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Heterogeneous and dynamic pass-through of a fuel subsidy to consumers: Evidence from Spain

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Abstract

The outbreak of the COVID-19 pandemic and Russia's invasion of Ukraine in early 2022 severely disrupted energy markets, triggering a spike in global oil prices. To mitigate the impact on consumers, Spain introduced a fuel discount of 20 cents per liter, effective until the end of 2022. This study assesses the pass-through of the discount to retail prices using a combination of regression discontinuity (RD), difference-in-differences (DiD), and quantile regression approaches with daily data from over 11,000 Spanish petrol stations. We analyze how different types of operators—vertically integrated, branded, and independent—responded to the policy and examine its impact on the retail price distribution. The results reveal a negative relationship between a station's initial price and the pass-through of the discount, with lower-priced stations raising prices more in response to the policy. This pattern is particularly pronounced for diesel and among independent and retailer-managed branded stations, which captured a larger share of the subsidy. The quantile regressions further highlight that price increases were concentrated in the lower end of the price distribution, amplifying differences across station types. However, our DiD analysis shows that these effects were temporary, with price differentials gradually converging after approximately 36 to 43 days. Overall, the findings highlight how generalized public discounts can temporarily distort market dynamics and affect competitive conditions in the market. The study offers insights for the design of future subsidy programs, particularly regarding the role of market structure and financial constraints in shaping pass-through.

Keywords: pass-through, discount, retail fuel prices, market structure, regression discontinuity, DiD, quantile regression

JEL Codes: D12, Q41, Q48

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1. Introduction

Since the COVID-19 pandemic, global energy markets have been in sustained turmoil. An initial collapse in demand was followed by a rapid recovery and supply constraints, putting upward pressure on prices. The situation worsened in early 2022 with Russia's invasion of Ukraine, which heightened fears of supply disruptions given Russia's role as a major oil and gas exporter. As a result, energy prices soared, with Brent crude oil rising more than 25% in the months following the invasion, breaking through the $100 per barrel mark.

The sharp increase in energy prices had significant economic and social impacts across Europe. As net importers of oil and gas, member states had little capacity to influence global market dynamics or contain the surge in prices. In response, many governments introduced measures in the spring of 2022 to cushion the impact on consumers and delay the pass-through of wholesale price increases to retail energy prices. Among these measures, price controls and tax cuts, particularly Value Added Tax (VAT) reductions, were widely implemented [36, 2].

In Spain, the escalation of fuel costs led to a strike by transport workers in mid-March, demanding government action to reduce the impact on their businesses. At the end of March, the government approved an extraordinary general discount of 20 cents per liter on the retail price of all types of fuel until the end of 2022. The policy was designed to achieve two goals: to mitigate the impact of higher energy prices on the economy as a whole and to help reduce inflation, which at the time stood at 9.8%.

While this and similar measures in other countries were intended to alleviate the impact of rising prices on consumers, their effectiveness in practice has been questioned. Recent studies have documented varying degrees of pass-through to final prices, with concerns that part of the relief intended for consumers may have been captured by fuel retailers or upstream suppliers [17, 18, 30, 40]. The risk of incomplete pass-through or strategic price adjustments by market participants is particularly relevant in concentrated markets such as the fuel distribution in Spain, where vertical integration and market power can shape pricing dynamics [35, 12, 9, 34]. Assessing how these factors affected the Spanish fuel discount is crucial to understanding the real incidence of the measure and the extent to which it benefited consumers.

In this paper, we employ two complementary methodological approaches to assess the pass-through of the discount and examine its differential effects across market participants. First, using a regression discontinuity (RD) approach with daily price data from December 2021 to June 2022 from more than 11,000 Spanish petrol stations, we estimate whether the discount implementation led to retail price increases not explained by market fundamentals such as international fuel quotations and exchange rates. Second, we implement a difference-in-differences (DiD) strategy that leverages the heterogeneous responses across station types to examine the dynamic evolution of prices following the policy intervention.

Our findings reveal significant heterogeneity in how different types of service stations responded to the discount policy. Independent petrol stations increased their diesel prices by approximately 4.4 cents per litre, effectively capturing about 22% of the intended discount. Retailer-managed branded stations showed similar behavior, with price increases of 3.1-4.5 cents depending on their affiliation. In contrast, stations directly managed by wholesalers with refining capacity demonstrated near-complete pass-through, even slightly reducing prices by around 0.4 cents. For gasoline, we observe similar patterns, though with smaller magnitudes: independent stations raised prices by 1.7 cents (8.5% of the discount), while vertically integrated operators slightly reduced prices.

Our quantile regression analysis further reveals a strong negative relationship between a station's initial price position and its price response. Stations with lower pre-policy prices, particularly independents, exhibited the largest price increases. For diesel, independent stations in the lowest price decile increased prices by approximately 8 cents per litre, those near the median by only 4 cents, while stations in the highest percentiles showed negligible effects. The DiD analysis complements these findings by demonstrating that the initial price increases were temporary, with differentials gradually converging over approximately 43 days for diesel and 36 days for gasoline.

The rest of the document is organized as follows. First, in Section 2 we conduct a review of the empirical evidence on this topic and outline our contributions to this area of research. Section 3 provides an overview of the policy and Sections 4 and 5 describe the data and the identification strategies used in our analysis. Then, section 6 presents our main RD and quantile regression results, and section 7 explores the dynamic effects through our DiD approach. Finally, in Section 8 we develop and discuss our conclusions and policy implications.

2. Related literature on market structure and pass-through to retail fuel prices

The economic literature provides substantial evidence on how cost changes are transmitted to consumers in fuel markets. Research has documented two key phenomena: the asymmetric "Rockets and Feathers" effect [5], where prices rise quickly but fall slowly in response to wholesale cost changes [8, 19, 4], and the heterogeneous pass-through of taxation. Regarding the latter, recent studies have identified several factors influencing pass-through rates, including market structure [7], where vertically integrated companies show higher pass-through, geographical location [6, 28], and demand-side characteristics such as consumer information [33] and wealth [25, 39].

Researchers have also examined the role of market structure in determining how the recent fuel tax cuts have been passed on to consumers. [41] use a Regression Discontinuity in Time (RDiT) to analyse the pass-through rates of the temporary German fuel discount in 2022 and show that competitive markets lead to higher pass-through rates and that petrol stations belonging to vertically integrated brands are able to pass on a significantly higher amount of the tax change. Also, for the German case, [21] estimate an event study model with France as control and find lower pass-through rates in regions with low levels of competition. Similarly, [15] evaluates the tax cuts implemented by the Korean government in 2018 using a matched DID estimator and finds that they increase pass-through rates as retail sellers face more competition.

Finally, two studies have specifically analyzed the pass-through effects of the Spanish discount. [29] employ a dynamic DiD approach using weekly data from Spain and a control group of EU countries. Their findings indicate that the discount led to a 5 cents per litre increase in the price of diesel, suggesting a pass-through rate of approximately 73.65%. In contrast, they find no significant change in the price of gasoline, consistent with full pass-through. The analysis also shows that results are very similar before and after accounting for VAT. Additionally, the dynamic analysis reveals that price effects for diesel remained relatively stable throughout the subsidy period, while no significant effects were found after the subsidy was removed. Similarly, [10] reach comparable conclusions regarding the asymmetry between fuels. Using a two-stage approach, they first estimate a nonlinear autoregressive distributed lag error-correction model (NARDL-ECM) on daily station-level data to predict net-of-tax prices in the pre-discount period. Then, they construct a counterfactual price series to assess deviations after the subsidy's introduction. Their results also show no significant increase in net prices for gasoline, indicating full pass-through. In contrast, diesel prices exhibit significant increases in net prices, leading to incomplete pass-through. The analysis also reveals heterogeneity across retailers: large companies increased net prices by 3 to 5 cents per litre, while independent stations raised prices by an average of 6.5 cents per litre. As a result, the reduction in final prices at independent stations amounted to only 60.7% of the subsidy value, reflecting lower pass-through.

Building on these contributions, our paper adds novel evidence by analysing in detail how petrol stations reacted to the Spanish discount implementation, with a particular focus on heterogeneity across station types. We contribute on three main fronts. First, we exploit the institutional design of the policy, which differentiates operators in terms of implementation and funding, to estimate a RD model that allows us to capture short-term strategic pricing adjustments around the policy implementation. This approach is particularly suited to identifying heterogeneous reactions across station types immediately after the policy shock. Second, we move beyond average effects by estimating quantile regression models, providing novel evidence on how the policy shaped the entire price distribution across different types of operators. This enables us to analyse changes in price dispersion and strategic behaviour that remain hidden in mean-based estimates. Third, we complement the RD analysis with a DiD strategy that exploits variation across station types to test the persistence of these effects over time and validate the RD results, offering new insights into the medium-term dynamics of pass-through.

Also, our findings on the heterogeneous pass-through of the fuel discount contribute to a broader literature on how financial constraints affect firm behavior under public policies. While traditional models of imperfect competition would predict greater subsidy capture by firms with market power [42], our results suggest that liquidity constraints can significantly alter this dynamic, especially when the policy requires firms to temporarily finance the discount. This observation is consistent with recent research demonstrating how financial constraints can affect firms' pricing decisions across various contexts [1].

3. The discount: design, financing and drawbacks

3.1. The discount policy: design and implementation

In response to the sharp increase in fuel prices and the social unrest that followed Russia's invasion of Ukraine, the Spanish government approved an extraordinary general fuel discount through Royal Decree-Law 6/2022. The measure, effective from April 1 until the end of 2022, introduced a universal discount of 20 cents per liter, applicable to all fuel types and service stations nationwide, regardless of size or corporate structure. Petrol stations were responsible for applying the discount directly at the point of sale, with the amount clearly displayed on receipts. The implementation timeline was immediate, giving operators minimal preparation time to adapt their systems and financial planning, creating operational challenges particularly for smaller operators with limited resources.

3.2. Financing and reimbursement mechanisms

In terms of financing, the Spanish government generally covered the full 20 cents per liter for all service stations. However, for wholesalers with refining capacity in Spain and an annual turnover of more than 750 million euros, that is, the historic major firms, the government financed only 15 cents per liter, leaving these operators to cover the remaining 5 cents. To meet their obligation, these companies could either contribute 5 cents per liter directly to the government discount program or provide an equivalent commercial discount through their own pricing structures or loyalty programs. This option allowed major players to potentially leverage their contribution for marketing purposes.

To operationalize the measure, the decree established a reimbursement system enabling petrol stations to recover the amount advanced to consumers. Each month, distributors were required to submit a claim to the tax authority during the first 15 calendar days—starting in May 2022 for discounts applied in April. The tax authority would then process these claims and issue payments approximately one month later. This mechanism created a time lag between when stations applied the discount and when they received compensation.

Aware of these risks, particularly for smaller operators, the Tax Agency introduced an advance payment system. Before April 15, 2022, petrol stations could request an advance equal to 90% of their average monthly sales volume of eligible products in 2021, providing immediate liquidity to offset the upfront cost of the discount.

3.3. Implementation challenges and their implications

There are several notable challenges in the design and implementation of the fuel discount policy that could potentially affect its effectiveness and market dynamics. From an environmental perspective, the policy runs counter to climate goals by effectively subsidizing fossil fuel consumption, with [31] estimating an increase in emissions of nearly 4 percent. Regarding equity concerns, [22] showed that benefits disproportionately accrued to higher-income households, which typically spend more on fuel.

The implementation structure created specific operational difficulties that varied by operator type. Vertically integrated companies with refining capacity bore part of the discount cost but could capitalize on it commercially. Smaller independent companies faced particularly acute challenges in managing the advance payments. Although the advance payment system was established to mitigate liquidity issues, several factors limited its effectiveness:

- The reliance on 2021 fuel consumption data as the reference period for calculating advances likely introduced downward bias due to COVID-19 mobility restrictions, making advances systematically lower than actual 2022 needs.
- Smaller operators typically operate with tighter margins and less financial buffer, making them more vulnerable to the timing gap between discount implementation and reimbursement.
- Many independent stations have less sophisticated pricing and accounting systems, creating additional administrative burdens.

These operational challenges, combined with pre-existing competition concerns in the Spanish fuel market [35, 9, 34], create a compelling rationale for analyzing heterogeneous pass-through effects across different types of operators. If these challenges resulted in differential abilities to pass the discount through to consumers, the policy may have inadvertently affected market competition dynamics. Under this framework, we develop specific hypotheses regarding expected pass-through patterns:

1. Operators with greater financial constraints (typically independents and smaller branded stations) might pass through less of the discount, effectively capturing part of it to mitigate liquidity challenges.
2. Vertically integrated operators, especially those required to contribute to the discount financing, might have strategic incentives to demonstrate full pass-through or even greater discounts through marketing and loyalty programs.
3. Stations with initially lower prices and tighter margins may have been more constrained in their ability to fully pass through the discount compared to stations with higher initial prices.

4. Data

4.1. Data sources and temporal coverage

The data used for the analysis comes from the Ministry for Ecological Transition and Demographic Challenge and covers the period from December 1, 2021, to June 17, 2022. This timeframe provides a balanced window of approximately four months before and two and a half months after the implementation of the discount policy on April 1, 2022, allowing us to observe both pre-intervention trends and post-intervention effects.

The dataset has a panel structure, containing daily closing prices for each type of fuel sold by each petrol station throughout Spain. This granular data structure is particularly valuable for our analysis as it enables us to exploit both temporal variations (how prices change over time) and cross-sectional variations (how prices differ across stations, related to the different pricing strategies they follow) to identify the causal effect of the discount policy. The daily frequency of observations allows us to precisely track immediate price responses following the policy implementation and subsequent adjustments.

In total, our dataset comprises 2,073,044 observations covering approximately 11,000 petrol stations, representing over 95% of all operating stations in Spain during this period. This near-comprehensive market coverage minimizes potential selection bias concerns and ensures our findings are representative of the broader Spanish fuel retail market.

For each station-day observation, we have the retail prices of different fuel types, with our analysis focusing primarily on the two most common fuel types in Spain: Diesel A and Gasoline 95. Beyond that, the dataset contains rich information on station characteristics, including geographical coordinates, brand affiliation, management model (whether data is submitted by a wholesaler or retailer, which provides insight into the operational structure), and location details. These variables are crucial for our analysis as they allow us to investigate heterogeneous effects of the discount policy across different types of market participants.

4.2. Classification of petrol stations

One of the key advantages of our dataset is the availability of detailed information on station characteristics, allowing us to classify petrol stations according to their management model and corporate structure. This classification is particularly relevant in the context of the discount policy, as the Royal Decree-Law 6/2022 imposed different obligations on wholesalers with refining capacity compared to other market participants.

A critical insight from our data is that even if a fuel station displays the brand and logo of a major company, this does not necessarily mean that the company manages it. The dataset provides information on whether the price data was submitted by a wholesaler or a retailer, offering valuable insights into the actual management structure beyond mere branding.

Taking into account these distinctions and the specific obligations imposed by the Royal Decree-Law 6/2022 on wholesale operators with refining capacity, we classify service stations into five groups (see Table 1):

- **Type 1.** Service stations operated and managed by one of the three wholesalers with refining capacity who are required to contribute to the discount financing.
- **Type 2.** Service stations operated and managed by other wholesalers who do not have refining capacity and are therefore exempt from participating in the rebate financing.
- **Type 3.** Branded petrol stations integrated into the distribution network of a type 1 wholesaler but operated by a retailer.
- **Type 4.** Branded petrol stations integrated into the distribution network of a type 2 wholesaler but operated by a retailer.
- **Type 5.** Independent fuel stations with no affiliation to major brands.

Table 1. Types of stations by management and refining capacity

	Directly Managed	Branded	Independent
With refining capacity	Type 1	Type 3	-
Without refining capacity	Type 2	Type 4	Type 5

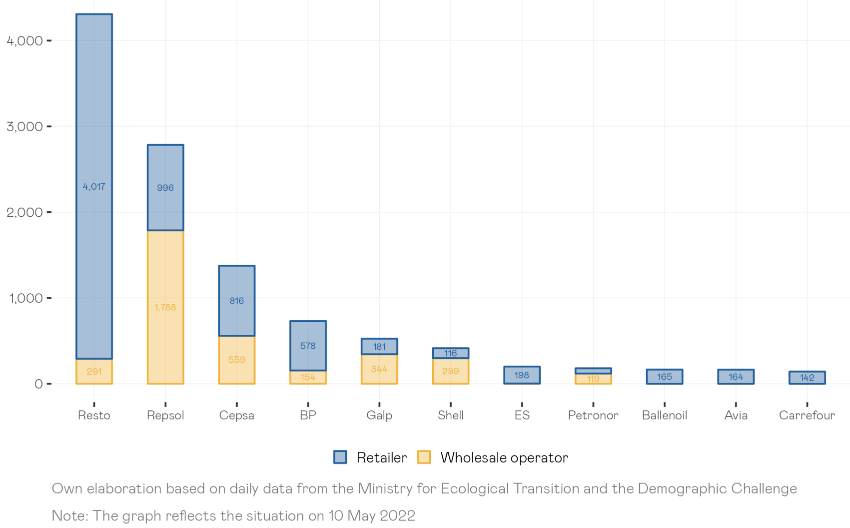
Source: Own elaboration

This classification is crucial for our analysis as it allows us to examine whether there is heterogeneity in the pass-through of the discount across different market segments, as demonstrated in previous studies [7, 24].

Figure 1 shows the distribution of the top ten companies with the highest number of service stations under their brand, categorized by who submits the information to the Ministry and thus manages it. Among the three wholesalers with refining capacity, Repsol stands out with 64% of stations directly operated by the company itself (type 1), followed by Cepsa with 40% and BP with 21%. The remaining 36%, 60%, and 79%, respectively, are dealers who act as brand ambassadors for these companies under exclusive supply contracts.

Despite lacking refining capacity, Galp and Shell also have a larger proportion of branded and managed stations (type 2) than branded and dealer-managed stations (type 4). Outside the top ten companies, as shown in the first column of Figure 1, stations managed by wholesalers account for only 7% of the total, indicating the fragmented nature of this market segment.

Figure 1. Number of petrol stations in Spain by brand and type of operator



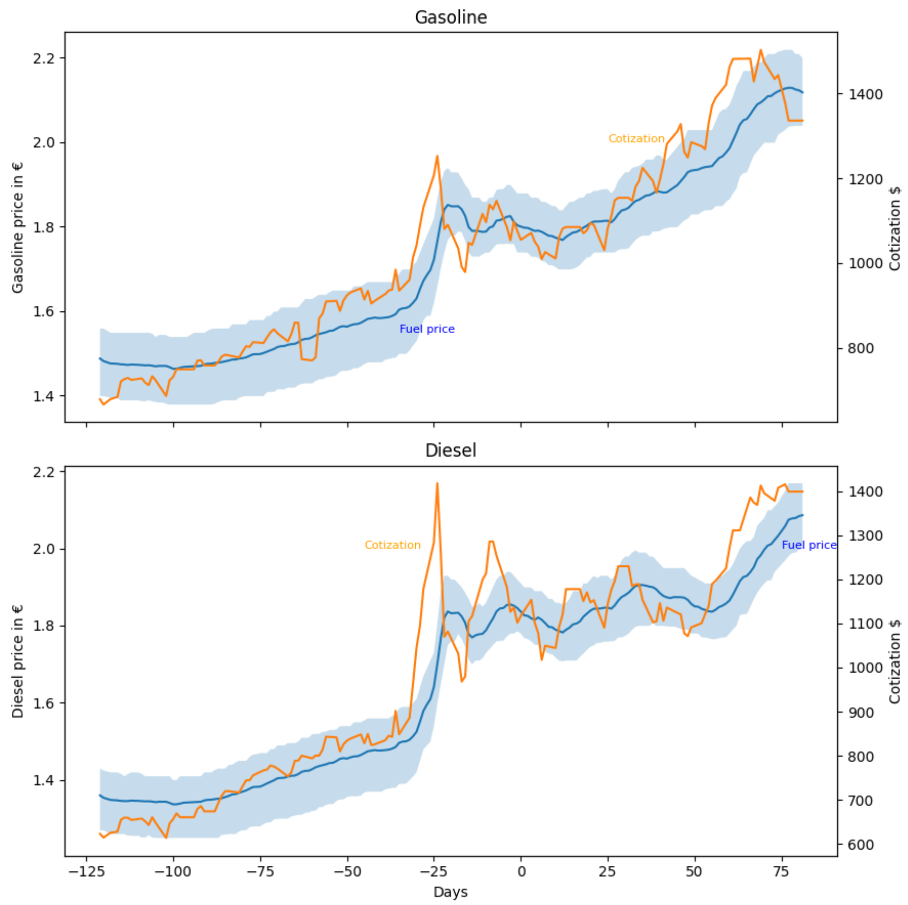
Source: Own elaboration based on data from the Ministry for Ecological Transition and Demographic Challenge

4.3. Explanatory and control variables

In addition to the station classification outlined above, we include several control variables to account for other factors that may influence retail fuel prices and their response to the discount policy. These variables help isolate the causal effect of the policy and capture heterogeneous impacts across station types. For clarity, we group them into categories based on their role in the empirical models:

1. **Type of petrol station** based on the five groups defined in Table 1.
2. **The daily international price in dollars for gasoline and diesel**. These series are preferred to the daily Brent crude oil price because retailers use them directly to set their daily sales prices. Specifically, we use the 70%-30% combination of Mediterranean (CIF-MED) and Northwest (CIF-NWE) prices used by the Spanish National Markets and Competition Commission (CNMC) in its analysis of international prices for both products. In addition, diesel prices rose significantly as a result of the invasion of Ukraine, which was not observed with the same intensity in crude oil and gasoline prices. This is because a large proportion of the main refineries for this type of fuel are located in Russia, which has had a strong impact on the price of this product. Figure 2 shows the variation of gasoline and diesel prices over time, together with their respective international quotations. The shaded areas around the average price lines represent the range between the 10th and 90th percentiles of the respective fuel prices.

Figure 2. Retail fuel price evolution (blue) and international quotation (orange)

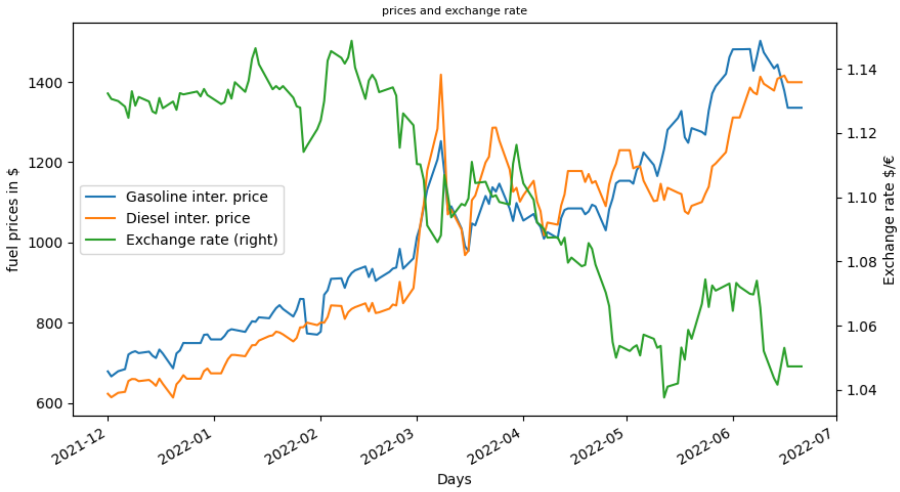


Note: The international daily price in dollars for gasoline and diesel used are the 70\%-30\% combination of prices for the Mediterranean (CIF-MED) and the Northwest (CIF-NWE).The shaded regions around the average price lines represent the range between the 10th and 90th percentiles of the respective fuel prices.

Source: Ministry for Ecological Transition and Demographic Challenge, ICE

3. **The exchange rate of the euro against the dollar.** Fuel prices on international markets are quoted in dollars, and the exchange rate, therefore, determines the value of imports. Figure 3 shows both gasoline and diesel price series together with the euro/dollar exchange rate.
4. **Station location and market characteristics.** We control for several aspects of station positioning and market structure: (a) station location type (road, motorway, expressway, or industrial area); (b) position indicators (whether the station is on the right or left side of the road); and (c) competition intensity, measured as the number of competing stations within a 2km Euclidean distance, following established approaches in the literature [14, 11].
5. **Seasonal and calendar effects** through day-of-week and holiday variables to capture strategic pricing behavior [34].

Figure 3. Evolution of international fuel prices and euro/dolar exchange rate



Source: ICE, Bank of Spain

4.4. Descriptive statistics

Before proceeding with the econometric analysis, we examine the evolution of fuel prices over our study period to provide context for the results that follow. While we can only compute aggregate price measures based on station-level data without information on sales volumes, this limitation is not critical to our analysis since our primary focus is on the impact of the policy on prices offered by different groups of stations rather than on market-weighted averages.

Table 2 presents summary statistics for our key variables before and after the implementation of the discount policy. Panel A shows that the average price of Diesel A increased by 26% (almost 40 cents) after the policy, while Gasoline 95 rose by 21% (33 cents). These raw differences must be interpreted in the context of the dramatic increases in international fuel prices during this period. Specifically, international diesel prices rose by 41%, and international gasoline prices by 40%. In parallel, the euro depreciated against the dollar by about 4.5%, further increasing the cost of fuel imports.

Panel B reveals notable patterns in pricing strategies across different types of stations. Independent stations (Type 5) consistently offer lower prices compared to other station types for both fuels. Before the discount, independent stations priced diesel at €1.45 per liter, significantly below the €1.53 charged by stations operated by wholesalers with refining capacity (Type 1). For gasoline, this gap was similar at 8 cents (€1.54 vs. €1.62). This pattern is consistent with previous literature documenting how independent stations typically exert downward pressure on market prices [9]. After the discount implementation, these price differentials persisted. This stability in the differentials suggests that different types of stations might have responded similarly to the discount policy despite their different initial price positions and operating constraints.

The price dynamics between fuel types also evolved during our study period. Before the discount, gasoline commanded a premium of 9 cents over diesel. After the discount implementation, this premium narrowed to 3 cents, reflecting the relatively higher increase in diesel prices compared to gasoline during this period. This price convergence between fuel types represents an important market dynamic that we will control for in our subsequent analysis.

Table 2. Descriptive statistics

	Before Discount		After Discount	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Panel A: Market prices and fundamentals				
Diesel A price (€/l)	1.49	0.20	1.88	0.13
Gasoline 95 price (€/l)	1.58	0.16	1.91	0.16
International diesel quote ($)	850.40	199.50	1199.42	113.34
International gasoline quote ($)	885.73	147.50	1236.81	155.22
Euro/dollar exchange rate	1.12	0.02	1.07	0.02
Panel B: Mean prices by station type				
Diesel A price (€/l)				
Type 1 (Wholesaler w/ refining)	1.53	0.18	1.92	0.12
Type 2 (Wholesaler w/o refining)	1.50	0.19	1.89	0.13
Type 3 (Branded, refiner)	1.52	0.19	1.91	0.14
Type 4 (Branded, non-refiner)	1.50	0.19	1.89	0.12
Type 5 (Independent)	1.45	0.20	1.84	0.13
Gasoline 95 price (€/l)				
Type 1 (Wholesaler w/ refining)	1.62	0.14	1.95	0.16
Type 2 (Wholesaler w/o refining)	1.60	0.15	1.92	0.16
Type 3 (Branded, refiner)	1.61	0.16	1.94	0.17
Type 4 (Branded, non-refiner)	1.59	0.15	1.92	0.15
Type 5 (Independent)	1.54	0.17	1.87	0.15

Source: Own elaboration

5. Identification strategy

We employ two complementary empirical strategies to identify the fuel discount policy's causal effect on retail prices. First, we implement an RD design that exploits the precise timing of the policy implementation as an exogenous cutoff. This approach allows us to estimate the immediate impact of the discount by comparing prices just before and after the policy went into effect. Second, to examine the dynamic evolution of price responses and validate our main findings, we develop a DiD strategy that leverages heterogeneity in how different types of stations responded to the policy.

This dual methodological approach offers several advantages. The RD design provides high internal validity for estimating the immediate policy impact under minimal assumptions, while the DiD approach captures medium-term adjustment patterns and allows for a richer exploration of heterogeneous effects. Together, these complementary methods provide a robust framework for understanding both the magnitude and dynamics of market responses to the fuel discount policy.

5.1. Regression Discontinuity Design

5.1.1. Panel data framework

Understanding the actual effect of the fuel discount policy on retail prices is crucial for assessing its effectiveness and informing the design of future interventions. However, isolating the causal impact presents challenges due to concurrent factors influencing fuel prices, including fluctuations in international oil prices, exchange rates, and local competitive conditions. To address this challenge, we employ an RD approach with panel data. This methodology enables us to compare prices before and after the discount introduction by treating the implementation date as a threshold or cutoff, thereby delineating control and treatment groups. Through appropriate weighting techniques and optimal bandwidth selection, we robustly estimate the Average Treatment Effect (ATE) of the intervention.

Our econometric specification incorporates all variables described in the previous section that influence pricing decisions at petrol stations. The model exploits the heterogeneity across stations by leveraging the panel structure of our data. We assume no correlation between the station-specific fixed component and the explanatory variables, making a random effects specification appropriate for three primary reasons. First, the station characteristics are independent and station-specific. Second, these variables capture a significant proportion of unobserved differences between petrol stations that remain constant over time. Third, a fixed effects approach would substantially restrict the scope of our analysis by excluding numerous time-invariant explanatory variables of interest.

To validate this methodological choice, we rely on two complementary strategies. First, we conduct a Hausman test to determine the consistency of random effects estimates relative to fixed effects. Failing to reject the null hypothesis indicates that the random effects model is consistent, allowing us to exploit its greater explanatory power for our research objectives. Second, we perform robustness checks by presenting estimates from both methods. As we demonstrate in Section 6, these estimates show minimal differences.

For our analysis, we calculate three distinct models for each fuel type. The first is a fixed effects model without time-invariant variables. The second is a random effects model with the same variable set as the fixed effects model. The third, our preferred specification, is a comprehensive random effects model incorporating time-invariant characteristics. While our discussion primarily focuses on this third model, we present all three for comparison and as a robustness exercise.

5.1.2. Causal effect identification

We utilize a regression discontinuity framework to infer the causal effect of the discount policy, treating April 1, 2022, the implementation date, as our threshold. Treatment and control groups are defined based on whether price observations occur before or after this date. The detailed mathematical formulation of our RD approach is presented in Appendix A.

5.1.3. Econometric specification

Our preferred econometric specification is a random effects model that allows for the estimation of both time-varying and time-invariant factors affecting fuel prices. The model includes a comprehensive set of controls for market fundamentals, seasonal patterns, and station-specific characteristics:

$$P_{it} = \beta_0 + \beta_1 d_t + \beta_2 1\{D \geq d\} + \beta_3 d_t 1\{D \geq d\} + \sum_{j=1}^{4} \gamma_j \mathrm{TypeJ}_i + \sum_{j=1}^{4} \delta_j \mathrm{TypeJ}_i \cdot 1\{D \geq d\} + \mathbf{X}'_{it}\boldsymbol{\theta} + \alpha_i + \varepsilon_{it} \tag{1}$$

where:

- P_{it} is the price of fuel (diesel A or gasoline 95) at station i on day t
- d_t represents days relative to the cutoff date (April 1, 2022)
- $1\{D \geq d\}$ is the treatment indicator for observations after the cutoff
- TypeJ_i are indicator variables for station types 1-4 (with type 5 as reference)
- $\mathbf{X}_{it}$ is a vector of control variables, including international quotations, exchange rates, and station characteristics
- α_i is the station-specific random effect
- ε_{it} is the idiosyncratic error term

In this specification, β_2 captures the average treatment effect for independent stations (Type 5, the omitted category), while the δ_j coefficients capture differential responses for each station type relative to independents. The interaction term $\beta_3 d_t 1\{D \geq d\}$ allows for different slopes before and after the intervention, capturing potential dynamic effects.

5.2. Difference-in-Differences Approach

While our RD design provides credible estimates of the immediate impact of the discount policy, it has important limitations. First, the RD approach inherently focuses on short-term effects around the threshold, offering limited insight into medium-term market adjustments. Second, its validity depends on the absence of precise manipulation at the cutoff, which might be a concern if stations anticipated the policy and adjusted pricing strategies beforehand. Third, the bandwidth selection involves inevitable trade-offs between bias and variance.

To complement the RD analysis and obtain a more comprehensive understanding of policy effects, we implement a DiD approach that exploits variation across station types. Our RD results reveal a particularly informative pattern: stations operated directly by wholesalers with refining capacity (Type 1) exhibited minimal price changes or even slight reductions following the discount implementation. This finding is consistent with interviews conducted with representatives from these companies, who confirmed they fully passed through the discount to consumers as part of their corporate strategy and in compliance with their obligations under Royal Decree-Law 6/2022. In contrast, independent stations (Type 5) showed significant price increases after the policy implementation.

This observed differential response provides a natural framework for a DiD analysis, where we can define:

- **Treatment group**: Independent stations (Type 5), which exhibited partial pass-through
- **Control group**: Stations operated by wholesalers with refining capacity (Type 1), which exhibited complete pass-through

The key identifying assumption in our DiD approach is that, absent the discount policy, price differentials between these station types would have followed parallel trends. While this assumption is not directly testable for the counterfactual period, we provide visual evidence of parallel pre-treatment trends and conduct robustness checks with flexible time trends to address potential violations of this assumption.

To enhance comparability between treatment and control groups, we employ a geographical matching strategy that ensures stations in both groups face similar local competitive conditions. This approach pairs each treatment station with its closest Type 1 counterpart within a 5-kilometer radius, creating matched pairs that operate in similar market environments. Further details on this matching procedure and our econometric specifications are provided in Appendix B.

Our baseline DiD specification uses the price differential between paired stations as the dependent variable:

$$P_{it} = \alpha + \beta_1 Post_t + \beta_2 Days_t + \beta_3 (Post_t \times Days_t) + \varepsilon_{it} \tag{2}$$

where P_{it} is the price difference between a non-Type 1 station i and its matched Type 1 station on day t, $Post_t$ indicates observations after April 1, 2022, and $Days_t$ measures time relative to the implementation date. In this specification, β_1 represents the average treatment effect, while β_3 captures how this effect evolves over time. We extend this basic model to examine heterogeneous effects across station types and to account for station-specific heterogeneity through fixed effects estimation.

6. Regression Discontinuity results

6.1. Price responses to the discount introduction

Figure 4a presents the estimated treatment effects for Diesel A across different model specifications. Our preferred specification—the random effects model that incorporates station characteristics—reveals a 4.4 cents per liter price increase for independent stations (Type 5) following the discount implementation. This effect is larger than the 2.9-3.0 cents estimate from models that exclude station-specific controls[1]. Similar patterns, though with smaller magnitudes, are observed for Gasoline 95 (Figure 4b).

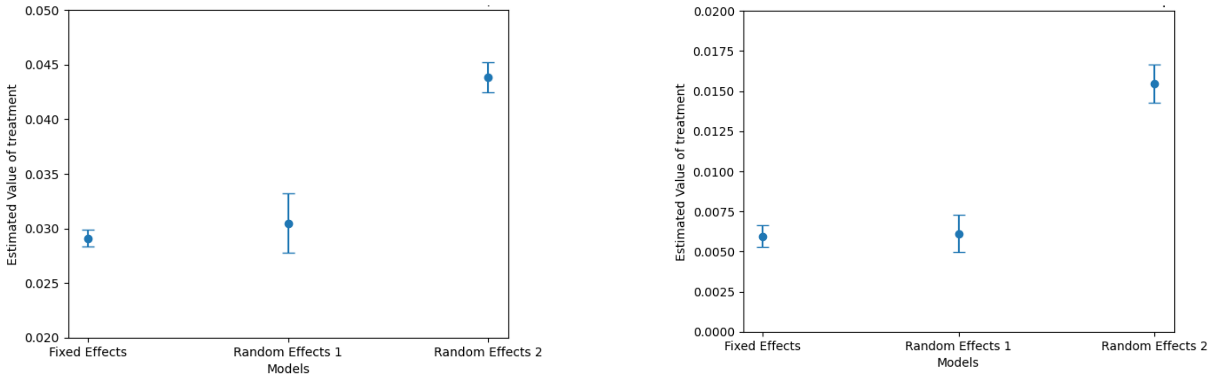
6.1.1. Effect heterogeneity by station type

The heterogeneity in responses across station types is substantial, as detailed in Table C.2 (Appendix C). The effects by station type, calculated as the reference effect plus the

[1]Table C.1 provides a comparison between fixed and random effects specifications. The Hausman test confirms the consistency of our preferred random effects model, which better accounts for station heterogeneity.

Figure 4. Estimated value of treatment for different models

(a) Diesel prices **(b)** Gasoline prices



Source: Own elaboration

corresponding interaction term[2], reveal a clear pattern:

- Independent stations (Type 5) increased prices by 4.4 cents per liter
- Wholesaler-branded stations without refining capacity and managed by retailers (Type 4) showed similar increases of approximately 4.5 cents
- Wholesaler-branded stations with refining capacity (Type 3) increased prices by about 3.1 cents
- Stations managed directly by wholesalers without refining capacity (Type 2) raised prices by 1.3 cents
- Stations managed directly by wholesalers with refining capacity (Type 1) exhibited no price increase and even slightly reduced prices by around 0.4 cents

For gasoline, the observed patterns are similar but the price changes are smaller. Independent stations raised prices by 1.7 cents per liter, while vertically integrated stations operated by wholesalers with refining capacity reduced their prices by approximately 1 cent (see Table C.2).

The empirical literature generally finds that independent stations exert downward pressure on prices and that vertically integrated operators tend to exercise market power in standard competitive environments [9, 23, 3]. In contrast, these findings indicate that vertical integration increases the pass-through rate of the discount to consumers, aligning with [10] and previous research on the German fuel tax cut [41] and tax pass-through in the Spanish market [38, 7, 24]. The results confirm our hypothesis that stations with lower financial

[2] The effect for each station type is calculated by adding the base treatment effect for independent stations to the coefficient of the interaction between the treatment indicator and the station type dummy.

capacity, particularly independents and retailer-managed branded stations without refining capacity, passed on a smaller portion of the discount to consumers.

While our primary interpretation attributes differential pass-through to liquidity constraints faced by independent and retailer-managed stations, several alternative explanations warrant consideration. First, major refining companies may have strategically chosen high pass-through rates as part of a deliberate market share acquisition strategy, particularly given their ability to cross-subsidize these activities from refining operations. Second, consumer awareness of the discount policy might have varied systematically across station types, with customers of larger branded stations potentially more informed about their entitlement to the full discount. Third, the interaction between existing loyalty programs, which were particularly prevalent among major operators, and the government discount may have enhanced the perceived value of the subsidy at these stations. As noted in Section 3.2, major refiners were permitted to fulfill their contribution obligation through commercial discount programs, potentially amplifying pass-through differences. Finally, consumers of independent stations might exhibit different price elasticities; if their customer base is less price-sensitive due to convenience factors or limited alternatives in certain geographic areas, this could facilitate lower pass-through rates. Further research incorporating consumer survey data and more detailed information on loyalty program participation could help disentangle these competing explanations.

6.1.2. Initial price level and pass-through rates

To further investigate the relationship between a station's market positioning and its response to the discount policy, we conduct quantile regressions that estimate the treatment effect at different points in the price distribution. This analysis explores whether the price response varies systematically with the station's initial price level, complementing our findings on heterogeneity across station types.

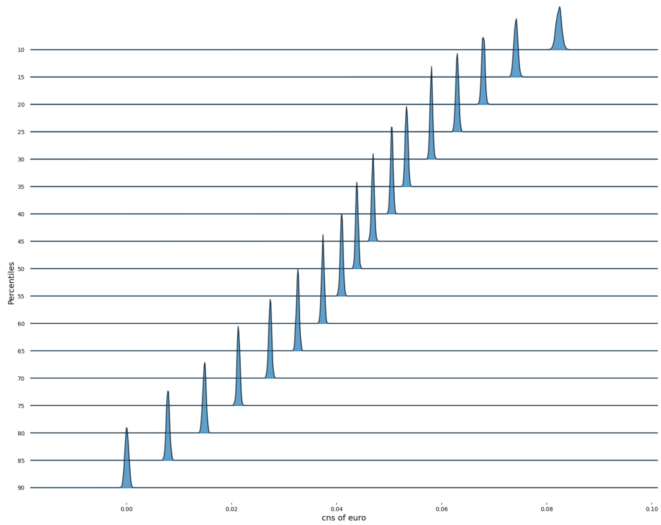
Figure 5a displays the estimated effect of the discount on Diesel A prices across percentiles of the price distribution. The results reveal a strong negative relationship between a station's initial price position and its price increase following the discount implementation. Stations in the lower percentiles (those with initially lower prices) raised prices substantially more than those in higher percentiles. At the 10th percentile, prices increased by up to 8 cents per liter—capturing nearly half the discount value—while stations in the higher percentiles showed minimal price increases or even price reductions.

This pattern varies across station types but remains consistent. Among independent stations, those in the 10th percentile increased prices by approximately 8 cents, those near the median by 4 cents, and those in the 90th percentile showed no significant effect. For stations in the networks of major wholesalers with refining capacity, low-priced stations (10th percentile) raised prices by about 6 cents, median-priced by 2 cents, and high-priced stations (90th percentile) reduced prices by approximately 1 cent.

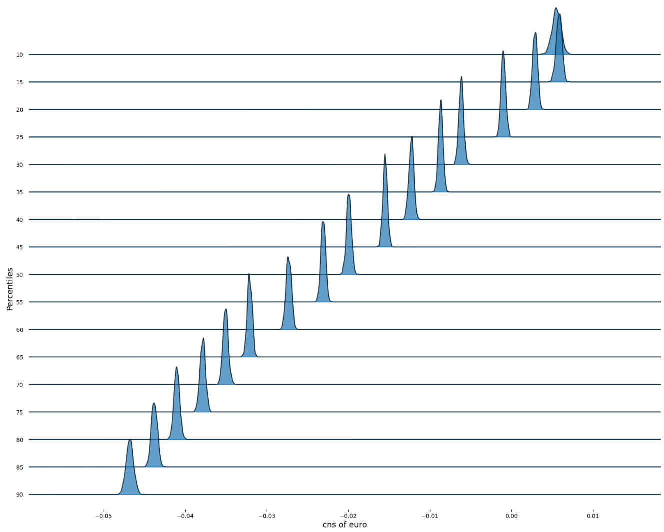
For Gasoline 95 (Figure 5b), the negative relationship between initial price and price increase persists but with greater heterogeneity across station types. Independent and branded stations (Types 3, 4, and 5) show more pronounced effects in the upper half of the distribution, while stations managed by wholesalers (Types 1 and 2) generally reduced prices by 2-4 cents in percentiles above the median.

Figure 5. Estimation by percentiles (vertical axis) of the price increase resulting from the introduction of the discount

(a) Diesel



(b) Gasoline

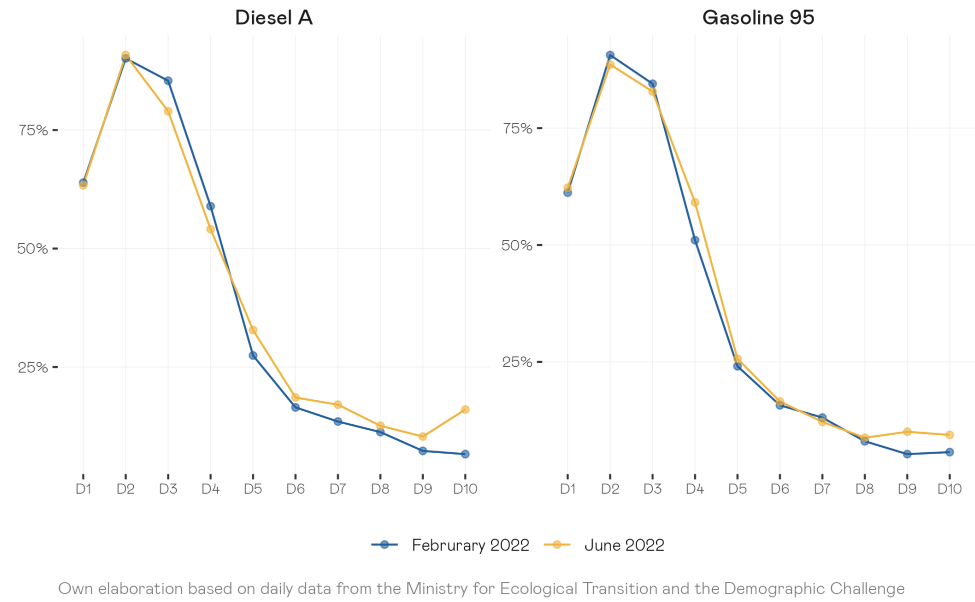


Source: Own elaboration

The differential distribution of station types across the price spectrum has important implications. Figure 6 illustrates that independent stations were predominantly concentrated in the lower segments of the price distribution in both February and June 2022, representing over 80% of stations in the second and third deciles but less than 20% above the sixth decile. Notably, independent stations shifted rightward in the distribution between February and June, consistent with our quantile regression findings, with this effect being more pronounced for diesel.

These results suggest that the policy design created divergent incentives based on sta-

Figure 6. Independent stations as a percentage of total, by price decile and fuel type



Source: Own elaboration

tions' initial price positioning and financial capacity. Stations with lower initial prices and limited financial resources were compelled to pass a larger portion of the advance funding burden to consumers, reducing the effective discount. Conversely, stations with higher initial prices and greater financial capacity could fully pass through the discount, narrowing price dispersion and providing a competitive advantage to premium-positioned stations with extensive networks.

6.1.3. Differential effects between diesel and gasoline

A striking finding from our analysis, in line with [29] and [10], is the substantial difference in pass-through rates between fuels. The average price increase following the discount was approximately 2.6 times larger for Diesel A than for Gasoline 95.

This differential can be explained partly by varying demand elasticities. [32] estimate that diesel demand exhibits lower price elasticity than gasoline in both the short and long term. Specifically, a 10% price increase reduces diesel demand by only 1.5% in the short term, compared to a 3% reduction for gasoline.

The lower elasticity for diesel likely stems from the composition of the Spanish vehicle fleet, as shown in Figure C.2. Heavy vehicles (trucks and buses) predominantly use diesel and, being used primarily for commercial purposes, exhibit less price-sensitive fuel demand. Consequently, stations were able to pass through less of the discount for diesel compared to gasoline, contrary to findings by [33] who attribute higher diesel pass-through to a larger proportion of well-informed consumers.

6.2. *Robustness checks for the RD estimates*

To ensure the validity of our RD estimates, we conducted several robustness checks (detailed in Appendix D). First, our bandwidth sensitivity analysis shows that the estimated effects remain significant across various bandwidth choices, particularly for diesel, though the magnitude varies somewhat for gasoline at wider bandwidths. Second, covariate balance tests confirm no systematic differences in station characteristics at the threshold, with discontinuities observed only in international market variables that are explicitly controlled for in our models. Finally, placebo tests using artificial cutoff dates reveal no consistent pattern of significant effects at non-policy dates, supporting the causal interpretation of our findings at the actual implementation date.

While our RD analysis provides credible estimates of the immediate impact of the discount policy, several limitations warrant a complementary analytical approach. First, RD inherently focuses on short-term effects around the threshold, providing limited insight into medium-term market adjustments. Second, though our tests do not indicate substantial manipulation at the cutoff, we cannot entirely rule out anticipatory pricing strategies by stations ahead of the widely announced policy. Third, the policy implementation coincided with significant market disruptions from the Ukraine war. Given these limitations, we complement our RD analysis with a DiD approach that exploits a natural control-treatment group structure in our data as set out in Section 5.2.

7. Difference-in-Differences analysis

7.1. *Main results*

Table 3 presents the results from our DiD analysis for both diesel and gasoline prices. For diesel (Panel A), the models consistently show a positive and significant effect of the discount policy on prices, with coefficients ranging from 0.0131 to 0.0384 euros per liter depending on specification. Similarly, for gasoline (Panel B), we find positive and significant effects ranging from 0.0153 to 0.0276 euros per liter.

A particularly valuable insight from the DiD analysis is the negative interaction between the post-treatment indicator and time. For diesel, this suggests that the initial price increase diminished over time at a rate of about 0.015 euros per month. Extrapolating this trend, we estimate that the initial price differential would converge back to pre-policy levels after approximately 42.5 days ($0.0209/0.0005 \approx 42.5$) for diesel.

For gasoline, this interaction coefficient is larger, implying a faster convergence rate of about 0.024 euros per month and an estimated time to convergence of approximately 35.7 days ($0.0276/0.0008 \approx 35.7$). This temporal dynamic, which is difficult to capture with the RD approach alone, reveals that while stations initially captured part of the discount, market forces gradually pushed prices back toward equilibrium levels.

7.2. *Heterogeneity by station type*

Our extended DiD analysis examines heterogeneity across all station types (see Appendix Table E.1 for detailed results). As visualized in Figure 7a, for diesel, Type 4 stations (branded, non-refiner managed) show the largest differential (0.0388 euros), followed by

Table 3. Difference-in-Differences estimates of discount policy effects

	Model 1 (Basic DiD)	Model 2 (With Trend)	Model 3 (With Interact.)	Model 4 (Fixed Effects)
Panel A: Diesel				
Post-treatment	0.0131***	0.0322***	0.0384***	0.0381***
	(0.001)	(0.001)	(0.001)	(0.001)
Days from cutoff	-0.0002***	-0.0003***	-0.0002***	-0.0002***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Post × Days		-0.0005***	-0.0004***	-0.0004***
		(0.00001)	(0.00001)	(0.00001)
Panel B: Gasoline				
Post-treatment		0.0153***	0.0276***	0.0272***
		(0.000)	(0.001)	(0.001)
Days from cutoff		-0.0002***	-0.0001***	-0.0000***
		(0.00001)	(0.00001)	(0.00001)
Post × Days			-0.0008***	-0.0008***
			(0.00001)	(0.00001)

Notes: Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Model 1 includes only the post-treatment indicator and linear time trend. Model 2 adds either trend or interaction between post-treatment and time trend. Model 3 incorporates interaction terms. Model 4 is a fixed effects version that controls for station-specific unobserved heterogeneity.

Source: Own elaboration

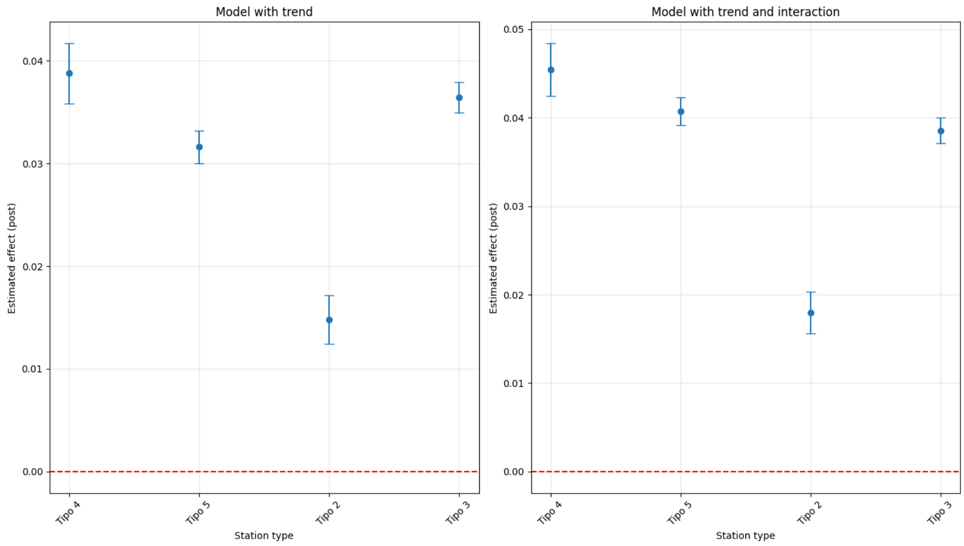
Type 3 stations (branded, refiner-affiliated) with 0.0364 euros, Type 5 stations (independent) with 0.0316 euros, and Type 2 stations (wholesaler-operated, non-refiner) with the smallest effect of 0.0148 euros.

For gasoline (Figure 7b), Type 5 stations (independent) exhibit the largest effect (0.0365 euros), followed by Type 4 stations (0.0278 euros), Type 3 stations (0.0201 euros), and Type 2 stations with a much smaller and marginally significant effect (0.0023 euros). This difference in patterns between diesel and gasoline may reflect the different consumer segments and pricing strategies across fuel types.

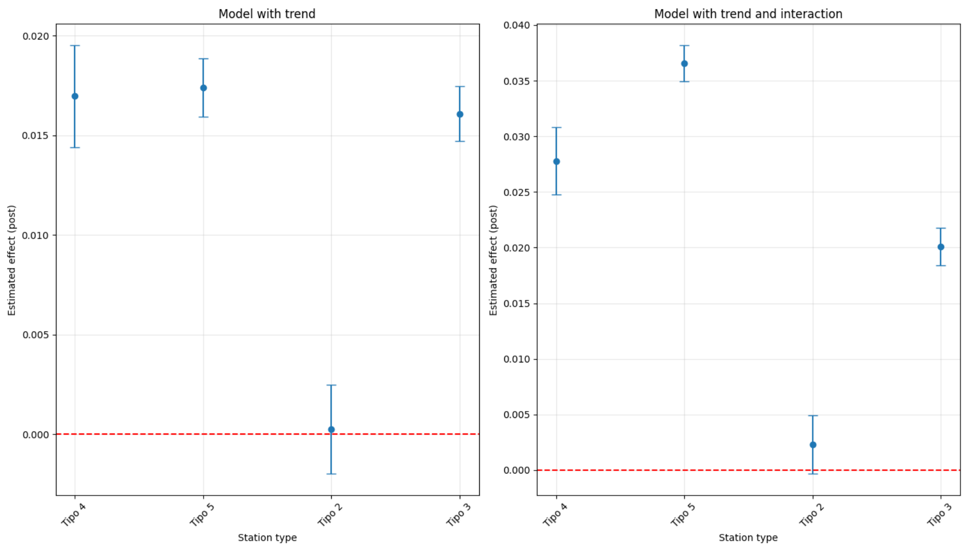
Taken together, the findings suggest a clear relationship between market structure and pass-through dynamics. Both vertical integration and direct management by wholesalers are associated with higher discount pass-through to consumers, while retailer-managed stations, regardless of branding, show lower pass-through rates. The pattern is particularly consistent for diesel, while for gasoline, the independent stations show an unexpectedly high differential effect.

Figure 7. Estimated treatment effects by station type under different model specifications

(a) Diesel



(b) Gasoline



Source: Own elaboration

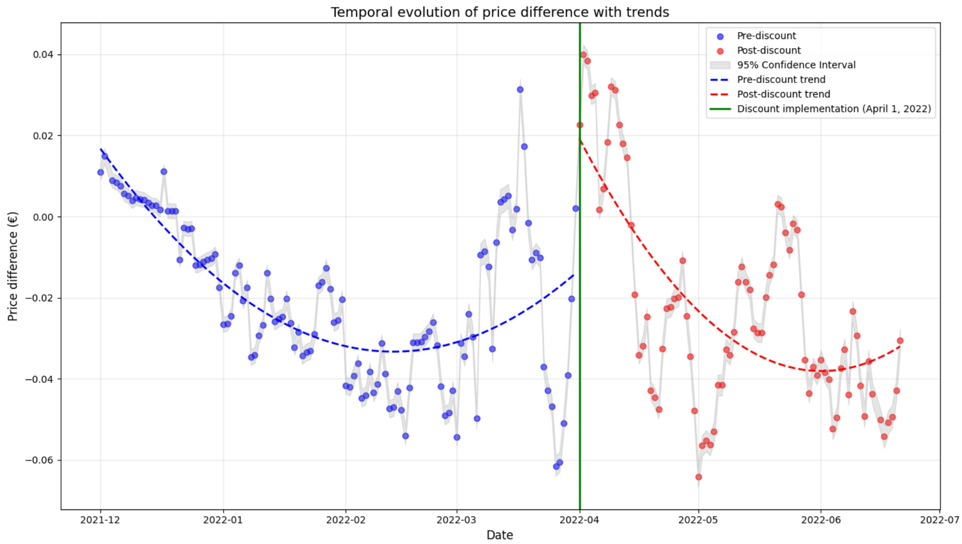
7.3. Temporal dynamics and market adjustment

Figure 8 illustrates the evolution of price differentials between treatment and control stations over time for both fuel types. The graphs clearly show the immediate jump in price differential following the discount implementation, followed by a gradual decline. This visualization corroborates our regression estimates of a convergence pattern, suggesting a market adjustment process whereby competitive pressures gradually pushed prices toward a new equilibrium.

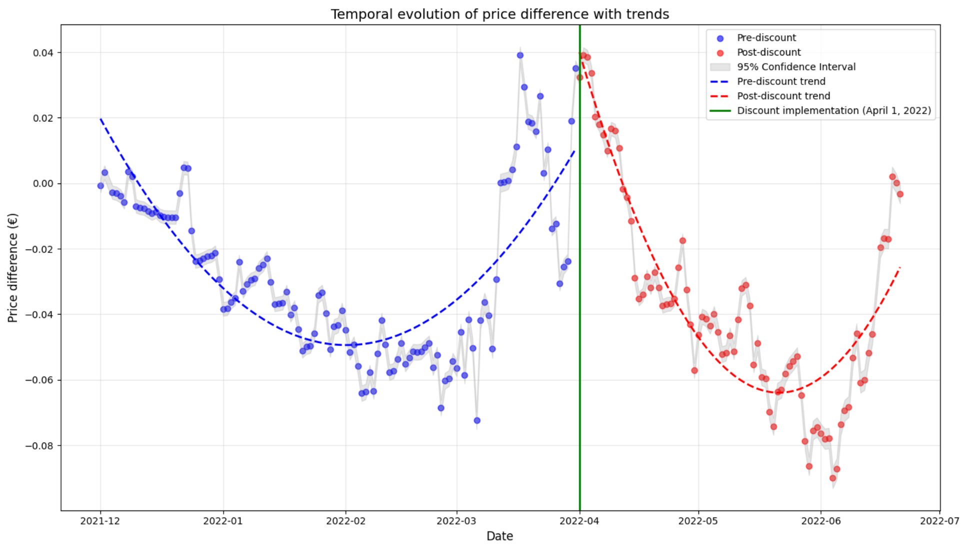
The estimated coefficients remain consistent across different model specifications (detailed in Appendix E), strengthening our confidence in the reliability of the results.

Figure 8. Temporal evolution of price differentials between treatment and control stations

(a) Diesel



(b) Gasoline



Source: Own elaboration

7.4. Comparison with RD findings and implications

The DiD results complement our RD findings in several important ways. First, they confirm the core result that independent stations and retailer-managed branded stations increased their prices following the discount implementation, capturing part of the intended consumer benefit. Second, they reveal that this effect was temporary, with prices gradually reverting toward pre-policy levels over approximately 4-6 weeks. Third, they demonstrate that the heterogeneity in pass-through rates across station types persisted even when controlling for pre-existing trends and station-specific fixed effects.

The magnitude of the DiD estimates is consistent with our RD findings. For diesel, our RD analysis estimated a price increase of 0.044 euros per liter for independent stations, while the DiD approach suggests an effect of 0.032-0.038 euros depending on specification. For gasoline, the RD estimate of 0.017 euros for independent stations is lower than the DiD finding of 0.037 euros, but still within a plausible range given the methodological differences.

A notable finding is the differential between fuel types. While our RD analysis found larger effects for diesel than for gasoline, the DiD results suggest more comparable effects, particularly for independent stations. This difference may reflect the medium-term market adjustments captured by the DiD approach but not by the RD design, which focuses on immediate effects around the policy implementation date.

Another important insight from the DiD analysis is the clear evidence of convergence over time, with the initial price differentials diminishing more rapidly for gasoline (converging in about 36 days) than for diesel (converging in about 43 days). This finding aligns with our understanding of market dynamics, as gasoline is typically characterized by higher price elasticity and more responsive consumer behavior.

8. Conclusions and Policy Implications

(Previous conclusions: This paper contributes to a better understanding of the pass-through dynamics of Spain's 20-cent fuel rebate policy. By combining a regression discontinuity approach, difference-in-differences analysis, and quantile regressions, we provide a comprehensive assessment of both the immediate and medium-term effects of the policy across the universe of Spanish service stations. This methodological combination allows us to capture not only the initial price responses, but also how these effects evolved over time and varied along the price distribution.

The empirical literature generally finds that independent stations exert downward pressure on prices and that vertically integrated operators tend to exercise market power in standard competitive environments [9, 23, 3]. In contrast, our findings reveal a more complex relationship between vertical integration, station management structures, and pass-through rates. The RD analysis shows significant heterogeneity: independent stations and retailer-managed branded outlets increased prices to capture part of the discount, particularly for diesel, while vertically integrated operators exhibited near-complete pass-through, in some cases slightly reducing prices. Our quantile regressions further demonstrate that this effect was most pronounced at the lower end of the price distribution, where independent low-cost stations increased prices the most.

Importantly, the DiD analysis confirms that these effects were not persistent. Initial price differentials gradually converged over time, about 43 days for diesel and 36 days for gasoline, suggesting that competitive pressures eventually pushed stations toward more complete pass-through. This dynamic adjustment highlights the relevance of analyzing both short-term shocks and medium-term market responses in evaluating such interventions.

Several factors help explain these results. The policy design created significant financial constraints, as stations were required to advance the discount value and later claim reimbursement. While major wholesalers possessed sufficient financial resources to manage this temporary liquidity shock, independent and smaller branded retailers faced greater challenges. The advance payment system established by the decree likely proved insufficient and may have arrived too late for operators with limited capital reserves, particularly as these stations were simultaneously experiencing increased demand due to their lower prices amid the broader fuel price surge of early 2022.

While our primary interpretation attributes differential pass-through to liquidity constraints faced by independent and retailer-managed stations, several alternative explanations warrant consideration. First, major refining companies may have strategically chosen high pass-through rates as part of a deliberate market share acquisition strategy, particularly given their ability to cross-subsidize these activities from refining operations. Second, consumer awareness of the discount policy might have varied systematically across station types, with customers of larger branded stations potentially more informed about their entitlement to the full discount. Third, the interaction between existing loyalty programs—which were particularly prevalent among major operators—and the government discount may have enhanced the perceived value of the subsidy at these stations. As noted in Section 3.2, major refiners were permitted to fulfill their contribution obligation through commercial discount programs, potentially amplifying pass-through differences. Finally, consumers of independent stations might exhibit different price elasticities; if their customer base is less price-sensitive due to convenience factors or limited alternatives in certain geographic areas, this could facilitate lower pass-through rates. Future research incorporating consumer survey data and more detailed information on loyalty program participation could help disentangle these competing explanations.

From a policy perspective, these results carry important implications for competition and the design of future subsidy programs. Of particular concern is how the fuel discount contributed to a compression of the price distribution from both tails: low-cost independent retailers increased their prices while vertically integrated wholesalers maintained or even reduced theirs. Moreover, the three wholesalers with refining capacity, which were required to help finance the subsidy through commercial discounts of at least 5 cents, implemented even more aggressive loyalty programs with discounts of up to 10 cents that continued beyond the policy's conclusion. This strategy likely strengthened their competitive position while potentially distorting market dynamics to the detriment of smaller operators. While prior research shows that independent stations have increased their market share following the introduction of Law 11/2013 of 26 July 2013 [16], recent developments such as the acquisition of the leading low-cost segment operator by a major refiner suggest potential market consolidation. This raises questions about the long-term impact of such policies on market structure and competition.

To enhance pass-through rates in future interventions, policymakers should consider direct-to-consumer rebates rather than retailer-advanced discounts, particularly in markets with heterogeneous financial capacities among firms. Alternatively, if administrative constraints necessitate retailer implementation, advance payments should be calibrated more generously and disbursed more rapidly to mitigate liquidity constraints. From an environmental perspective, the incomplete pass-through we identify further undermines the already questionable cost-effectiveness of fossil fuel subsidies as tools for economic relief. Regulators should implement real-time monitoring of pass-through rates across different station types during future interventions, potentially with automatic adjustments to implementation mechanisms if systematic differences emerge.

Future research could explore geographical and income-based heterogeneity in pass-through effects [25], as well as analyze price dynamics following discount removal. For instance, [13] found that prices increased by 12% above predicted levels after a similar policy ended in Hungary, suggesting important short- and medium-term consequences that merit further investigation.)

New conclusions:

This paper provides empirical evidence on the pass-through dynamics of Spain's 20-cent fuel discount. Through a combination of regression discontinuity, difference-in-differences, and quantile regression analyses, we show the policy's immediate and medium-term effects across the universe of Spanish service stations.

Our findings indicate that independent and retailer-managed branded stations captured a substantial share of the intended consumer discount through immediate price increases, particularly for diesel. At the same time, vertically integrated operators passed nearly all the discount to consumers. The DiD analysis reveals that this behavior was temporary, as competitive market forces pushed price differentials back toward pre-policy equilibrium within approximately 36 to 43 days. Nonetheless, quantile regressions further demonstrate that the fuel discount policy compressed the price distribution from both ends: low-cost independent retailers notably increased prices, while vertically integrated wholesalers maintained or even reduced theirs.

From a policy perspective, these results have important implications for designing and implementing effective instruments to mitigate the effects of high energy prices. First, the heterogeneous responses observed among service stations and the different regulatory requirements across operators for applying the discount dilute its effectiveness and may have significant consequences for market competition. Consider the three major refiners (Repsol, Cepsa, and BP), which had to partially finance the subsidy through commercial discounts of at least 5 cents per liter. During that time, they also implemented aggressive loyalty programs offering discounts of up to 10 cents per liter that continued beyond the subsidy period[3]. In fact, the Spanish competition authority (CNMC) investigated Repsol, Cepsa, and BP[4] for possible abuse of a dominant market position during the period when the discounts were in place, following complaints filed by the National Association of Automatic Service Stations (AESAE) and the Association of Independent Fuel Retailers (ACIH). Ultimately, the authority opened a formal investigation against Repsol, focusing specifically on its alleged strategy to increase its retail market share by offering additional discounts through

[3]The existence and terms of these loyalty programs were publicly announced through press releases and official communications on the companies' websites: Repsol, Cepsa, and BP.

[4]See CNMC's official press release on the opening of the investigation.

loyalty programs, while raising wholesale fuel prices charged to independent stations[5].

Such practices likely distorted market dynamics and facilitated strategic acquisitions, such as Cepsa's recent purchase of the leading low-cost operator[6], signaling potential market consolidation risks. These dynamics also raise questions about the post-policy evolution of prices, which future research could investigate by analyzing price adjustments after the removal of the discount [13]. Although the CNMC was explicitly mandated by the Royal Decree regulating the discount to ensure compliance by wholesalers, its current resources may not have been sufficient to detect and effectively prevent this strategic behavior in real time. Policymakers should allocate additional resources and establish robust real-time monitoring systems to oversee policy implementation actively. Enhanced monitoring should also include independent retailers, who may have perceived themselves as less scrutinized and thus undermined the effectiveness of the policy.

Second, the significant share of the discount captured by market participants, in particular independent stations who captured around 22% of it, raises concerns about the efficient use of public funds. Given that the Spanish government estimates the total subsidy cost in 2022 to be more than €6,000 million[37], our pass-through estimates suggest that more than €800 million, or about 13%, did not reach final consumers and resulted in additional revenues for oil operators. Indeed, a smaller fraction was indirectly returned to the public budget through increased collections of VAT and fuel excise duties [31]. However, a significant part of the funding was still transferred to companies, which deviated from the primary objective of the policy, which was to cushion consumers from the effects of high fuel prices.

Third, regarding distributional effects, broad-based fuel subsidies disproportionately benefit higher-income groups, who are more likely to own vehicles and consume more fuel than lower-income households. Estimates by Labandeira and coauthors [31] show that the associated tax loss is highly concentrated in the highest income deciles, with the wealthiest 40% of the population accounting for more than half of the tax revenue loss. A better understanding of how pass-through varies across income levels and geographic areas [25] could help quantify these effects more accurately and support more equitable policy design.

Fourth, from an environmental point of view, generalized fuel subsidies conflict directly with decarbonization objectives. These measures undermine efforts to reduce fossil fuel dependence and emissions. The contradiction is particularly stark in light of the geopolitical context in which the policy was implemented: Russia, one of the world's largest producers of fossil fuels, had just invaded Ukraine, causing severe disruptions in global energy markets. In this context, subsidizing fossil fuel consumption goes against climate goals and reinforces the energy dependencies that European policy seeks to reduce.

Policymakers should therefore pursue instruments that balance economic relief with long-term climate and equity goals. A better alternative would be targeted consumer rebates or lump-sum transfers rather than generalized and retailer-administered discounts. This approach is not only more fiscally efficient, but also feasible. Recent policy initiatives in Spain, such as the €200 cash transfer to low-income households established in Royal Decree-Law 11/2022, provide a clear precedent for its potential implementation in similar contexts.

[5] See CNMC's press release on the opening of sanctioning proceedings against Repsol.

[6] See Cepsa's press release on the agreement to acquire the Ballenoil service station network.

This preserves important price signals necessary for efficient energy use and improves equity by ensuring that assistance reaches those who need it most.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Claude AI in order to revise grammatical expressions in this paper. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Appendix A. Regression Discontinuity mathematical formulation

Appendix A.1. Causal effect identification

In RD designs, a cutoff point separates observations on either side of the threshold, acting as a boundary that defines control and treatment groups[7].

Consider T_i as the treatment variable, defined as a discontinuous function over a time variable, D:

$$T_i = 1\{D \geq d\} \tag{A.1}$$

where i represents the petrol station and the function takes value one if the observed day falls after the threshold date (d) and zero otherwise. Specifically, it returns a sequence of natural integers taking value zero when $D = d$, with increments of one moving forward in time and decrements of one moving backward.

Technically, the RD approach involves estimating two regressions simultaneously, where the intervention generates a new estimate of the intercept and potentially different slopes on either side of the threshold. Let $P(1)_{it}$ and $P(0)_{it}$ be the "potential" prices with intervention (1) and without intervention (0) for petrol station i at time t. We can represent both scenarios with the following equation:

$$P_{it} = \beta_0 + \beta_1 d_t + \beta_2 1\{D \geq d\} + \beta_3 d_t 1\{D \geq d\} + \varepsilon_{it} \tag{A.2}$$

where each coefficient captures specific aspects of the discontinuity model.

For observations where $D < d$ (pre-intervention), the equation simplifies to:

$$P(0)_{it} = \beta_0 + \beta_1 d_t + \varepsilon_{it} \tag{A.3}$$

While for observations where $D \geq d$ (post-intervention), we have:

$$P(1)_{it} = (\beta_0 + \beta_2) + (\beta_1 + \beta_3) d_t + \varepsilon_{it} \tag{A.4}$$

The key insight is that the difference between intercepts determines the estimated effect of the intervention—the causal link between the policy and price changes. Specifically, if we assume:

$$\beta_0 = \lim_{d_t \to d^-} E[P_{it} | D = d] \tag{A.5}$$

$$\beta_0 + \beta_2 = \lim_{d_t \to d^+} E[P_{it} | D = d] \tag{A.6}$$

[7]In our regression discontinuity approach, we adopt a sharp design because it implies that the probability of being treated after treatment reaches 100% for all individuals. This sharp discontinuity allows a clear comparison between the treated and untreated groups and provides a simple framework for estimating the treatment effect with precision.

Then, $\lim_{d_t \to d^-} E[P_{it}|D = d]$ represents the expected value of potential prices just before the threshold, corresponding to prices without intervention. Conversely, $\lim_{d_t \to d^+} E[P_{it}|D = d]$ represents the expected value of potential prices just after the threshold, corresponding to prices with intervention.

The difference between these conditional expectations yields the Average Treatment Effect (ATE) in the regression discontinuity framework—the causal effect of the discount policy on fuel prices:

$$E[ATE|D = d] = \lim_{d_t \to d^+} E[P_{it}|D = d] - \lim_{d_t \to d^-} E[P_{it}|D = d] = \beta_2 \tag{A.7}$$

Appendix A.2. Kernel weighting and optimal bandwidth selection

Expression (7) implies that coefficient β_2 must be estimated by comparing intercepts on both sides of the cutoff. However, standard regression techniques utilize all available data, which may introduce bias when observations far from the threshold influence the estimates.

To mitigate this potential bias, we assign higher weights to observations closer to the cutoff using a triangular kernel function:

$$K(D, d, h) = 1\{|D - d| \leq h\} \left(1 - \frac{|D - d|}{h}\right) \tag{A.8}$$

This function ensures that only observations within h days of the cutoff receive non-zero weights that decrease linearly with distance from the threshold.

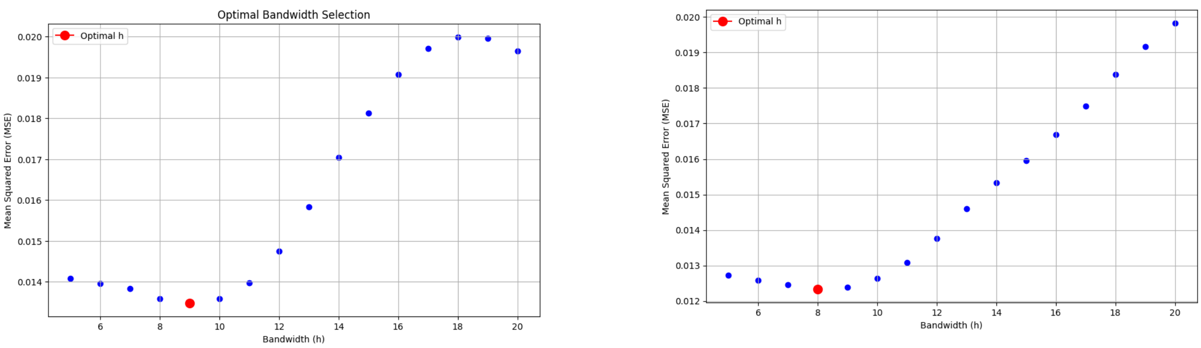
Following [27] and [26], we employ a cross-validation method to determine the optimal bandwidth objectively. We partition our sample into training (80%) and testing (20%) subsets and evaluate RD models with bandwidths ranging from 4 to 20 days using Mean Squared Error as the performance metric. This approach optimizes model selection while mitigating data-specific idiosyncrasies [20].

This procedure identified optimal bandwidths of $h = 9$ days for diesel and $h = 8$ for gasoline, balancing bias-variance trade-offs while minimizing prediction error. Figure A.1 illustrates this bandwidth selection process[8].

[8]This optimal bandwidth search was conducted using our preferred specification: the random effects model with all available control variables.

Figure A.1. Optimal bandwith selection

(a) Diesel **(b)** Gasoline



Source: Own elaboration

Appendix B. Difference-in-Differences methodology details

Appendix B.1. Geographical matching strategy

A challenge in implementing the DiD approach is that different types of stations may operate in systematically different local markets, potentially confounding our estimates. To address this concern, we employ a geographical matching strategy that enhances the comparability between treatment and control groups by ensuring they face similar local competitive conditions.

Specifically, we construct our matched sample as follows:

1. For each station not operated by wholesalers with refining capacity (Types 2-5), we compute a 5-kilometer radius bounding box based on geographical coordinates.
2. Within this radius, we identify the closest station operated by a wholesaler with refining capacity (Type 1).
3. We pair each treatment station with its closest Type 1 counterpart, creating matched pairs that operate in similar local competitive environments.
4. Stations without a suitable match within the specified radius are excluded from the analysis to maintain comparable local market conditions across our sample.

This spatial matching is implemented using a computationally efficient approach. We convert the 5-kilometer radius into corresponding latitude and longitude differentials using the Earth's radius ($R = 6371$ km) and standard spherical trigonometry:

$$\Delta lat = \frac{d}{R} \cdot \frac{180}{\pi}$$
$$\Delta lon = \frac{d}{R} \cdot \frac{180}{\pi} \cdot \frac{1}{\cos(lat)}$$

where $d = 5$ km is our matching distance. These differentials create a bounding box around each control station, allowing for efficient spatial indexing and matching.

This geographical matching procedure resulted in 1,537,890 station-day observations across 8,165 unique stations, with treatment stations classified into their respective types. The matched sample ensures that our treatment and control groups face similar demand conditions, competitive pressures, and local economic environments, thereby strengthening the validity of our parallel trends assumption.

Appendix B.2. Extended econometric specifications

To examine heterogeneous effects across different station types, we extend our basic DiD model to include station type indicators and their interactions with the treatment variable:

$$\begin{aligned} P_{it} = \alpha + \beta_1 Post_t + \beta_2 Days_t + \beta_3 (Post_t \times Days_t) + \sum_{j=2}^{5} \gamma_j (TypeJ_i \times Post_t) + \\ + \sum_{j=2}^{5} \delta_j (TypeJ_i \times Post_t \times Days_t) + \varepsilon_{it} \end{aligned} \tag{B.1}$$

where $TypeJ_i$ are indicator variables for stations of types 2-5. In this specification, γ_j captures the differential immediate effect of the policy for each station type, while δ_j captures how this effect evolves over time for each type.

To account for unobserved station-specific heterogeneity, we also estimate models with station fixed effects:

$$P_{it} = \alpha_i + \beta_1 Post_t + \beta_2 Days_t + \beta_3 (Post_t \times Days_t) + \varepsilon_{it} \tag{B.2}$$

where α_i represents station-specific fixed effects that capture time-invariant characteristics of each station pair, such as exact location, local market structure, and station amenities.

Appendix B.3. Robustness checks

To assess the robustness of our DiD results, we implement several additional analyses that address potential concerns with our baseline specification.

First, we test the sensitivity of our results to the choice of time window by estimating our models using different temporal ranges around the policy implementation date:

- Narrow window: ±15 days around April 1, 2022
- Medium window: ±30 days around April 1, 2022
- Wide window: ±45 days around April 1, 2022

This approach helps determine whether our results are driven by short-term responses or reflect more persistent market adjustments. It also addresses concerns that longer time windows might confound the policy effect with other market developments.

Second, we explore potential non-linearities in time trends by incorporating quadratic terms in our specifications:

$$P_{it} = \alpha + \beta_1 Post_t + \beta_2 Days_t + \beta_3 Days_t^2 + \beta_4 (Post_t \times Days_t) + \beta_5 (Post_t \times Days_t^2) + \varepsilon_{it} \tag{B.3}$$

This flexible specification allows for non-linear pre and post-treatment trends, relaxing the strict parallel trends assumption and accommodating more complex temporal dynamics in price differentials.

Third, we test the heterogeneity of treatment effects across different subgroups. Of particular interest is the variation in response across different station types (Types 2-5), which allows us to examine how vertical integration, brand affiliation, and management structure affect the pass-through of the discount. Additionally, we explore heterogeneity along other dimensions that might influence a station's ability or incentive to pass through the discount:

- Station location (urban vs. rural, highway vs. local roads)
- Competition intensity (number of competing stations within various radii)

- Initial price level (pre-policy price quartiles)

Finally, we conduct a placebo test by artificially shifting the treatment date to periods before the actual policy implementation. This falsification test helps assess whether our estimated effects could be driven by pre-existing trends or other confounding factors rather than the discount policy itself.

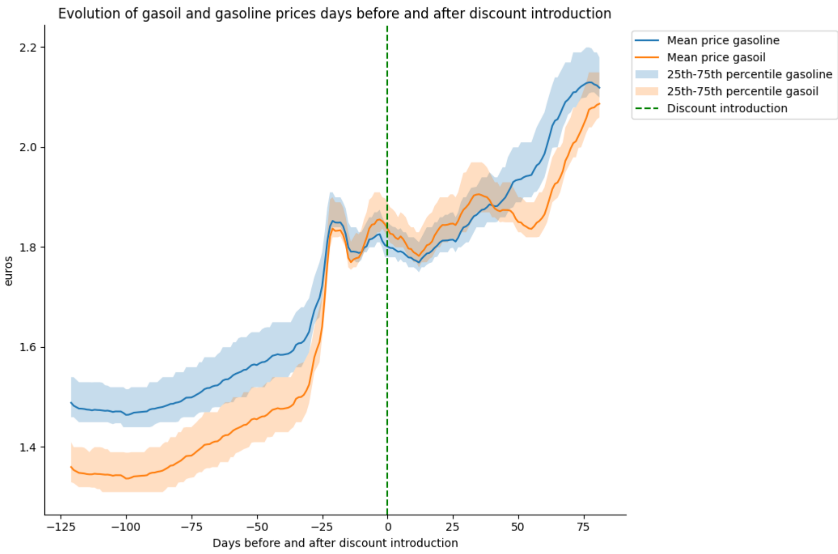
Appendix C. Detailed results of the RD estimation

Table C.1. Results of Hausman Test for the diesel and gasoline model

	Test Statistic	P-Value
Diesel	-158.859	1.0
Gasoline	-512.765	1.0

Source: Own elaboration

Figure C.1. Evolution of diesel and gasoline prices days before and after discount introduction



Source: Own elaboration

Table C.2. Regression Discontinuity Estimation Results

	Fixed Effects	Random Effects 1	Random Effects 2
Panel A: Diesel			
Intercept	0.5890	0.6428	0.6001
	(37.694)	(21.283)	(36.949)
Treatment	0.0291	0.0305	0.0438
	(71.599)	(22.014)	(62.524)
Days	0.0013	0.0013	0.0013
	(183.06)	(54.584)	(93.133)
Treatment × Days	-0.0003	-0.0004	-0.0002
	(-36.618)	(-6.615)	(-8.810)
War	0.1055	0.1048	0.1048
	(168.56)	(94.250)	(128.84)
Stations within 2km	—	—	-0.0013
			(-5.484)
Treatment × Stations	—	—	-0.0002
			(-4.007)
Type 3 (Branded, refiner)	—	—	0.0500
			(16.863)
Type 4 (Branded, non-refiner)	—	—	0.0398
			(10.417)
Type 2 (Wholesaler w/o refining)	—	—	0.0501
			(12.607)
Type 1 (Wholesaler w/ refining)	—	—	0.0642
			(25.814)
Treatment × Type 3	—	—	-0.0128
			(-15.742)
Treatment × Type 4	—	—	0.0009
			(0.655)
Treatment × Type 2	—	—	-0.0314
			(-27.889)
Treatment × Type 1	—	—	-0.0484
			(-74.943)
Panel B: Gasoline			
	Fixed Effects	Random Effects 1	Random Effects 2
Intercept	1.4887	1.5214	1.5046
	(160.61)	(65.583)	(136.70)
Treatment	0.0092	0.0089	0.0172
	(22.439)	(11.611)	(26.891)
Days	0.0004	0.0005	0.0005
	(78.342)	(26.830)	(42.355)
Treatment × Days	0.0003	0.0002	0.0005
	(22.518)	(2.616)	(31.855)
War	0.0789	0.0791	0.0767
	(156.87)	(85.614)	(124.91)
Stations within 2km	—	—	-0.0010
			(-4.335)
Treatment × Stations	—	—	-0.0003
			(-6.377)
Type 3 (Branded, refiner)	—	—	0.0300

Continued on next page

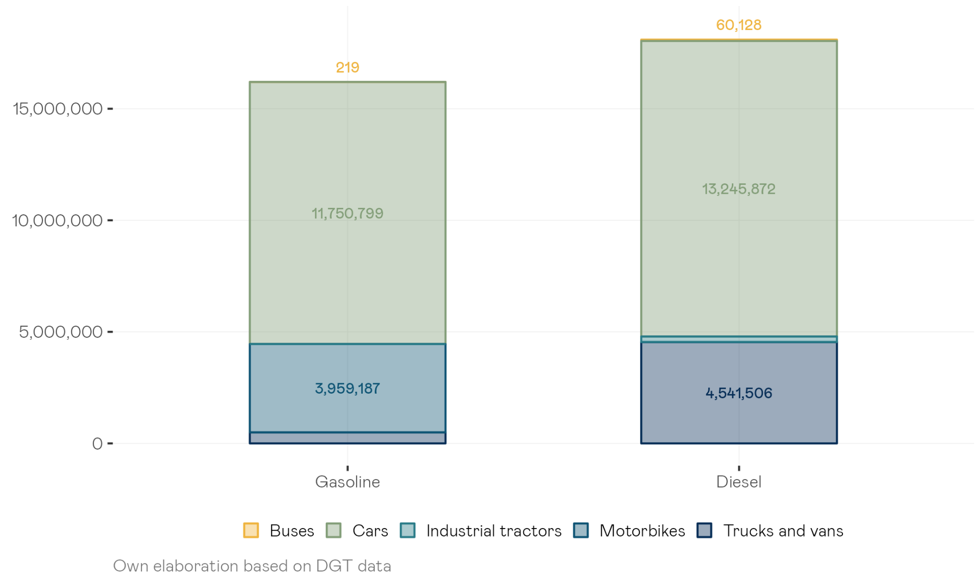
Table C.2 (continued)

Panel A (cont.) and Panel B: Gasoline	Fixed Effects	Random Effects 1	Random Effects 2
			(11.172)
Type 4 (Branded, non-refiner)	—	—	0.0336
			(9.455)
Type 2 (Wholesaler w/o refining)	—	—	0.0210
			(5.938)
Type 1 (Wholesaler w/ refining)	—	—	0.0181
			(7.966)
Treatment × Type 3	—	—	-0.0081
			(-11.865)
Treatment × Type 4	—	—	0.0011
			(0.895)
Treatment × Type 2	—	—	-0.0198
			(-25.426)
Treatment × Type 1	—	—	-0.0273
			(-49.767)

Note: T-statistics in parentheses. Type 5 (Independent stations) is the reference category. 'Random Effects 1' omits station-specific controls, while 'Random Effects 2' includes them. Additional control variables are included but omitted for brevity.

Source: Own elaboration

Figure C.2. Distribution of the vehicle fleet by fuel type in 2022



Source: Own elaboration

Appendix D. Robustness Checks for RD Estimates

Appendix D.1. Bandwidth sensitivity analysis

The choice of bandwidth in RD designs crucially affects the estimation by determining which observations around the cutoff contribute to the treatment effect estimation. To verify that our results are not artifacts of our selected bandwidth, we conduct a sensitivity analysis using a range of bandwidths from 4 to 14 days around our optimal bandwidth of 9 days (determined through cross-validation).

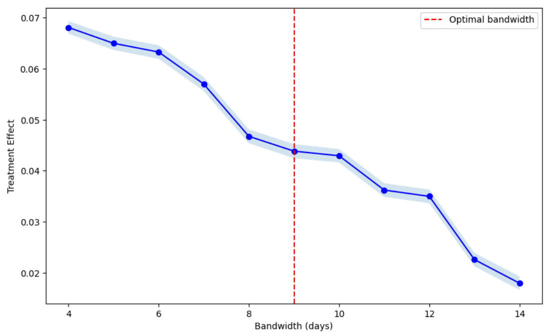
For Diesel A (Figure D.1a), the analysis reveals that the estimated treatment effect decreases as the bandwidth increases, from approximately 0.065-0.07 euros with narrow bandwidths (4-6 days) to about 0.02 euros with a 14-day bandwidth. Despite this variation, the effect remains positive and statistically significant across all bandwidth values, reinforcing the robustness of our main finding.

For Gasoline 95 (Figure D.1b), the relationship is more complex. The effect initially increases slightly from 4 to 5 days (reaching about 0.019 euros) before gradually declining. At our optimal 9-day bandwidth, the estimated effect is approximately 0.015 euros. With wider bandwidths (13-14 days), the effect becomes negative. This non-monotonic pattern suggests that the treatment effect for gasoline is more sensitive to bandwidth selection than for diesel, though it remains positive for most reasonable bandwidth choices.

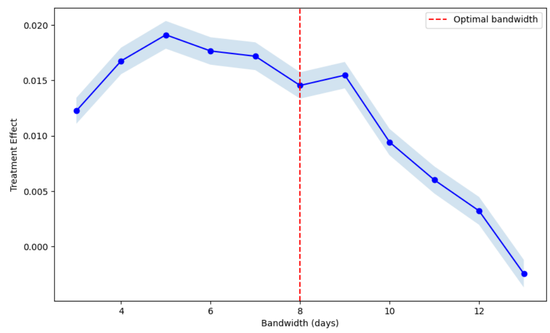
While this sensitivity underscores the importance of our data-driven bandwidth selection approach, the generally consistent direction of effects across various bandwidths supports the validity of our core findings.

Figure D.1. Sensitivity of treatment effect in fuel price to bandwidth choice

(a) Diesel



(b) Gasoline



Note: This figure shows the estimated treatment effect of the fuel discount policy on fuel prices across different bandwidth choices. The blue line represents the point estimates, while the shaded area indicates the 95% confidence intervals. The vertical red dashed line marks the optimal bandwidth of 9 days, as determined by data-driven methods.

Source: Own elaboration

Appendix D.2. Covariate balance tests

To validate the key RD assumption that treatment assignment is as good as random near the cutoff, we test for discontinuities in predetermined station characteristics at the threshold. If the RD design is valid, we should not observe systematic differences in these covariates between observations just above and below the cutoff.

Table D.1 presents the results of this analysis for an extensive set of covariates. For all structural characteristics of petrol stations—including ownership types, location attributes, competitive density, and demographic factors—we find no statistically significant discontinuities (all p-values > 0.89). The estimated discontinuities for these variables are extremely small in magnitude (on the order of 10^{-4} to 10^{-3}), confirming the absence of meaningful differences at the threshold.

Table D.1. Covariate Balance Test

Covariate	Discontinuity	p-value
Branded stations (refiner)	-0.000	0.974
Branded stations (non-refiner)	0.000	0.899
Non-branded stations (non-refiner)	0.000	0.987
Refiner-operated stations	-0.000	0.894
Independent stations	0.000	0.944
Retailer-managed	0.000	0.967
Road location	0.000	0.920
Highway location	0.000	0.914
Freeway location	-0.000	0.978
Industrial park location	0.000	0.936
Stations within 2km	-0.003	0.932
Driver percentage	-0.000	0.933
Gasoline international quotation	5.277	0.000***
Diesel international quotation	69.666	0.000***
Euro/dollar exchange rate	-0.011	0.000***

Note: *** p<0.01, ** p<0.05, * p<0.1

Source: Own elaboration

The only significant discontinuities appear in global market variables (international quotations for gasoline and diesel, and the euro/dollar exchange rate). This pattern is expected given the international market volatility during this period, particularly following Russia's invasion of Ukraine. Importantly, these discontinuities do not invalidate our RD design for two reasons. First, they reflect external market shocks rather than systematic differences in station characteristics. Second, our main specifications explicitly control for these market fundamentals.

The absence of discontinuities in structural station characteristics strongly supports the validity of our RD design. These findings indicate that units just above and below the cutoff are indeed comparable, strengthening the causal interpretation of our estimated treatment effects.

Appendix D.3. Placebo tests

As a final validation of our RD design, we conduct placebo tests by estimating treatment effects at artificial cutoff dates where no policy change occurred. If our RD correctly identifies the causal effect of the discount policy, we should not observe significant effects at these placebo cutoffs.

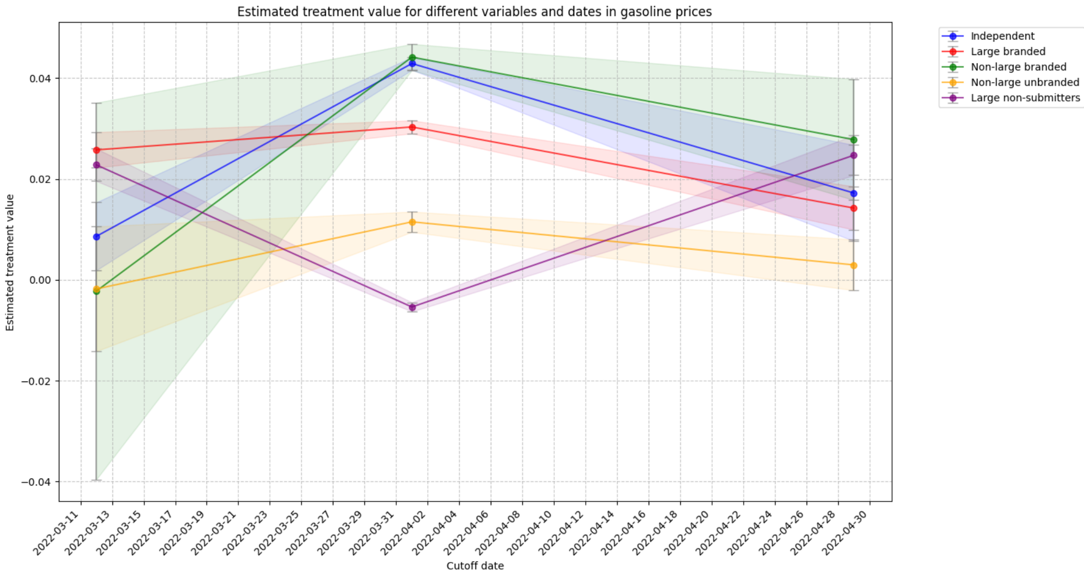
Figure D.2a presents the estimated effects for Diesel A across three cutoff dates: March 12, April 1 (the actual implementation date), and April 29, 2022. For each date, we estimate effects separately for different station types. The estimates at placebo dates generally fall within a range of -0.02 to 0.05 euros, with 95% confidence intervals frequently including zero. In contrast, estimates at the true cutoff date (April 1) show larger magnitudes and narrower confidence intervals, particularly for independent stations and those managed by wholesalers with refining capacity.

Similarly, Figure D.2b shows the results for Gasoline 95. The placebo estimates typically range from -0.04 to 0.02 euros, with substantial overlap of confidence intervals with zero. We do not observe a consistent pattern of significant effects across placebo dates, which would otherwise undermine the validity of our RD.

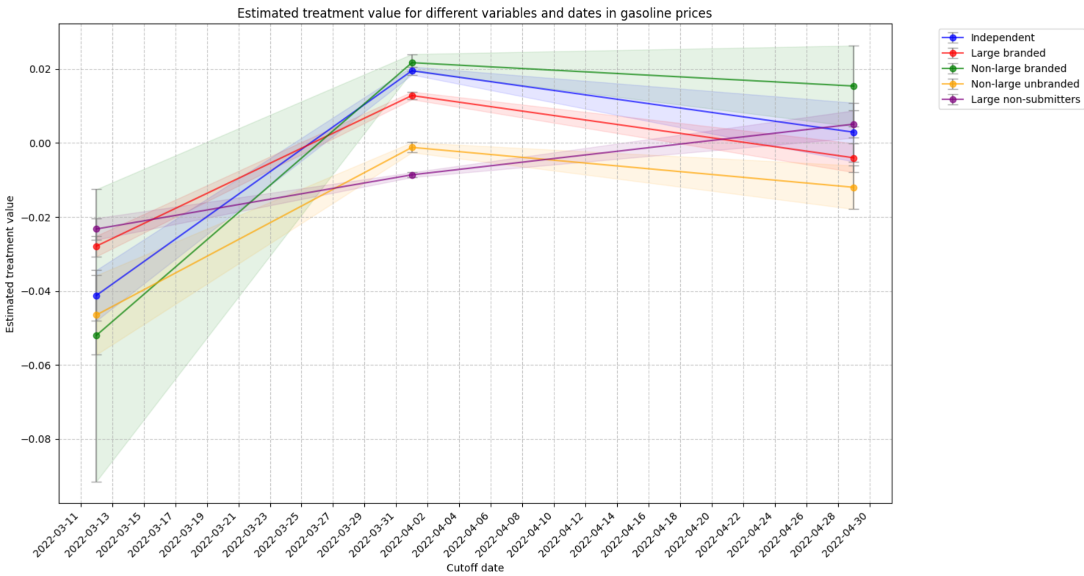
These placebo test results strengthen the credibility of our main findings by demonstrating that the observed discontinuities are likely attributable to the discount policy rather than to underlying trends or chance. However, the variability in estimates across dates highlights the complexity of fuel price dynamics during this period.

Figure D.2. Treatment effect at different cutoffs

(a) Diesel



(b) Gasoline



Note: This figure displays the estimated treatment effects for fuel prices across various cutoff dates, including the true implementation date (April 1st, 2022) and placebo dates. Each line represents a different type of service station. The shaded areas indicate 95% confidence intervals. Observe the larger magnitude and narrower confidence intervals near the true cutoff date, particularly for Independent and Large branded stations, suggesting a more pronounced effect of the policy at the actual implementation date.

Source: Own elaboration

Appendix E. Additional Difference-in-Differences results

Appendix E.1. Alternative model specifications

Our main analysis employs several DiD specifications to ensure robustness. Figure E.1 shows the consistency of estimated treatment effects across these different specifications. For diesel, models with interaction terms or fixed effects yield consistent estimates around 0.035-0.038 euros. For gasoline, while the basic trend model produces a lower estimate (approximately 0.015 euros), models incorporating interactions or fixed effects converge to consistent estimates of 0.027-0.028 euros. This consistency across specifications reinforces confidence in our findings.

Appendix E.2. Heterogeneous effects and time window sensitivity

Table E.1 presents detailed results on heterogeneity across station types and sensitivity to different time windows. Panel A shows the effect magnitudes for each station type under our preferred specifications, while Panel B demonstrates how these effects vary with the choice of time window around the policy implementation date.

The time window analysis reveals a clear pattern: the effect is strongest when using a narrow window of ±15 days for both diesel (0.0907-0.0914 euros) and gasoline (0.0582-0.0563 euros). The effect progressively diminishes as we extend to ±30 days and ±45 days, with the gasoline effect becoming negligible at the widest window. This pattern confirms our convergence finding, demonstrating that the initial shock dissipated as the market adjusted to the new policy environment, with gasoline prices converging more rapidly than diesel prices.

Appendix E.3. Non-linear specifications and additional robustness checks

To accommodate potential non-linearities in time trends, we also estimated models incorporating quadratic terms:

$$P_{it} = \alpha + \beta_1 Post_t + \beta_2 Days_t + \beta_3 Days_t^2 + \beta_4 (Post_t \times Days_t) + \beta_5 (Post_t \times Days_t^2) + \varepsilon_{it} \tag{E.1}$$

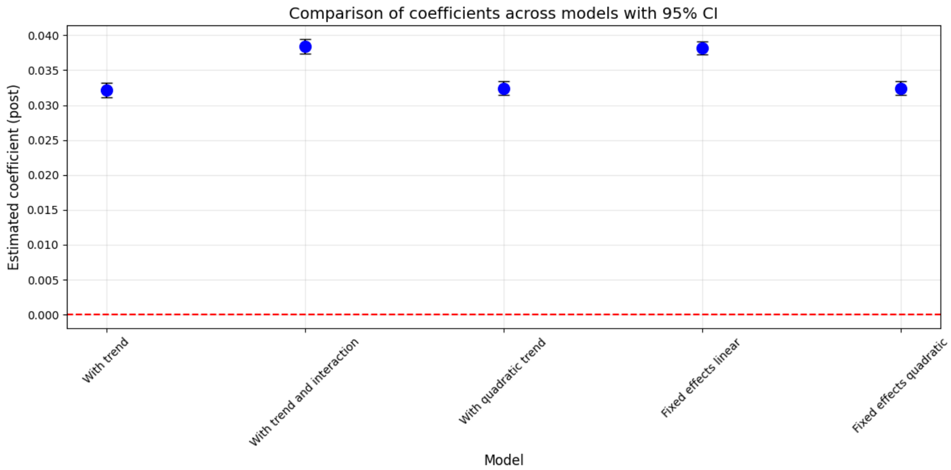
These flexible specifications produced results consistent with our main findings, with the quadratic interaction term reinforcing the convergence pattern observed in our linear models.

Additional heterogeneity analyses examined variation across station location types (urban vs. rural, highway vs. local roads), competition intensity levels, and initial price quartiles. These analyses revealed that the pass-through effect was most pronounced for stations in areas with lower competition intensity and for those in the lower quartiles of the initial price distribution, further supporting our main conclusions about the role of market structure and financial constraints in determining pass-through rates.

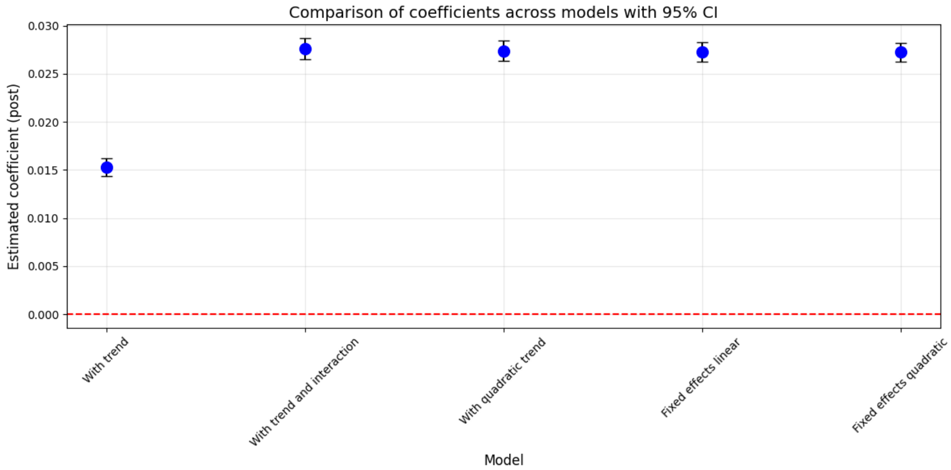
Finally, placebo tests using artificially shifted treatment dates confirmed that our estimated effects were indeed attributable to the discount policy rather than to pre-existing trends or other confounding factors.

Figure E.1. Comparison of estimated treatment effects across different model specifications

(a) Diesel



(b) Gasoline



Source: Own elaboration

Table E.1. Heterogeneity in DiD Estimates by Station Type and Time Window

Panel A: Effects by Station Type (Model with Interactions)				
	Diesel		Gasoline	
	Coefficient	Observations	Coefficient	Observations
Type 4 (Branded, non-refiner)	0.0388***	140,292	0.0278***	140,392
	(0.0015)		(0.0015)	
Type 5 (Independent)	0.0316***	804,971	0.0365***	809,851
	(0.0009)		(0.0009)	
Type 2 (Wholesaler w/o refining)	0.0148***	149,015	0.0023*	150,278
	(0.0012)		(0.0013)	
Type 3 (Branded, refiner)	0.0364***	479,612	0.0201***	479,989
	(0.0010)		(0.0008)	
Panel B: Sensitivity Analysis with Different Time Windows				
	Diesel		Gasoline	
	Trend model	Interaction model	Trend model	Interaction model
±15 days	0.0907***	0.0914***	0.0582***	0.0563***
	(0.0023)	(0.0025)	(0.0018)	(0.0019)
±30 days	0.0632***	0.0606***	0.0152***	0.0097***
	(0.0016)	(0.0017)	(0.0012)	(0.0013)
±45 days	0.0354***	0.0332***	0.0050***	0.0008
	(0.0013)	(0.0014)	(0.0010)	(0.0010)
Observations (approx.)	125K / 246K / 367K		126K / 247K / 368K	

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Panel A reports coefficients for each station type from our preferred model with interactions. Panel B shows how estimates vary with different time windows around the implementation date.

Source: Own elaboration