# The Causal Effects of Tariff-Rate Quota Policies on Agricultural Product Retail Prices

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**Abstract**

This study examines the causal effect of Korea's Tariff-Rate Quota on consumer price reduction and stabilization, in contrast to previous foreign studies that focused on the domestic producer price support effects of Tariff-Rate Quotas. Using daily retail price data for 40 agricultural products from 2021 to 2025, this study analyze retail price changes in response to the intensity of tariff reductions using the Local Projection Difference-in-Differences method. The results indicate that while no significant price reduction was observed for leafy and root vegetables, fruits exhibited a causal retail price decline of approximately 0.9% for every one percentage point reduction in tariff rates. This implies that the tariff pass-through rate for fruits is approximately 90%. These findings suggest that when the policy objective is price stabilization, priority consideration should be given to applying Tariff-Rate Quotas to fruits.

Keywords: Tariff-Rate Quota, Price Stabilization, Local Projection Difference-in-Differences, Tariff Pass-through, Agricultural Trade Policy

JEL Classification: F13, F14, Q17, C23

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Replication data and code: https://github.com/jayjeo/github_TRQ

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# 1 Introduction

A Tariff-Rate Quota (TRQ) constitutes a two-tier tariff system wherein a lower tariff rate is applied up to a specified quantity, while a higher tariff rate is imposed on imports exceeding that threshold. The economic effects of TRQs are fundamentally contingent upon the quota level —specifically, the magnitude of the quota relative to domestic demand (Lee, 2011). When the quota is established below domestic demand, imports are constrained within the quota, and the TRQ operates as a conventional protectionist instrument that insulates domestic producers from foreign competition (Loginova et al., 2021; Abbott and Paarlberg, 1998). Conversely, when the quota surpasses demand, imports expand due to preferential tariff treatment, effectively eliminating import restrictions and fostering domestic market competition in a manner analogous to tariff reductions.

The majority of developed countries employ TRQs as a mechanism for protecting domestic industries, particularly within the agricultural sector. In contrast, Korea operates a distinct TRQ system under its *Customs Act* in addition to the WTO's TRQ framework, utilizing it in a manner that is rarely observed internationally. Korea's TRQ system is primarily oriented toward stabilizing domestic prices, with particular emphasis on inducing price reductions (Song, 2023). Unlike developed countries that restrict imports by establishing low quotas on sensitive products, the Korean government activates TRQs when domestic prices for specific products experience sharp surges. It temporarily reduces tariff rates and substantially expands quotas to augment import volumes and suppress price escalation.

Notably, in April 2024, the government entirely abolished quantity restrictions on certain products such as bananas and pineapples —which previously had lower tariffs applied only up to a specified volume— and applied a 0% TRQ rate to all import volumes for a designated period. This demonstrates that Korea effectively operates the system with attenuated quantitative restriction functions.[1]

Meanwhile, causal research on the price stabilization effects of TRQs provides

[1] Furthermore, this suggests that unlike the WTO's TRQ system —introduced to guarantee minimum market access following the tariffication of non-tariff barriers— Korea's TRQ system is administered with greater flexibility and exceptionality in accordance with the policy objective of domestic price stabilization.

substantial contributions to the Korean government's policy formulation. As of 2024, the application of TRQs to agricultural products has expanded considerably, with the number of covered products increasing from 20 in 2020 to 72 in 2024. The cumulative tariff reduction amounts to approximately 1.4 trillion KRW, resulting in substantial fiscal revenue losses (Jang, 2025). Given that approximately 66% of these measures were implemented for price stabilization purposes, a comprehensive analysis is warranted to ascertain whether these policies are effectively achieving their intended objective of consumer price stabilization.

To the best of the authors' knowledge, only a limited number of prior studies have analyzed the price effects of TRQs employing causal inference methodologies, and these exist exclusively within the context of protectionist trade policy. For example, Loginova et al. (2021) employed a Difference-in-Differences (DiD) analysis utilizing price data from Switzerland and neighboring countries, confirming that producer prices for Swiss vegetables increased during the protection period. However, it is noteworthy that not all products exhibited uniform price increases.

However, prior studies have predominantly concentrated on the protective effects of TRQs in supporting domestic producer prices or suppressing imports. No extant research has been identified that analyzes the causal effects of policies employing TRQs to reduce and stabilize consumer prices, as practiced in Korea. This study examines the issue from the perspective of price stabilization. Specifically, we applied the DiD method for causal analysis. To address the bias problems arising from weighted average distortions and the utilization of contaminated control groups inherent in conventional Event-study DiD models, we employed the Local Projection DiD method developed by Dube et al. (2023).

This study obtained daily retail price data from *Nongnet* for a total of 40 products —including apples, pears, mangoes, onions, and napa cabbage— spanning from 2021 to 2025. Additionally, through the specialized expertise of licensed customs brokers, we rigorously calculated the 'applied tariff rate' for each product (the actual tariff rate that would apply in the absence of TRQs). This was utilized as a continuous treatment intensity variable in the LP-DiD model to estimate the percentage change in retail prices causally attributable to each one percentage point (%p) reduction in tariff rates due to TRQs. The treatment intensity of TRQs is defined as the applied tariff rate minus the TRQ rate. For instance, the applied tariff rate for onions averages 79.9%, and the

TRQ rate is 0%, yielding a treatment intensity of 79.9%. For kiwifruit, the applied tariff rate averages 6.5% and the TRQ rate is 5%, resulting in a treatment intensity of 1.5%.

The LP-DiD analysis results are as follows. First, in the baseline analysis treating all 11 products among the 40 items as a single treated group, no significant change in retail prices attributable to TRQs was observed. However, when the 11 products were reclassified according to their characteristics to account for treated group heterogeneity, noteworthy results emerged. Specifically, when the treated group was disaggregated into Group 1 (leafy and root vegetables) and Group 2 (fruits), distinct heterogeneous effects were identified between the two groups. For Group 1 (leafy and root vegetables), no statistically significant change in retail prices was observed following TRQ application. In contrast, Group 2 (fruits) exhibited minimal price changes initially but demonstrated statistically significant declines after 90 days. Specifically, at 250 days following TRQ application, retail prices were estimated to have declined by approximately 39% attributable to the TRQ policy.

The LP-DiD analysis incorporating product-specific tariff reduction magnitudes yielded the following results. For Group 1, no significant change in retail prices was similarly observed, whereas for Group 2, comprising fruits, significant price reduction effects were observed commencing 200 days after TRQ implementation. Taking the 250-day mark as an illustrative example, for every 1%p reduction in tariff rates, retail prices causally declined by 0.9%. This indicates a tariff pass-through rate of approximately 90%, implying that distribution entities —encompassing producers, importers, wholesalers, and retailers— retained only approximately 10% of the tariff reduction as profit while transmitting the remainder to consumers.

The policy implication derived from this study is as follows When selecting products for TRQ application with price stabilization as the policy objective, priority consideration should be accorded to fruits over leafy or root vegetables. According to the empirical analysis results of this study, TRQ application to fruits such as cherries, kiwifruit, avocados, mangoes, bananas, and pineapples demonstrated significant effects on consumer price stabilization. In contrast, for leafy and root vegetables such as napa cabbage, cabbage, radish, onions, and carrots, the price stabilization effects were negligible.

Data and code for replication of this study are available at the following link:

https://github.com/jayjeo/github_TRQ. This study is organized as follows. Section 2 reviews prior research related to tariffs and taxation, including empirical studies on tax (tariff) pass-through rates. Section 3 provides a detailed description of the data collection and construction process employed in this study. Section 4 presents the empirical analysis of the causal effects of TRQs on retail prices. We first present the baseline LP-DiD analysis results with all 11 treated products integrated as a single group, followed by LP-DiD analysis results for the treated group disaggregated into Group 1 (5 leafy and root vegetable products) and Group 2 (6 fruit products). Section 5 presents the principal findings of the study and their policy implications.

## 2 Literature Review

The price effects of TRQs vary contingent upon policy design and market conditions. TRQs with low quotas function as powerful protective measures that maintain domestic prices above world market levels. In the Swiss vegetable case, most products exhibited double-digit domestic price increases. According to Son and Lim (2025), TRQs on rice in the Korean grain market demonstrated trade restriction effects equivalent to tariffs exceeding 100%.

Conversely, TRQs that establish quotas exceeding domestic demand or reduce tariff rates function as policy instruments that effectively liberalize imports and suppress domestic price escalation. Korea's strategic TRQ implementations contributed to domestic price stabilization during periods of rising international commodity prices; however, the magnitude and velocity of these effects varied considerably across products. According to Lee (2011), products with substantial weights in the consumer price index and straightforward cost pass-through channel —such as energy—exhibited clear downward pressure on consumer prices when tariffs were reduced. In contrast, for products where raw material costs constitute a minor proportion of final product prices or involve multiple processing stages —such as wheat and sugar— identical tariff reductions yielded negligible effects on final consumer prices.[2]

The majority of developed countries employ TRQs as a mechanism for protecting

[2] This study estimated that a uniform 10%p reduction in TRQ rates on major raw materials would reduce the consumer price index by 1.78% through natural gas tariff reductions, whereas the effect of sugar tariff reductions would be merely 0.0037%.

domestic industries, particularly the agricultural sector. Switzerland's seasonal vegetable TRQ system constitutes a representative case: it permits imports at low tariff rates outside the domestic harvest season but imposes high tariffs to impede imports during the harvest season (protection period) when domestic production is concentrated. Loginova et al. (2021) analyzed weekly producer price data from Switzerland and neighboring countries for the 2014∼2019 period utilizing the DiD method. The results confirmed the price support effect of TRQs, with Swiss vegetable prices during the protection period averaging more than 20% higher than those in neighboring countries, with some products exceeding 50%. Notably, although Loginova et al. (2021)'s findings demonstrated clear price support effects for most vegetables, not all products exhibited uniform price increases.[3]

Meanwhile, Korean research institutions publish annual policy reports on the consumer price reduction effects of TRQs; however, to the best of the authors' knowledge, no report has yet rigorously analyzed causal relationships.[4]

Meanwhile, the incidence of tariff reductions has been analyzed in the international trade economics literature as tax pass-through. Baek et al. (2021) analyzed firm-level wholesale margin data from Japan and found that when tariff rates decreased by 1%p, import wholesalers' margin rates increased by approximately 0.25%p. Foreign exporters also partially offset tariff reductions through export price increases, resulting in minimal final consumer price declines. In other words, foreign producers captured the

[3]By product, fresh vegetables with low storability and limited cross-border mobility exhibited larger price increases. During the protection period, Swiss producer prices for regular tomatoes were 91.2%p higher than Italian prices, cherry tomatoes were 35.7%p higher than German prices, eggplants were 25.6%p higher, and cauliflower was 60.7%p higher.

However, certain products such as Batavia lettuce, red lettuce, leeks, and zucchini exhibited no significant price differences even during the protection period. Organic vegetables exhibited minimal or even adverse price effects compared to conventionally grown produce. Organic fennel (−22.2%p), organic cucumbers (−20.0%p), and organic zucchini (−34.0%p) actually experienced price declines during the protection period, while organic regular tomatoes (+90.8%p) and organic eggplants (+28.1%p) still exhibited significant price increases. They attributed these product-specific differences to market structural characteristics and perishability.

[4]For instance, Song (2023) did not identify the 'causal effect of TRQ application on consumer prices' but rather identified 'the effect of import price changes on consumer prices.' While TRQs can certainly affect import prices, this represents merely one partial mechanism among the various pathways through which TRQs influence consumer prices. In fact, it is more appropriate to conceptualize TRQs as operating through a more direct channel: intensified domestic market competition via increased 'import volumes.' Moreover, when pass-through rates are extremely low, import prices may exhibit minimal change even when TRQs are applied. Therefore, we consider the key assumption required for his research design —that TRQ application significantly affects import prices— to be untenable.

largest share of tariff reduction benefits, domestic wholesalers absorbed a substantial portion, and the share ultimately accruing to final consumers was extremely limited.

In contrast, studies has demonstrated that the burden of tariff increases is largely passed through to importing country consumers. Analysis of the United States tariffs imposed on China during the 2018 U.S.-China trade dispute revealed that import price increases in the United States nearly corresponded to the tariff rates increases, with tariff pass-through rates reaching 95∼100% (Cavallo et al., 2021; Amiti et al., 2019). Cavallo et al. (2021) reported, through analysis of detailed U.S. consumer price index data, that U.S. import prices (including tariffs) rose by an average of 19% following tariff imposition, while prices excluding tariffs remained virtually unchanged. This indicates that the tariff shock was transmitted almost entirely to U.S. importers and consumers. Interestingly, exchange rate fluctuations during the same period were reflected in import prices by only approximately 20%, demonstrating that tariffs —as a policy shock— exerted a far more direct and complete impact on domestic prices than exchange rates —a market factor.[5]

# 3 Data Construction

## 3.1 Data Overview

The dataset constructed in this study comprises a product-level daily panel spanning from January 1, 2021, to March 31, 2025, encompassing 40 agricultural products, including apples, pears, mangoes, and tomatoes. Of these 40 products, 11 have been subject to TRQ implementation at some point during the observation period (treated), whereas the remaining 29 have never received TRQ treatment (never-treated).

Daily retail prices by product were obtained from *Nongnet* and employed as the dependent variable in the regression analysis. Data pertaining to TRQ application status, commencement dates, termination dates, and treatment intensity by product —

[5] In certain markets, the impact of tariff increases has been observed to exceed 100% pass-through to consumer prices. Flaaen et al. (2020) analyzed the 2018 U.S. safeguard tariff case on washing machines and found that import washing machine prices rose substantially, while U.S. manufacturers also raised domestic washing machine prices by 13∼17%. Consequently, the price increases borne by consumers far exceeded the tariff rates, with pass-through rates estimated at 108∼225%. Additionally, prices of complementary goods such as clothes dryers also increased, with indirect effects compounding household burdens.

constituting the most critical explanatory variables in the regression analysis— were compiled from publicly available information in accordance with the *Regulations on the Application of Quota Tariffs under Article 71 of the Customs Act.* A comprehensive explanation is provided in Section 3.4.

This study rigorously calculated 'applied tariff rates' by product and month. The derivation of applied tariff rates necessitates complex calculations based on various tariff agreements and Basic tariff rates for each country, product, and month —a task requiring specialized expertise in customs administration. The applied tariff rates were calculated through the following procedure. First, data published on the *Korea Customs Service's Customs Laws Information Portal* were collected to construct applied tariff rates by country, product, and month. Second, import volume data by country, product, and month were obtained from the *Korea Agro-Trade Information (KATI)* website operated by the *Korea Agro-Fisheries & Food Trade Corporation (aT)*. Finally, applied tariff rates by product and month were derived by calculating weighted averages of the country-product-month applied tariff rates, utilizing import volumes as weights. A detailed explanation is provided in Section 3.5.

For agricultural products, climatic conditions constitute an exogenous determinant of supply. First, based on climatic information from the preceding year, producers determine planting quantities to achieve their target production for the current year. Second, unanticipated weather events during the current production period induce supply fluctuations independent of both consumer and producer intentions. Climatic conditions from both the preceding and current years ultimately exert exogenous influences on final retail prices, rendering them essential control variables in the LP-DiD methodology. Average climatic data for Korea were obtained on a daily basis from January 1, 2020, to March 31, 2025, through the *Korea Meteorological Administration API Hub*, specifically encompassing temperature, humidity, precipitation, and sunshine duration.

Oil prices, which are also exogenously determined, exert a decisive influence on retail prices. This study obtained daily oil price data in USD from *Yahoo Finance*, adjusted these values using the Consumer Price Index to derive real oil prices, and subsequently converted them to KRW using exchange rate data.

To ensure analytical consistency, the analysis was conducted exclusively on products for which all aforementioned variables were available with sufficient time series coverage. The final set of 40 products selected for analysis is as follows: dried red pepper, sweet potato, perilla leaf, oyster mushroom, carrot, green onion, peanut, lemon, garlic, mango, radish, water dropwort, banana, cherry tomato, pear, napa cabbage, red pepper, apple, lettuce, king oyster mushroom, ginger, watermelon, spinach, avocado, cabbage, onion, young napa cabbage, young summer radish, cucumber, scallion, kiwifruit, cherry, bean, tomato, pineapple, bell pepper, adzuki bean, green pepper, bell pepper, and squash. Among these, 11 products have been subject to TRQ application at least once: mango, cherry, kiwifruit, banana, avocado, pineapple, napa cabbage, radish, cabbage, onion, and carrot.

## 3.2 Removing Seasonality

The removal of seasonality from product-level price and sales volume time series data constitutes a fundamental task in this study. Agricultural products exhibit pronounced seasonal patterns, and when the timing of TRQ policy implementation coincides with periods of seasonal fluctuation, distinguishing whether price movements are attributable to policy effects or to recurring seasonal patterns becomes problematic. Consequently, the reasonableness of the seasonality removal procedure directly influences the analytical outcomes of this study.

The complete removal of seasonality from weekly or daily data presents considerably greater complexity than from monthly data. The non-fixed annual cycle (with some years comprising 52 weeks and others 53) and the presence of multiple seasonal cycles (e.g., day-of-week patterns and annual patterns in daily data) preclude the direct application of standard seasonal adjustment tools. Indeed, official methodologies widely employed for seasonal adjustment —such as X-12-ARIMA and X-13-ARIMA-SEATS— were designed for monthly or quarterly data and assume fixed 12-month or 4-quarter cycles (Mollins and Lumb, 2024). As a result, X-12 and X-13 programs cannot be applied to weekly or daily frequency data; seasonal adjustment of weekly data necessitates workarounds such as aggregating the data to monthly frequency (Bandara et al., 2025). However, such aggregation entails the loss of detailed information on weekly variation and is therefore inconsistent with the objectives of this study.

STL decomposition (Seasonal-Trend decomposition using Loess) is a non-parametric method capable of extracting seasonality by specifying the desired period, and has been extensively applied to weekly and daily data (Cleveland et al., 1990).[6] However, because STL employs non-parametric smoothing techniques, there exists a risk that trends or policy shocks in the data may be partially absorbed during the seasonal decomposition process. This limitation can be critical in policy effect evaluation using DiD models —if treatment effects are removed during the seasonality removal stage, policy effects may be distorted in the subsequent DiD analysis.[7]

To address these limitations, this study adopted a regression-based seasonal adjustment approach utilizing dummy variables and Fourier terms. The Fourier method removes seasonality by expressing seasonal variation as a combination of sine and cosine functions. While representing annual seasonal patterns with a single periodic function is difficult, combining multiple Fourier terms (sine and cosine functions) with different frequencies enables the approximation of complex seasonal variations. By fitting data with a regression model incorporating these Fourier terms, annual seasonal effects can be estimated as smooth wave patterns, and seasonally adjusted time series can be obtained by subtracting these estimated seasonal factors from the original data.

Specifically, for weekly data, cyclical patterns were removed using week-of-year fixed effects (52 weekly dummies plus week-53 adjustment), whereas for daily data, day-of-week dummies (Monday through Sunday) and annual seasonal effects were modeled and extracted using Fourier terms (Pierce et al., 1984). Major holidays and public holidays were controlled through separate dummy variables. This regression approach is highly effective at systematically removing seasonal patterns that recur in identical form every year. Since it estimates the average effect of each week or day of the week and removes it from the original data, seasonal factors are theoretically eliminated from the adjusted time series.

The utility of this method for seasonal adjustment of weekly data is particularly

[6] Furthermore, MSTL (Multiple STL) is an extended method capable of simultaneously decomposing multiple seasonal factors, such as 7-day cycles and annual cycles (Bandara et al., 2025).

[7] Additionally, STL-based methods assume that seasonal cycles are fixed, and therefore cannot fully resolve the week-53 problem or cycle variations attributable to leap years (Mollins and Lumb, 2024). In practice, applying STL with an annual 52-week cycle assumes that exactly the same cycle repeats every year, which may leave subtle seasonal residuals in year-end weeks that vary from year to year. Furthermore, the absence of functionality to adjust for moving holidays or trading day effects implies that variations due to holiday timing changes or weekly fluctuations from holidays are not adequately removed (Mollins and Lumb, 2024).

evident from the case of the *U.S. Bureau of Labor Statistics (BLS)*. When seasonally adjusting indicators such as weekly unemployment insurance claims, the BLS developed and has employed `MoveReg` —a week dummy-and-Fourier-based moving weighted regression method— instead of traditional X-13 techniques (Mollins and Lumb, 2024). This approach removes week effects and moving holiday effects through regression analysis, thereby overcoming the limitation that X-13 could not be applied to weekly data. Consequently, the regression approach represents a practically validated solution for removing weekly seasonality, and the same principle can be applied to daily data for removing day-of-week and annual effects, ensuring methodological consistency.

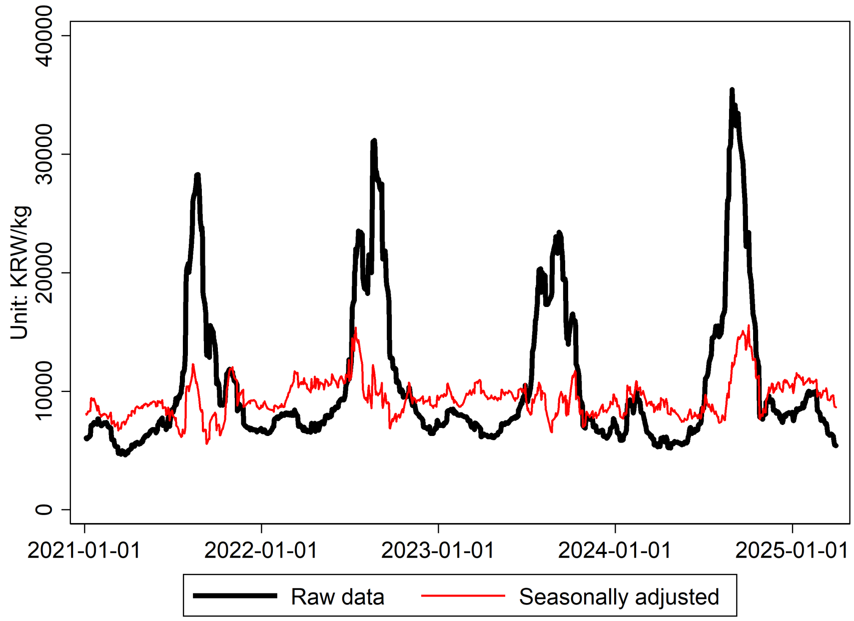
An additional advantage of the dummy variable and Fourier regression approach is analytical stability. In the regression model, seasonal dummies are included as fixed effects independent of the treatment variable, ensuring that seasonality removal is performed separately without being confounded with trends or policy effects. In other words, while seasonal patterns do not remain in the residuals following seasonality removal, trend changes and policy implementation effects are fully preserved. This represents a distinct advantage over non-parametric decomposition methods such as STL discussed above, and enhances the reliability of policy effect analyses such as DiD models. Figure 1 presents an example of the original series and seasonally adjusted results for spinach retail prices.

## 3.3 Retail, Wholesale, and Import Prices

This study did not employ import prices and wholesale prices as direct analytical variables. However, these data were utilized to indirectly verify the reliability of retail price data through comparative analysis. A particularly noteworthy pattern is that while import prices and wholesale prices exhibit virtually no difference, the transition from wholesale to retail prices involves an average price increase of approximately twofold. Figure 8 in Appendix A presents pineapple as an illustrative example, displaying import prices, wholesale prices, and retail prices. It should be noted that because import prices could only be constructed on a monthly basis, they appear less volatile in the figure compared to wholesale and retail prices.

Daily retail prices by product were obtained from *Nongnet*, daily wholesale prices by product from *KAMIS (Korea Agricultural Marketing Information Service)*, and monthly

Figure 1: Examples of Seasonally Adjusted Prices (Spinach)




import prices by product[8] from *KATI (Korea Agro-Trade Information)*. All price data were standardized to KRW/kg. When raw data were provided in units of KRW per an item or KRW per head, actual market surveys were conducted to measure the weight per an item or per head, which was subsequently converted to KRW/kg. This standardization enables all econometric analysis results to be interpreted consistently in KRW/kg units and facilitates direct comparison among retail prices, wholesale prices, and import prices.

## 3.4 Tariff-Rate Quota Implementation and Intensity

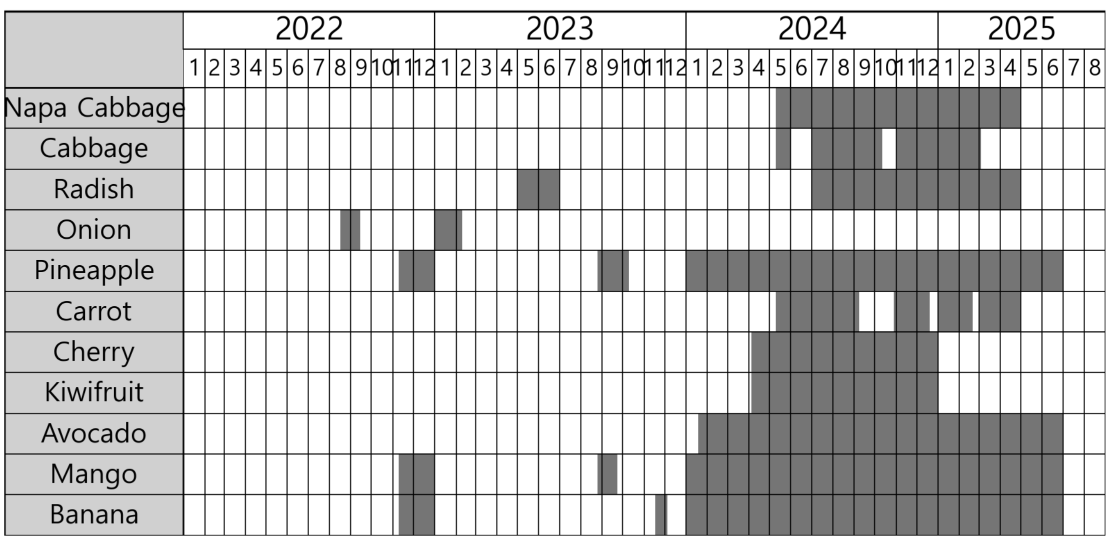
The daily TRQ implementation commencement dates, termination dates, and treatment intensity by product (HS code) constitute the core explanatory variables of this study. These data were constructed utilizing publicly available information pursuant to the *Regulations on the Application of Quota Tariffs under Article 71 of the Customs Act.*

[8] CIF basis, excluding tariffs.

### 3.4.1 TRQ Implementation Status

This subsection introduces the variable pertaining to TRQ implementation status. Among the 40 products analyzed in this study, 11 products have been subject to TRQ implementation at least once, as previously noted: mango, cherry, kiwifruit, banana, avocado, napa cabbage, radish, cabbage, onion, pineapple, and carrot. Their TRQ implementation status is presented on a daily basis in Table 1, where border lines indicate monthly boundaries. In the table, white cells denote periods without TRQ implementation, whereas black cells denote periods with TRQ implementation. For example, the TRQ for cherries commenced on April 5, 2024, and terminated on December 31, 2024. Due to space constraints, data prior to 2022 are not presented; however, this study constructed daily TRQ implementation status for all products from 2015 onward. From 2015 to 2022, TRQ implementations were exceedingly rare, with a marked increase beginning in 2024.

Table 1: TRQ Implementation Table




An important consideration is that there are intermittent instances where TRQs terminated due to quota exhaustion. For products with established quotas, TRQs apply only to quantities that have received recommendations from the recommending authority. However, since this study could not verify recommendation status for individual import transactions, TRQ-applied quantities were calculated under the assumption that quotas are exhausted sequentially from the commencement date of the TRQ implementation period. For example, carrots have been subject to TRQ implementation four times since 2015: (1) May 10, 2024 $\sim$ September 30, 2024, (2) October 29, 2024 $\sim$ December 31, 2024, (3) January 1, 2025 $\sim$ February 28, 2025, and (4) March 1, 2025 $\sim$ April 30, 2025. Connecting these periods reveals they are continuous except for September 30 $\sim$ October 29, 2024.

Importantly, each of the four TRQ implementations has a separate quota. For instance, period (1) had a quota of 40,000 tons, whereas period (2) had 18,000 tons. Taking period (1) as an example and calculating actual import volumes, the quota was exceeded on September 8. Specifically, cumulative imports from May calculated in August 2024 amounted to 36,800 tons, whereas cumulative imports from May calculated in September totaled 49,400 tons —clearly exceeding 40,000 tons. Therefore, from September 8 until the termination of the quota period on September 30, although the TRQ system remained in effect, the TRQ rate benefits could no longer be received. By calculating quota exhaustion status and timing for all products in this manner, the white cells appearing mid-period for cabbage and carrots in Table 1 become evident.

Consequently, Table 1 displays alternating white and black cells. A configuration in which white cells appear first chronologically and, once transitioning to black, never revert to white is termed 'absorbing' (Bach et al., 2025). In contrast, configurations permitting reversion from black to white are termed 'non-absorbing' (Dube et al., 2023), which allows for indefinite white-black-white-black repetition. This study further defines a restricted case within non-absorbing structures —permitting at most a single white-black-white sequence— as 'semi-non-absorbing.'

This study employs the non-absorbing format presented in Table 1 without modification for the main analysis (baseline). After acknowledging the limitations of this non-absorbing data format, additional analysis results are provided in Section 4.4 using a semi-non-absorbing data format for robustness checks.

### 3.4.2 TRQ Treatment Intensity

In causal analysis employing LP-DiD, two approaches exist for utilizing TRQs as an explanatory variable. The first approach employs only the TRQ implementation status as a binary variable (0, 1). The second approach utilizes the intensity of the tariff rate reduction shock resulting from the TRQ system as a continuous variable. The shock intensity is defined as the applied tariff rate minus the TRQ rate. The applied tariff rate refers to the tariff rate that would actually be imposed in the absence of TRQs.

For example, for napa cabbage, the applied tariff rate at the time of TRQ implementation was 27% and the TRQ rate was 0%, yielding a shock intensity from the TRQ system of 27%p. In contrast, for kiwifruit, the applied tariff rate at the time of TRQ implementation was 6.5% and the TRQ rate was 5%, resulting in a shock intensity of 1.5%p. Consequently, the rigorous and accurate calculation of the applied tariff rate constituted one of the core tasks of this study. A detailed explanation of the applied tariff rate construction is provided in the following section.

## 3.5 Applied Tariff Rate

This subsection introduces the concept and function of the applied tariff rate, which serves as a key determinant of TRQ treatment intensity. The applied tariff rate represents the baseline tariff that would have been imposed in the absence of TRQ implementation. By measuring the differential between this rate and the TRQ rate, we estimate the magnitude of retail price decline per 1%p tariff reduction attributable to TRQ policy effects.[9]

Additionally, the applied tariff rate serves as an essential covariate in the econometric model. During periods without TRQ implementation, the applied tariff rate directly influences import volumes, which in turn transmit to domestic retail prices. Conversely, during periods of TRQ implementation, the TRQ rate —rather than the applied tariff rate— governs import volumes. Consequently, including the applied tariff rate as a covariate does not induce endogeneity.[10]

### 3.5.1 Concept and Function of the Applied Tariff Rate

Tariff rates applicable to imported goods comprise various rates by HS code, including Basic Tariff Rates and Preferential Tariffs under the Free Trade Agreement (FTA). The

[9]The applied tariff rate interact with explanatory variables distinguishing between products subject to TRQ and those that are not, thereby enabling estimation of treatment intensity —specifically, the magnitude of tariff reductions attributable to TRQ policy implementation.

[10]Moreover, while the applied tariff rate may influence the decision to implement TRQ, the reverse does not hold. Given this causal structure, including the applied tariff rate as a covariate does not create a bad control problem. Conversely, excluding the applied tariff rate from the model would introduce estimation bias due to omitted variable problems.

priority order of rate application is governed by *Article 50 of the Customs Act*. Even for identical products, the actual rate applied may vary depending on the country of origin, product specifications, and importer circumstances. Because multiple rates may apply to a single HS code, accurately identifying the baseline tariff rate in the absence of TRQ using a single rate alone is infeasible. Thus, an indicator such as the 'applied tariff rate' is necessary to account for both the range of applicable rates and observed import patterns.

In this study, import performance data were utilized to determine the 'most favorable tariff rate' applicable to each country's monthly imports, following the tariff rate priority hierarchy established under the *Customs Act*. Monthly applied tariff rates were subsequently derived by computing weighted averages based on each country's monthly import volumes. Although this approach does not permit direct verification of whether Preferential Tariff Rates were actually applied in individual transactions, it provides a meaningful estimation of tariff burden levels that closely approximate reality by incorporating both the structural characteristics of the tariff system and observed import patterns.

### 3.5.2 Tariff Rate Priority Structure

To determine the final applicable rate among multiple tariff rates that may apply to a single HS code, the priority order of rate application was examined in accordance with *Article 50 of the Customs Act*. The priority order ranges from first to seventh, with the application method as follows.

The rates applied with the highest priority are Special Tariff Rates designed to protect domestic industries or correct trade imbalances, including Anti-Dumping Duty, Retaliatory Duty, and Countervailing Duty. The second-priority rate is the FTA rate under the *Act on Special Cases of the Customs Act for the Implementation of Free Trade Agreements*. If this rate is equal to or lower than rates under the *Customs Act* (excluding first-priority rates), the FTA rate is applied preferentially upon the importer's request. Third-priority rates include International Cooperation Tariffs, such as WTO General Tariff Concessions, and Beneficial Tariffs. Among third-priority rates, Tariff Concessions for agricultural, forestry, and livestock products —conceded at rates equivalent to the domestic-foreign price differential or at rates exceeding Basic Tariff Rates in conjunction with domestic market opening under the *Regulations on Tariff Concessions in the Framework of the Agreement Establishing the World Trade Organization*— take precedence over Basic Tariff Rates and Provisional Tariff Rates. Fourth-priority rates include Adjusted Duty[11], TRQ, and Seasonal Tariffs. TRQ takes precedence when it is lower than Preferential Tariffs for least developed countries, and it also supersedes Basic Tariff Rates and Provisional Tariff Rates. The fifth-priority rate is Preferential Tariffs for least developed countries. Provisional Tariff Rates and Basic Tariff Rates correspond to the sixth and seventh priority rates, respectively. However, due to data availability limitations, Specific Duties were not considered in this study.

### 3.5.3 Calculation Process for the Applied Tariff Rate

To calculate the applied tariff rate, this study utilized country-specific monthly import weight data by product from the *KATI (Korea Agricultural Trade Information)*. The analysis encompasses a total of 40 products, with data collected for the period from January 2021 to March 2025 based on each product's HS code.

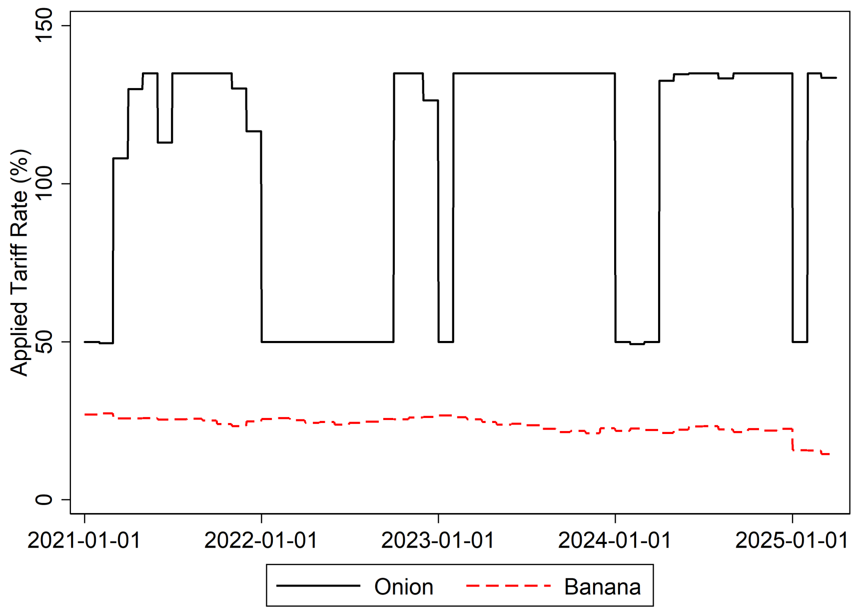
Since the data are organized by country, different tariff rates may apply to the same product depending on the exporting country. Accordingly, the applicable tariff rate for each country was first determined following the tariff rate priority structure presented in Section 3.5.2. The monthly 'applied tariff rate' was then calculated as a weighted average of the country-specific confirmed tariff rates, using each country's import volume for the corresponding month as the weight. By repeating this calculation process for all months from January 2021 to March 2025, panel data of monthly applied tariff rates by product were constructed.

For example, as of July 2024, the country-wise import share for banana under HS code 0803.90-0000 was highest for the Philippines, followed by Vietnam and Ecuador. Ecuadorian banana is not subject to first-priority rates (such as Anti-Dumping Duty, Retaliatory Duty, or Countervailing Duty), and Ecuador is not an FTA partner country; therefore, the review begins from third-priority rates. Since fourth- through sixth-priority rates do not apply and the third-priority WTO Tariff Concession Rate (90%) exceeds the seventh-priority Basic Tariff Rate (30%), the Basic Tariff Rate is ultimately applied. Vietnamese banana is subject to a 0% tariff under the Korea-Vietnam FTA,

[11] Article 69, Subparagraphs 1, 3, and 4 of the Customs Act

while Philippine banana, which accounts for approximately 61% of imports, is subject to the 30% Basic Tariff Rate. Calculating the weighted average of these country-specific tariff rates by import volume share yields an 'applied tariff rate' of approximately 23.3% for banana in July 2024. Meanwhile, with the Korea-Philippines FTA entering into force on December 31, 2024, the applied tariff rate for banana has declined to approximately 14∼15% as of the first quarter of 2025, as illustrated in Figure 2.

Figure 2: Applied Tariff Rate (Banana, Onion)




Fresh unpeeled onion is not subject to first-priority rates; thus, the review begins from second-priority rates. Notably, Chinese onion accounts for the majority of total import volume but receives no Tariff Concession Benefits under FTA agreements, and therefore third-priority rates apply. The third-priority rate is the WTO Tariff Concession applicable to agricultural, forestry, and livestock products with established Market Access Quota. Imports within the Market Access Quota are subject to the Recommended Tariff Rate of 50%, while imports exceeding the quota are subject to the non-recommended rate of 135%. Consequently, the monthly applied tariff rate for onion varies depending on whether the Market Access Quota is exceeded.

When the applied tariff rate is employed as a variable representing the intensity of tariff reduction shocks from TRQ policy, this variable must be a fixed value that does not vary over time. To satisfy this requirement, a fixed applied tariff rate value for each product was calculated by averaging the applied tariff rates over the 365 days preceding the TRQ implementation start date for each product. This approach mitigates the influence of short-term fluctuations attributable to single-point applied tariff rates and enhances the reliability of policy effect analysis. The product-specific applied tariff rate values are presented in Table 2 of Section 4. Notably, the applied tariff rates for days following the TRQ start date were excluded from the average due to endogeneity concerns. Utilizing historical values of the applied tariff rate that were determined prior to TRQ implementation avoids the risk of endogeneity.

# 4 Causal Analysis

## 4.1 Event-Study Difference-in-Differences Model

This study measured the causal impact of TRQ policies on consumer prices employing a DiD model. TRQs represent a staggered adoption situation wherein policy implementation timing differs across products. In such cases, an Event-study DiD model must be employed, which realigns the time axis based on each product's policy implementation timing.

However, the traditional Event-study DiD approach that applies the Two-Way Fixed Effect DiD method after simply realigning the time axis produces biased estimates due to the following problems. First, for the control group (never-treated), the policy has never been applied, rendering the time axis impossible to realign based on policy implementation timing. Second, in non-absorbing situations where the policy commences and subsequently terminates, products are utilized as controls after policy termination, which is methodologically problematic. Products to which the policy was previously applied cannot function as appropriate controls because lagged effects may persist even after policy termination. For example, cherries had TRQs applied from April 5 to December 31, 2024; utilizing cherry retail prices in February 2025 as a control would be inappropriate because the effects of TRQs applied during 2024 may persist into February 2025.

The problem of biased estimates arising from inappropriate comparisons using groups with prior treatment history as controls has been documented in several recent studies (Goodman-Bacon, 2021; Callaway et al., 2024). To address this issue, Sun and Abraham (2021), De Chaisemartin et al. (2022), Callaway et al. (2024), Gardner (2022), and Dube et al. (2023) have proposed improved techniques.[12] This study employs the Local Projection Difference-in-Differences (LP-DiD) method to address these problems.[13] LP-DiD resolves the aforementioned bias problems by utilizing only 'clean controls' when estimating effects at each lead or lag. Specifically, when estimating the effect at a particular time $t$, products with prior treatment history before that time are excluded from the control group, and only not-yet-treated products or never-treated products are employed as controls. This approach blocks composition effects arising from previously treated products being mixed into the control group, ensures comparison between pure control and treated groups, and fundamentally prevents bias from contaminated comparisons.

## 4.2 Treatment of Quota Exhaustion Periods

As presented in Table 1, certain products such as carrots and cabbage experienced periods when quotas were exhausted. During these periods, although the TRQ system remains in effect, the tariff reduction benefits corresponding to the TRQ rate cannot be obtained. Accordingly, this study did not classify such 'quota exhaustion periods' as *treated status*. Naturally, not being classified as treated status does not imply that products during these periods become controls. Following the 'clean control' principle explicated earlier, products that have received treatment even once in the past can

[12]However, some of these methodologies retain certain limitations. For example, Sun and Abraham (2021)'s method has the limitation of being unable to accommodate continuous treatment intensity. Additionally, the Two-Stage DiD technique proposed by Gardner (2022) can accommodate continuous treatment intensity but possesses other limitations. Specifically, while it resolves the negative weighting problem identified by Goodman-Bacon (2021), the issue of inconsistent control group composition remains. The first stage employs only untreated groups as controls, but the second stage utilizes all data collectively, creating a contaminated control problem. That is, groups that have already been treated or will soon be treated are included in the control group, undermining the validity of comparisons and potentially diluting or distorting effect estimates.

[13]The most standard form of Local Projection (LP) was first developed by Jordà et al. (2015), with numerous subsequent studies following. The first advantage of LP models is that, unlike Vector Autoregression (VAR), Impulse Response Functions can be implemented through regression analysis (Adämmer, 2019). Second, whereas VAR is applicable only to time series data, LP models can also be applied to panel data, enabling richer analysis (Owyang et al., 2013; Jordà et al., 2015). Since this study employs panel data consisting of products and dates, LP models can derive Impulse Response Functions that would be impossible to estimate with VAR. Third, LP models can be applied to DiD models. This technique developed by Dube et al. (2023) is termed LP-DiD.

never become controls again. Ultimately, such products are treated as missing observations.

However, treating quota exhaustion periods as *not-treated status* introduces certain logical complications. The robustness check section addresses this limitation in detail, presenting LP-DiD analysis results derived from data restructured into a 'semi-non-absorbing' format, which alternatively flags quota exhaustion periods as *treated status*.

## 4.3 LP-DiD Analysis Results

This study derives a total of four analysis results employing the LP-DiD method. First, among the 40 products analyzed in this study, the 11 products that have received TRQ treatment are integrated into a single treated group for analysis. Second, the 11 products are divided into two treated groups comprising 5 and 6 products, respectively, and analyzed separately. Specifically, LP-DiD is performed with 29 control products (never-treated) and 'Treated Group 1' consisting of 5 products, followed by a separate LP-DiD with the same 29 controls and 'Treated Group 2' consisting of the remaining 6 products, with results from both groups presented in a single graph.

The criteria for dividing the 11 treated products into the specific 5 : 6 split are explained in Section 4.3.3. Following this explanation, Treated Group 1 comprises napa cabbage, cabbage, radish, onion, and carrot, whereas Treated Group 2 comprises cherry, kiwifruit, avocado, mango, banana, and pineapple. Group 1 is composed entirely of leafy and root vegetables, whereas Group 2 consists entirely of fruits.

Both the first and second methods described above are further subdivided into two approaches for analysis. (i) Analysis is conducted by specifying TRQ implementation status as a binary variable (implemented$=1$, not implemented$=0$). (ii) A more refined analysis is performed by specifying treatment intensity from TRQs as a continuous variable. The results from the first approach measure the percentage change in retail prices attributable to TRQ implementation itself, irrespective of the magnitude of tariff rate reduction from TRQs. The results from the second approach measure by what percentage retail prices change for every 1%p reduction in tariff rates due to TRQs.

Causal identification in DiD models depends entirely on the parallel trends assumption. Whether causal meaning can be attributed to DiD analysis results depends on whether this assumption holds, regardless of which variant of DiD technique is employed.[14] Below, the LP-DiD results for each of the four cases are presented graphically, and the pre-treatment parallel trends verification along with coefficient interpretation is discussed. It should be noted that in all four LP-DiD analyses, error terms were clustered by product to mitigate serial correlation.

### 4.3.1 Estimation Using TRQ Implementation Status (Binary)

This subsection first addresses the case where the treated group is combined into a single group of 11 products. The regression equation for implementing LP-DiD is given by Equation (1) below.

$$\Delta^h \ln P_{it} = \beta^h \Big( D_i \cdot \Delta D_{it} \Big) + T_t + X_{it} + \varepsilon_{it}^h \;\; , \quad -500 \leq h \leq 273. \tag{1}$$

In Equation (1), $i$ and $t$ denote product and time (day), respectively. $P_{it}$ in the dependent variable represents retail price in units of KRW/kg. Following Dube et al. (2023) rigorously, the dependent variable is transformed to $\Delta^h \ln P_{it}$, defined as $\ln P_{i,t+h} - \ln P_{i,t-1}$. This represents the difference between the log-retail price at $h$ periods after (or before) the event and the log-retail price immediately preceding the event. $h$ denotes the relative time point, with the TRQ implementation commencement date set as $h = 0$. For instance, 300 days prior to TRQ commencement corresponds to $h = -300$. The maximum range of data obtained and utilized in this study is $-500 \leq h \leq 273$. Meanwhile, since the equation already takes a first difference with respect to time using $\Delta$, the product fixed effect dummy ($I_i$) is eliminated. $T_t$ is the time fixed effect dummy, referring to absolute calendar dates rather than relative time points aligned by TRQ implementation timing.

The main explanatory variable is $D_i \cdot \Delta D_{it}$, where $D_i = 0$ indicates products without TRQ implementation (control group) and $D_i = 1$ indicates products with TRQ

[14]The rationale for why the parallel trends assumption must hold is as follows. The DiD model has a fundamental premise that potential outcomes in the absence of treatment can be explained solely by product fixed effects, time fixed effects, and control variables. According to this premise, since both treated and control groups are untreated at pre-treatment time points, the outcomes after removing fixed effects and control variables should be identical between the two groups. That is, the difference in adjusted outcomes between treated and control groups at pre-treatment time points should be zero, which is precisely what pre-treatment parallel trends signifies. Ultimately, the parallel trends assumption holding implies that the fundamental premise of the DiD model is satisfied. Therefore, if parallel trends do not hold, DiD model results cannot be interpreted as causal. For this reason, verification of the parallel trends assumption is essential in all DiD analyses.

implementation (treated group). $\Delta D_{it} = 1$ if the product is at the time point when the TRQ commences, and $\Delta D_{it} = 0$ otherwise. That is, $\Delta D_{it} = 1$ only when the product is in the treated group, the TRQ was not implemented at time $t - 1$, and the TRQ commenced at time $t$. For example, if a product is in the treated group and the TRQ was already implemented at time $t - 1$ and continues at time $t$, then $\Delta D_{it} = 0$. For control group products, $\Delta D_{it} = 0$ unconditionally.

The core of LP-DiD is utilizing only 'clean controls' as the control group. To adhere to this principle, preprocessing must be performed on the original data prior to regression, although this preprocessing is not visible in Equation (1) above. For all time periods $t$ and each $h$, observations are employed as clean controls regardless of whether they belong to the treated group if all of the following conditions are satisfied: (i) if $h \geq 0$, the product must not have received TRQ implementation even once during the period $t \sim t + h$; (ii) if $h < 0$, the product must not have received TRQ implementation even once during the period $t - h \sim t$; (iii) the product must not have received TRQ implementation even once during the period $-\infty \sim t$. According to this rule, all products not in the treated group serve as controls for all $h$ across all time periods $t$. Additionally, even products belonging to the treated group may satisfy the above rules in certain cases, in which case they serve as controls. For example, cherries satisfy all three conditions when $t = (\text{2024-1-1})$ and $h = -500$. Onions also satisfy all three conditions when $t = (\text{2025-2-1})$ and $h = +50$.

$X_{it}$ represents various control variables, specified as follows:

$$X_{it} = A_{it} + I_i \cdot O_t + I_i \cdot W1_t + I_i \cdot W2_t$$

In the equation above, $A_{it}$ denotes the 'applied tariff rate.' Since the applied tariff rate refers to the effective tariff rate in the absence of TRQs, it does not introduce endogeneity problems in the LP-DiD model by definition. Additionally, during the pre-TRQ-implementation period, applied tariff rates that vary by time and product directly affect retail prices by determining import volumes, thus playing an important role in controlling for pre-treatment parallel trends.

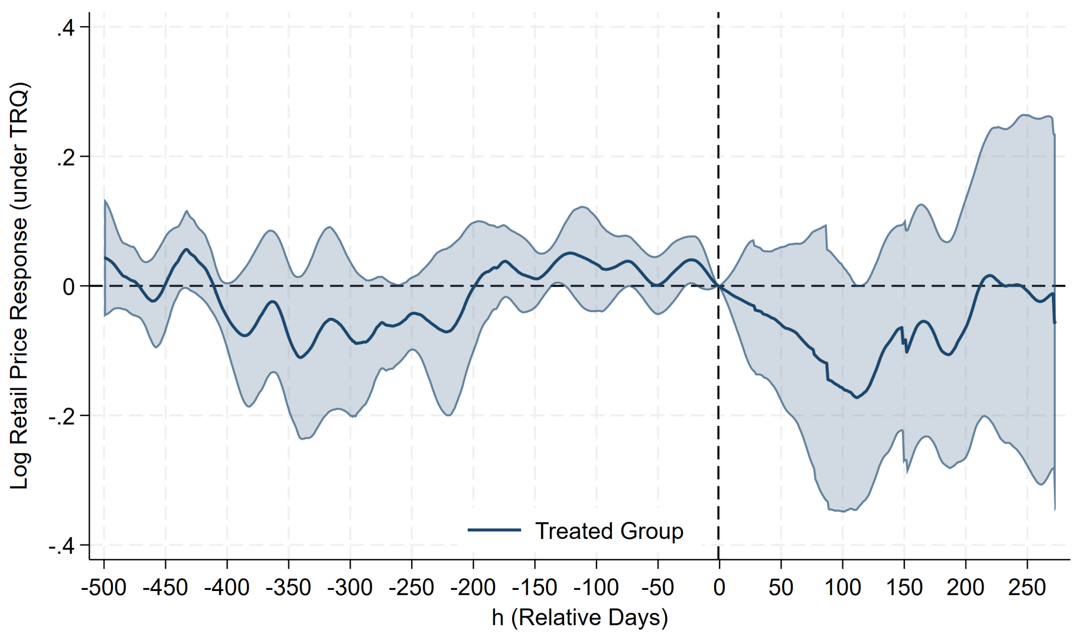
$O_t$ denotes the oil price converted to KRW. Oil prices affect retail prices; however, TRQ implementation cannot induce oil price fluctuations, so oil prices are not endogenous in the LP-DiD model. That is, including oil prices as a control variable does not create a bad control problem. Oil prices may exert heterogeneous effects on retail prices across products. For example, for onions, oil prices affect retail prices through vehicle transportation costs from domestic production areas to Seoul (the capital of Korea), whereas cherries, being highly perishable and unsuitable for maritime transport, are predominantly imported by air, so oil prices affect retail prices through air freight costs. To account for these heterogeneous effects across products, the oil price variable was interacted with a product dummy.

$W1_t$ and $W2_t$ are climate variables, inspired by the methodology of Roberts and Schlenker (2013), who employed climate variables as Instrumental Variables to estimate price elasticities of demand and supply. $W1_t$ represents the average climate value over the preceding 100 days from the current date, specifically including daily temperature, humidity, precipitation, and sunshine duration in Korea. Climate values at recent time points ($W1_t$) are exogenous as they are naturally determined. Climate is unpredictable and affects agricultural cultivation as a force majeure, causing supply fluctuations that consequently affect retail prices. Additionally, supply disruptions due to climate may influence the government's decision to implement TRQs. However, TRQ implementation cannot conversely affect naturally occurring climate. Therefore, including climate variables as control variables does not create a bad control problem; rather, excluding them would induce bias due to omitted variables. Thus, climate variables constitute essential control variables.

$W2_t$ represents the value of $W1_t$ from one year prior, specifically the average climate value from 465 to 365 days ago. Previous year's climate serves as a key decision-making indicator when producers plan current year production. According to Roberts and Schlenker (2013), when previous year's climate conditions were unfavorable, producers adopt a strategy of increasing planting quantities to achieve target production. Therefore, previous year's climate variables affect current year supply, which in turn forms a pathway directly affecting retail prices. Additionally, previous year's climate variables may exert a certain influence on current year TRQ implementation decisions. For example, when previous year's climate conditions were favorable, producers determine planting quantities based on this, and if current year climate deteriorates, supply shortages occur, leading to TRQ implementation —a logical mechanism exists. Ultimately, following the same logic as current year recent climate variables, previous year's climate variables also function as important control variables in the analytical model.

The results of estimating Equation (1) are presented in Figure 3. The estimated coefficients for pre-TRQ periods ($-\infty \sim -1$ days) are not statistically significant at the 5% significance level, confirming that the pre-treatment parallel trends assumption is satisfied. However, the estimated coefficients for post-TRQ periods ($+1 \sim +\infty$ days) are also not statistically significant. This indicates that the 11 treated products on average did not exhibit retail price reduction effects from TRQ implementation.

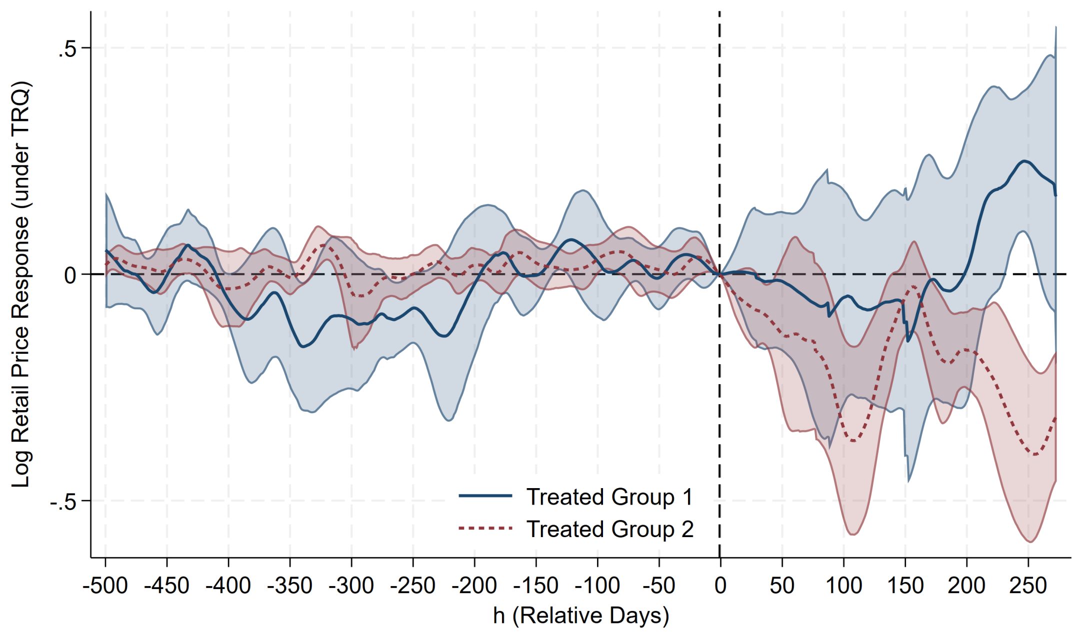
Figure 3: Single Treated Group Results for TRQ Implementation Status




Subsequently, the 11 treated products were partitioned into Group 1 (5 products) and Group 2 (6 products), with separate LP-DiD analyses conducted for each; the criteria for this partition are detailed in Section 4.3.3. Group 1 comprises leafy and root vegetables (napa cabbage, cabbage, radish, onion, and carrot), while Group 2 comprises fruits (cherry, kiwifruit, avocado, mango, banana, and pineapple). Equation (1) was estimated for each group paired with the same 29 control products (never-treated), with results presented in Figure 4. Importantly, these separate estimations yield results identical to simultaneous estimation of Equation (2) below, where $\beta_1^h$ and $\beta_2^h$ denote the coefficients for Group 1 and Group 2, respectively.

$$\Delta^h \ln P_{it} = \beta_1^h \Big( D1_i \cdot \Delta D1_{it} \Big) + \beta_2^h \Big( D2_i \cdot \Delta D2_{it} \Big) + T_t + X_{it} + \varepsilon_{it}^h$$
$$, \quad -500 \leq h \leq 273. \tag{2}$$

Figure 4: Two Treated Groups Results for TRQ Implementation Status




The analysis results reveal noteworthy heterogeneous effects between the two treated groups. First, both Group 1 and Group 2 satisfied the pre-treatment parallel trends assumption. For the post-implementation period, however, Group 1, consisting of leafy and root vegetables, exhibited estimated coefficients that were not significant for periods other than 230∼260 days following TRQ implementation, and were significantly positive during the 230∼260 day period. In contrast, Group 2, consisting of fruits, exhibited no significant retail price changes until approximately 90 days following TRQ implementation, but statistically significant price reduction effects emerged from 90 days onward (with the exception of the $145 \sim 175$ day period). For example, the retail price response at 250 days following TRQ implementation was estimated at $-0.39$, indicating that retail prices for Group 2 declined by approximately 39% due to TRQ implementation.

### 4.3.2 Estimation Using TRQ Treatment Intensity (Continuous Variable)

The preceding Section 4.3.1 estimated LP-DiD using only TRQ implementation status without considering treatment intensity. Therefore, the interpretation pertains to the retail price reduction effect 'when TRQs are implemented.' This section estimates LP-DiD incorporating TRQ treatment intensity. The interpretation in this case is the magnitude of retail price change for every 1%p reduction in tariff rates due to TRQs.

The regression equation for this implementation is given by Equation (3) below. This equation is identical to Equation (1) except for the addition of $G_i$ on the right-hand side. $G_i$ represents the intensity of the TRQ policy, defined as 'applied tariff rate − TRQ rate,' which varies by product. Detailed values are provided in Table 2. For example, bananas had an applied tariff rate of 24.2%, which was reduced to 0% due to TRQ implementation, resulting in a tariff rate reduction intensity of 24.2%p.

$$\Delta^h \ln P_{it} = \beta^h \Big( G_i \cdot D_i \cdot \Delta D_{it} \Big) + T_t + X_{it} + \varepsilon_{it}^h \ , \quad -500 \leq h \leq 273. \qquad (3)$$

Table 2: TRQ Treatment Intensity

| Product | Applied Tariff Rate (%) | TRQ Rate (%) | Treatment Intensity (%p) |
|---|---|---|---|
| Napa cabbage | 27.0 | 0 | 27.0 |
| Cabbage | 27.0 | 0 | 27.0 |
| Radish | 30.0 | 0 | 30.0 |
| Onion | 79.9 | 0 | 79.9 |
| Carrot | 28.7 | 0 | 28.7 |
| Cherry | 0.3 | 0 | 0.3 |
| Kiwifruit | 6.5 | 5 | 1.5 |
| Avocado | 8.0 | 0 | 8.0 |
| Mango | 15.8 | 0 | 15.8 |
| Banana | 24.2 | 0 | 24.2 |
| Pineapple | 29.5 | 0 | 29.5 |

The results of estimating Equation (3) with the intensity variable, integrating 11 products into a single treated group, are presented in Figure 5. This exhibits a pattern similar to Figure 3, which considered only TRQ implementation status. Pre-treatment parallel trends are satisfied, and no statistically significant retail price decline is observed following TRQ implementation.

Figure 5: Single Treated Group Results for 1%p TRQ Intensity Reduction

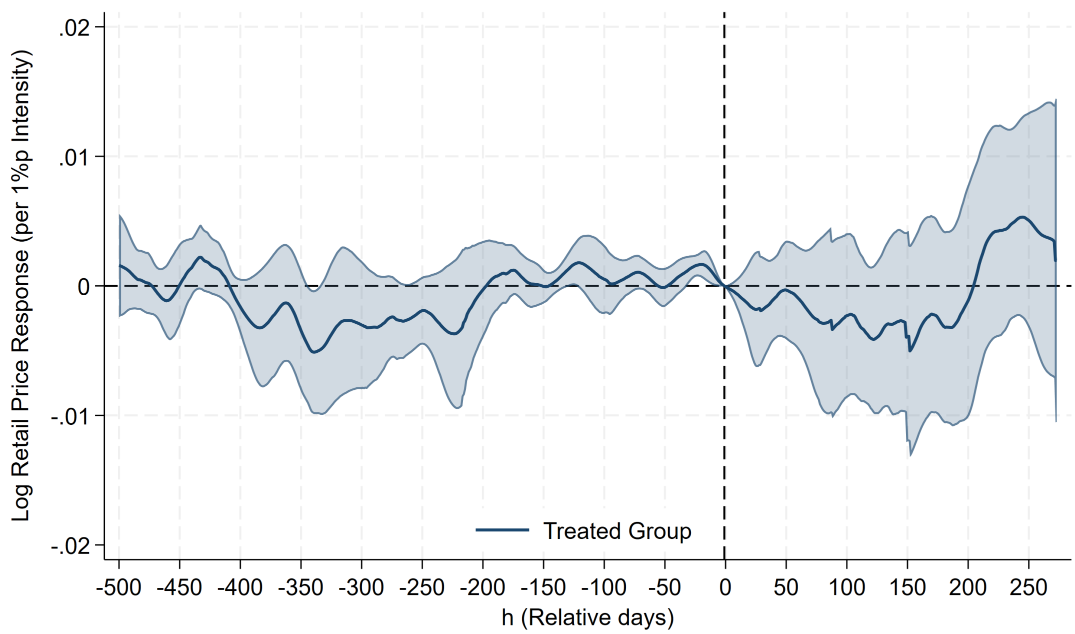
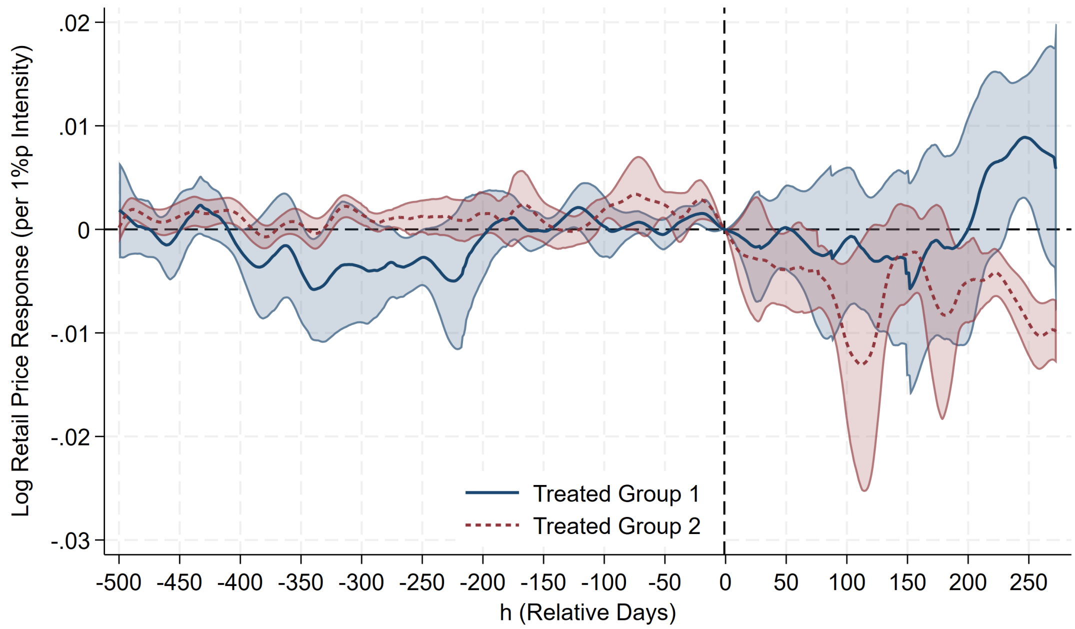



Figure 6 presents the analysis results with the treated group divided into Group 1 and Group 2, employing the same group division as Figure 4 but measuring retail price changes per 1%p TRQ reduction. Pre-treatment parallel trends are satisfied for both groups, with minor exceptions in Group 1. Group 1, consisting of leafy and root vegetables, exhibited no statistically significant retail price reduction effect following TRQ implementation; rather, it exhibited a brief increase effect during days 240∼260. The absence of retail price reduction effects in Group 1 can be interpreted through several factors. First, the tariff pass-through rate to consumers may be close to 0%. That is, distribution entities —including producers, importers, wholesalers, and retailers— may have absorbed all the gains from tariff rate reductions. Second, although the government introduced TRQs to suppress price increase trends for Group 1 products, TRQs may have been ineffective and price increases may have persisted.

In contrast, Group 2, consisting of fruits, exhibited no significant retail price changes until approximately 200 days following TRQ implementation, but price reduction effects emerged from 200 days onward. For example, the estimated coefficient multiplied by 100 at 250 days was calculated as $-0.904$, indicating that a 1%p tariff rate reduction

Figure 6: Two Treated Groups Results for 1%p TRQ Intensity Reduction




due to TRQs causally induced a 0.904% decline in retail prices.[15] This indicates a tariff pass-through rate to consumers of approximately 90%, implying that distribution entities captured only approximately 10% of the gains from tariff rate reductions while passing the remainder on to consumers.

### 4.3.3 Method for Dividing the Treated Group

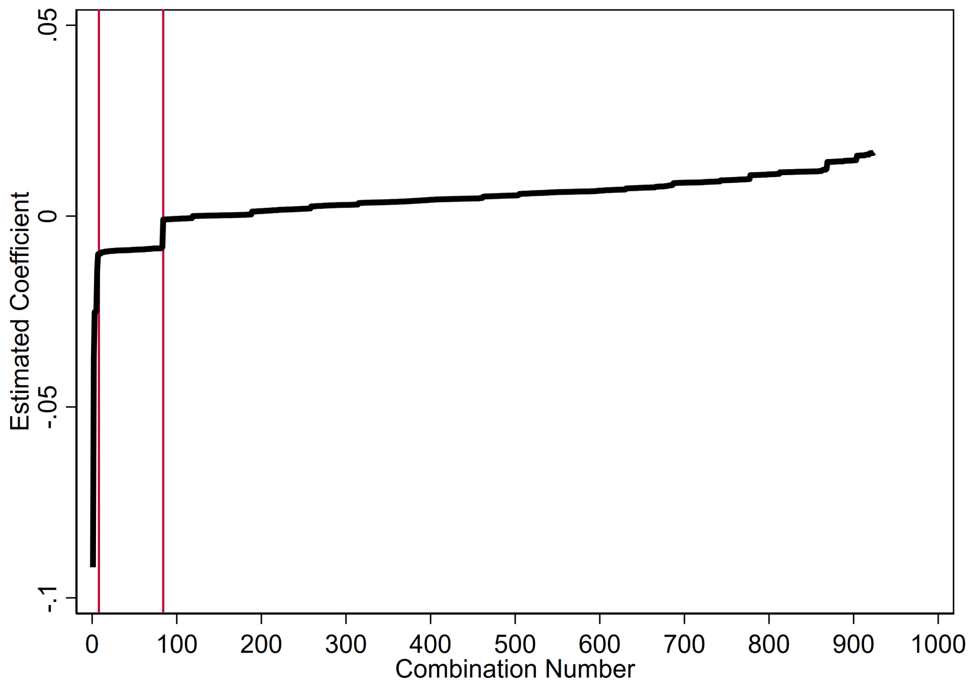
As presented above, this study divided the 11 products into groups of 5 and 6 to form two treated groups. This section explicates the division criteria and procedures in greater detail. The procedure is as follows. The 11 treated products were partitioned into all 462 possible 5 : 6 splits[16], with each split assigning one subset to Group 1 and the other to Group 2. For each configuration, the coefficient at $h = 250$ was calculated using Equation (1). This yielded coefficient values for a total of $462 \times 2 = 924$ groups, with each group consisting of a list of 5 or 6 products. These calculated coefficient values

[15] The more rigorously calculated value is $-0.896\%$. In a log-linear specification, the exact semi-elasticity of $P_{it}$ with respect to a one-percentage-point increase in $G_i$ is computed as $(e^{\beta^h} - 1) \times 100$. Accordingly, with $\beta^h = -0.009$, we obtain $(e^{-0.009} - 1) \times 100 \approx -0.896\%$.

[16] ${}_{11}C_5 \times 2$

were sorted in ascending order, and Figure 7 presents the results.

Figure 7: Coefficient Values for All Possible Group Combinations




Among the coefficients sorted in ascending order, the coefficients for combinations ranked 1st through 8th exhibit values substantially smaller than $-0.01$, qualifying as outliers. For example, a coefficient value of $-0.07$ corresponds to a tariff pass-through rate of 700%, which is deemed unrealistic as it is a level rarely observed in practice. Meanwhile, as evident in the figure, relatively stable negative coefficients persist from the 9th through 83rd positions, after which the coefficient increases sharply to approximately 0 at the 84th position and transitions to positive coefficients. Accordingly, this study regarded combinations ranked 9th through 83rd as 'effective treated groups' where TRQs significantly reduce retail prices.

Subsequently, the products in each group ranked 9th through 83rd were classified into fruits versus leafy and root vegetables, and the overall frequency was tallied. The results indicated that fruit products appeared 342 times while leafy and root vegetable products appeared 97 times, indicating that approximately 78% of the total were fruits. In particular, the combination closest to the median and mean values in the coefficient distribution for this interval (9th∼83rd) is the 44th group, which is characterized by all constituent products being exclusively fruits.

In summary, the retail price reduction effect from TRQ implementation can be interpreted as generally stronger for fruits. Based on these findings, this study selected the 44th group, composed entirely of fruits, as the representative combination for the fruit treated group and conducted all preceding and subsequent empirical analyses centered on this group.

### 4.3.4 LP-DiD Analysis at 250 Days Following TRQ Implementation

Table 3 consolidates all LP-DiD analysis results at 250 days following TRQ implementation. These results employ the same regression equations utilized in the figures examined above. Coefficient values and standard errors in the table are multiplied by 100 for improved readability.

Table 3: LP-DiD at 250 Days Following TRQ Implementation

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | TRQ Implementation Status | | | TRQ Treatment Intensity (1%p) | | |
| | Full | Group 1 | Group 2 | Full | Group 1 | Group 2 |
| TRQ Shock | -0.785 | 24.745*** | -38.985*** | 0.505 | 0.880** | -0.904*** |
| | (13.922) | (8.616) | (10.320) | (0.427) | (0.325) | (0.171) |
| Observations | 30578 | 28917 | 28555 | 30578 | 28917 | 28555 |
| $R^2$ | 0.600 | 0.600 | 0.574 | 0.601 | 0.600 | 0.574 |
| Adjusted $R^2$ | 0.583 | 0.582 | 0.555 | 0.583 | 0.582 | 0.555 |
| Within $R^2$ | 0.551 | 0.546 | 0.519 | 0.551 | 0.547 | 0.519 |

Standard errors clustered by product to mitigate serial correlation
Calculated at 250 days following TRQ implementation
Coefficient values and standard errors multiplied by 100 for improved readability
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Columns 1, 2, and 3 in this table present results considering only TRQ implementation status, using Equation (1). The interpretation of these coefficients is by what percentage retail prices changed due to TRQ implementation. The full treated group (Column 1) was not significant even at the 10% significance level. In contrast, Treated Group 1 (Column 2) was significantly positive even at the 1% significance level. Treated Group 2 (Column 3) was significantly negative at the 1% significance level, with a coefficient value multiplied by 100 of $-38.99$. Therefore, for Treated Group 2, which corresponds to fruits, the interpretation is that the tariff shock from TRQ implementation causally reduced retail prices by approximately 39% after 250 days.

Meanwhile, Columns 4, 5, and 6 present results considering TRQ treatment intensity, using Equation (3). The interpretation of these coefficients is by what percentage retail prices changed for every 1%p reduction in tariffs due to TRQs. Similarly, the full treated group (Column 4) was not significant, and Treated Group 1 (Column 5) was significantly positive at the 5% significance level. In contrast, Treated Group 2 (Column 6) was significantly negative at the 1% level, with a coefficient value multiplied by 100 of $-0.904$. Therefore, for Treated Group 2, which corresponds to fruits, for every 1%p reduction in tariff rates due to TRQ implementation, retail prices causally declined by approximately 0.9% after 250 days. This implies a tariff pass-through rate of approximately 90%.

## 4.4 Robustness Check

This section presents results based on alternative data preprocessing, while retaining the LP-DiD regression equations from Section 4.3. As Table 1 illustrates, certain products, such as carrot and cabbage, experienced quota exhaustion during specific periods. Although the TRQ system remains formally in effect during such periods, the tariff reduction benefits associated with the TRQ rate are unavailable to importers. The baseline analysis in Section 4.3 therefore classified these periods as *not-treated status*, consistent with this economic reality (corresponding to the white cells in Table 1). This principled approach, however, introduces several complications.

First, we examine cases where products belonging to the treated group are 'utilized as controls' under certain circumstances. For treated group products, regardless of whether quota exhaustion periods are classified as *treated status* or as *not-treated status* per the original data, quota exhaustion periods can never become controls. This is attributable to the clean control principle —products already belonging to the treated group have a history of receiving treatment over extended periods, even if they no longer receive TRQ benefits due to quota exhaustion. Therefore, from the perspective of being 'utilized as controls,' it is inconsequential which approach is adopted.

A further problem emerges when considering the treated products themselves.

Table 4: TRQ Implementation Table (Carrot)

| | 2022 | | | | | | | | | | | | 2023 | | | | | | | | | | | | 2024 | | | | | | | | | | | | 2025 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Carrot | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

Classifying quota exhaustion periods as *not-treated status* (white cells in the table), consistent with the original data, precludes the tracking of cumulative long-term treatment effects for these products. Taking carrots presented in Table 4 as an example, we cannot observe the 153-day effect from October 29, 2024 to March 31, 2025. This is because for this period to be recognized as a treated group under the LP-DiD method, the entire period from October 29, 2024 to March 31, 2025 must be *treated status* (black cells in Table 1 or 4) without exception. However, because quota exhaustion periods were classified as *not-treated status* per the original data, the periods December 20∼31, 2024 and February 20∼28, 2025 are not in *treated status* (i.e., very small white gaps appear in the table). Yet concluding that TRQs were not maintained long-term due to these minor interruptions is not logical. Therefore, quota exhaustion periods should be exceptionally classified as *treated status*.

A further complication arises from the treated products' perspective. Classifying quota exhaustion periods as *not-treated status* per the original data implies that when the TRQ system resumes after quota exhaustion (e.g., January 1, 2025 for carrot), this date is effectively recognized as a de novo treatment initiation —as though the product had never previously received TRQ coverage. Consequently, price changes are computed from this resumption date as if treatment were commencing anew.

This too is logically problematic. Recognizing January 1, 2025 as a new treated group merely because there was a very minor interruption period (*not-treated status*) immediately prior is not desirable. The January 1, 2025 time point has already had extended TRQ implementation periods in the past, and their effects have already accumulated. Conversely, if quota exhaustion periods had been exceptionally classified as *treated status*, the January 1, 2025 time point would never be recognized as a TRQ system commencement date under LP-DiD principles (because $\Delta D_{it} = 0$ in Equation (1)). Therefore, this case also provides grounds for why quota exhaustion periods should be exceptionally classified as *treated status*.

To summarize, this section presents robustness results from LP-DiD estimation using the same regression equations as the baseline analysis in Section 4.3, with the key distinction that quota exhaustion periods are reclassified as *treated status*. This robustness check adopts a different approach from Loginova et al. (2021), who employed a DiD model. In their approach, the treated period was defined as 'the harvest season when domestic production is concentrated (protection period)' —the period during which the Swiss government implements TRQs. These protection and non-protection periods alternate annually. Over their 5-year analysis period, they classified all protection periods as *treated status* and all non-protection periods as *not-treated status* without exception. This had its own valid reasoning: because the data under analysis had protection periods on an annual cycle, the non-protection periods were sufficiently long. Therefore, protection periods newly commencing after one year could be recognized as completely new treated groups.

### 4.4.1 Single Treated Group Results for TRQ Implementation Status

To conserve space, all figures from the Robustness Check section are presented in Appendix A. Figure 9 in Appendix A presents single treated group results for TRQ implementation status only, irrespective of the intensity of tariff rate reduction from TRQs. This is nearly identical to the baseline Figure 3, the result from Section 4.3. Pre-treatment parallel trends are satisfied, and no post-treatment effect is observed.

### 4.4.2 Two Treated Groups Results for TRQ Implementation Status

Figure 10 in Appendix A is identical to the preceding figure but presents results with the treated group divided into two. The two groups are identical to those employed in the baseline analysis in Section 4.3. This figure is nearly identical to the baseline Figure 4; however, whereas the baseline figure exhibited a brief absence of retail price reduction effect around 150 days following TRQ implementation, Figure 10 in Appendix A demonstrates the retail price effect being sustained continuously.

### 4.4.3 Single Treated Group Results for 1%p TRQ Intensity Reduction

Figure 11 in Appendix A is almost entirely identical to the baseline Figure 5.

#### 4.4.4 Two Treated Groups Results for 1%p TRQ Intensity Reduction

In the baseline Figure 6, Treated Group 2 briefly exhibited no retail price reduction effect around 150 days post-TRQ implementation; however, Figure 12 in Appendix A demonstrates a steady decline without such exceptions. Meanwhile, the retail price reduction effect for Group 2 at 250 days post-TRQ implementation was estimated at $-0.904$ in Figure 6, whereas it is estimated at $-0.969$ in Figure 12 in Appendix A. This indicates that for every 1%p reduction in tariff rates due to TRQ implementation, retail prices decline by approximately 0.90∼0.96%. That is, we can infer that the tariff pass-through rate to consumers lies between 90∼96%.

# 5 Conclusion and Policy Implications

This study empirically analyzed the causal effects of the Tariff-Rate Quota (TRQ) system on consumer prices employing econometric methodology. Among prior studies, Loginova et al. (2021) analyzed Switzerland's seasonal TRQs with a focus on domestic producer price,[17] establishing domestic producer protection through price decline prevention as the core objective of the system. In contrast, this study is differentiated by reexamining the same TRQ system from the perspective of an opposing policy objective —consumer price stabilization— and rigorously identifying effects on consumer prices employing a causal identification strategy.

This study identified causal effects based on Local Projection Difference-in-Differences (LP-DiD). In particular, considering the environmental characteristics that TRQs were introduced at different time points across products (staggered event) and that the magnitude of tariff rate reductions varied substantially across products (heterogeneous intensity), LP-DiD was introduced to overcome the limitations of conventional Two-Way Fixed Effect Difference-in-Differences (TWFE DiD) models (Dube et al., 2023). As Goodman-Bacon (2021) noted, in environments where staggered adoption and heterogeneous intensity coexist, traditional TWFE DiD approaches carry significant risk of producing biased estimates due to contaminated control problems and distorted weighted average structures.

In terms of data, this study constructed daily retail price data for a total of 40

[17] At the shipment stage.

agricultural products from 2021 to 2025. Among these, 11 products including mango, cherry, kiwifruit, banana, avocado, napa cabbage, and radish were classified as the TRQ treated group, whereas the remaining 29 products were classified as the never-treated control group. Additionally, through the professional expertise of licensed customs brokers, the 'applied tariff rate' that would have been imposed for each product in the absence of TRQs was precisely calculated. The applied tariff rates constructed in this manner were utilized as core variables for measuring tariff rate reduction intensity through their difference from TRQ rates.

The dependent variable was defined as the difference between the log retail price immediately preceding TRQ implementation and the log retail price at each lag (or lead) following implementation, enabling tracking of the dynamic path of how retail prices respond as time elapses following TRQ introduction. The pre-treatment parallel trends assumption was also confirmed to be satisfied, as estimated values at all pre-TRQ time points were not statistically significant.

The first key finding derived from this methodology and data is that when all 11 TRQ-treated products were analyzed as a single integrated treated group, the price stabilization effect of TRQs was not statistically significant. No significant price reduction effect was detected in either the analysis specifying TRQ implementation status as a binary variable or the analysis considering tariff rate reduction intensity as a continuous variable. This suggests the possibility that heterogeneous responses across products were offset in the averaging process, demonstrating that disaggregated analysis of the treated group is essential for precisely understanding TRQ policy effects.

Accordingly, this study reclassified the 11 treated products into two subgroups based on product characteristics. Group 1 consisted of leafy and root vegetables: napa cabbage, cabbage, radish, onion, and carrot. Group 2 consisted of fruits: cherry, kiwifruit, avocado, mango, banana, and pineapple. Group division did not rely on intuitive classification; rather, retail price responses at 250 days following TRQ introduction were estimated for all possible combinations of dividing the 11 products into groups of 5 and 6, and the most representative group among those exhibiting the largest reduction effects was ultimately selected.

The LP-DiD analysis results by group revealed noteworthy heterogeneity. Group 1 (leafy and root vegetables) exhibited no retail price reduction effect from TRQs, whereas Group 2 (fruits) demonstrated minimal price changes for a certain period immediately following TRQ implementation, followed by statistically significant declines. Specifically, at 250 days following TRQ implementation: (i) retail prices declined by 39% due to TRQ implementation, and (ii) a 1%p tariff rate reduction from TRQs causally induced a 0.9% decline in retail prices. This indicates a tariff pass-through rate of approximately 90% for fruits, suggesting that only 10% of cost savings from tariff reductions were absorbed in the distribution process while the remainder was reflected in consumer prices.

These empirical results demonstrate that the price stabilization effects of the TRQ system do not manifest uniformly across all products but differ fundamentally depending on product characteristics and distribution structures. From a policy perspective, if the TRQ system is to be utilized for 'consumer protection' rather than 'producer protection,' the results of this study suggest that prioritizing implementation for fruits would be more effective than broadly implementing it for leafy and root vegetables.

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# A Appendix: Figures

Figure 8: Retail, Wholesale, and Import Prices (Pineapple)

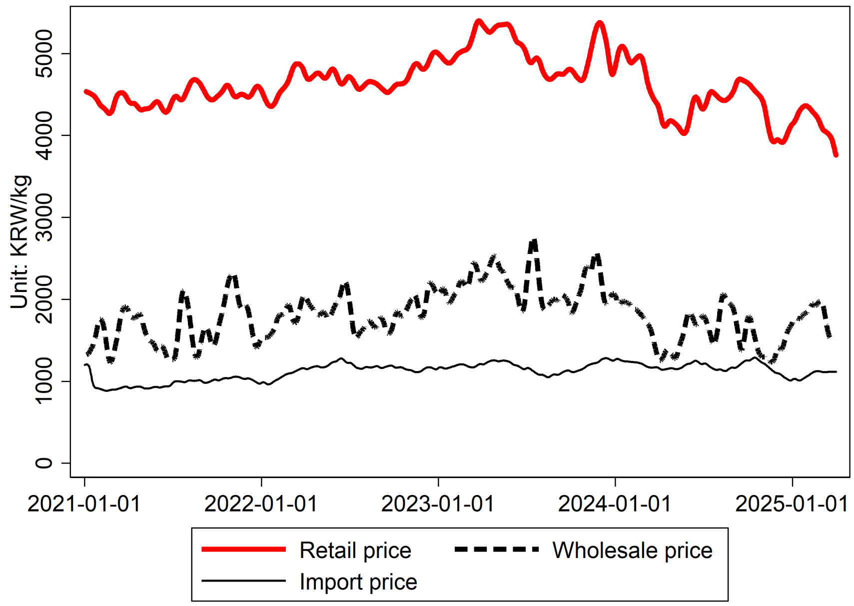

Figure 9: Single Treated Group Results for TRQ Implementation Status

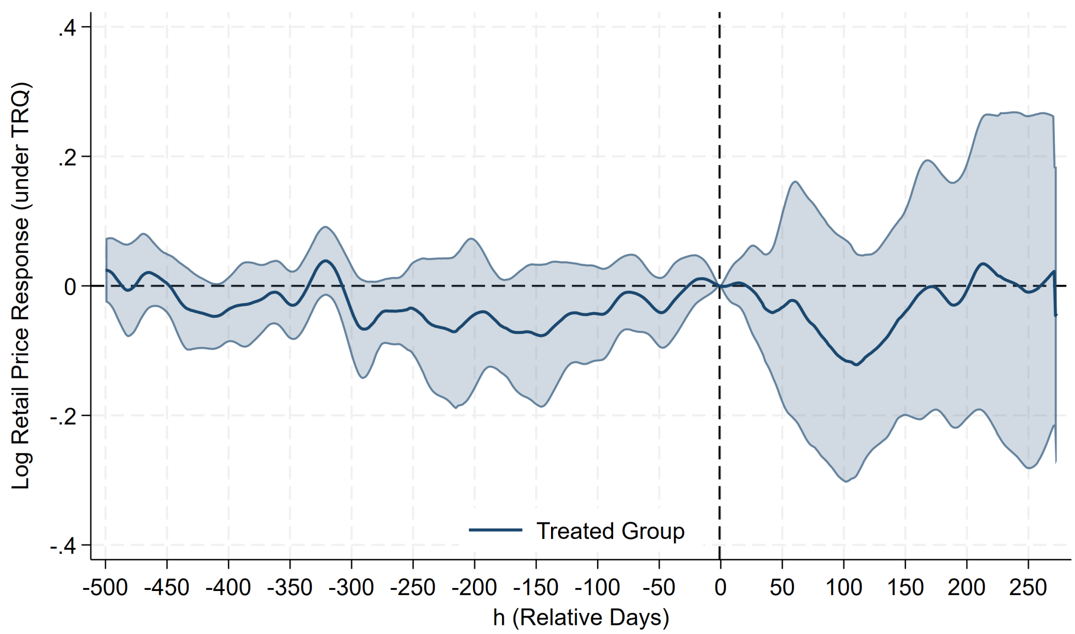


Figure 10: Two Treated Groups Results for TRQ Implementation Status

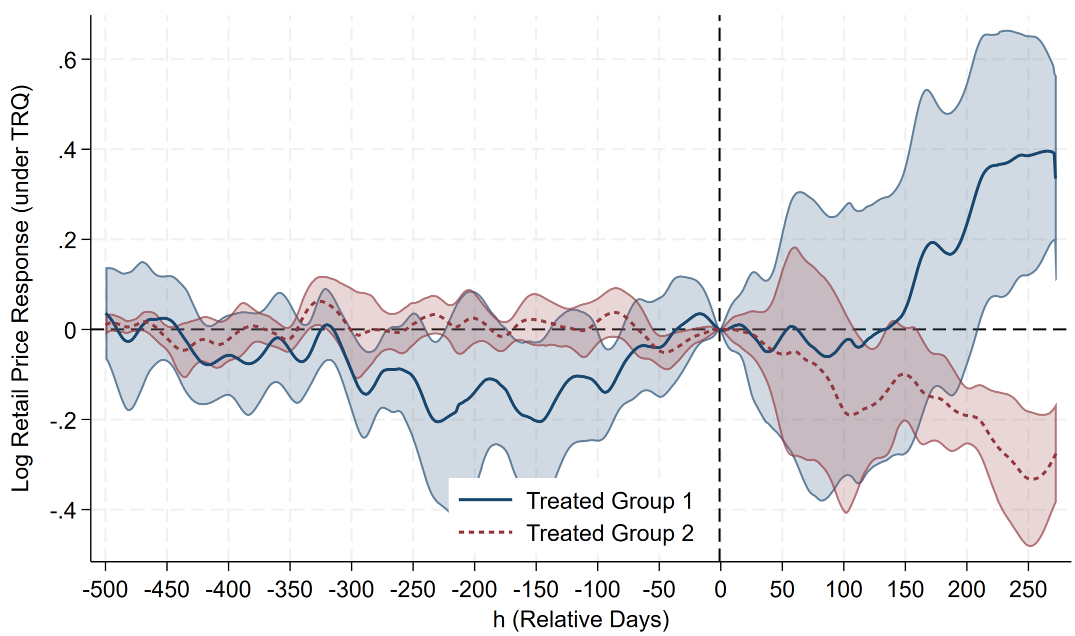

Figure 11: Single Treated Group Results for 1%p TRQ Intensity Reduction

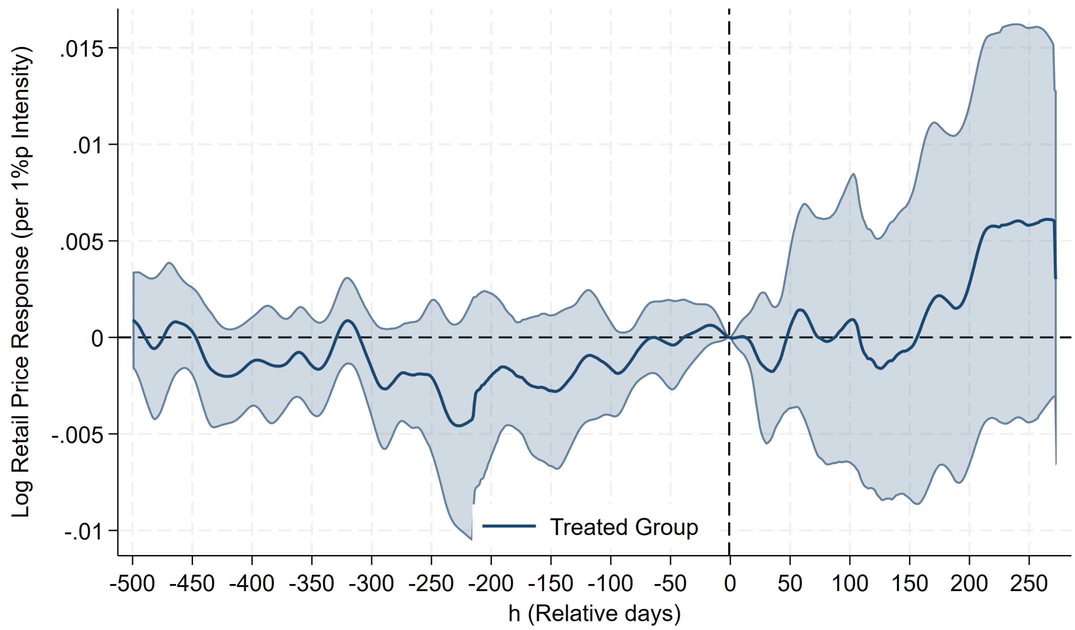


Figure 12: Two Treated Groups Results for 1%p TRQ Intensity Reduction