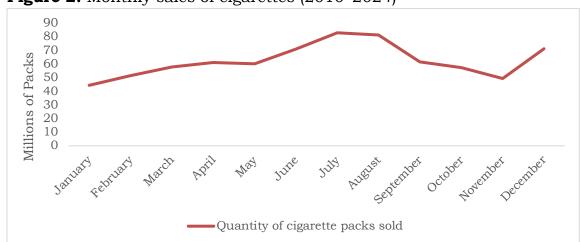


Figure 2. Monthly sales of cigarettes (2010–2024)

Source: Ministry of Finance, Directorate for Issuing Permits for the Production, Processing, and Trade of Tobacco Products

We included several additional dummy variables to capture key market and regulatory changes during the observed period. Specifically, one dummy variable was used to account for the period from 2018 to 2021, when the share of the illicit tobacco market was particularly high (Tobacconomics, 2023). Another dummy variable captured the impact of a major policy intervention implemented in July 2021, a ban on cigarette storage in the Port of Bar's free-trade zone, which led to a significant reduction in illicit trade. Additionally, the model incorporated a full set of





monthly time-fixed effects and brand-fixed effects to control for unobserved heterogeneity across time and products.

A potential concern in estimating price elasticities of cigarette demand is the endogeneity of prices. Endogeneity of prices may arise due to reverse causality or omitted variables that simultaneously affect both prices and cigarette consumption, potentially biasing elasticity estimates. For example, unobserved variables such as industry marketing activities and shifts in consumer preferences can simultaneously affect both prices and quantities sold, leading to potentially biased and inconsistent elasticity estimates if not properly accounted for.

To address this concern, we used several instrumental variables. The primary instrument is the specific component of the excise tax, which is widely used in the literature as it is strongly correlated with retail prices but does not directly influence consumption decisions, which depend on the final price level (Kohler et al., 2023). As shown in Table A1.3 in Appendix 1, Montenegro's specific excise tax on cigarettes increased significantly—from €5 per 1,000 cigarettes in 2010 to €53.5 in 2025—while the ad valorem rate decreased from 37 percent in 2011 to 24.5 percent in 2023 and remained stable through 2024 and 2025. Figures A1.2 and A1.3 in Appendix 1 show that the weighted average excise tax share in retail prices in the total market fluctuated from approximately 56 percent to 60 percent, being the highest for economy⁴ and lowest for the premium segment.

⁴ The excise tax share for the economy segment appears more volatile than for mid-price or premium brands. This likely reflects greater price variability among low-cost products, as small changes in retail price can significantly affect the tax share due to the lower price base. In addition, frequent price adjustments, product turnover, and sensitivity to market pressures such as illicit trade may contribute to short-term fluctuations in observed tax shares within this segment.





In addition to the tax variable, we use a set of non-price product attributes such as flavor, color as an approximation for perceived cigarette strength,⁵ cigarette length, and slim format as instruments for prices, following Berry et al. (1995). These characteristics remain constant over time and are determined independently of short-term pricing strategies or demand fluctuations, making them predetermined and potentially exogenous.

Two primary sets of instruments are constructed under the assumption that product characteristics are exogenous:

- Within-firm instruments: The sum of characteristics of other products from the same firm in a given month (excluding the product itself). These capture firm-level pricing strategy based on the existing portfolio.
- Competitor instruments: The sum of characteristics of rival products in the same month. These reflect competitive market pressure while remaining external to the product's own demand shock.

To address the potential issue of endogeneity of observed characteristics, we additionally followed Petrin et al. (2022) and included lagged characteristics of both competitors' and own-firm products. These lagged variables are considered relevant, since firms respond to past market conditions when setting current characteristics, and exogenous, as they are predetermined and not affected by current-period unobserved shocks.

⁵ Color is used as a proxy for perceived cigarette strength, as packaging color often signals tar and nicotine levels to consumers, even though, scientifically, they are not clearly related to the overall harm levels of these products. Darker colors are generally associated with stronger variants, while lighter colors (such as white, yellow, and gold) imply milder or "light" options. This color signal indicates perceived cigarette strength, especially when explicit strength labeling is not provided.





Finally, we include product lagged prices and lagged average prices at the firm and market levels. These are correlated with current prices but not influenced by contemporaneous demand shocks, satisfying the exclusion restriction.

Control variables, including average wage, consumer price index, and gross domestic product (GDP) per capita, are obtained from the Statistical Office of Montenegro (more details are provided in Table A1.4 in Appendix 1). The lagged quantity of cigarette packs sold per brand is included in the model to serve as a proxy for brand loyalty and consumption habits that tend to adjust slowly over time. The lag captures persistence in consumer behavior and unobserved factors such as availability or personal preferences.⁶

Methodology

The empirical approach applied in this paper draws on recent studies' methodologies (see Shimul et al., 2024; Divino et al., 2022; Berry et al., 1995) with adaptations to reflect the structure of the Montenegro-specific dataset. Estimating cross-price elasticities requires information not only on the prices and quantities of brands within each market segment but also on the characteristics and prices of potential substitutes from other segments. However, since each brand is observed only within its own segment, we cannot directly observe substitution across segments.

To identify substitute products across market segments, we compute Mahalanobis distances between products based on observed

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⁶ It also serves as an additional variable to indirectly account for changes in the market due to illicit trade. A stable lag suggests brand resilience—possibly due to strong consumer loyalty or limited competition from other brands or the illicit market. A sudden drop in consumption, despite prior stability, may also indicate substitution towards illicit products not captured in the dataset.





characteristics such as flavor, perceived strength, cigarette size, slim format, and price. The approach builds on the widely accepted principle that products with similar characteristics are more likely to be substitutes, as established in differentiated product demand models (Berry et al., 1995; Nevo, 2001). Different studies confirm that greater similarity in product characteristics is associated with stronger substitution patterns, and that Mahalanobis distance is a valid and robust method for capturing this proximity (Rubin, 1980; Bloom et al., 2013; Armona et al., 2021).

This approach is a non-parametric method used to identify the most comparable products across groups by measuring the multivariate distance between them and is conceptually related to a machine-learning algorithm, k-nearest neighbor (k-NN) (Halder et al., 2024). This method is particularly useful when individual-level or demographic data are not available, as it relies solely on product-level attributes. In our research, we will utilize it as an alternative to propensity-score matching (PSM), which has been employed for a similar purpose (Divino et al., 2022).

Although widely used in empirical social science research (Caliendo & Kopeinig, 2008; Keller-Hamilton et al., 2021; Havstad et al., 2012), logistic regression in PSM may have limited predictive power when consumer-level or demographic variables are absent, resulting in propensity scores that fail to differentiate between groups adequately. This reduces the method's ability to produce high-quality matches and accurately approximate substitution behavior across segments.

Unlike propensity score matching, which reduces all observed characteristics into a single predicted probability of group membership, Mahalanobis distance compares brands directly based on their original set of features, while adjusting for differences in scale and accounting for





correlations among variables. It allows matching products based on their observable characteristics without relying on predictive modeling.

The Mahalanobis distance can be interpreted as measuring the distance between observations in terms of standard deviations of the covariates, while also considering the correlation structure. It can be understood as a generalized form of the Euclidean (or Pythagorean) distance that adjusts for correlations among variables and differences in their measurement scales.

Let $i \in S_k$ denote a brand in market segment $k \in \{low, mid, premium\}$, and let $X_i \in R^p$ be the vector of standardized observable product characteristics (for example, cigarette length, flavor, pack color, and price). For each brand i, we identify its closest substitute $j \in S_{kr}$ in a different segment $k' \neq k$, using the Mahalanobis distance (Mahalanobis, 1936; De Maesschalck et al., 2000):

$$d(i,j) = \sqrt{(X_i - X_j)'S^{-1}(X_i - X_j)}$$
 (1)

where d is the Mahalanobis distance between products i and j, while S is the sample covariance matrix of covariates X.

For each brand i from a given market segment, we identify its most similar counterpart j* from an alternative segment S_k , by selecting the product with the smallest Mahalanobis distance. Results are estimated when multiple neighbors are used (as in k-nearest-neighbor logic). In such a case, a weighted average of prices across the k closest matches is computed.





After addressing the issue of substitute prices, we apply a panel fixed-effects model to estimate the intensity of own- and cross-price elasticities, measuring the responsiveness of the number of cigarette packs sold to changes in price. To address potential endogeneity of prices, we also estimate an instrumental-variable (IV) panel regression model, using specific excise tax levels and other instruments described in the data section. Furthermore, to account for persistence in brand choice over time, we include the lagged dependent variable in the model, following Tauras et al. (2006). In this context, we apply the dynamic panel generalized method of moments (GMM) estimator (Blundell & Bond, 1998) to address potential endogeneity, unobserved heterogeneity, and serial correlation in the dependent variable. Prior to estimation, we tested the variables for the presence of unit roots, and the null hypothesis of a unit root was rejected at the level (see Table A1.5 in Appendix 1).

In all specifications, the dependent variable is the quantity of cigarettes sold per brand, observed monthly over time.

$$Q_{it} = \alpha'_i + \beta_0 P_{it} + \gamma'_i Z_{it} + \varepsilon'_{it}$$
(2)

$$Q_{it}^{L} = \alpha_i^L + \beta_L' P_{it}^L + \beta_M' P_{it}^M + \beta_P' P_{it}^P + \gamma_L Z_{it} + \varepsilon_{it}^L$$
(3)

$$Q_{it}^{M} = \alpha_i^{M} + \beta_{L}^{"} P_{it}^{L} + \beta_{M}^{"} P_{it}^{M} + \beta_{P}^{"} P_{it}^{P} + \gamma_M Z_{it} + \varepsilon_{it}^{M}$$

$$\tag{4}$$

$$Q_{it}^{P} = \alpha_{i}^{P} + \beta'''_{L} P_{it}^{L} + \beta'''_{M} P_{it}^{M} + \beta'''_{P} P_{it}^{P} + \gamma_{P} Z_{it} + \varepsilon_{it}^{P}$$
(5)

Equation (2) establishes a basic estimate of overall price elasticity by utilizing a single aggregated price variable that does not distinguish between market segments. This approach aims to capture the average response of cigarette demand to price fluctuations throughout the market. Conversely, equations (3) to (5) include prices for each segment, enabling the distinct identification of both own-price and cross-price effects within those segments. P_{it}^L, P_{it}^M , and P_{it}^P are prices of brands from respective





segments, and Zit represents control variables (including lagged brand quantity, dummy variables, and GDP per capita or average wage).

As a robustness check, we apply the almost-ideal demand system (AIDS), a widely used approach in the analysis of differentiated product markets (Davis & Garcés, 2009). Originally developed by Deaton and Muellbauer (1980), 7 the AIDS model offers a flexible and theoretically consistent framework for modeling budget shares as a function of log prices and total expenditure while satisfying key consumer theory conditions such as adding up, homogeneity, and symmetry. Extensions of the model also allow for the use of instrumental variables to address potential price endogeneity (Lecocq & Robin, 2015). In this research, according to the likelihood-ratio test, the use of the quadratic almost-ideal demand system (QUAIDS) model instead of the linear almost-ideal demand system (AIDS) model is justified.

In our analysis, we estimate a simplified version of the demand system, focusing on how aggregate expenditure shares across three cigarette market segments, observed over a period of 180 months, respond to changes in segment-level prices and total cigarette expenditure. This approach does not represent the full QUAIDS system, which would require data on total consumption and prices of all combustible tobacco products (López-Nicolás & Drope, 2024). Rather, it captures shifts in relative demand among observed cigarette segments.

The model is estimated to regress monthly market-share-weighted average prices (WAP) by segment—controlling for fixed effects, seasonal and regulatory dummies, and GDP per capita as a proxy for macroeconomic

⁷ A detailed overview of consumer choice theory and demand systems can be found in Deaton and Muellbauer (1980) and in Chapter 3 of Mas-Colell et al. (1995).





conditions—on the expenditure share of cigarettes per segment and month. However, the limited price variation in the Montenegrin cigarette market, combined with the use of aggregated data, may constrain the model's ability to capture substitution patterns and thus introduce aggregation bias. Additional challenges include high collinearity among segment prices and the absence of individual-level demographic data. Despite these limitations, the QUAIDS model in this research provides a valuable alternative framework for assessing the direction and magnitude of price responsiveness across segments.

Additionally, to estimate brand-level elasticities for a specific month, we apply the random coefficients logit model developed by Berry et al. (1995), a widely used framework for analyzing demand in differentiated product markets. This model enables estimation of own- and cross-price elasticities at the brand level, captures substitution patterns within and across market segments, and provides a foundation for tax policy simulations that reflect product-level heterogeneity. The details of the structural demand model and estimated results are available in the Appendices (Appendix 2 and Appendix 3).

Results

Descriptive statistics

Between 2010 and 2024, cigarette consumption in Montenegro showed significant variation, as illustrated in Figure 3, which plots annual cigarette pack sales alongside weighted average nominal and real prices. From 2010 to 2018, consumption declined steadily, coinciding with a rise in prices. However, beginning in 2021, consumption began to rise again despite continued nominal price increases. This reversal is largely attributed to rapid income growth and high inflation, which improved





cigarette affordability, as well as a significant decline in illicit trade due to the implementation of effective policy measures after 2021 (Tobacconomics, 2023).

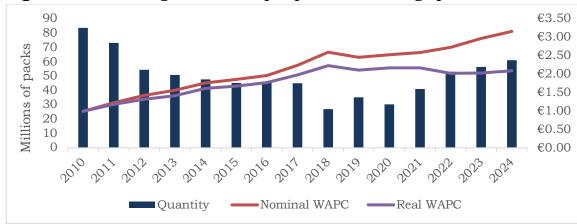


Figure 3. Annual cigarettes sold per pack and average price

Source: Ministry of Finance, Directorate for Issuing Permits for the Production, Processing, and Trade of Tobacco Products

Panel A of Figure 4 shows that nominal prices across all market segments followed a broadly increasing trend. However, when real prices are considered (see Figure A2.1 in Appendix 2), this trend appears much flatter, with stagnation or slight declines after 2019, particularly in the premium segment. These developments underscore the need for stronger implementation of Article 6 of the WHO FCTC, which calls for tax increases that outpace both inflation and real income growth to reduce tobacco use (WHO, 2021).

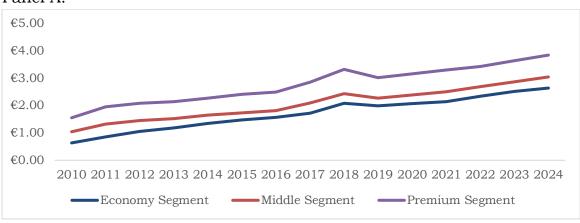
The increase in legal sales after 2021 is likely explained by a shift from the illicit to the licit market, particularly in the immediate post-reform period (Panel B, Figure 4). However, over the past two years, this effect has begun to taper off, with signs of decline in the economy segment. More details on prices and quantities of cigarettes sold by market segment are given in Table A1.2 in Appendix 1.



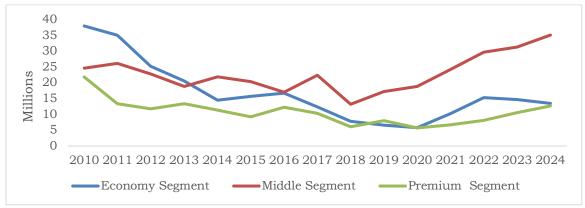


Figure 4. Average price (Panel A) and quantity of cigarette packs sold by segments (Panel B)

Panel A.



Panel B.



Source: Ministry of Finance, Directorate for Issuing Permits for the Production, Processing, and Trade of Tobacco Products

Note: Prices are in nominal values.

In terms of product characteristics, the most prevalent cigarette types are slim variants and those with perceived medium or the lowest tar and





nicotine contents⁸ (Figure A2.2 in Appendix 2). Figure 5 indicates that the most notable growth in the market share of slim cigarettes occurred within the economy segment, where their share rose from 30 percent in 2018 to 84 percent in 2024. This trend suggests a targeted industry strategy to increase the affordability of slim cigarettes, which are particularly appealing to women and youth-key consumer groups for this product type (STC-SEE, 2020).

90% 80% 70% 60% 50% 40% 30% 20% 10% 0% 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023 2024 ■ Strong ■ Medium ■ Light ■ Ultralight ■ Flavored ■ Longcig ■ Slims

Figure 5. Characteristics of brands in economy segment

Source: Ministry of Finance, Directorate for Issuing Permits for the Production, Processing, and Trade of Tobacco Products

Note: Prices are in nominal values. Shares are calculated using the quantity of respective brands sold as weights.

8 Cigarette packs with the lightest color—cream, pink, rose, and similar.





Table 1 presents the estimated own-price elasticity of demand for cigarette consumption using the full sample. Column (1) reports results from a fixed-effects panel regression, column (2) from an instrumental-variables (IV) regression addressing potential price endogeneity, and column (3) from a dynamic GMM regression that accounts for both endogeneity and potential serial correlation in the dependent variable.

Across all three specifications, the estimated own-price elasticity is stable, ranging from -0.61 to -0.66 depending on the estimation method. This implies that a 10-percent price increase is associated with a 6.1-percent-to-6.6-percent reduction in the quantity of cigarette packs consumed.

Control variables display expected signs. Higher income levels are associated with increased cigarette consumption, and consumption also tends to rise during seasonal periods. Given the high degree of brand loyalty in the cigarette market, the lagged quantity of cigarette packs sold per brand is a strong and statistically significant predictor of current consumption in all models.

Table 1. Own-price demand elasticity – whole sample

	FE		IV		GMM	
Variables	coef.	se	coef.	se	coef.	se
Inprice	-0.659***	-0.033	-0.628***	-0.038	-0.612***	-0.055
Lag pack quantity	0.810***	-0.005	0.811***	-0.01	0.830***	-0.018
Wage	0.148**	-0.061	0.146***	-0.057	0.101	-0.131
Reg. dummy	0.054***	-0.016	0.049***	-0.017	0.241***	-0.022
Illicit dummy	-0.048***	-0.013	-0.042***	-0.014	-0.116***	-0.028
Season	0.244***	-0.009	0.244***	-0.008	0.234***	-0.012
Constant	1.184***	-0.38			2.438***	-0.79

Source: Authors' calculations

***p<0.01, **p<0.05, *p<0.1. Driscoll-Kraay standard errors - robust to cross-sectional dependence, error structure is assumed to be heteroskedastic, autocorrelated.

Note: In IV regression, the first-stage F-statistic (Kleibergen-Paap rk Wald F) was 10546, far exceeding the Stock-Yogo threshold (16.38), indicating a strong instrument. The underidentification test confirmed the instrument's relevance (Kleibergen-Paap LM x^2 = 3207.89, p < 0.001). Although the formal endogeneity test, the Durbin-Wu-Hausman test for price x^2 = 1.189, p = 0.2756, did not reject exogeneity, we kept the IV estimation to ensure robustness given theoretical concerns about endogeneity. In the GMM regression: Arellano-Bond test for AR(2) in first





differences: Pr > z = 0.261; Sargan test: Prob > chi2 = 0.113. In the IV and GMM, specific tax was used as an instrumental variable.

The estimated own- and cross-price elasticities by segment, as determined by IV panel regression, are presented in Table 2. Table A2.1 and A2.2 in Appendix 2 give results estimated using fixed effects and the GMM approach. In these regressions, substitute products across market segments are identified using Mahalanobis distances between brands, based on characteristics such as flavor, perceived strength, cigarette size, slim format, and price. Table A2.3 in Appendix 2 provides evidence of improved covariate balance (reflected in reduced standardized differences and variance ratios closer to one) that supports the validity of the matching procedure by showing that the treated and untreated groups are more comparable after matching.

Table 2. Own- and cross-price cigarette demand elasticity per market segment

	Economy		Middle		Premium	
Variables	coef.	se	coef.	se	coef.	se
Economy price	-0.711**	-0.284	0.096*	-0.055	0.246	-0.169
Middle price	0.210**	-0.085	-0.819**	-0.323	-0.022	-0.159
Premium price	0.211	-0.223	0.421***	-0.127	-0.632***	-0.18
Lnwage	0.250**	-0.103	0.252*	-0.135	0.278*	-0.144
Lag qpack	0.607***	-0.022	0.421***	-0.019	0.414***	-0.022
Reg. dummy	0.033	-0.03	0.026	-0.016	0.101**	-0.021
Illicit dummy	-0.106***	-0.031	-0.050**	-0.023	-0.049*	-0.029
Season	0.183***	-0.013	0.287***	-0.01	0.323***	-0.052

Source: Authors' calculations

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⁹ Similar coefficients were estimated using WAPC per segment, instead of using substitute prices derived from Mahalanobis distance. However, due to low variability and high multicollinearity in the segment price variables, some coefficients were nonsignificant, and certain price variables were dropped when time fixed effects were included. Given the low price variation within segments, substitute prices, estimated using Mahalanobis distance and averaging the 3–5 nearest neighbors, closely aligned with the substitute segment average but still provided enough variability for estimation.





***p<0.01, **p<0.05, *p<0.1. Driscoll-Kraay standard errors - robust to cross-sectional dependence, error structure is assumed to be heteroskedastic, autocorrelated.

Note: IV- Specific excise tax, lag of competitors' and within-firm brand characteristics, lagged prices and lagged average prices at the firm and market level. The results of the instrumental-variable validity tests are presented in Table A1.6 in Appendix 1.

The estimates of own-price cigarette demand elasticities across all segments indicate that the strongest effects of price increases on consumption are in the middle and economy segments (-0.819 and -0.711), compared to premium (-0.632). For example, a 10-percent price increase in the economy segment prices leads to a 7.11-percent decrease in its cigarette consumption. Cross-price elasticities highlight significant downwards substitution between segments. For instance, an increase in middle-segment prices leads to higher demand for economy cigarettes (0.210), while higher premium prices shift demand towards the middle segment (0.421).

Considering that wage data by segment are unavailable, the wage coefficient reflects how demand responds to changes in overall income. ¹⁰ Higher wages positively affect demand in all segments, with the strongest impact in the premium segment. As in the overall sample, lagged consumption significantly influences demand, particularly in the economy segment, indicating persistent consumption habits. The illicit trade dummy reveals that the illicit market negatively affects legal demand, especially for economy cigarettes. Seasonal effects also have a positive influence across segments, with the most pronounced impact in the premium segment.

Robustness analysis

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¹⁰ Estimates using GDP per capita instead of average wage give similar results.





One of the limitations of the database for the Montenegrin cigarette market used in this research is the lack of regional market division and demographic data, resulting in low variation when using average data (price and quantity per month and segment). To address this, the main part of the working paper presents results based on a large sample of disaggregated brand-level data, which maximizes price variation.

Additionally, we controlled for unobserved time-varying shocks and time-invariant unobservable brand characteristics using time- and brand-fixed effects. However, to check the consistency of the estimates with alternative aggregated data structures and to more explicitly account for the correlation between segments, we also estimate a demand system using a quadratic extension of the AIDS model (QUAIDS).¹¹ To validate the use of this approach, we first check the stationarity properties of the data, confirming that the variables do not contain a unit root at the level (Table A2.4 in Appendix 2).

Additionally, to address the endogeneity of prices, we apply an extension of the model that allows for the inclusion of instrumental variables, as proposed by Lecocq and Robin (2015). Although not all elasticity coefficients in this specification are statistically significant, their signs and relative magnitudes remain consistent with the disaggregated brand-level model. The limited variation, higher collinearity of prices, and smaller number of observations likely contribute to the larger standard errors in this version of the model.

 $^{^{11}}$ According to likelihood-ratio test the use of the QUAIDS model instead of the linear AIDS model is justified ($x^2 = 69.75$, p = 0.000).





Table 3. Own- and cross-price elasticity between segments – QUAIDS model

	Economy		Middle		Premium	
	coef.	se	coef.	se	coef.	se
Economy	-0.683**	-0.209	0.090*	-0.048	-0.217	-0.382
Middle	0.472*	-0.24	-1.027	-0.999	0.555	-0.787
Premium	-0.187	-0.328	0.612	-1.297	-0.725	-1.023

Source: Authors' calculations

***p<0.01, **p<0.05, *p<0.1

Note: Bootstrap standard errors based on 1,000 replications.

The middle segment represents 47 percent of total cigarette expenditure, followed by 28 percent in the premium segment and 25 percent in the economy segment. In order to measure how the proportion of a consumer's budget spent on cigarettes changes in response to changes in income or total expenditure, we provide estimates of budget elasticities. Budget elasticities show an elasticity close to one in all segments, with the highest elasticity in the middle segment (1.09) and the lowest in the economy segment (0.90), implying that demand in all three segments changes almost proportionally with total cigarette expenditure (Table A2.5 in Appendix 2).

Discussion and Conclusions

This paper presents important empirical evidence on cigarette demand elasticity in Montenegro, using a detailed dataset that combines monthly brand-level sales and pricing data from 2010 to 2024. The Montenegrin tobacco market is characterized by high product diversity, with a total of 281 product variants across 55 generic brands recorded during the observation period. Over time, the market has undergone noticeable changes, with the number of brand variants decreasing from 164 in 2012 to 83 in 2024. The composition of cigarette characteristics also shifted: so-called medium-strength and ultra-light cigarettes dominate the market,





and the share of slim cigarettes grew significantly, particularly in the economy segment. Between 2018 and 2024, the share of slims in the low-price segment increased from 30 percent to 84 percent, reflecting industry strategies aimed at maintaining affordability and targeting specific consumer groups, such as women and youth (STC-SEE, 2020).

Additionally, the absence of consumer-level information limited the variability in prices and constrained the use of average values. Assuming that substitution is most likely between products with similar characteristics (for example, price, strength, cigarette length) (Berry et al., 1995; Nevo, 2001), we employed a relatively novel approach to impute substitute prices across market segments using Mahalanobis distance matching. This approach is conceptually aligned with the propensity score matching technique used by Divino et al. (2022), but adapted to brand-level aggregate data without individual-level characteristics. The matching procedure helped address limited within-segment price variation and facilitated more realistic estimation of cross-segment substitution patterns.

The results show that increasing cigarette prices is an effective tool for lowering cigarette consumption. Across all three methods used to estimate the own-price elasticity of demand for the entire market (fixed effects, instrumental variables, and dynamic generalized method of moments), the findings are consistent. Estimated elasticities range from -0.61 to -0.66, meaning that a 10-percent increase in price leads to a 6.1-percent-to-6.6percent drop in the number of cigarette packs sold. Income elasticity was positive and statistically significant, suggesting that cigarette consumption rises with income. This is especially important in recent years because of increased affordability due to significant wage growth.





Seasonal trends were clear, with cigarette consumption rising during certain times of the year, especially during the tourist season.

Segment-level price elasticities of demand were estimated using panel regression models based on disaggregated brand-level data. The strongest demand responses to price changes were observed in the middle and economy segments, with elasticities of -0.819 and -0.711, respectively. In contrast, the premium segment exhibited slightly lower sensitivity at -0.632. These findings show that consumers of lower-priced brands, who are more likely to be lower-income and more price-sensitive (Cizmovic et al., 2022), are more likely to reduce consumption in response to tax-driven price increases. This finding strongly supports the pro-poor effects of tobacco taxation on public health outcomes, assuming that low-income smokers mainly consume cheaper brands.

The estimation also revealed limited but, in some cases, significant substitution patterns across segments. A 10-percent price increase in the mid-price segment is associated with a 2.1-percent rise in demand for economy brands, while a 10-percent rise in premium cigarette prices leads to a 4.2-percent increase in middle-segment consumption. These results confirm that consumers are prone to downwards substitution when prices rise in their preferred segment. This emphasizes the importance of ensuring that tax increases are sufficiently large and frequent to mitigate strategic price changes by the industry within each segment and to reduce brand-switching behavior.

To further capture substitution dynamics at the product level, we employed a random coefficients logit model (Berry et al., 1995), which estimates brand-level own- and cross-price elasticities and accounts for heterogeneity in consumer preferences. Results confirmed substitution within and across segments, with stronger substitution in the economy





segment. This offers a more detailed basis for future tax simulations, especially in scenarios that involve assumptions about consumer switching between similar brands.

Despite the strengths of the analysis, several small limitations must be acknowledged. First, the dataset for the observed period does not include other tobacco products, such as roll-your-own and heated tobacco products, which have grown in popularity in recent years (Cizmovic et al., 2024). Even though cigarettes still represent a major share of tobacco products in Montenegro, the exclusion of other products limits the scope of this demand estimation and potentially can reduce the precision of simulated tax effects on total tobacco consumption and the government's overall excise revenue.

Second, the dataset lacks consumer demographic information, which prevents an analysis of heterogeneous responses across income or age groups, which is particularly important given recent increases in affordability. Third, the price variation in the aggregated models is limited, and price collinearity remains a challenge inherent to the system of equation demand models (Bae, 2018).

Finally, the models do not directly account for the size and dynamics of the illicit tobacco market. Although some indirect controls such as dummy variables and fixed effects were included, the absence of comprehensive data on illicit trade introduces potential bias in elasticity estimates. Considering this limitation, the estimated elasticities should be interpreted as upper-bound estimates, since part of the decline in legal consumption may be due to substitution towards illicit products. However, it should be noted that neither a study on Pakistan's cigarette market (Sabir & Iqbal, 2024), nor a study on Brazil (Divino et al., 2022) found evidence that





increases in legal cigarette prices lead to a demand shift towards the illicit market.

In summary, the study provides valuable empirical evidence that cigarette consumption in Montenegro is price-sensitive, especially among consumers of low- and middle-priced brands. The observed substitution behaviors highlight the need for consistent tax policies that reduce incentives for brand switching. Including industry behavior and consumer diversity in tax policy development is essential to maximizing both health and fiscal benefits.

Future research should aim to improve demand estimates by addressing several gaps. First, incorporating illicit cigarettes into cross-price elasticity estimates would enable more accurate modeling of consumer switching between legal and illicit products. Second, analyzing the stability or variability of both own- and cross-price elasticities across different market conditions—such as regulatory changes, tax reforms, or shifts in affordability—would offer valuable insights into how sensitive consumer behavior is to external shocks over time. Lastly, developing simulation models, whether based on aggregate or brand-level data that reflect these elasticities, would greatly enhance policy makers' ability to forecast the health and revenue impacts of various tobacco tax scenarios under current and future market conditions.





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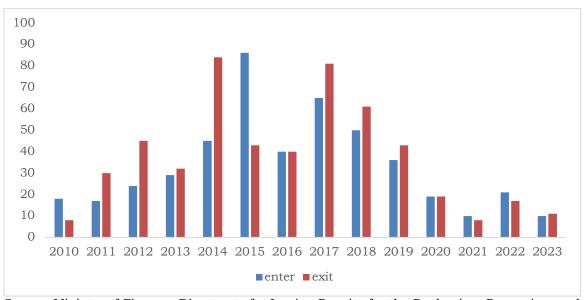




Appendices

Appendix 1. Additional Figures and Tables

Figure A1.1 Number of brands entering/exiting the market by year, 2010–2024



Source: Ministry of Finance, Directorate for Issuing Permits for the Production, Processing, and Trade of Tobacco Products

Table A1.1 Most-sold, premium, and cheapest brands' nominal prices (in €) (2010–2024)

Year	The most- sold brand	Nom price	Real price	Premium brand	Nom price	Real price	Cheape st brand	Nom price	Real price
2010	Drina	0.7	0.7		1.7	1.70	Cuba	0.4	0.4
2011	denifin	1	0.97		2	1.93	Monte crni York YLB	0.5	0.48
2012	е	1.2	1.11		2.2	2.04		0.75	0.70
2013	Code blue	1.3	1.18	N. 11	2.4	2.18		1	0.91
2014	Ronhill wave	1.5	1.37	Marlboro	2.5	2.29	hard pack	1	0.91
2015	black	1.6	1.44		2.6	2.34		1	0.90
2016	L&M	1.8	1.63		2.7	2.44	Negro	1	0.90
2017	loft blue	2	1.76		3	2.65		1	0.88





2018		2.3	1.98	3.4	2.92	Code red	1.6	1.38
2019		2.3	1.97	3.4	2.91	LD red	1.8	1.54
2020	Winsto n xstyle	2.4	2.06	3.3	2.83	LD Club compac t blue	2	1.72
2021	long	2.5	2.10	3.4	2.85		2	1.68
2022	blue	2.7	2.00	3.5	2.60	Una slims	2.3	1.71
2023		2.9	1.98	3.7	2.53	gold	2.5	1.71
2024	7.5	3.1	2.05	 3.9	2.58	D 1 ::	2.6	1.72

Table A1.2 Prices (in €) and number of packs sold (in millions) of economy, middle, and premium cigarette brands (in nominal and real terms)

			egment	Mic	idle seg	gment	Pre	mium s	egment
Year	Nom. price	Real price	No. of packs sold	Nom. price	Real price	No. of packs sold	Nom. price	Real price	No. of packs sold
2010	0.64	0.64	37.9	1.05	1.05	24.1	1.56	1.56	21.4
2011	0.85	0.82	35.0	1.33	1.29	24.8	1.97	1.9	13.2
2012	1.05	0.98	22.6	1.45	1.35	20.6	2.09	1.94	11.1
2013	1.18	1.08	17.5	1.53	1.39	20.9	2.15	1.95	12.3
2014	1.35	1.24	12.9	1.65	1.51	20.6	2.28	2.09	14.1
2015	1.47	1.33	10.9	1.74	1.57	22.3	2.42	2.18	12.1
2016	1.58	1.42	8.1	1.82	1.64	25.5	2.5	2.25	12.2
2017	1.72	1.52	9.2	2.1	1.85	23.1	2.86	2.52	12.8
2018	2.09	1.8	5.9	2.44	2.1	14.2	3.33	2.86	6.9
2019	2.00	1.71	6.1	2.28	1.95	18.4	3.02	2.59	10.7
2020	2.08	1.79	5.8	2.4	2.06	17.3	3.17	2.72	7.2
2021	2.15	1.8	10.4	2.52	2.11	22.1	3.31	2.78	8.5





2022	2.35	1.74	17.2	2.7	2	25.7	3.43	2.55	10.0
2023	2.53	1.73	13.7	2.88	1.97	30.2	3.65	2.49	12.6
2024	2.65	1.75	13.9	3.05	2.02	32.4	3.85	2.55	14.9

Note: Nominal prices of economy, middle, and premium brands of cigarettes are obtained from the Tobacco Agency. The real prices of all three categories of cigarette brands are calculated by the authors using the corresponding CPI obtained from Monstat.

Table A1.3 Excise tax calendar from 2010 to 2024

Year	Specific excise tax (in € per 1,000 sticks)	Ad valorem excise tax (% cigarette retail price)	Value-added tax (%)
2010	5	35	17
2011	10	37	17
2012	15	36	17
2013	17.5	35	19
2014	19	35	19
2015	20	34	19
2016	22	33	19
2017	24	33	19
2017	30	32	19
2018	40	32	21
2019	30	32	21
2020	33.5	30.5	21
2021	37	29	21
2022	40.5	27.5	21
2022	44	26	21
2023	47.5	24.5	21
2023	49	24.5	21
2024	50.5	24.5	21
2024	52	24.5	21

Source: Law on Excise Taxes (Ministry of Finance, 2017)

Figure A1.2 Weighted average excise tax share in retail prices





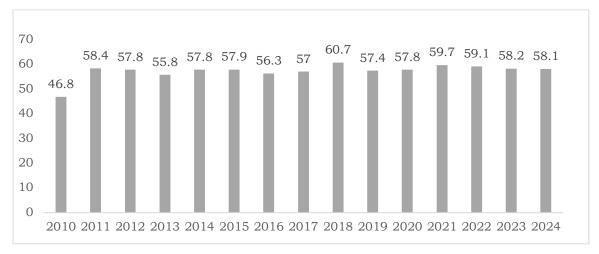
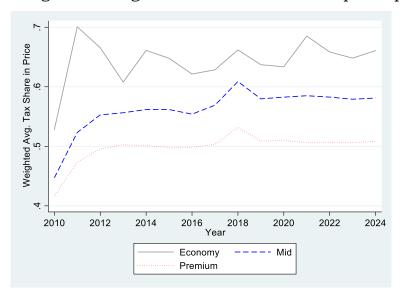


Figure A1.3 Weighted average excise tax share in retail prices per segment



Source: Ministry of Finance, Directorate for Issuing Permits for the Production, Processing, and Trade of Tobacco Products

Table A1.4 Average nominal and real net wage and GDP per capita





Year	Average nominal net wage (€)	Average real net wage (€)	Nominal GDP per capita (€)	Real GDP per capita (€)
2010	479	479	5,045	4,966
2011	441	426	5,265	5,202
2012	487	452	5,126	5,117
2013	479	435	5,413	5,303
2014	477	436	5,561	5,504
2015	480	432	5,874	5,746
2016	499	451	6,354	6,046
2017	510	450	6,907	6,653
2018	511	439	7,495	7,260
2019	515	441	7,959	7,802
2020	524	450	6,737	6,749
2021	532	446	8,002	7,641
2022	712	528	9,598	8,543
2023	792	541	10,814	9,916

Source: Monstat, Labour Force Survey

Note: Real values for average net wage are calculated by the authors by applying the corresponding CPI (2010=100) obtained from Monstat.

Table A1.5 Panel unit-root test

	Fisher-type panel unit-root test				
Variables	H0: All panels contain unit roots Ha: At least one panel is stationary				
	Test	Decision			
Price – whole sample	Inverse chi-squared(562) Inverse normal Inverse logit t(1399) Modified inv. chi-squared	p= 0.0000 p= 0.0000 p= 0.0000 p= 0.0000	No unit root		
Price – economy segment	Inverse chi-squared(308) Inverse normal Inverse logit t(734) Modified inv. chi-squared	p= 0.0000 p= 0.0000 p= 0.0000 p= 0.0000	No unit root		
Price – middle segment	Inverse chi-squared(348) Inverse normal Inverse logit t(844) Modified inv. chi-squared	p= 0.0000 p= 0.0256 p= 0.0000 p= 0.0000	No unit root		





Price – premium segment	Inverse chi-squared(168) Inverse normal Inverse logit t(409) Modified inv. chi-squared	p= 0.0000 p= 0.0232 p= 0.0000 p= 0.1784	No unit root
Quantity – whole sample	Inverse chi-squared(562) Inverse normal Inverse logit t(1334) Modified inv. chi-squared	p= 0.0000 p= 0.0000 p= 0.0000 p= 0.0000	No unit root
Quantity – economy segment	Inverse chi-squared(308) Inverse normal Inverse logit t(679) Modified inv. chi-squared	p= 0.0000 p= 0.0000 p= 0.0000 p= 0.0000	No unit root
Quantity – middle segment	Inverse chi-squared(348) Inverse normal Inverse logit t(794) Modified inv. chi-squared	p= 0.0000 p= 0.0000 p= 0.0000 p= 0.0000	No unit root
Quantity – premium segment	Inverse chi-squared(168) Inverse normal Inverse logit t(404) Modified inv. chi-squared	p= 0.0000 p= 0.0000 p= 0.0000 p= 0.0000	No unit root

Source: Authors' calculations

Table A1.6 Instrument validity tests

Test	Economy Segment	Middle Segment	Premium Segment
First-stage F-statistic (Kleibergen-Paap rk Wald F)	F = 94.41 (> 24.58, strong)	F = 269.87 (> 24.58, strong)	F = 211.47 (> 24.58, strong)
Underidentification test (Kleibergen-Paap LM x²)	$x^2 = 269.05$ (p < 0.001, relevant)	$x^2 = 651.55$ (p < 0.000, relevant)	$x^2 = 334.44$ (p < 0.000, relevant)
Endogeneity test (Durbin-Wu-Hausman x²)	x ² = 17.469 (p = 0.000, reject exogeneity)	x ² = 68.276 (p = 0.000, reject exogeneity)	$x^2 = 4.998$ (p = 0.1719, fail to reject exogeneity)
Hansen J test (validity)	J = 0.628 (p = 0.4281, valid)	J = 0.005 (p = 0.9461, valid)	J = N/A (since exogeneity not rejected)

Source: Authors' calculations





Appendix 2. BLP Model Description

Structural demand estimation using a discrete-choice framework

The random coefficients logit model introduced by Berry et al. (1995) is widely used for estimating demand in differentiated product markets. This structural model assumes that consumers choose among brands by maximizing utility based on brand characteristics and price, while allowing for random taste heterogeneity and flexible substitution patterns.¹²

The BLP model is particularly well suited to the cigarette market in Montenegro, which features substantial product differentiation and oligopolistic pricing. Unlike reduced-form methods, BLP explicitly corrects for price endogeneity, using instrumental variables to account for unobserved product characteristics (for example, brand characteristics and image) that may influence both price and demand. It also includes an outside good that captures the option not to purchase any of the observed brands, which is important in modeling real-world behavior such as quitting or switching to illicit or other tobacco products (Olesiński, 2020).

While computationally intensive, the BLP framework provides internally consistent estimates based on microeconomic theory and is often used in policy simulations, including tax scenarios. Essentially, the model posits

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¹² Standard demand systems, such as the almost-ideal demand system (AIDS) (Deaton & Muellbauer, 1980), require estimating many parameters and often impose restrictive assumptions, such as preference separability, which limit their flexibility in capturing substitution patterns. While discrete choice models like the multinomial or conditional logit provide more manageable alternatives, they rely on the independence of irrelevant alternatives (IIA) assumption. This assumption implies that the relative odds of choosing between two products remain unaffected by the presence or characteristics of other products, which is an unrealistic assumption in markets like cigarettes. For example, if a low-priced brand is removed from the market, consumers are more likely to substitute for another low-priced brand than for a premium one, violating IIA (Vincent, 2015).





that each consumer selects a cigarette brand (or opts not to purchase, referred to as the "outside option") based on the utility derived from it, influenced by price, product attributes, and, if available, consumer demographic data. Each individual possesses distinct preferences, represented in the model through random draws (for example, from a normal distribution). Leveraging this assumption, the model forecasts the number of purchasers for each brand (market share) by simulating random consumer preferences to reflect variations in tastes.

By analyzing observed market shares (derived from quantities), the model seeks to identify parameters (such as price sensitivity) that align the predicted shares with the actual shares as closely as possible. This process employs the generalized method of moments (GMM), which aims to minimize the disparity between predicted and actual shares. Consequently, the model yields estimates of how price and characteristics influence demand. In contrast to simpler models, the BLP framework considers the diversity of consumer tastes and the complex competition among brands. More detailed information about the model can be found in Berry et al. (1995), Nevo (2000), and Olesiński (2020).

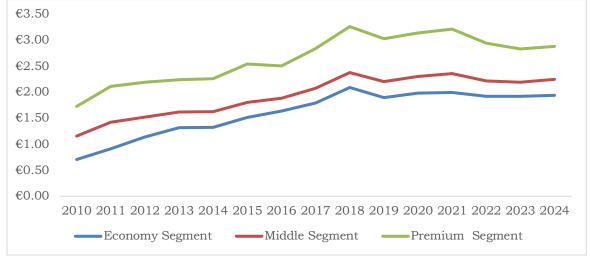
Despite its advantages, this model has some limitations. It requires strong and valid instruments, is sensitive to the specification of random coefficients, and may encounter convergence issues in settings with a large number of products or limited variation.¹³

¹³ Notwithstanding these challenges, studies such as Brunner et al. (2017) and Armstrong (2016) show that, when carefully specified and implemented, BLP-type models can yield robust and policy-relevant estimates of consumer demand.



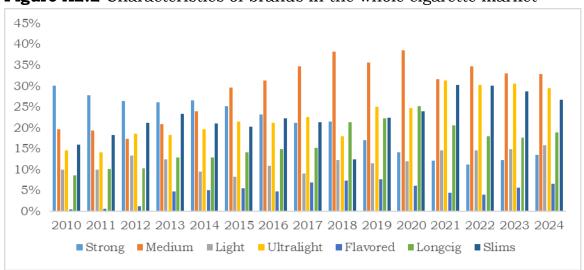


Figure A2.1 WAPC per segment in real terms



Note: Nominal prices of economy, middle, and premium brands of cigarettes are obtained from the Tobacco Agency. The real prices of all three categories of cigarette brands are calculated by the authors using the corresponding CPI obtained from Monstat.

Figure A2.2 Characteristics of brands in the whole cigarette market



Source: Ministry of Finance, Directorate for Issuing Permits for the Production, Processing, and Trade of Tobacco Products

Notes: Prices are in nominal values. Shares are calculated using quantity of respective brand sold as weights.





Table A2.1 Own- and cross-price cigarette demand elasticity per market segment – FE

beginerit 11	Econor	ny	Middle	;	Premi	ım
Variables	coef.	se	coef.	se	coef.	se
Economy price	-0.670***	-0.159	0.097**	-0.051	0.149	-0.12
Middle price	0.315*	-0.168	-0.798***	-0.258	0.44	-0.392
Premium price	-0.111	-0.205	0.378*	-0.203	-0.671*	-0.356
Lnwage	0.145	-0.236	0.479***	-0.135	0.280*	-0.144
Lag qpack	0.571***	-0.034	0.405***	-0.037	0.513***	-0.032
Reg. dummy	0.09	-0.083	0.044***	-0.016	0.051***	-0.019
Illicit dummy	-0.053	-0.057	-0.039	-0.031	-0.031	-0.031
Season	0.190***	-0.016	0.297***	-0.016	0.385***	-0.026
Constant	4.013**	-1.615	4.197***	-0.915	4.603***	-0.795

Source: Authors' calculations

Table A2.2 Own- and cross-price cigarette demand elasticity per market segment – GMM

	Econo	my	Middle		Premium	
Variables	coef.	se	coef.	se	coef.	se
Economy price	-0.75***	-0.288	0.076	-0.198	0.082	-0.161
Middle price	0.29**	-0.091	-0.82*	-0.425	-0.364	-0.38
Premium price	0.674	-0.532	0.354*	-0.193	-0.692*	-0.381
Lnwage	0.314**	-0.162	0.415**	-0.18	0.453**	-0.18
Lag qpack	0.821***	-0.037	0.494***	-0.049	0.530***	-0.03
Reg. dummy	0.219***	-0.056	0.185***	-0.04	0.035	-0.058
Illicit dummy	0.04	-0.039	-0.158**	-0.067	0.064	-0.097
Season	0.188***	-0.022	0.276***	-0.017	0.367***	-0.022
Constant	1.897***	-0.524	2.309*	-1.163	1.327	-1.258

Source: Authors' calculations

Note: Economy segment – Arellano-Bond test for AR(2) in first differences: Pr > z = 0.161; Sargan test: Prob > chi2 = 0.998. Middle segment – Arellano-Bond test for AR(2) in first differences: Pr > z

^{***}p<0.01, **p<0.05, *p<0.1

^{***}p<0.01, **p<0.05, *p<0.1





= 0.130; Sargan test: Prob > chi2 = 0.357. Premium segment – Arellano-Bond test for AR(2) in first differences: Pr > z = 0.894; Sargan test: Prob > chi2 = 0.844. Specific tax was used as an additional instrumental variable, along with GMM instruments.

Table A2.3 Covariate balance – standardized differences and variance ration

	Ra	w		Ma	tched (ATE	')	
Means	Treated	Untreated	StdDif	Treated	Untreated	StdDif	
strong	0.304	0.200	0.239	0.259	0.280	-0.050	
medium	0.109	0.200	-0.252	0.138	0.165	-0.075	
light	0.109	0.133	-0.075	0.122	0.129	-0.020	
ultralight	0.043	0.156	-0.377	0.049	0.056	-0.060	
flavored	0.000	0.022	-0.211	0.000	0.000	0.000	
longcig	0.065	0.178	-0.346	0.082	0.114	-0.098	
slims	0.130	0.089	0.132	0.120	0.118	0.036	
	Ra	w		Matched (ATE)			
Variances	Treated	Untreated	Ratio	Treated	Untreated	Ratio	
strong	0.216	0.164	1.323	0.198	0.207	0.954	
medium	0.099	0.164	0.605	0.123	0.132	0.933	
light	0.099	0.118	0.838	0.110	0.115	0.958	
ultralight	0.043	0.134	0.316	0.048	0.052	0.928	
flavored	0.000	0.022	0.000	0.000	0.000	-	
longcig	0.062	0.149	0.417	0.078	0.081	0.958	
slims	0.116	0.083	1.400	0.109	0.102	1.066	

Source: Authors' calculations

Note: ATE stands for average treatment effect. Better balance means reduced standardized differences (closer to 0), and a variance ratio closer to 1. The data are tabulated as an example for one month in the middle segment, with the remaining data not included due to space constraints.

Given the data's potential structural changes, we implemented the Zivot-Andrews unit-root test, which allows for a single break in intercept and/or trend to check the stationarity of variables. The test showed that the variables are stationary at the level.





	Zivot-Andrews				
Variables	H_0 : variable has a unit root with a structural break in the intercept/trend				
	Minimum t-statistic	Break			
Share of consumption in economy segment	-7.359***	09/2108			
Share of consumption in middle segment	-7.550***	09/2108			
Share of consumption in premium segment	-6.767***	01/2021			
WAPC – economy segment	-5.053**	07/2017			
WAPC – middle segment	-5.666***	07/2017			
WAPC – premium segment	-5.458**	07/2017			

Source: Authors' calculations

Table A2.5 Shares and budget elasticities - OUAIDS model

- 4210 11210 82	narco arra suagot c	Q OTHE S INIOGOT				
	Shares		Budget elast.			
	coef.	se	coef.	se		
Economy	0.246***	-0.006	0.899***	-0.12		
Middle	0.469***	-0.006	1.088***	-0.074		
Premium	0.285***	-0.004	0.941***	-0.09		

Source: Authors' calculations





Appendix 3. Results of the BLP Model

To get additional insight into the elasticity between brands and within-segment elasticity, the random coefficients logit model (BLP) approach was applied. This model assumes that consumers choose among brands by maximizing utility based on brand characteristics and price, while allowing for random taste heterogeneity and flexible substitution patterns. Price elasticities of demand are estimated at the product-specific level. The specification in Table A3.1 represents the mean utility simulated for 1,000 consumers and includes different brand characteristics and real prices as a random variable. ¹⁴ The standard deviation of the random price coefficient indicates heterogeneity in consumer preferences regarding price sensitivity, suggesting that different consumers exhibit varying degrees of responsiveness to price changes.

Table A3.1 Mean utility BLP estimation

Variable	coef.	se
Strong	0.12**	0.059
Light	0.24**	0.092
Slims	0.22**	0.117
Medium	0.19**	0.090
Season	2.42***	0.933
Price	-1.84**	0.864
Constant	-2.01**	1.212
Price SD	2.35**	1.041

Source: Authors' calculations

***p<0.01, **p<0.05, *p<0.1

¹⁴ Different specifications, including various combinations of random variables, were estimated; however, due to computational complexity, most of them failed to converge.





The model provides elasticity matrices for each market, with our case representing each segment/month. Table A3.2 shows the substitution matrix for the 13 most-sold brands in the economy segment during the last month of the observation period.

Table A3.2 The substitution matrix for 10 brands with highest share in economy segment (December 2024)

Brand	1	2	3	4	5	6	7	8	9	10
1	-1.645	0.016	0.007	0.010	0.080	0.008	0.003	0.073	0.008	0.019
2	0.009	-1.638	0.007	0.010	0.080	0.008	0.003	0.073	0.008	0.019
3	0.010	0.018	-1.785	0.011	0.089	0.009	0.003	0.081	0.009	0.021
4	0.010	0.018	0.007	-1.781	0.089	0.009	0.003	0.081	0.009	0.021
5	0.010	0.018	0.007	0.011	-1.703	0.009	0.003	0.081	0.009	0.021
6	0.011	0.019	0.008	0.011	0.093	-1.834	0.004	0.085	0.010	0.022
7	0.010	0.017	0.007	0.010	0.084	0.009	-1.726	0.077	0.009	0.020
8	0.011	0.019	0.008	0.011	0.093	0.009	0.004	-1.759	0.010	0.022
9	0.009	0.016	0.007	0.010	0.080	0.008	0.003	0.073	-1.646	0.019
10	0.009	0.016	0.007	0.010	0.080	0.008	0.003	0.073	0.008	-1.635

Source: Authors' calculations

It can be observed that own-price elasticities between brands are much higher compared to the aggregate model, which is expected, as they represent the effect of increased demand for a product in response to its own price increase, while holding the price of substitutes constant. Results also showed that brands within each segment are substitutes, with crossprice elasticity being highest for the economy segment (0.28), followed by the premium (0.22) and middle (0.11) segments.