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Drivers of beer pricing in Argentina

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ABSTRACT

This study uses web data from the retail beer segment to explore beer pricing dynamics in Argentina amid chronic inflation. We address three main questions: the impact of product attributes on pricing under high inflation, evolving pricing patterns over time, and the effect of the 2020 lockdown. Our analysis unveils the interplay between product attributes, seasonal trends, and inflationary pressures in shaping pricing strategies. While inflation drives rapid adjustments, seasonal trends and product attributes significantly influence pricing decisions. Consumers can benefit from insights into currency fluctuations, fuel costs, and seasonal variations. Beer industry managers can refine pricing strategies to maximize revenue potential amidst economic volatility.

***Keywords**: Beer; pricing; weekly data; web scraping; Argentina.*

1 Introduction

Product attributes play a crucial role in determining a product's price. The attributes of a product are specific characteristics or features that make it unique and different from those of other products in the market. When pricing a product, managers consider the attributes that their product offers and how these attributes compare to similar products in the market. If a product has more desirable attributes than its competitors do, it can be priced higher to reflect its higher value. Conversely, if a product lacks certain attributes or has lower-quality attributes than its competitors, it may need to be priced lower to compete in the market. The rule of thumb can also be altered when inflation is prevalent.

For instance, productive sectors in Argentina face pricing problems due to rising inflation. Problems arise in the form of difficulty in predicting costs, reduction in the purchasing power of consumers, increased competition, a negative impact on consumer confidence that affects non-primordial items, and price instability. Inflation is also directly affected by the exchange rate pass-through (ERPT) on imported goods. When updating prices, sellers observe the product and its attributes as drivers to consider when changing and updating prices faster than in more stable environments. It is a situation where prices are likely to rise at rates higher than any potential future reductions. How do product attributes affect changing prices?

Beer production in Argentina has a rich history that dates back to 1738 when it first began, largely attributed to Non-Spanish immigration. Over the years, distinct cultural patterns shaped its consumption, primarily catering to exclusive segments of society, with wine being its main competitor. However, a significant shift in this trend has occurred in the last two decades (contrary to what is observed in the UK; Tomlinson and Branston, 2014). Today, beer has surged in popularity, especially among the younger generation, surpassing wine as the preferred beverage of choice, with per capita consumption reaching nearly 45 liters per year, which is double the figure for wine (Larrosa et al., 2023).

Specifically, this study examines a sector that has not been previously investigated, namely the off-premise retail beer segment (also referred to as off-trade) in Argentina. Our sample encompasses retail sales from super- and hypermarkets, with at-home prices reflecting retail selling prices including all applicable sales and consumption taxes. To the best of our knowledge, no prior research has explored the weekly pricing of retail beer within this specific market. The primary focal point of our study is the rate of price variation from any given week to the preceding week. During periods of inflation, the pricing mechanism is heavily influenced by the need to keep up with rising prices. While a commonly used hedonic approach could be employed to investigate the connection between attributes and prices, we deem it inappropriate for two reasons: first, inflation alters relative prices, and second, the approach disregards the dynamic nature of the data. However, the research hypothesizes that attributes still have a differential impact on beer price variation, which serves as a marketing tool in the hands of sellers, even in an unstable context. Our work explores potential explanations of the obfuscation and asymmetric pricing approaches to pricing. The research underscores the importance of understanding both the cyclical and seasonal factors affecting beer pricing, offering valuable insights for both consumers and managers in navigating the complexities of the market.

The objectives of this study are to address three main research questions: i) What was the effect of beer attributes on pricing during periods of high inflation? ii) What pricing trends developed over time? Specifically, is time more influential than specific attributes in explaining weekly beer pricing? iii) How did the lockdown associated with the pandemic in 2020 influence pricing?

As a result, diverse attributes present a significant impact on how weekly beer prices vary. However, time variables and specific events exert a much higher impact, controlled by exchange rate devaluations and a transportation cost proxy. Market power, while statistically significant, plays a negligible role in pricing. Lessons for consumers and managers are posited.

The contribution follows with section 2 where a literature review is performed. Section 3 is next with the methodology and estimations; section 4 presents the analysis of the results and section 5 follows with discussions. The section 6 concludes the work.

2 Literature Review

Theoretical contributions suggest that tactics such as obfuscation (Ellison and Wolinsky, 2009; Ellison and Fisher Ellison, 2009) and asymmetric pricing (Chandra and Tappatá,2011; Tappatá, 2009) can contribute to price dispersion in competitive markets. In highly inflationary economies, pricing is further complicated by added uncertainty. Beer pricing, in particular, may exhibit this behavior due to the very short-term expectation horizon in such contexts. Obfuscation can occur when attributes are added that make it challenging for consumers to compare the overall features of a product. On the other hand, asymmetric pricing tends to arise naturally in an inflationary economy, as prices rarely retract due to increasing repurchase costs, inflation expectations, and various other determinants.

Toro-González et al. (2014)'s study highlights how imported beers often command higher prices due to transportation costs and perceived prestige. This can be seen as a form of obfuscation, where the perceived value (prestige) adds complexity to the pricing structure, making it harder for consumers to compare these beers directly with mass-produced ones. Identifying packaging strategies and alcohol content as key determinants of consumer choice suggests that firms use these attributes to differentiate their products (Smith et al., 2016). By emphasizing unique packaging and varying alcohol content, firms can create additional layers of complexity that make it harder for consumers to compare products purely on price. The emergence of diverse beer styles, such as the variety of Ales in the Argentine craft beer market (Libkindy et al., 2018). contributes to obfuscation. The proliferation of different styles and flavors can overwhelm consumers with choices, increasing their search costs and complicating direct price comparisons (Kaderian, 2018; Ablin, 2012).

The segmentation of consumers into "industrial beer consumers" and "craft beer enthusiasts" reflects varying preferences and levels of commitment. This segmentation can be used by firms to tailor marketing and pricing strategies that exploit these differences, adding to the complexity consumers face when making purchasing decisions (Aquilani et al., 2015; Gómez-Corona et al., 2016; Cardello et al., 2016; Calvo-Porral et al., 2018).

The emphasis on attributes such as beer type, price, and origin in consumer selection underscores the role of product differentiation in obfuscation (Meyerding et al., 2019). By highlighting specific attributes, firms can make it difficult for consumers to directly compare products, thereby maintaining price dispersion in the market. These studies illustrate how firms use various attributes (such as packaging, alcohol content, beer styles, and origin) to differentiate their products and create complexity. This differentiation increases search costs for consumers and aligns with the strategies described in the obfuscation literature in search models, where firms benefit from reduced price transparency and increased consumer difficulty in making direct comparisons.

On the other hand, we can explore what role asymmetric pricing may play in the beer market. Both (Grosová et al., 2017) and Fogarty (2010) highlight consumer sensitivity to price changes. The finding that even slight price increases can significantly impact consumption patterns is related to asymmetric pricing, as firms may be quicker to raise prices than to lower them, knowing that consumers are more responsive to increases. This behavior can lead to persistent price asymmetries in the market.

Rojas et al. (2008) explore how firms' pricing and advertising strategies affect consumer demand. Asymmetric pricing can result from strategic advertising that emphasizes price increases less than price decreases, making consumers more accepting of higher prices. This can create a situation where firms adjust prices asymmetrically to maximize their profits. The study on brewing company mergers by Ashenfelter et al. (2015) highlights how production scale and transportation costs influence pricing. Mergers often lead to increased market power, enabling firms to implement asymmetric pricing strategies by raising prices more easily than lowering them, due to reduced competition and increased control over the market.

Empen and Hamilton's (2015) examination of beer price changes during Bundesliga weekends illustrates how regional preferences and external events can lead to temporary price asymmetries. Retailers might increase prices during high-demand periods (such as sporting events) but are slower to reduce them afterward, creating asymmetric pricing patterns. Coloma's (2023) analysis of beer demand in Argentina reveals distinct responses to price changes among different market segments. The varying degrees of price elasticity among high, medium, and low-end beers, as well as super-premium, premium, and high-end subcategories, suggest that firms may use asymmetric pricing strategies tailored to each segment. For example, they might raise prices more quickly for segments with lower price sensitivity and decrease them more slowly for segments with higher price sensitivity. These contributions show that firms strategically use pricing tactics that lead to asymmetric pricing, influenced by factors such as consumer sensitivity, market power from mergers, regional preferences, and market segmentation. These tactics align with the asymmetric pricing literature, where firms exploit consumer search costs and demand elasticity to implement price changes that favor maintaining higher prices over time.

3 Methods and Data

We examine our hypothesis on beer pricing strategies by estimating the weekly rate of price variations for a selected sample of products. The approach aims to identify regular pricing patterns. Our data collection involved gathering prices from various mainstream retail sources, including supermarkets, hypermarkets, and large-volume retailers' websites, using web scraping algorithms (Uriarte et al., 2019). We compiled data from 284 items spanning 37 different beer brands available online at the time of data collection. Price information was collected weekly from store websites, covering the period from the first week of December 2015 to the fourth week of February 2021. Each week was defined as a seven-days period, starting from the 1st to the 7th, the 8th to the 14th, the 15th to the 21st, and the 22nd to the 28th day of each month. This methodology ensured that each month contributed at least four weeks of data, resulting in a total of 252 observations or weeks per series over the 63-months period.

Consider a dynamic panel data model with units $i = 1,2,\dots,284$, and a fixed number of time periods $t = 1,2,\dots,252$, with $T \geq 2$.

$$y_{it} = \beta_0 + \beta_1 x'_{it} + \beta_2 f'_{it} + \varepsilon_{it}, \quad \varepsilon_{it} = \alpha_i + \mu_{i,t} \tag{1}$$

where x'_{it} is a $K_x \times 1$ vector of time-varying variables, where α_i is an unobserved unit-specific time-invariant effect (call it unobserved effect) and x'_{it} can be correlated with $\mu_{i,t}$. The initial observations of the dependent variable, y_{i0} represents the weekly price variation of beer *i*, and the regressors, x_{i0}, are assumed to be observed. f_i is a $K_v \times 1$ vector of observed time-invariant variables that includes an overall regression constant, and α_i is an unobserved effect fixed effect of the *i*-th cross section and is allowed to be correlated with all of the explanatory variables x_{it} and f_i. It is also a random effect if it is independently distributed and correlated with the lagged dependent variable by construction. We assume that there exists a set of valid instruments $z_i = (z_{i1}, z_{i2}, \dots, z_{it})$ such that $E(\epsilon|z_{it}) = 0$ for estimating $\hat{x}_{it}$. A first stage regression implies to estimate the endogenous variable to their instruments.

$$\hat{x}_{it} = \beta_0 + \sum_{j=1}^{l} \gamma_t x_{it-l} + \sum_{j=1}^{l} \delta_t z_{kt-l} + \vartheta \tag{2}$$

Once estimated on first stage, we reintroduce the fitted values back in (1)

$$y_{it} = \beta_0 + \beta_1 x'_{it} + \beta_2 f'_{it} + \beta_2 \hat{x}'_{it} + \varepsilon_{it}, \quad \varepsilon_{it} = \alpha_i + \mu_{i,t} \tag{3}$$

We instrumented fuel cost through inflation and exchange rate variables. We consider fuel cost as an endogenous variable and instrument it in terms of the effects of inflation, exchange rate variations, and of their own lagged values. In all cases, we consider 4-period lags (a month in terms of our concept of a week). We also test different financial variables replacing exchange rate variables as instruments.

3.1 Dependent variables

In the pricing model we use as the explained variable the rate of variation per week of each beer presentation:

- y_{it}: Weekly rate of price variation of item *i* on time *t* (*t* runs from the 1st week of December 2015 to the 4th week of February, 2021)

We evaluate off-premise beers sold online on the websites of three hypermarkets and supermarkets in the Bahia Blanca area, Argentina. One of these is a regionally based chain store (referred to as 'supermarket 1'). while the other two are national-scope hypermarkets ('supermarkets 2 and 3').

3.2 Attributes

We also control for specific product attributes: package weight, average price during the period, type, brand, processing, grain, packing and if it is promoted as imported.

- **Brands:** x_{it}^{b-i}: There are 37 brands reported included: x_{it}^{b-1}: Ac/Dc, Amstel, x_{it}^{b-2}: Andes, x_{it}^{b-3}: Antares, x_{it}^{b-4}: Barba Roja, x_{it}^{b-5}: Bavaria, x_{it}^{b-6}: Berlina, x_{it}^{b-7}: Bieckert, x_{it}^{b-8}: Bitburger, x_{it}^{b-9}: Brahma, x_{it}^{b-10}: Budweiser, x_{it}^{b-10}: Clausthaler, x_{it}^{b-11}: Corona, x_{it}^{b-12}: Czechvar, x_{it}^{b-13}: Dab, x_{it}^{b-14}: Erdinger, x_{it}^{b-15}: Estrella Damm, x_{it}^{b-16}: Estrella Galicia, x_{it}^{b-17}: Grolsch, x_{it}^{b-18}: Heineken, x_{it}^{b-19}: Iguana, x_{it}^{b-20}: Imperial, x_{it}^{b-21}: Isenbeck, x_{it}^{b-22}: Kapuziner, x_{it}^{b-23}: Kunstmann, x_{it}^{b-24}: Miller, x_{it}^{b-25}: Modelo, x_{it}^{b-26}: Oettinger, x_{it}^{b-27}: Oranjeboom, x_{it}^{b-28}: Otro Mundo, x_{it}^{b-29}: Palermo, x_{it}^{b-30}: Patagonia, x_{it}^{b-31}: Quilmes, x_{it}^{b-32}: Schneider, x_{it}^{b-33}: Shofferho, x_{it}^{b-34}: Sol, x_{it}^{b-35}: Stella Artois, x_{it}^{b-36}: Warsteiner, x_{it}^{b-37}: Weidmann.
- **Liter:** x_{it}^{l}**:** represents the liter by beer presentation.
- **Alcoholic degree**: x_{it}^{a} represents the degree of alcohol of the beer.
- **Fermentation:** x_{it}^{fer}, a dummy that identifies top or bottom fermentation.
- **Ale:** x_{it}^{ale}, a dummy ale (stout/IPA) variants.
- **Lager:** x_{it}^{lag}, a dummy lager variant.
- **High-ABV:** x_{it}^{hg} is a dummy for high Alcohol by Volume beer (7% or higher).
- **Refundable:** x_{it}^{ref} is a binary variable used to distinguish refundable bottles, which results in a cost-effective option for purchasing beer.
- **Container:** x_{it}^{con}, indicates if beer is sold in can (1) or bottle (0).
- **Origin:** x_{it}^{ori}, reports if the beer is locally produced (1) or imported (0).

- **Supermarket**: x_{it}^{sup1}: Supermarket 1; x_{it}^{sup2}: Supermarket 2; x_{it}^{sup3}: Supermarket 3.
- **Market Share:** x_{it}^{ms}, Data was extracted from Coloma (2023). Beer market shares were concentrated in a few producers/distributors in the period 2013-15 but they were slowly disputed by incumbent, mainly regional independent producers. The event triggered a slow deconcentrating process as revealed by Figure 1. There is evidence of the opposite direction towards more concentration in other markets, such as the Czech Republic (Maier, 2012: 62). the USA (Richards and Rickard, 2021) or the UK (Slade, 2004).

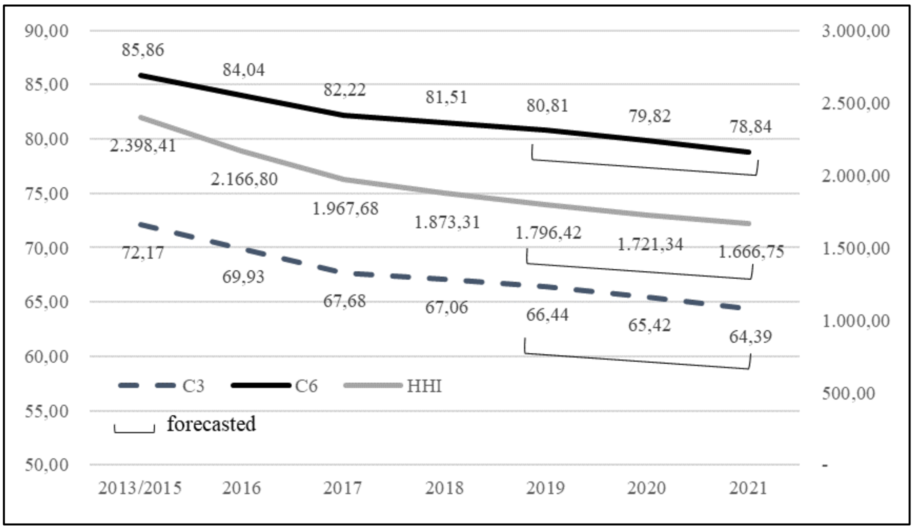

Figure 1. Concentration index evolution in the Argentine beer market
(Note: C3/C6 measures the total contribution of the 3/6 largest market shares;
HHI: Herfindahl-Hirschman Index. Data from 2013/15 to 2018 extracted from Coloma (2023).
Data from 2019 on is a linear projection of precedent data).

3.3 Cost and Time Variables

Following Su et al. (2019) we consider the potential pass-through effect of gasoline on prices and include the variation of gasoline prices.

- $f_{it}^{cost-fuel}$: Weekly fuel price variation.

Finally, time control variables are considered for capturing seasonal and cyclical effects. To the traditional adding of the month and year effects, we also take into account weekly effects. This is important because pricing at a tactical level implies updating prices at a high frequency for promotions and specific marketing actions.

- **Week dummies**:f_{it}^{s1}: dummy for 1st week; f_{it}^{s2}: dummy for 2nd week; f_{it}^{s3}: dummy for 3rd week. The fourth week is out for collinearity.
- **Month dummies:** f_{it}^{m12}: December; f_{it}^{m1}: January; f_{it}^{m2}: February; f_{it}^{m3}: March; f_{it}^{m4}: April; f_{it}^{m5}: May; f_{it}^{m6}: June; f_{it}^{m7}: July; f_{it}^{m8}: August; f_{it}^{m9}: September: f_{it}^{m10}: October. November is discarded by collinearity.
- **Year dummies:**f_{it}^{y16}: year 2016; f_{it}^{y17}: year 2017; f_{it}^{y18}: year 2018; f_{it}^{y19}: year 2019; f_{it}^{y20}: year 2021; f_{it}^{y21}: year 2021. 2015 year (having only one month) was discarded.
- **Lockdown**: f_{it}^{lock}: the time from 3rd week March 2020 to 4th week November 2020 has been a strict lockdown period for the entire country given the SARS-CoV-2 pandemics (Larrosa, 2021). We create a dummy for this period to test its consequences on pricing.
- **Political variables**: We examine political events linked to significant increases in the inflation rate (Zorzoli, 2019). More specifically, we focus on the mandatory primary elections in the country, known locally as "*Primarias Abiertas Simultáneas y Obligatorias*" or PASO. These PASO elections precede the presidential election and have had a notable impact on price expectations in the past. We add a dummy variable f_{it}^{PASO} that take into account the 2017 PASO and 2019 PASO.
- **Festivities**: We also consider the effect on prices on beer-related festivities such as Saint Patrick's Day (March, 1st week) and Oktoberfest (October, 1st and 2nd weeks). modelled by the dummies f_{it}^{spd} and f_{it}^{of}, respectively.

3.4 Financial Variables

We also add metrics related to exchange rate at the weekly frequency.

- f_{it}^{offic}: weekly average variation of daily official selling dollar in Argentina.
- $f_{it}^{parallel}$: weekly average variation of daily non-official or parallel selling dollar in Argentina.

Financial variables are used as control for exchange rate pass-through effects. Estimations will be used one at time control for how exchange rate variations affect pricing.

4 Estimations and Analysis

Through Equation 1, we conducted three separate estimations, each incorporating one of the following variables: the official exchange rate, parallel exchange rate, or domestic fuel price. This approach aimed to address potential endogeneity concerns. However, by the end of 2017, accessing the formal foreign exchange market became significantly restricted, leading to challenges in acquiring foreign currency through legal channels. In contrast, the parallel exchange rate remained prevalent in numerous transactions within unregulated informal markets (Hoffman, 2014).

Furthermore, during the initial period covered by our study until 2017, the price of local crude oil was regulated in dollars. Starting in January 2017, efforts were made to gradually align the local price with international quotations under the Agreement for the Transition to International Prices in the Argentine Hydrocarbon Industry (2017). Nonetheless, in August 2019, a regulated pricing scheme was reintroduced, persisting throughout the relevant timeframe. As a result, simultaneously including both fuel prices and exchange rates in the estimation could introduce endogeneity. Panel estimations took into account correlation in panels and 1-lag autocorrelation present in the series.

Since the data utilized in our research consists of panel data, it is crucial to ensure the stationarity of the time variables to maintain constancy in mean, variance, and covariance over the temporal period. These variables include the official exchange rate, parallel exchange rate, and domestic fuel price. To assess stationarity, we employed the Augmented Dickey-Fuller (ADF) test, which initially assumes the null hypothesis that the series possesses a unit root and is, therefore, non-stationary (Dickey and Fuller, 1981). The results of these hypothesis tests, presented in Table 3, indicate stationarity at a 95% confidence level.

Table 3.
ADF Test Results (No Drift or Trend)

Variable	τ_0	p-value	Result
$f_{it}^{cost-fuel}$	-9,15	0,01	Stationarity
f_{it}^{offic}	-10,8	0,01	Stationarity
$f_{it}^{parallel}$	-9,15	0,01	Stationarity

Source: The Authors

To examine heteroscedasticity in beer price variations, we conducted the Levin, Lin, and Chu test (2002). accounting for both presentation and week due to the panel data structure. The results (Z-Statistic = -307.89, p-value = 0.000) strongly indicate the presence of stationarity at a 95% confidence level.

Moreover, working with panel data commonly presents two issues: serial correlation and heteroscedasticity. Serial correlation, the first concern, pertains to temporal dependence, resulting in inconsistent and biased estimators. This occurs because disturbances at a given time (u_t) are correlated with past disturbances, leading to non-zero autocovariance between them $E\ (u_t\ , u_{t-s}) \neq 0$.

For the data analyzed in this study, we tested for the presence of first-order serial correlation using the method proposed by Wooldridge (2010). The null hypothesis of no first-order serial correlation for panel data was examined, and the results, detailed in Table 4, confirm the existence of autocorrelation.

Another concern related to panel data is heteroscedasticity, which occurs when the variance of errors differs across observations, violating the assumption of homoscedasticity necessary for efficient estimators. In this study, we applied the Breusch-Pagan test (1979). starting with the null hypothesis of homoscedasticity. This test assesses whether there is a quadratic linear relationship between residuals derived from the estimated model and the explanatory variables utilized. The findings, outlined in Table 5, reveal the presence of heteroscedasticity across all examined specifications.

Table 4.
Correlation serial test

Model	F-statistic	p-value	Result
$f_{it}^{cost-fuel}$	23,427	0,00	First-order serial correlation.
f_{it}^{offic}	23,589	0,00	First-order serial correlation.
$f_{it}^{parallel}$	23,5	0,00	First-order serial correlation.

Source: The Authors

Table 5.
Breusch-Pagan test

Model	X^2-statistic	p-value	Result
$f_{it}^{cost-fuel}$	2,11E+07	0,00	Heteroscedasticity
f_{it}^{offic}	2,10E+07	0,00	Heteroscedasticity
$f_{it}^{parallel}$	2,10E+07	0,00	Heteroscedasticity

Source: The Authors

In this scenario, the standard estimations using Ordinary Least Squares (OLS) encounter inefficiencies stemming from the non-spherical nature of the variance-covariance matrix. These inefficiencies arise due to the existence of autocorrelation, heteroscedasticity, and contemporaneous correlation (Wooldridge, 2010). Consequently, the adoption of Feasible Generalized Least Squares (FGLS) estimation is suggested as an alternative to tackle this challenge.

The FGLS model considers the conditional variance of the error term given that X is a known matrix Ω. However, as the true variance-covariance matrix is not directly known, it is possible to estimate a matrix $\breve{\Omega}$ to obtain the coefficients derived from FGLS (Bai et al., 2021). These coefficients can be formulated as:

$$\breve{\beta}_{FGLS} = \left[X'\breve{\Omega}^{-1}\right]X'\breve{\Omega}^{-1}\,\mathrm{Y} \qquad (2)$$

However, the procedure for estimating Ω depends on the chosen specification. An alternative method, suggested by Beck and Katz (1995, involves using the Parks-Kmenta method. This approach involves two sequential transformations within FGLS. In the first step, the goal is to eliminate both the contemporaneous and serial correlation of the error terms, which are estimated using Ordinary Least Squares (OLS).

The residuals obtained from this initial estimation are critical as they are used to estimate the specific serial correlation of unit errors. In the second step, these estimated values are applied to transform the original model into one in which errors become serially independent, effectively addressing serial correlation. Subsequently, the residuals from this new estimation are used to calculate the contemporaneous correlation of errors. Once this stage is completed, the data is transformed once more, allowing for an estimation using OLS, with errors considered spherical, i.e., exhibiting no correlation. Thus, the resulting variance-covariance matrix is as follows:

$$\breve{\Omega} = \mathrm{diag}\,(s_1^2\,,\ s_2^2 \ldots s_n^2) \qquad (3)$$

The elements on the diagonal of this matrix (s_i^2) account for heteroscedasticity, serial correlation between panels, and contemporaneous correlation (Kmenta and Klein, 1971; Beck and Katz, 1995).

Given the exploratory nature of our research, we decided to include a wide range of variables. We aimed to comprehensively identify potential predictors and understand the complex relationships within our dataset. This broad inclusion was a deliberate first step to ensure no potentially important variable was overlooked. To address the issues associated with a "comprehensive inclusion strategy" model, we have implemented several measures: i) we focus our analysis on theoretical basis, as we mentioned in the review of relevant literature; ii) we utilize regularization methods, such as LASSO, to handle multicollinearity and penalize the inclusion of irrelevant predictors, and iii) we employ cross-validation techniques to ensure the robustness and generalizability of our model, minimizing the risk of overfitting.

Another technique utilized in this research is the Least Absolute Shrinkage and Selection Operator (LASSO). Developed by Tibshirani (1996). this method allows for estimating the impact of explanatory variables adjusted through an L2 regularization process. LASSO presents two significant advantages over typical regressions performed using OLS. The first advantage pertains to the interpretability of the estimated model, as the reduction in variables helps preserve those independent variables with the greatest impact on the dependent variable. Second, the elimination of variables that contribute little to the model enhances estimation prediction while introducing some bias, significantly reducing variance (Tibshirani, 1996).

In this manner, each of the coefficients ($\hat{\beta}_{LASSO}$) is obtained through a typical minimization problem of the following objective function:

$$\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{i,j})^2 + \lambda \sum_{j=1}^{p} |\beta_j| = RSS + \lambda \sum_{j=1}^{p} |\beta_j| \quad (4)$$

Equation 4 can be understood as the sum of squared residuals plus a penalty parameter determined by λ (James et al., 2013: 18). A smaller penalty results in smaller differences between the coefficients obtained by LASSO and those obtained by OLS. In an extreme case where λ=0, $\hat{\beta}_{LASSO}$ equals to $\hat{\beta}_{OLS}$. Conversely, with a sufficiently large λ, some estimated coefficients are forced to be zero (Hastie et al., 2009). It is important to note that LASSO estimations deviate from traditional statistical approaches due to the challenge of ensuring the typically assumed distribution of *p*-values.

As previously mentioned, we use various models that incorporate diverse instruments as controls, including exchange rates, fuel costs, and additional variables that may pose potential multicollinearity issues and require cross-validation. For instance, we included dummy variables representing October and Oktoberfest festivities to examine their individual and combined significance in the estimations. The swap cases scrutinized are as follows:

- f_{it}^{m10}: October vs and f_{it}^{of};
- x_{it}^{fer} vs x_{it}^{ale}/x_{it}^{hg} ;
- x_{it}^{hg} vs x_{it}^{a} ;

In this manner, models were fitted across various combinations. Subsequent analysis revealed small disparities among the models; consequently, a decision was made to aggregate the results, culminating in the presentation of a comparative visual representation.

4 Results

The results will be presented as the median of multiple significant estimations that agree in direction and exhibit relatively close final adjusted coefficients. In the empirical analysis, various instruments, including both the parallel and official dollar rates, as well as fuel costs, influence the outcomes. Notably, fuel costs, serving as a proxy for transportation expenses, exert a six-fold greater impact than the official dollar rate and dozens of times more influence than the parallel dollar rate. All estimations are available upon request for the sake of space.

Time variables demonstrate a significantly greater influence compared to attribute variables, consistently displaying a negative bias towards undercutting. This effect peaks approximately a hundred times higher on average in the former case (Figure 2 and Figure 3 are deliberately presented at the same scale). The temporal impact is particularly notable during traditional festivities such as Oktoberfest, which undeniably affects pricing throughout the entire month with a significant positive peak on a weekly basis. Conversely, the impact of Saint Patrick's Day in March is comparatively minor, with both the first week and July showing overshooting. These time variables are key findings. Other significant observations indicate undershooting, with extreme cases more prevalent during the Austral Summer.

As previously noted, the initial week exhibits a positive effect, followed by a consistently negative effect in the subsequent week. This pattern aligns with an inflationary environment where prices are typically adjusted following the receipt of new price lists in the first week, while promotional activities emerge during the second week. Over the months, a recurring pattern of undershooting is observed from January to June, August, September, and December, while overshooting is evident in July and October. The latter is attributed to the Oktoberfest celebration, which spans a couple of weeks. In contrast, Saint Patrick's Day demonstrates no discernible impact on pricing.

The Post PASO (Primary Elections) effect is consistently associated with undershooting across all terms, with magnitudes ranging from -0.00672 to -0.00984 (-2.66%/-3.88% monthly, -27.65%/-37.79% yearly accumulated). contingent upon the chosen instrument, whether it be the official or parallel dollar or fuel cost. Over the years, the years 2016, 2017, and 2019 exhibit prevalent undershooting, coinciding with the lockdown period in 2020, where an average effect of approximately -0.006 is observed.

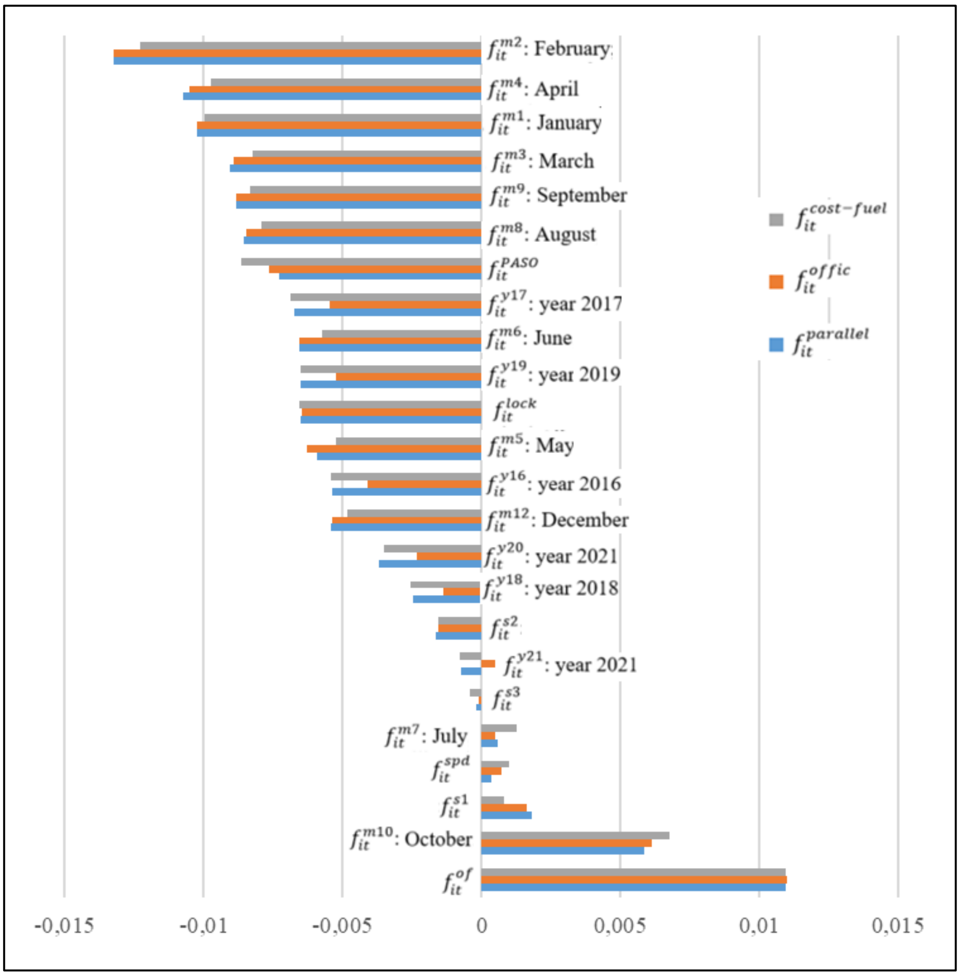

Figure 2. Estimation values (median of several models) for time parameters

When examining attributes, the volume (x_{it}^{l}) is positively related to overshooting in price updating, ranging from .000827 to .00116, depending on the adjusted model. That explains .33%/.46% in month or 4.05%/5.72% in a year of beer price. This is the effect on the average weekly price variation. Bigger bottles and cans are updating at higher rates than their smaller counterpart. It seems like demand is inelastic to the speed of price updating. This is also observed when considering refundable options (x_{it}^{ref}) or if beer is sold in cans (x_{it}^{con}). The alcohol content variables (x_{it}^{a}, x_{it}^{hg}) are both associated with undershooting, analyzed jointly or isolated in the range from -0.0005 to -0.0004 depending on the control (-.16%/-.2% monthly and 2.43%/1.94% yearly accumulated). The same sign is observed in imported beer (x_{it}^{ori}).

The principal differentiation between ales and lagers resides in the yeast type employed and the conditions of fermentation. Ales employ top-fermenting yeast at elevated temperatures, yielding a flavor profile characterized by increased complexity. Conversely, lagers employ bottom-fermenting yeast at lower temperatures, resulting in a flavor profile characterized by heightened clarity. The categorization of a beer as an ale or a lager offers a heuristic approximation of its yeast characteristics and the associated brewing methodology. Three variables are instrumental in delineating this dimension of beer classification: a dummy variable denoting fermentation type (x_{it}^{fer}) (with a value of 0 indicating top fermentation and 1 indicating bottom fermentation). along with two additional dummy variables signifying ale (x_{it}^{ale}) and lager (x_{it}^{lag}) variants. Whether employed collectively or in isolation, all three variables exhibit a positive sign (indicative of overshooting). Notably, lager beers manifest a coefficient twofold that of ale beers, a trend substantiated by the statistical significance and positive coefficient of x_{it}^{fer}. Smith et al. (2016) indicates ale beer is correlated to higher average price.

The statistical impact between market share, (x_{it}^{ms}). and undershooting is low but discernible (Figure 4). Notably, most-known brands demonstrate a proclivity to lag behind sectorial inflation trends. Conversely, smaller brands, commonly represented by incumbent Small and Medium-sized Enterprises (SMEs). presumably contend with diminished economies of scale, leading to pricing strategies more closely aligned with mitigating elevated costs (overshooting). Overall, market share negligibly affects pricing at the weekly time frequency.

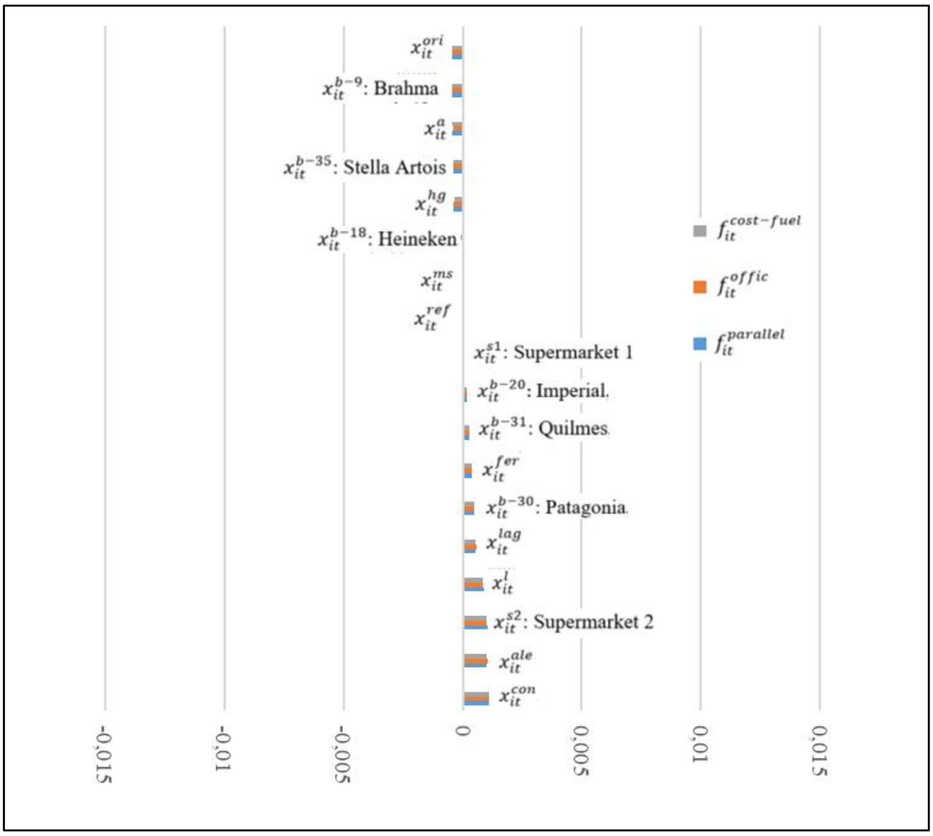

Figure 3. Estimation values (median of several models) for attribute parameters

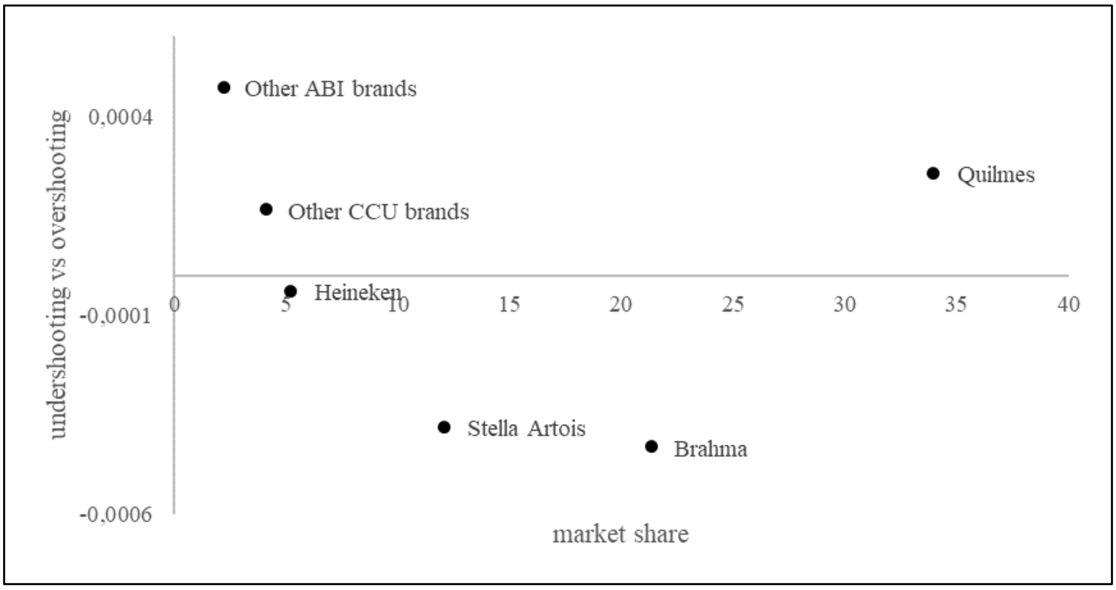

Figure 4. Market share and under/overshooting

5 Discussions and Lessons

The findings of this study highlight a significant influence of seasonality and economic cycles on short-term beer pricing tactics. Regular price updates are observed throughout the year, with a pronounced tendency toward price undercutting in high-inflation contexts. Additionally, other variables, though less important, still play a significant role in pricing strategies.

Consumers can gain several benefits from these insights. First, understanding the factors influencing beer pricing, such as currency exchange rates, fuel costs, and seasonal trends, can enhance price sensitivity. For instance, recognizing that fuel costs have a more substantial impact on prices than exchange rates enables consumers to predict potential price fluctuations more accurately, leading to more informed purchasing decisions.

Second, the research highlights how traditional events like Oktoberfest significantly impact beer prices, with notable increases during such periods. In contrast, events like Saint Patrick's Day have a minor effect. This knowledge allows consumers to plan their purchases strategically, taking advantage of lower prices during periods of undershooting and avoiding higher prices during major festivities.

Third, the study reveals that attributes such as volume, alcohol content, and packaging options influence beer prices. Larger bottles and cans are updated more frequently than smaller ones, indicating price variations based on packaging size. Additionally, the research suggests that demand is relatively inelastic to the speed of price updating, allowing consumers to choose between different packaging options without significant price differences.

Managers, on the other hand, can also profit from these findings. By incorporating factors like currency exchange rates, fuel costs, and seasonal trends into their pricing strategies, managers can better navigate the complexities of the market. Understanding the effect of the post-primary elections (PASO) on pricing, which typically leads to undershooting, helps managers adjust their pricing to maintain profitability. Recognizing recurrent patterns of undershooting or overshooting in certain months also enables better alignment of pricing strategies with market trends.

Furthermore, the timing of promotional activities, which often follow price adjustments and typically emerge in the second week of the month, can be leveraged to plan effective promotional campaigns. This maximizes sales opportunities while minimizing the impact of inflation. Aligning promotional efforts with seasonal events like Oktoberfest can further capitalize on increased consumer demand.

In terms of product portfolio management, understanding how product attributes influence price updating allows managers to optimize their offerings. For instance, knowing that larger bottles and cans are updated more frequently enables adjustments in product offerings to meet consumer demand. Additionally, recognizing that lager beers exhibit a higher coefficient in price overshooting compared to ales suggests a strategic emphasis on lager variants to maximize revenue.

The study also reveals that offering a wide variety of product sizes and packaging can complicate price comparisons for consumers, increasing search costs and making direct comparisons more challenging. This differentiation can confuse consumers, especially during events with significant price increases like Oktoberfest, while minor events like Saint Patrick's Day has less impact. Moreover, the rapid price adjustments driven by inflationary pressures indicate asymmetric pricing behavior, where prices rise quickly in response to economic conditions but decrease more slowly or strategically.

6 Conclusions

The beer market in Argentina is in an upward trend, displacing traditional spirits such as wine and white drinks in terms of consumption. We explore a specific market where prices are unstable given chronic inflation. The investigation into the dynamics of beer pricing within the Argentine retail market has unearthed essential insights crucial for both consumers and managers.

Firstly, amidst the backdrop of rising inflation, the research underscores the pivotal role of product attributes in shaping pricing strategies. Attributes significantly influence beer prices, showcasing the intricate interplay between product differentiation and pricing dynamics. Moreover, the study elucidates that while inflationary pressures drive rapid price adjustments, certain timeless variables, including seasonal trends and product attributes, exert a notable albeit nuanced impact on pricing decisions. Time shocks affect pricing more than 10 times on average than attributes. Market share is statistically associated with undercutting but its impact is negligible.

Secondly, consumers stand to benefit from a deeper understanding of the multifaceted factors driving beer pricing. Armed with insights into the impact of currency exchange rates, fuel costs, and seasonal variations on pricing, consumers can make more informed purchasing decisions. The research highlights the potential for consumers to capitalize on periods of undershooting, such as during traditional feasts like Oktoberfest, and underscores the influence of product attributes on price differentials, enabling consumers to navigate pricing variations based on packaging sizes and other product features.

Thirdly, managers in the beer industry can leverage the research findings to refine their pricing strategies, promotional activities, and product portfolio management. By incorporating insights into the influence of currency fluctuations, fuel costs, and seasonal trends on pricing dynamics, managers can develop more robust pricing strategies that balance profitability with market competitiveness. Furthermore, the research underscores the importance of aligning promotional activities with pricing patterns and optimizing sales opportunities while mitigating the impact of inflationary pressures. Additionally, an understanding of how product attributes shape price updating allows managers to tailor their product portfolios to meet consumer demand effectively, maximizing revenue potential.

Fourthly, seasonal trends and events like Oktoberfest significantly influence pricing. These periodic changes add complexity, as prices fluctuate based on the time of year and specific events. Consumers must navigate these variations, which can act as a form of obfuscation by introducing irregularities in pricing patterns.

Finally, the research underscores the rapid price adjustments driven by inflationary pressures. It is noted that time shocks (such as economic events) affect pricing more significantly than product attributes. This rapid adjustment in response to inflation indicates an asymmetric pricing behavior, where prices are increased quickly in reaction to economic conditions, but may not decrease as rapidly once those conditions stabilize. Factors like currency exchange rates and fuel costs also play a crucial role. Understanding these impacts can help managers adjust their pricing strategies to account for asymmetric price movements, where costs are passed onto consumers more readily during adverse economic conditions.

In essence, the findings underscore the intricate relationship between product attributes, pricing dynamics, and market conditions within the Argentine beer retail sector. By illuminating the factors driving pricing decisions and consumer behavior, the research equips stakeholders with valuable insights essential for navigating the complexities of the beer market amidst economic fluctuations and changing consumer preferences. Product differentiation and complex pricing strategies can obscure true price comparisons for consumers, and how firms leverage economic conditions to adjust prices asymmetrically to maintain profitability.

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Appendix

Table 6.

FGS Estimations

	FGS			LASSO		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	$f_{it}^{parallel}$	f_{it}^{offic}	$f_{it}^{cost-fuel}$	$f_{it}^{parallel}$	f_{it}^{offic}	$f_{it}^{cost-fuel}$
Coefficient	.0167***	.0155***	.0162***	.0186	.0184	.0177
	.00156	.00153	.00148			
f_{it}^{s1}	.00192***	.00174***	.000861**	.0024	.0022	.0014
	.000418	.000403	.000406			
f_{it}^{s2}	-.00132***	-.00121***	-.00122***		-.0017	-.0017
	.000414	.000406	.000394			
f_{it}^{s3}	-.000105	-4,10E-05	-.000388	-.0018	.0000	-.0001
	.00043	.000419	.00041			
f_{it}^{m12}	-.00673***	-.00670***	-.00619***	-.0080	-.0079	-.0071
	.000732	.000707	.000696			
f_{it}^{m1}	-.0111***	-.0112***	-.0109***	-.0126	-.0125	-.0122
	.000711	.000693	.000677			
f_{it}^{m2}	-.0141***	-.0141***	-.0131***	-.0157	-.0156	-.0145
	.000713	.000693	.000689			
f_{it}^{m3}	-.0106***	-.0106***	-.00992***	-.0114	-.0113	-.0105
	.000785	.000765	.000753			
f_{it}^{m4}	-.0117***	-.0115***	-.0107***	-.0137	-.0135	-.0127
	.000733	.000707	.000698			
f_{it}^{m5}	-.00680***	-.00722***	-.00618***	-.0073	-.0075	-.0065
	.000732	.000718	.000695			
f_{it}^{m6}	-.00765***	-.00766***	-.00682***	-.0085	-.0084	-.0075
	.000726	.000707	.000699			
f_{it}^{m7}	-.00139*	-.00151**	-.000719	-.0022	-.0022	-.0013
	.000729	.000709	.000696			-.0103
f_{it}^{m8}	-.00969***	-.00962***	-.00908***	-.0112	-.0110	-.0103
	.00074	.000712	.000701			
f_{it}^{m9}	-.00904***	-.00905***	-.00858***	-.0103	-.0102	-.0096
	.000738	.000713	.000698			
f_{it}^{m10}	-.000111	.000161	.000899	-.0006	-.0002	.0001
	.00116	.00113	.00111			
f_{it}^{y16}	-.00446***	-.00330**	-.00477***	-.0042	-.0041	-.0043
	.00147	.00144	.00139			

f_{it}^{y17}	-.00607***	-.00490***	-.00649***	-.0060	-.0058	-.0062
	.00147	.00145	.00139			
f_{it}^{y18}	-.00175	-.000817	-.00216	-.0017	-.0017	-.0018
	.00148	.00144	.00139			
f_{it}^{y19}	-.00430***	-.00313**	-.00452***	-.0041	-.0039	-.0040
	.00147	.00144	.00139			
f_{it}^{y20}	-.00136	-.000127	-.00143	.0039	.0038	.0034
	.00152	.00149	.00144			
f_{it}^{y21}	.00319*	.00425**	.00264*	-.0073	-.0070	-.0070
	.00168	.00165	.0016	-.0042	-.0041	-.0043
f_{it}^{lock}	-.00531***	-.00529***	-.00540***			
	.000756	.000737	.00072	-.0060	-.0058	-.0062
f_{it}^{PASO}	-.00399**	-.00413**	-.00476***	-.0025	-.0028	-.0033
	.00169	.00165	.00161			
f_{it}^{spd}	.00138	.00165	.00191	.0020	.0023	.0024
	.00123	.0012	.00117			
f_{it}^{of}	.00823***	.00815***	.00812***	.0093	.0093	.0096
	.0012	.00118	.00115			
x_{it}^{l}	.00101***	.00101***	.00101***	.0010	.0010	.0010
	2,54E-05	2,54E-05	2,54E-05			
x_{it}^{ref}	2,52e-05***	2,52e-05***	2,52e-05***			
	4,30E-06	4,30E-06	4,30E-06			
x_{it}^{con}	.00107***	.00107***	.00107***	.0012	.0012	.0012
	3,90E-05	3,90E-05	3,90E-05	-.0003	-.0003	-.0003
x_{it}^{a}	-.000654***	-.000654***	-.000654***			
	2,45E-05	2,45E-05	2,45E-05	-.0005	-.0005	-.0005
x_{it}^{ori}	-.000584***	-.000584***	-.000584***			
	2,30E-05	2,30E-05	2,30E-05	.0002	.0002	.0002
x_{it}^{fer}	-1,04E-05	-1,04E-05	-1,04E-05			
	8,24E-06	8,24E-06	8,25E-06	.0007	.0007	.0007
x_{it}^{ale}: Ale	.000600***	.000600***	.000600***			
	1,74E-05	1,74E-05	1,74E-05	-.0002	-.0002	-.0002
x_{it}^{lag}: Lager	.000993***	.000993***	.000993***			
	3,31E-05	3,31E-05	3,31E-05	.0001	.0001	.0001
x_{it}^{b-9}: Brahma	-.000257***	-.000257***	-.000257***			
	1,75E-05	1,75E-05	1,75E-05	.0001	.0001	.0001
x_{it}^{b-18}: Heineken	.000145***	.000145***	.000145***			
	1,35E-05	1,35E-05	1,35E-05	.0003	.0003	.0003

x_{it}^{b-20}: Imperial	.000273***	.000273***	.000273***			
	1,61E-05	1,61E-05	1,61E-05	.0002	.0002	.0002
x_{it}^{b-30}: Patagonia	.000541***	.000541***	.000541***			
	1,80E-05	1,80E-05	1,80E-05	-.0002	-.0002	-.0002
x_{it}^{b-31}: Quilmes	.000240***	.000240***	.000240***			
	1,54E-05	1,54E-05	1,54E-05	-.0003	-.0003	-.0003
x_{it}^{b-35}: Stella Artois	-.000251***	-.000251***	-.000251***	-.0005	-.0005	-.0005
	9,15E-06	9,15E-06	9,15E-06			
x_{it}^{hg}: High ABV	-.000335***	-.000335***	-.000335***	.0002	.0002	.0002
	1,31E-05	1,31E-05	1,31E-05			
x_{it}^{sup1}	-.000357***	-.000357***	-.000357***			
	3,64E-05	3,64E-05	3,64E-05			
x_{it}^{ms}	-4,05e-06***	-4,05e-06***	-4,05e-06***			
	.00000	.00000	.00000			
x_{it}^{sup2}	.000599***	.000599***	.000599***	.0010	.0010	.0010
	3,43E-05	3,43E-05	3,43E-05			
x_{it}^{sup3}	-.000446***	-.000447***	-.000446***	-.0001	-.0001	-.0001
	4,09E-05	4,09E-05	4,09E-05			
$f_{it}^{parallel}$	.00697			.0114		
	.00476					
f_{it}^{offic}		.0106***			.0093	
		.00226				
$f_{it}^{cost-fuel}$			.0697***			.0676
			.00753			
N	70,782	70,782	70,782	70,782	70,782	70,782