STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
BE551 Degree project in Economics
Fall 2025

The Pass-Through of a Large and Permanent VAT Reduction on Food to Consumer Prices: Evidence from Romania

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Abstract: We analyze a large and permanent VAT rate reduction implemented in Romania in 2015 for foods and non-alcoholic beverages, which its PM argued would "almost entirely be reflected in lower prices, not in higher profits for some retailers". Using the SDID method introduced by Arkhangelsky et al. (2021), we create a Romanian Doppelgänger to analyze the food price effects of the VAT cut using monthly food price data from EU member states. Our results reveal prices falling by 9.14%, suggesting that 75.77% of the reduction in VAT passed through to consumers. We argue that this incomplete shift in consumer prices was caused primarily by two factors, the relative elasticity of demand and imperfect competition. In the case of the prior, retail sales volumes for food increased by 11.4% in the month following the cut and remained high, thus putting upward pressure on prices. As for the latter, retailers report increasing profits after the cut, pointing towards it allowing them to raise margins. In contrast to prior papers finding complete price shifts, we note an absence of price monitoring made visible to consumers, in combination with doubts over the Competition Council's authority to intervene and enforce sanctions against unjust price setting. Finally, we find large variations in pass-through between product groups, but fail to identify a pattern pointing towards underlying mechanisms explaining this result.

Keywords: Value-added tax, Pass-through, Prices, Synthetic difference-in-differences
JEL: E31, H2, H22

Supervisor: Andreea Enache
Date submitted: 2025-12-06
Date examined: 2025-12-15
Discussants: Isak Westelius and Esaias Hedin
Examiner: Johanna Wallenius

Acknowledgements

We want to express our sincerest gratitude to our supervisor, Andreea Enache, for her inputs and encouragement during the entire fall period. A warm thank you also goes out to Yicheng Sun for his invaluable feedback during the later stages of our writing.

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1. Introduction

In the EU, the value-added tax applied to consumer goods and services is one of the most important sources of taxation, accounting for 15.7% of total government tax revenue (General Secretariat of the Council, 2025). Reductions in VAT rates, especially for necessities such as food, has been a fiscal policy tool growing in popularity in recent years, where a common argument used is to increase affordability for consumers. In turn, the effectiveness of such a reduction is directly tied to its ability to reduce consumer prices, where the more of it is passed through to prices, the more the consumer is at benefit (Fedoseeva and Van Droogenbroeck, 2024; Crossley et al., 2014). However, the ability of a VAT rate cut to reduce prices for consumers is far from a given. According to the standard theoretical model under perfect competition, the less elastic side of the market bears the burden of a tax (Chetty et al., 2009). In consequence, the less elastic the consumer base, the more of a VAT reduction is expected to pass through to consumer prices. Meanwhile, under imperfect competition, cuts in the VAT rate can allow firms to raise margins, with mechanisms such as market structure, price salience to consumers and menu costs determining to the extent which this is possible. In extension, pass-through of VAT rate changes range from 0% to over 100% in previous empirical literature (Vàn and Olah, 2018; Frey and Haucap, 2024).

In this thesis, we analyze the pass-through of a large and permanent VAT rate reduction on foodstuffs in Romania. The government both argued and forecasted that the cut would pass through to consumer prices near fully (Chiriac, 2015), through price reductions of 12% (99.2% pass-through). However, several reasons exist for why these forecasts may have been inaccurate, where both demand effects and imperfect competition are likely to have impacted pass-through, both on aggregate as well as at the product level. Given the significant costs of a large VAT reform to the government budget, in this case estimated at over 5 billion RON (1.12 billion euros) per year (Dumitru, 2015), it is key to understand to what extent it succeeds in its goal of reducing consumer prices. Hence, we define the following research questions:

(1) *To what extent did Romania's 2015 VAT reduction on food pass through to consumer prices?*
(2) *Was there heterogeneity in VAT pass-through across food categories?*
(3) *What mechanisms drove this pass-through rate?*

By addressing these questions and analyzing the Romanian example, we contribute to a growing set of recent empirical literature published on pass-through for VAT rate reductions on food. In general, these studies find high rates of pass-through, primarily explained through food being a necessity with low demand elasticity. Most recent examples study temporary small cuts introduced in 2022 and 2023 by EU member states and find full or near full pass-through,[1] suggesting the effectiveness of a VAT cut of food in reducing prices. However, temporary cuts have lower effects on consumer purchasing power due to the knowledge of their later reversal, likely implying less effects on demand. Moreover, these cuts were

[1] See e.g. Bernardino et al. (2025), Forteza et al. (2025) and Jaworski and Olipra (2025)

characterized by environments of high inflation, which may make consumers more attentive to prices, putting higher pressure on retailers to pass a cut on to consumers (Jaworski and Olipra, 2025). As for literature on permanent cuts on food, the literature is more scarce. The most prominent example comes from Gaarder (2019), who analyzes a 2001 VAT reduction from 24% to 12% in Norway and finds full pass-through, arguing that “taxes levied on food are completely shifted to consumer prices”. There is reason to believe that such a conclusion is too far drawn, with Norway being one of the richest countries in the world, presumably making price effects on consumer demand smaller. Additional empirical examples on permanent cuts on food analyze product specific product outcomes, finding high levels of product heterogeneity, putting further doubt on an assumption of full pass-through (Vàn and Olah, 2018; Politi and Mattos, 2011).

Against this background, our thesis distinguishes itself from prior empirical studies on VAT pass-through in two key ways, allowing us to make new policy relevant insights. First, we address a cut which is relatively larger than in prior papers, is implemented in a low inflation environment and reaches a relatively poorer population, spending a higher portion of income on food. In turn, this is likely to, for example, result in higher impact on consumer demand which would reduce pass-through according to the standard theoretical model. The Romanian example thus provides more policy relevant insights for other Eastern European countries where economic and food market conditions are similar. These apply both to a current EU member such as Bulgaria, as well as candidates such as Moldova or Bulgaria where reform of VAT systems are likely to be required for EU accession. Second, our thesis also implements a novel identification strategy by using the Synthetic Difference in Differences estimator, introduced by Arkhangelsky et al. (2021), which addresses several of the problems for identification that prior papers face. Prior papers use two main strategies for identification. The first such strategy compares trends between untreated and treated products, seen for example in Forteza et al. (2025), which raises concerns over treated products being endogenously chosen and sharing different characteristics to those untreated. The second strategy uses single neighboring countries as a counter-factual instead, exemplified by Jaworski and Olipra (2025) who compare outcomes in Poland to Czechia. For causal identification, this requires the assumption that absent a VAT cut, two separate economies would have seen identical price developments. Meanwhile, the SDID estimator which we implement, creates a counterfactual entity for which price trends most closely resemble the treated entity, weighting both on unit and time trends. By giving more weight to countries in the untreated group that exhibit trends similar to Romania and pre-treatment periods which are the most informative of the counterfactual trend of Romania, this makes results more robust to violations of the parallel trends assumption.

Consequently, our results point toward incomplete pass-through of the VAT cut of 75.77%, reaching its peak three months after the cut at around 86%. The pass-through rate stays consistent when changing our control group based on several economic factors which could impact our result. In addition, we find no significant effects when replacing the treated country. Finally, at a product category level, we find substantial heterogeneity in pass-through rates.

Using suggestive evidence, we attribute lower pass-through estimates than in prior examples to two main mechanisms. The first of these connects to Romania, likely being characterized by relatively higher elasticity of demand, which is supported by large increases in food quantities sold following the cut, not observed in prior examples. The second comes from imperfect competition, where a lack of price visibility and transparency to consumers allowed retailers to pocket part of the VAT reduction by increasing margins. Unfortunately, our data does not allow us to disentangle the contribution from each mechanism, and we are also unable to find a clear pattern explaining product pass-through heterogeneity. In turn, this suggests a need for additional research quantifying effects of these mechanisms on food price pass-through.

The rest of this thesis is structured as follows. Section 2 covers theory and past empirical literature on pass-through. In Section 3, we describe institutional details on the VAT reform, the Romanian economy and retail market. Section 4 introduces the data and empirical strategy that we use to obtain our results, covering both the DiD and SDID methods. Subsequent results from these methods are presented in Section 5, for which robustness is shown in Section 6. Finally, Section 7 discusses these results in relation to past empirical research and theoretical mechanisms, with Section 8 concluding our findings.

2. Literature Review

Under the simplest theoretical case of perfect competition, where both sellers and buyers are price takers and choose welfare maximizing quantities, the relative elasticities of demand and supply determine the price effect of a VAT change. As is shown by Weyl and Fabinger (2013), the more inelastic side of the market bears the burden of tax increase, or vice versa, receives the benefits of tax reduction. If the quantity demanded is inelastic, moving little in response to price changes, whereas supplied quantities adjust at low cost, the price change relative to a VAT change is larger, implying higher pass-through to consumers. For an illustrative example, consider two extreme cases, one where demand is perfectly inelastic and the demand curve thus is vertical, the other where demand is perfectly elastic and the demand curve is horizontal. In the first, consumers demand the same quantity regardless of price, and thus quantities remain constant after a tax increase or decrease, which is solely reflected in prices. Conversely, in the second situation, consumer prices remain constant as quantities adjust to absorb the tax change, implying no pass-through of the tax to consumer prices.

In practice, neither the elasticities of demand nor supply are observed and thus, the pass-through rate of a VAT cut is difficult to predict beforehand. Prediction is also made more difficult in markets characterized by imperfect competition, common in grocery retail, where firms no longer are price-takers (Gaarder, 2019). In extension, this creates a need for empirical analysis of a VAT reform's effectiveness. Prior such studies find widely varying pass-through rates, ranging from 0% for catering services in Hungary (Vàn and Olah, 2018), to pass-through of over 100% for a VAT reduction on female hygiene products in Germany (Frey and Haucap, 2024). In general, empirical examples find higher pass-through for necessities, such as food, presumably characterized by inelastic demand, than for other goods and services (Fuest et al., 2025; Vàn and Olah, 2018). In addition, literature has identified four mechanisms causing variations pass-through: consumer income- and substitution effects, supplier and retailer market structure, menu costs and finally consumer attention, to both a tax itself and product prices.

Income and substitution effects.

On the demand side of the market, both income and substitution effects have been found empirically to affect consumer response to a VAT change and thus, in turn, prices. An income effect arises from consumers needing to spend less to buy the same basket of goods if prices fall, effectively raising their purchasing power and allowing them to buy more goods from the same basket (Crossley et al., 2014). Meanwhile, a substitution effect arises within-period if consumers substitute goods not subject to the cut for those where the rate is unaffected. In addition, a VAT cut may induce intertemporal substitution effects, where consumption of goods, where possible, is delayed until a lower rate is implemented. Such an effect varies by product, as it is easier for a consumer to postpone purchases of luxuries and durable goods than necessities (Browning and Crossley, 2000; Crossley et al., 2014). Empirically, these effects also reflect in price shifts following VAT changes. For a temporary cut in the standard VAT in the UK in 2009, implemented in order to raise consumer spending, Crossley et al. (2014) find that firms initially passed the cut through to consumers, but that at least part of this was reversed thereafter. This pattern coincides with purchases, which increase in the immediate period following the cut when prices are low. After the cut's expiration, the authors find a drop in sales, pointing towards an intertemporal substitution effect where consumers bring purchases forward. Meanwhile, at a product level, Carare and Danninger (2008) observed a process of "inflation smoothing" in Germany, where following the announcement of a VAT hike, consumers brought forward spending which allowed suppliers to raise prices. In turn, they find that this effect is the most prevalent for durable goods. Benedek et al. (2020) extend this finding by analyzing pass-through of VAT changes in Eurozone countries between 1999 and 2013 and observe higher pass-through for durables.

Market structure.

On the supply side of the market, a common mechanism found to affect pass-through in the literature is market structure, where multiple studies find that a higher degree of competition between producers leads to pass-through rates closer to 100%. For example, Dimitrakopoulou et al. (2024) find that when a 2018 VAT reform in Greece on gas harmonized rates across islands, pass-through in islands with eight or more stations reached 80% as opposed to 50% where there was just one gas station. With the amount of stations on an island determined by land area, the authors argue that this variation is exogenous. Similar conclusions are reached by Alm et al. (2009), who study U.S. gas stations and find lower pass-through in rural areas, as well as for Hindriks and Serse (2019), finding that the intensity of local competition was strongly related to pass-through for alcohol excise taxes in Belgium. Additional evidence on the effects of competition on pass-through is found in areas characterized by cross-border competition. Cawley and Frisvold (2017), study a sugar tax implemented in Berkeley, California and find that for each additional mile to a store unaffected by the tax, stores were able to pass more of the tax through to consumers. A similar tax increase was analyzed by

Campos-Vázquez and Medina-Cortina (2019) on soft drinks in Mexico, finding that stores in general overshifted the tax to consumers but that pass-through was closer to 100% when the number of stores in the area increased.

In turn, several empirical papers find evidence that lower levels of competition allows firms to increase margins, in turn reducing pass-through. Using a panel of 14 Eurozone countries and over 800 VAT changes from 1999-2014, Copestake and Bellon (2022), find that firms retain more of VAT cuts through higher markups when the upstream sector is less competitive. Benzarti et al. (2020) observe the same phenomenon for two equally large VAT changes for hairdressers in Finland, a decrease and an increase, finding that markups after the former rose by double the amount that they dropped following the VAT increase.

At the same time, not all studies are able to find a clear relationship between more intense competition and higher pass-through of a tax change. For example, Shrestha and Markowitz (2016) estimate pass-through of tax-increases on U.S. beer prices and find overshifting, where a 10 cent increase in taxes led to price increases by 17 cents. This estimate, they argue, is remarkably similar to the one found in 1991 following a federal tax increase, despite the industry becoming less competitive following several mergers of leading beer producers. In addition, Gaarder (2019) finds full pass-through of a VAT reduction of a twelve percentage point reduction on foodstuffs in Norway in 2001, despite pointing out that the Norwegian retail market is highly concentrated.

Menu costs.

Another mechanism affecting price setting following VAT changes, is the presence of menu costs, as updating prices is costly which in turn can have an effect differing both due to policy context and by firm. Relating to the nature of policy, a VAT cut which is implemented for a temporary period, is expected to face higher menu costs as firms have to bear costs of updating prices twice, which thus could reduce pass-through (Fuest et al., 2025). Meanwhile, at a firm level, there is evidence that menu costs that firms face differ. Analyzing a temporary VAT cut in Germany in 2020, implemented in order to stimulate consumption, Fuest et al. (2025) find a pass-through rate of 80% for foods, where the rate was reduced from 7% to 5%. This pass-through is higher than for other products for which VAT also was cut, which they argue stems from food being a necessity with low demand elasticity. However, they also find variations in pass-through at a product level, where prices dropped more for private label brands than independent ones. In turn, they argue that this is consistent with theory, where in the instance of private labels, a retailer controls brand design, pricing, and marketing, meaning that it can update prices as it wishes. Meanwhile, for independent brands, retailers and the producer negotiate over pricing strategy and presentation of the product. In turn, as the VAT rate is included in the sales price observed by the consumers, these negotiations cover the after tax price, reducing retailer flexibility in case of a VAT change. Jonker et al. (2004) finds additional evidence that menu costs vary by firm, using price data from the Netherlands between 1998 and 2003. Their evidence suggests that pass-through of a VAT increase is passed through fully, while also observing that prices are more flexible in cases where a firm is large or when a retail firm consists of the owner only.

Tax salience to consumers.

Commonly cited as an important mechanism in recent empirical findings of high pass-through is tax or VAT salience (visibility) to consumers. Chetty et al. (2009) provide both a theoretical framework as well as empirical evidence to prove that consumers' behavioral response is stronger to a tax which is salient, thus making consumers attentive to it. By running a field experiment in a U.S. supermarket, where sales taxes are not reflected in the price displayed to consumers, they find that demand falls by 8% when adding tags displaying tax-inclusive prices for cosmetics, hair care accessories and deodorant.

Several empirical papers since have argued for similar effects from certain characteristics of VAT interventions. Analyzing a temporary VAT cut in Portugal between April 2023 to January 2024 where rates on basic food were reduced from 6% to 0% in order to alleviate pressures from high inflation, Bernardino et al. (2025) find complete and immediate pass-through to consumer prices. The authors obtain this estimate by using an event study approach comparing treated and untreated products by using daily price data on 43,283 store items, and further verify robustness using a number of different specifications, such as comparing with outcomes in Spain. In turn, they argue that full pass-through was facilitated by the policy's high salience, which they exemplify by supermarkets having to label affected products, intense media reporting and the high-inflation environment, all of which would have made consumers more attentive, pressuring retailers to pass the cut onto consumers. In addition, they also note that wholesale prices fell during the time of the VAT cut, reducing the cost of inputs, which could have made it easier for retailers to pass the cut onto consumers. A similar conclusion is reached by Jaworski and Olipra (2025) studying a temporary VAT cut on basic foods in Poland in 2022. Using monthly Eurostat Harmonized Index of Consumer Prices (HICP) data for a variety of food categories, the authors implement a dynamic event-study approach, with Czech food prices used as a counterfactual. In turn, they find that between 44.0% and 58.2% of the cut shifted to consumers in the first month, growing to 94.8%, which the authors argue was facilitated by the multitude of measures taken by the Polish competition authority. The authors list price monitoring, inspections and mandatory display of information on the cut at the point of sale to consumers.

Product visibility to consumers

Closely related to the salience of a VAT change itself, other empirical studies report pass-through varying between product categories due to differences in consumer attention. Politi and Mattos (2011) analyze the price response of ten goods in the Brazilian basic food basket to state-level VAT changes between 1994 and 2008. In turn, they find asymmetry, where prices respond more to increases than decreases, a phenomenon most visible for goods with a smaller share of household expenditure. This, they argue, stemmed from the benefits of searching for lower prices for a product diminishing, the less of it that the consumer purchases. In a study on a permanent VAT cut in Germany on female hygiene products, Frey and Haucap (2024) find similar patterns in product pass-through heterogeneity. In an environment where demand effects are unlikely given that biological factors guide need, the authors find overshifting (pass-through of above 100%) on average, with the largest shifts observed for the most quantitatively significant product type and in specialized retailers. In addition, they observe that for products offered by more than one retailer, pass-through increased. Jaworski and Olipra (2025) find similar patterns, observing the highest pass-through for categories with the largest share of the Polish food expenditure basket. However, they also note an absence of significant price reductions in most categories, acknowledging that each food category in their Eurostat HICP dataset constrained products sharing different economic characteristics, in turn elevating standard errors.

Further effects on pass-through as a result of product visibility to consumers, are found by Vàn and Olah (2018), who study product pass-through heterogeneity of VAT cuts in Hungary between 2016 and 2017. The authors implement the Synthetic Control Method, introduced by Abadie and Gardeazabal (2003), and construct a synthetic Hungary using prices from other EU countries during eight pre periods. In turn, they find full pass-through for product categories *pork* and *poultry*, while estimating a rate of 58% for *fresh milk* and *eggs*. This discrepancy, the authors argue, stemmed partly from that the reduced rate only applied to fresh milk, while excluding non-fresh milk, thus making it harder for consumers to distinguish between the two. For comparison, they apply the same method in other contexts, including for two HICP categories in Romania, but do not display weights or countries included in their control group.

3. Institutional Details

The value added tax (VAT) in Romania and other EU countries, is an indirect tax collected by the state from sellers, which is included in the price that the consumer pays for goods and services. In case the seller has paid VAT on product inputs, they are able to deduct this amount before paying the state, effectively meaning that VAT is paid by the consumer.

Following years of fiscal policy mismanagement, Romania raised its VAT rate of 24% on all goods and services on 1 July 2010 in order to reduce its budget deficit (Bryant, 2010). Unlike in many other EU member states, this rate was not differentiated for foodstuffs. However, by September 2013, a 9% for bread in order to reduce tax evasion in the sector (Chiriac, 2013). Following discussions around broadening the reduced rate after improved fiscal stability, the Romanian government announced on 7 April 2015 the implementation of a 9% rate for all foods and non-alcoholic beverages by 1 June of the same year (Romanian Government, 2015). The intervention was forecast to cause state budgetary income loss of over 5 billion RON (1.12 billion Euros) annually (Dumitru, 2015). As motivation for this cost, the government stated a need for reducing the burden of food costs on households, with its prime minister arguing that “This VAT cut should almost entirely be reflected in lower prices, not in higher profits for some retailers” (Chiriac, 2015). This notion was also reflected in government forecasts where price drops of around 12% were predicted (Chiriac, 2015), notably corresponding to full pass-through of the VAT cut to consumer prices.[2]

[2] A product that previously had a price of 124 RON (of which 24 RON is VAT) experiences full pass-through if it trades at 109 RON following the VAT cut. This corresponds to a price drop of $15/124*100\% \approx 12.1\%$

Subsequently, concerns were raised during the announcement period over retailers raising prices in anticipation of the VAT rate reduction (Grigoras, 2015). This was followed up by the president of the Romanian Competition Council arguing that retailers were blocking a "Price Monitor" approved by the government in the year prior (Toma, 2015). In turn, big retailers were called to Romania's parliamentary committee of agriculture while the PM threatened retailers stating that any trader not realizing the VAT cut in prices, would see taxes raised to the point where "they should lose all they gain on speculation" (Grigoras, 2015). Further, a month after the cut, the Ministry of Agriculture and Rural Development published a report on measures taken to ensure that the VAT cut would reflect in prices. These included inspections carried out in a variety of stores, as well as an agreement with retail chains Auchan and Carrefour to freeze prices until the VAT cut's implementation (Stirile ProTV, 2015). However, doubts also existed with regards to the state's ability to enforce sanctions against unjust price-setting, with the Competition Council only able to intervene upon demonstration of cartel price-fixing (Stirile ProTV, 2015).

By 1 June, a 15 percentage point VAT rate cut was implemented for food and non-alcoholic beverages, but in order to understand the effects that this cut eventually went on to have, it is key to understand the market in which it was implemented. As an EU economy, Romania stands out in several ways. In 2014, consumer spending on food and non-alcoholic beverages reached 31% of consumer expenditures, which was higher than in any other EU country (Eurostat, 2025a). Much of this may be explained by its real GDP per capita of 7,800 EUR in 2014, placing Romania second to last in the EU, only ahead of Bulgaria (Eurostat, 2025b). In the same year, GDP grew at a rate of 2.5%, above the EU average of 1.3% and in line with countries such as Slovakia, Sweden and Lithuania (Bourgeais, 2015). Meanwhile, inflation reached 1.1% in 2014, having stabilized following years of instability in the early 2000s (World Bank Group, 2025). As for its retail sector, prices in Romania were comparatively low, seeing potential savings for Hungarians traveling across its border of up to 19.5% in 2015 (European Commission, 2017). Following its EU accession in 2007, the amount of available shops in Romania by 2015 had grown rapidly, reaching 1,713 in 2015 compared to 612 in 2010, with 81% of these being either convenience stores, supermarkets or discounters (Stoenescu, 2017). In this market, no clear leader had yet emerged, where the top 3 largest chains Kaufland, Carrefour and Auchan gathered market shares of 12.3%, 7.4% and 5.9% respectively (FRD Center, 2017). This also placed the Romanian modern retail market at an HHI score,[3] of 1880 in 2012, slightly below the EU average of 1919 (European Commission, 2014). Nevertheless, such a score still indicates that the market was "moderately concentrated" (Bromberg, 2025). By year-end of 2015, following the VAT cut on 1 June, Romania's top 13 biggest international retailers reported 13% growth in turnover while seeing reported profits rise by 131% (Stoenescu, 2017).

[3] A measure for retail store concentration, defined as "sum of the squares of the market shares" for retail chains, reaching a value between 0 and 10,000, where the lower the score, the more competitive the market

4. Data and Empirical Strategy

4.1 Data

The main outcome variable which we study to estimate the pass-through effect of Romania's VAT rate cut in 2015, is the Harmonized Index of Consumer Prices (HICP), which is divided into 12 product categories by Classification of Individual Consumption According to Purpose (COICOP). Two of our 12 categories are reported at a broader level, namely *Food and non-alcoholic beverages* and *Food* whereas the rest are reported at the 4-digit level. These categories are *Bread and cereals*, *Meat*, *Fish and seafood*, *Milk, cheese and eggs*, *Oils and fats*, *Fruit*, *Vegetables*, *Sugar, jam, chocolate, honey and confinery*, *Food products n.e.c (not elsewhere classified)* and *Non-alcoholic beverages*. The data for each category is sourced via Eurostat (2025c) from the dataset *prc_hicp_midx*. Each country reports monthly prices in each product category, with 2015 as the reference year, allowing for comparison over time. In total there are 31 countries in the data during the time period: the 28 EU member states in 2015, Norway and Iceland, both part of the European Economic Area (EEA) internal market, and Switzerland. Reporting definitions and classifications are harmonized in legal acts, allowing for comparability between member states Eurostat (n.d.).

We use data from three years before the VAT cut was implemented until three years after and thus use months between June 2012 and May 2018. During this period, there is no missing data in any food category. However, we exclude Hungary due to large-scale VAT cuts in 2016 (Ván and Olah, 2018), thus biasing our estimate if included as Hungary is essentially treated by a similar reform itself. In addition, we also exclude the product category *Bread and cereals* due to Romania implementing a 9% VAT rate for bread, bakery specialties, certain types of flour, wheat and rye starting September 2013 (Romanian Government, 2015). In turn, a graphical representation of price developments in Romania and other European countries during this period is shown in Figure 1 in Section 5.1.

4.2 Difference-in-Differences

To answer our research question of to what extent the Romanian VAT reduction on food passed through to consumers, we first acknowledge that this cannot be examined by comparing Romanian food prices before the VAT rate cut to prices after. In this setting, a number of omitted factors, besides the VAT reduction, are likely to affect food prices in the same period. These include, for instance, exchange rate fluctuations affecting the price of imports, weather events impacting agricultural yield and consumer demand seasonality, where certain months are characterized by higher consumption due to, for example, holidays.

For this reason, we introduce the Difference-in-Differences (DiD) methodology as an initial strategy to estimate the effect of the VAT reduction on food prices. The idea behind the DiD approach in this context is thus to compare the change in prices before and after the VAT cut in Romania to a counterfactual group. One such approach could have been through comparing treated to untreated products, however, in a general sense, this presents issues around endogeneity of treated products, while in the Romanian example, the VAT cut affects the entire food basket. Thus, as a counterfactual, we use the change in prices, for the exact same food product categories, across a control group of 29 European countries. In turn, this singles out the VAT effect on pass-through, conditional on food prices in these countries showing parallel trends to Romania's. The DiD regression is specified as follows:

$$(1)\ \text{Price index}_{it} = \beta_0 + \beta_1 \text{Romania}_i + \beta_2 \text{Post}_t + \beta_3 (\text{Romania}_i \times \text{Post}_t) + \varepsilon_{it}$$

The outcome variable in Eq(1) is the *price index*, for a country *i*, at date *t* (a monthly observation). We regress the price index on two dummy variables: $Romania_i$ which takes the value one for a product observed in Romania and zero for other countries and $Post_t$, which is equal to one for an observation made in June 2015 or after, the month in which the VAT cut was implemented. Our coefficient of interest is β_3, for which the country and post-treatment dummy are interacted, and thus reflects the difference in price index changes between Romania and counterfactual countries after the cut.

Additionally, we run the same regression but transform the outcome variable by taking the natural logarithm of the *price index*. Consequently, we are able to obtain the percentage change in price levels following the cut by using the formula: $(e^{\beta 3-1})\times 100\%$, which in turn is necessary to obtain the pass-through rate. Our second baseline regression Eq (2) is thus specified as:

$$(2)\ \log(\text{Price index})_{it} = \beta_0 + \beta_1 \text{Romania}_i + \beta_2 \text{Post}_t + \beta_3 (\text{Romania}_i \times \text{Post}_t) + \varepsilon_{it}$$

The key identifying assumption to interpret results from both these regressions casually is parallel trends, stating that absent the VAT cut in June of 2015, Romanian food prices would have followed the same trend as those of the counterfactual countries. In practice, one can imagine a variety of factors that violate this assumption, including for example, agricultural conditions and currencies. With regards to the first factor, our sample countries span over a wide range of climate, weather and soil conditions, implying effects on agricultural yield and thus, in turn, food prices. As for the second, Romania uses its own currency, the RON, as opposed to the Euro which is adopted by most other EU member states. In case of a macroeconomic shock where one currency depreciates vis-à-vis the other, food prices are directly affected, thus violating parallel trends. Food price index trends in Romania compared to the control group are displayed in Figure 1 in Section 5.1, from which we observe that trends are similar, although price level changes appear more volatile in Romania. To thus deal with this and similar issues, we implement the Synthetic Difference-in-Differences method, introduced by Arkhangelsky et al., (2021). Section 4.3 both motivates and explains our use of this method in this context. From Figure 2 of Section 5.2, we are able to see that trends in price levels for Romania and the SDID counterfactual are parallel. Finally, to scrutinize the parallel trends assumption further, we implement a series of placebo and robustness tests in Section 6.

4.3 Synthetic Difference-in-Differences

The following section describes our usage of the SDID estimator. In Section 4.3.1, we motivate the feasibility of using SDID as opposed to established DiD methods in the Romanian context. Subsections 4.3.1, 4.3.2 and 4.3.3 thereafter describe SDID estimation in more technical detail, while in subsection 4.3.5, we present unit and time weights of the Romanian counterfactual.

4.3.1 Motivation for Using Synthetic Difference-In-Differences Estimation

The Synthetic Difference-in-Differences approach, developed by Arkhangelsky et al. (2021), is a method that closely resembles both standard DiD as well as the Synthetic Control Method (SCM), introduced by Abadie and Gardeazabal (2003). All three aim to estimate the treatment effect using a representative counterfactual entity. When using regular DiD, the counterfactual is created by using all units in the control group, even if these are likely to vary in similarity to the treated unit, in this case Romania. The SCM (Abadie and Gardeazabal, 2003), works around this issue by weighting control so that units with pre-trends in the outcome variable most similar to the treated unit receive a higher weight. In turn, this ensures a counterfactual less likely to violate parallel trends than regular DiD. Like the SCM, the SDID estimator constructs a counterfactual through weighting of units, however, in addition, it also adds time weighting. Thus, it not only reweights untreated units so that the pre-trend in the outcome variable is aligned with the one of the treated group, but also assigns time-weights which are optimized to balance the pre-trend with the post-exposure time periods for the untreated units. In doing this, the pre-exposure time periods that are the most useful in predicting the counterfactual trend of the treated group, in our case Romania, receive a higher weight. Ultimately, the SDID estimator thus allows us to weaken the reliance on strong parallel trends type assumptions. In addition, unlike the SCM, it also allows for different intercepts of the outcome variable for the treated unit and counterfactual, which helps avoid overfitting. Finally, by implementing the SDID estimator, we are also able to compare whether our pass-through estimate of the Romanian VAT cut changes compared to the regular DiD estimate, commonly used in other papers.

4.3.2 The SDID estimator

At a deeper level, the SDID estimator computes the treatment effect by minimizing the sum of weighted squared residuals with respect to four parameters: the treatment effect, the intercept (overall mean), unit fixed effects and time fixed effects. The residuals are calculated by taking the observed outcome and subtracting the predicted outcome, which consists of an intercept, country fixed effects, time fixed effects and finally an interaction term for the treatment. In other words, the intuition of the model is very similar to a regular Ordinary Least Squares Difference-in-Differences model. However, the key difference is that the SDID estimator is subject to both unit and country weights, which means that certain units and time periods will be more relevant in determining the parameters of the model. Specifically, untreated units that are more similar to the treated unit will gain greater weight. At the same time, pre-periods that are more informative of the post-periods are upweighted. For a more detailed discussion on how the weights are selected, see Section 4.3.3. In summary, the described optimization problem can be illustrated in the following two-way fixed effects regression equation:

$$(3)\ (\hat{\tau}^{sdid},\hat{\mu},\hat{\alpha},\hat{\beta}) = \underset{\tau,\mu,\alpha,\beta}{\arg\min}\left\{\sum_{i=1}^{N}\sum_{t=1}^{T}(Y_{it} - \mu - \alpha_i - \beta_t - D_{it}\tau)^2\,\hat{\omega}_i^{sdid}\,\hat{\lambda}_t^{sdid}\right\}$$

Where, τ is the treatment effect, μ is the intercept, α_i is the unit fixed effect, β_t is the time fixed effect, Y_{it} is the observed outcome, D_{it} is the the treatment dummy which takes the value 1 if treated and 0 else, and finally ω_i and λ_i are unit and time weights respectively. The unit and time weights are non-negative and sum to 1.

Given that we have a balanced panel of data from a total of 30 countries (Hungary is excluded) over 72 months, of which 32 months are part of the pre-treatment period and the rest part of the post-treatment period and where Romania is the first and only treated country (i = 1), we apply the SDID algorithm on our data using the following equations:

$$(4)\ (\hat{\tau}^{sdid},\hat{\mu},\hat{\alpha},\hat{\beta}) = \underset{\tau,\mu,\alpha,\beta}{\arg\min}\left\{\sum_{i=1}^{30}\sum_{t=1}^{72}(Y_{it} - \mu - \alpha_i - \beta_t - D_{it}\tau)^2\,\hat{\omega}_i^{sdid}\,\hat{\lambda}_t^{sdid}\right\}$$

$$(5)\ D_{it} = \begin{cases} 1 & \text{if } i = 1 \text{ and } t \geq 32 \\ 0 \text{ else} \end{cases}$$

As such, we are able to obtain the coefficient of interest (τ) which captures the effect of the Romanian VAT rate cut on price levels. The null hypothesis is that there is no effect on price levels, i.e. that the treatment effect is 0. However, we are also interested in whether we can reject the scenario where the treatment effect is different from the intended effect of a full pass-through. Therefore, we also construct 95% confidence intervals and inspect whether the effect of a full pass-through is included in the confidence interval. Furthermore, we specify the SDID model with both the regular price index and log-transformed prices as the outcome variable. The purpose of the former is to better visualize the index point change while the latter allows for estimation of pass-through rates.

4.3.3 Selection of Unit- and Time Weights and the Regularization Parameter

Since the unit and time weights are a central part to the SDID methodology as they are used to calculate the point estimate, this section discusses the weighting process in more detail. Unit weights are used to construct a weighted average of the untreated unit's outcome, with the goal of making its weighted average pre-trend parallel to the pre-trend in the treated group, in our case Romania. Time weights are assigned to each pre-treatment period, in order to balance pre- and post-exposure periods, in our case months. In other words, the months which are the least noisy and the most predictive of the counterfactual trend post-treatment, are given higher weights. Thus, if there is a smooth pre-period trend where the treated unit spikes in one month, for instance due to a local shock or measurement error, this month is downweighted. On the contrary, if the spike happens for both treated and untreated units, then the month is of higher explanatory power and is therefore upweighted. As such, problems related to overfitting are reduced and the post-trend of the control group is more prone to being a better comparison to the treated group, allowing for relaxation of the parallel trends assumption. Formally, we determine the unit weights by solving the following minimization (of loss function) problem:

$$(6)\ (\hat{\omega}_0, \hat{\omega}^{sdid}) = \underset{\omega_0 \in \mathbb{R}, \omega \in \Omega}{\arg\min}\ \ell_{unit}(\omega_0, \omega)$$

Where:

$$\ell_{unit}(\omega_0, \omega) = \sum_{t=1}^{T_{pre}} \left(\omega_0 + \sum_{i=1}^{N_{co}} \omega_i Y_{it} - \frac{1}{N_{tr}} \sum_{i=N_{co}+1}^{N} Y_{it} \right)^2 + \zeta^2 T_{pre} ||\omega||_2^2$$

$$\Omega = \left\{ \omega \in \mathbb{R}_+^N : \sum_{i=1}^{N_{co}} \omega_i = 1,\ \omega_i = N_{tr}^{-1} \text{ for all } i = N_{co} + 1, \ldots, N \right\}$$

Additionally, the regularization parameter ζ, is set to the following:

$$(7)\ \zeta = (N_{tr}\, T_{post})^{1/4}\, \hat{\sigma} \quad \text{with} \quad \hat{\sigma}^2 = \frac{1}{N_{co}(T_{pre} - 1)} \sum_{i=1}^{N_{co}} \sum_{t=1}^{T_{pre}-1} (\Delta_{it} - \bar{\Delta})^2,$$

$$\Delta_{it} = Y_{i(t+1)} - Y_{it} \quad \text{and} \quad \bar{\Delta} = \frac{1}{N_{co}(T_{pre} - 1)} \sum_{i=1}^{N_{co}} \sum_{t=1}^{T_{pre}-1} \Delta_{it}$$

In summary, equation (6) above tells us that the unit weights are chosen to minimize the total differences between the treated group and the control group, for each pre-treatment period, while allowing for an intercept difference. The intercept difference is made possible since fixed effects will adjust for the different starting points of each unit. In other words, weights are ultimately computed for pre-trends for the control group to be parallel to the treated group, but not to necessarily match perfectly. Furthermore, a penalty term ($\zeta^2\, T_{pre}\, // \omega //_2{}^2$) is introduced to ensure that weights are unique. In this term, the regularization parameter ζ spreads out weights so that they are not concentrated across a few singular units. It is set to match the size of an average pre-treatment one period change in the outcome variable for unexposed units, in our case the monthly change in prices of the "Doppelgänger" Romania, multiplied by "a theoretically motivated scaling", as seen in Eq(7). For deeper insights on this scaling, we refer the reader to Arkhangelsky et al., (2021).

Meanwhile, time weights "balance pre- and post exposure periods for unexposed units" and are constructed as follows:

$$(8)\ (\hat{\lambda}_0, \hat{\lambda}^{sdid}) = \underset{\lambda_0 \in \mathbb{R}, \lambda \in \Lambda}{\arg\min}\ \ell_{time}(\lambda_0, \lambda)$$

Where:

$$\ell_{time}(\lambda_0,\lambda) = \sum_{i=1}^{N_{co}} \left(\lambda_0 + \sum_{t=1}^{T_{pre}} \lambda_t Y_{it} - \frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} Y_{it}\right)^2$$

$$\Lambda = \left\{\lambda \in \mathbb{R}_+^T : \sum_{t=1}^{T_{pre}} \lambda_t = 1, \lambda_t = T_{post}^{-1} \text{ for all } t = T_{pre} + 1,...,T\right\}$$

In essence, Eq(8) minimizes the difference between the average outcome after the treatment and the control group's time weighted average pre-treatment. Once again, an intercept allows for a level difference between the pre and post-treatment period for the control group. Notably, time weight calculation does not feature regularization through a penalty term which is motivated by the original authors' formal SDID results, for which we refer the reader to Arkhangelsky et al., (2021). In turn, using the calculation steps from the discussion above, we present both the country and month weights in Section 4.3.5, which in turn allow us to determine the pass-through of Romania's VAT cut on foods, from equation 4.

4.3.4 SDID Standard Error Estimation

To be able to draw conclusions from the SDID point estimate, we also need an accompanying variance estimator. As is described by Arkhangelsky et al., (2021), there are three approaches which one can use for variance estimation when using SDID: Bootstrap, Jackknife and Placebo, each with their own benefits and drawbacks.

The first approach to standard error estimation when using SDID employs Bootstrap, which independently resamples units (in our case countries) and obtains new estimates. In turn, the variability in these estimates gives a standard error. It is the most reliable approach for large panels of data where there is likely to be serial correlation across the units. However, it is computationally burdensome and more importantly, less reliable with few treated units, which is a concern for a study like ours where Romania is the only treated unit. Similar problems are shared in our context by the second approach: the Jackknife variance estimator. Jackknife obtains a variance estimate through keeping all weights fixed while leaving one unit out at a time. However, it is deemed unreliable when there are few treated units and is even undefined for when there is only one treated unit. Thus, it is inapplicable for our study.

The third method for variance estimation when using SDID is Placebo, which we use for our regressions. By replacing units that would have been treated with untreated units, Placebo allows for variance estimation in a synthetic control setting where there is only one treated unit. However, a major drawback of this method is that it relies on the assumption of homoskedasticity, or in other words, that units have similar noise structure. Specifically, "nonparametric variance estimation for treatment effect estimators is in general impossible if we only have one treated unit and so homoskedasticity across units is effectively a necessary assumption in order for inference to be possible" (Arkhangelsky et al., 2021, p.4110). The 30 countries in our regression are all part of the internal market and in that way share common market mechanisms. However, we recognize that heterogeneity in, for instance, exchange rate fluctuations and competition may reflect in unobservables varying across units, which in turn could result in misrepresentative standard errors, either too high or too small. Therefore, we proceed cautiously when using Placebo variance estimation and discuss the Placebo standard errors in relation to those obtained from the DiD estimate in Section 5.2.

4.3.5 SDID Unit and Time Weights

Before the results section presenting estimates of pass-through, we present and comment briefly on the weights for each country and period, which can be found in Table A.1 in Appendix A**.** When we use the regular price index as the outcome variable, the SDID estimator assigns Bulgaria the greatest weight of 14.56%. This is in line with expectations, as Bulgaria and Romania are neighboring countries, share similar geographical conditions and GDP per capita and joined the EU in the same year. When instead transforming the price index using the natural logarithm, Bulgaria remains the largest "donor" at a slightly lower 14.07% weighting. Moreover, the top 5 countries (Bulgaria, Croatia, Malta, Belgium and Latvia) make up slightly less than half of the weighting in the log-transformed version (49.02%). Besides Belgium, every country with considerable weighting is located in the eastern and southern parts of Europe. Meanwhile, the 6 out of 29 countries that do not receive a weight in the donor pool are Iceland, Luxembourg, Norway, Portugal, Sweden and Switzerland. These are all countries located far away from Romania, characterized by higher income as well as different climatic conditions and cultures, making omission intuitive. Interestingly, none of the non-EU countries in our sample (Iceland, Norway and Switzerland) are weighted. Notably, the order of countries does not change between the regular and log-transformed outcome variable. However, the weights are marginally more even for the latter version.

Looking at time weights, we observe an uneven distribution where April and May 2015, the two months before treatment, are given the most weight with a split of 38.84% and 61.16% respectively. This may raise concerns over Romania's VAT cut announcement in April 2015 affecting prices and in turn biasing our estimates. We discuss this issue more in-depth in Section 6.1.

5. Results

Transitioning to our results where we estimate both pass-through on aggregate as well as per product category, we commence by presenting regular DiD results in Section 5.1. Thereafter, Section 5.2. presents results from SDID estimation of aggregate pass-through while Section 5.3 finishes with an overview of heterogeneity in treatment effect across categories, using SDID estimation.

5.1 Regular DiD Pass-through

We commence by plotting the average price index over time for product categories in Romania and the counterfactual group of other European countries. From Figure 1, we observe that Romania had a higher average price index level than in the donor pool until the treatment date of June 2015. However, for causal inference, what matters is that trends are parallel. Here, we observe similarity between Romania and the donor countries, although Romania appears to be more volatile with higher magnitude of shifts, in turn also pointing towards the use of the SDID method. As expected, we note that there was a major drop in the Romanian price level once the treatment was implemented.

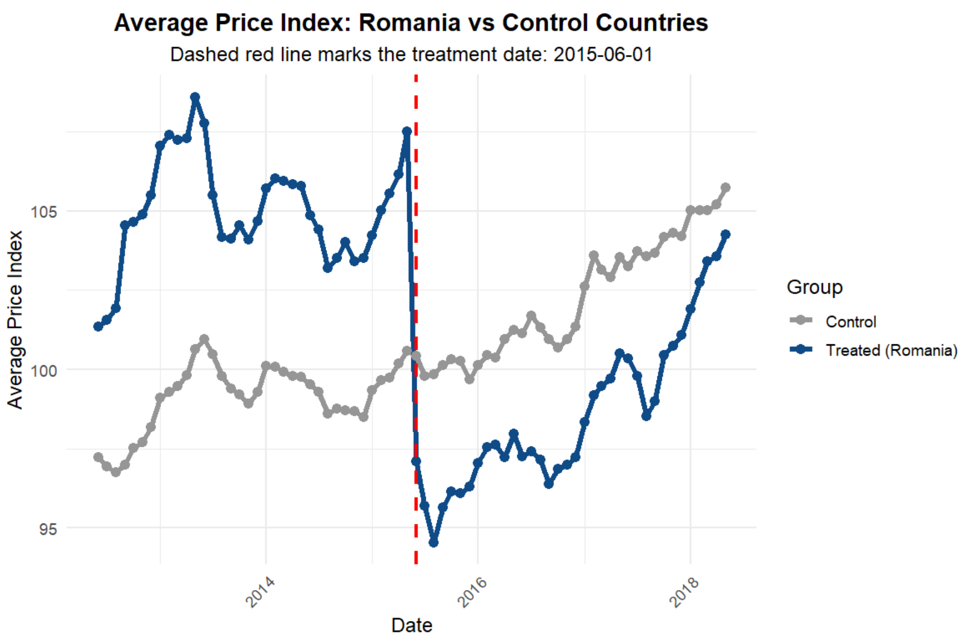

Figure 1. A month-to-month representation of average price index level for Romania and counterfactual consisting of EU countries, from 2012-06-01 to 2018-05-01. This is the visual equivalent to Eq (1).

Source: Authors' own calculations using data extracted from Eurostat (2025c).

We proceed by obtaining estimates from Eq (1), where we find a 9.496 price index point decrease in Romania relative to control countries in the post period. For variance estimation, we test using both regular standard errors as well as clustered standard errors, results from which are listed in Table A.2 and Table A.3, respectively, in Appendix A. The latter is clustered at the country (treatment) level, and thus allows for category food price correlation within countries. Clustering also requires a sufficiently high number of clusters. In our case, there are 30 countries, which we deem more than sufficient. Nevertheless, clustering does not change significance levels.

To obtain results on the pass-through rate of the Romanian VAT cut implemented on 1 June 2015, we need an exact percentage change in price levels and thus proceed to estimates from Eq(2), where the outcome variable is the log price index. In Table 1, we observe a log price estimate of -0.093 for the coefficient of interest. This corresponds to a decrease in price level of 8.88% (($e^{-0.093}$−1) = -0.0888) for Romania after the policy implementation, relative to the counterfactual EU countries. Full shifting to consumer prices of the cut, reducing VAT on food from 24% to 9%, would have occurred if prices dropped by 12.1% (-15/124*100% = -0.121). In turn, by dividing our estimate with the price drop under full shifting, we find a pass-through of 73.39%, suggesting incomplete shifting to consumer prices. Furthermore, we test adding month and country fixed effects to Eq(2) in case of time invariant differences or global shocks bias our estimate. Nevertheless, the estimated pass-through remains the same, as is shown in Table A.5.

Table 1. Regression estimates from Eq(2) where the dependent variable is log price index. Analysis adopts clustered standard errors clustered at the country level.

Difference-in-Differences Regression:
Log(Price Index) (Clustered SE)

	Clustered SE Model
Intercept	4.595***
	(0.003)
Treated (Romania)	0.058***
	(0.003)
Post-Treatment	0.031***
	(0.005)
Treated × Post	-0.093***
	(0.005)
Num.Obs.	19440
R2	0.101

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Authors' own calculations using data extracted from Eurostat (2025c).

From the standard errors in Table 1, we can also construct a 95% confidence interval of the pass-through rate obtained from the regular DiD regression. At the upper bound, we observe price decreases of 7.98%, whereas at the lower bound, prices decreased by 9.77%. For comparison, full pass-through would imply price reductions of 12.1%, further pointing towards the VAT cut not being fully reflected in lower prices for consumers.

5.2 SDID Pass-through

Besides our regular DiD regressions, we gather results from the SDID analysis. First, we obtain an SDID plot, which is illustrated in Figure 2. It is similar to the one in Figure 1 in terms of plotting the average price index level for Romania and the counterfactual, as well as highlighting the drop around the treatment date. However, the SDID plot uses a more carefully constructed control group with unit and time weighting. As a result, we see that trends of Romania and its "Doppelgänger" are much more aligned than previously, which is a strong indication of improved satisfaction of the parallel trends assumption.

To clarify interpretation of the SDID graph in Figure 2, the upward sloping linear red line seen between the two vertical black dashed lines, illustrates the price index change for the Doppelgänger before and after the VAT cut in June 2015. Thus, this change represents the counterfactual trend for Romania, which it is assumed to have followed after June 2015, absent the cut. To adjust for pre-treatment differences in price index level, the linear red line is shifted up which is represented by the upwards sloping linear black dashed line. From there, the difference between the black dashed line and the blue line, represents price effects of treatment. The black curved arrow illustrates the exact estimated treatment effect, which is visibly negative, thus suggesting that the Romanian VAT cut on food had a considerable impact on food prices, which is in line with our previous analysis.

In addition, we also observe from Figure 1 that the time weights are concentrated to the two months before the treatment date. In other words, the dates the closest to June of 2015 are more predictive of the post-treatment trend for the untreated units. This is also the reason for why the thick red and blue lines are plotted from close to the treatment date, as other periods are effectively only used for the optimization of parallel trends through weighting, and are thus not a part of estimating the treatment effect.

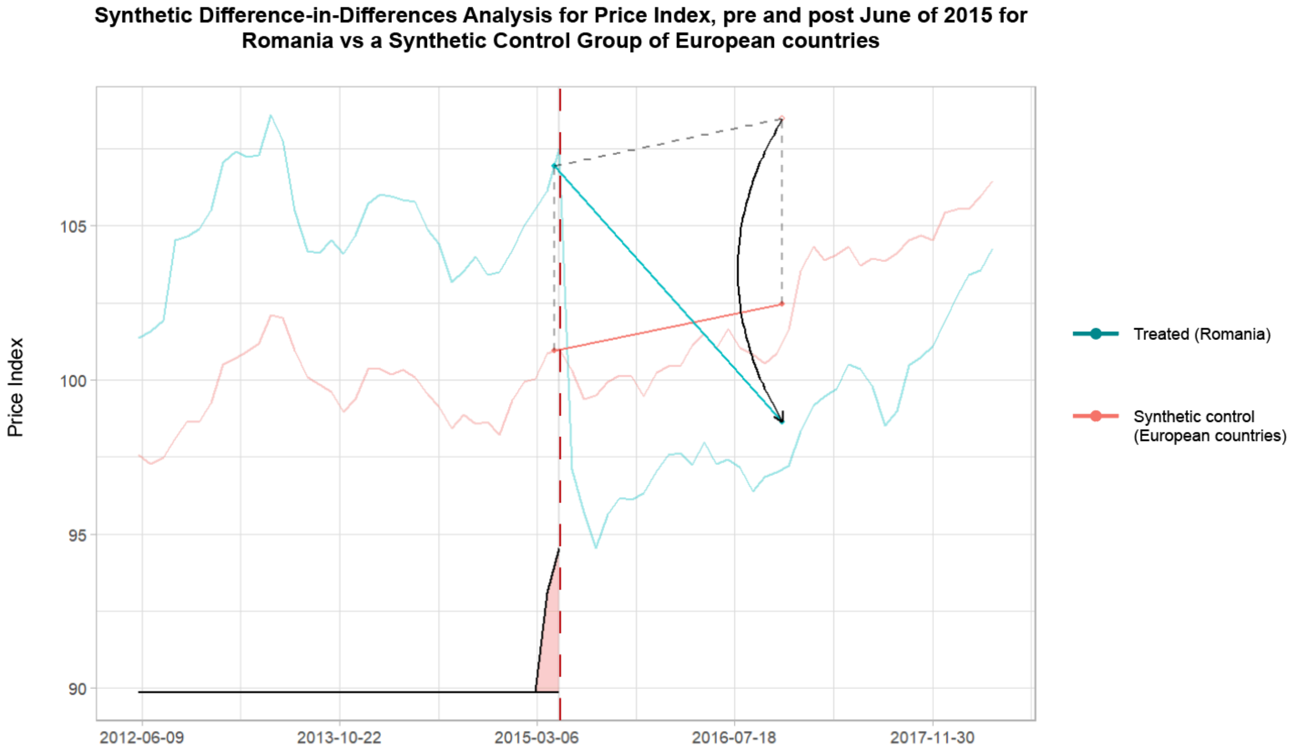

Figure 2. Synthetic Difference-in-Differences plot from June of 2012 till May of 2018, highlighting trends in the average price index for Romania (blue line) and the "Doppelgänger" (red line). The treatment date is represented by the red dashed line, with the black arrow displaying the average treatment effect. The red diagram denotes time weights per period. The vertical dashed black lines highlight the pre-treatment differences between Romania and the control group, while the upwards sloping linear dashed black line interpolates forward the trend of Romania, using the counterfactual ("Doppelgänger") post-treatment trend.

Source: Authors' own calculations using data extracted from Eurostat (2025c).

We translate the visual effect found in Figure 2, into the corresponding price index estimates from Eq (4), in Table A.6. More specifically, we observe a highly significant SDID corresponding to a drop in Romanian food prices of 9.8298 price index points as a result of the VAT cut. Notably, this magnitude is in line with the treatment effect from the regular DiD regression, showing a drop of 9.496 price index points.

As with DiD, we then proceed to change the outcome variable to the natural logarithm of the price index, to in turn obtain a percentage shift in prices and in turn pass-through from the VAT cut. Using log(Price Index) as the outcome variable, we thus obtain estimates for our primary specification in Eq(4). In Table 2, we observe a log treatment effect of -0.0959, corresponding to a price drop of 9.14% ($e^{0.0959}$ - 1 ≈ -0.0914). In turn, this equates to a pass-through rate of 75.77% (-0.0914/-0.1210 ≈ 0.7577). The results from the SDID estimator are thus once again in line with the regular DiD, although the latter finds a slightly lower pass-through rate of 73.39%.

Table 2. Estimates and parameters for the Synthetic Difference-in-Difference analysis using log(Price Index) as the dependent variable.

SDID Treatment Effect Estimates, Dependant Variable is log(Price Index)

	Uncertainty			Penalty Params	
Estimate	**Std. Error**	**95% CI Lower**	**95% CI Upper**	**Unit Regularization**	**Time Regularization**
-0.0959	0.0169	-0.129	-0.0627	0.0212	0

Source: Authors' own calculations using data extracted from Eurostat (2025c).

Further, we also observe from Table 2 that the standard error obtained for the SDID estimation using Placebo is 0.0169, which is considerably larger than the 0.005 for regular DiD. In extension, when constructing 95% confidence intervals we find a lower bound of -0.129 and a higher bound of -0.0627. In turn, the bounds are at price drops of 6.08% to 12.10% respectively, equating to pass-through between 50.24% and 100.04%. Hence, we are not able to reject the null hypothesis that the pass-through rate is different from full pass-through at a 5% significance level when using Placebo variance estimation. Firmly concluding that the VAT cut did not fully pass through to customers under SDID is thus not possible, as opposed to regular DiD for which the 95% confidence interval was between 65.97% and 80.76%. Section 4.3.4, provides an explanation for why Placebo variance estimation may yield larger standard errors. Nonetheless, we proceed with caution in drawing strong conclusions of incomplete pass-through based on this result.

5.3 SDID Heterogeneous Treatment Effects in Product Categories

By splitting up the SDID regression for each of the nine product categories in our data separately, we are able to obtain a unique price change estimate for each category, and thus a separate pass-through rate. These results are displayed in Table 3 and allow us to observe if effects of the VAT cut vary by product category, which, in turn, may be connected to different product characteristics as discussed in Section 2. Most notably the product categories *Fruits* and *Vegetables* receive log estimates being -0.0686 and -0.0047 respectively, which correspond to a pass-through rates of 54.79% and 3.88%. Thus, for neither of these estimates, are we able to reject the null hypothesis that the VAT cut had no effect on prices at the 5% significance level. On the contrary, the remaining product categories: *Meat*, *Fish and seafood*, *Milk cheese and eggs*, *Oils and fats* and *Non-alcoholic beverages*, all receive higher log estimates, ranging from between -0.1018 to -0.1391, corresponding to pass-through rates of between 79.99% and 107.32%.

Furthermore, it is important to note that by running the SDID regression separately by product, each food category now receives a unique control group based on the SDID optimization algorithm. Thus, the "Doppelgänger" created for the Romanian meat market is separate from the one created for the fish market. While this reduces comparability across categories, as countries and months receive different weight from category to category, we argue that a Romanian counterfactual meat market is best represented by weighting based on other meat markets, rather than the aggregate food basket.

Table 3. SDID estimates showing treatment effect heterogeneity over product categories. The dependent variable is log(Price index) for each of the nine categories analyzed. Standard errors are obtained using Placebo variance estimation, and confidence intervals are reported at the 5% significance level.

SDID Log-Model Summary

Metric	meat	fish_seafood	milk_cheese_eggs	oils_fats	fruit	vegetables	sugar_sweets	food_nec	non_alcoholic
Estimate	-0.1026	-0.1281	-0.1018	-0.1391	-0.0686	-0.0047	-0.0829	-0.1150	-0.1234
StdError	0.0207	0.0331	0.0253	0.0414	0.0439	0.0421	0.0314	0.0220	0.0216
CI_Lower	-0.1432	-0.1930	-0.1513	-0.2202	-0.1547	-0.0872	-0.1444	-0.1582	-0.1658
CI_Upper	-0.0620	-0.0632	-0.0523	-0.0579	0.0175	0.0779	-0.0213	-0.0719	-0.0810
Unit_Reg	0.0174	0.0320	0.0188	0.0349	0.0884	0.1259	0.0228	0.0191	0.0276
Time_Reg	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Source: Authors' own calculations using data extracted from Eurostat (2025c).

6. Robustness

Due to potential questions around satisfaction of the parallel trends assumption, which still remain after expanding from the regular DiD framework to the SDID framework, we run a variety of tests in the following chapter. Section 6.1 discusses how the treatment effect may vary over time and how an announcement effect could influence the validity of our results. Section 6.2 covers placebo testing. Finally, in Section 6.3, we test for the sensitivity of our estimates to the choice of donor countries for the control group.

6.1 Announcement Effect and Heterogeneous Treatment Effect Over Time

One of the limits that come with the main SDID regression that we run is that it only presents an average effect on prices due to the cut, thus missing a potentially heterogeneous treatment effect over time which would appear plausible given, for example, short-term inelastic supply. By estimating and plotting monthly effects, we are not only able to observe such heterogeneity, but also able to test for the presence of an anticipation effect, which could bias our estimates. Such an effect would stem from firms or consumers adjusting behavior in anticipation of the cut, and is commonly discussed in previous literature. For instance, Frey and Haucap (2024) found that retailers started reducing prices immediately upon a law passing on the reduction of VAT for female hygiene products, and not only after it was implemented. Meanwhile, studying VAT changes in Eurozone countries between 1999 and 2013, Benedek et al. (2020) find an absence of anticipation effects for goods subject to the reduced VAT rate, including food. In our case, one way in which this effect could have occurred is if retailers raised prices after the announcement of the VAT cut, so that price shifts upon implementation appear larger than they are, while in reality, part of the cut is used to increase margins. As is mentioned in Section 3, fears and alleged examples of this happening were raised in news media, which if true, would imply that our assumption of parallel trends is violated, as such an effect would not be present in countries where no VAT cut on food were implemented. In turn, our estimates would be biased upwards by pass-through appearing larger than it is. Further, testing for monthly effects is motivated by the fact that the SDID algorithm aggressively weighted months April and May 2015, after announcement, in our results. For these reasons, we implement two plots that show month-by-month effects, which we construct utilizing the codeset *synthdid_est_per.R* by Nguyen (2023). Figure 3 plots monthly treatment effects with June 2015 used as the treatment date, the month in which the VAT cut was implemented, to test for heterogeneous treatment effects over time. Meanwhile, Figure 4 changes the treatment date to April 2015, the month of announcement, allowing us to observe if prices rose ahead of the cut and if pass-through estimates after implementation shrink. Exact estimates for each month are shown in Table A.7-A.8.

In Figure 3, we first note that the highest observed pass-through of 85.87% $((e^{-0.1097}-1)/0.121 \approx 0.8587)$ is reached after 3 months, in August 2015. Thereafter, the pass-through remains relatively stable with a slight uptrend starting in late 2017. One potential explanation for the pass-through taking time to reach its highest level could come from short-term inelastic supply, with producers and retailers needing time to adjust due to short-term capacity constraints. Meanwhile, the reason for the effect of the price-cut reversing slightly in 2018 is more difficult to assess.

Moreover, from Figure 4, we find that there was a slight uptick in the prices level right before the VAT cut. Although the estimate is not significantly different from zero we acknowledge that this could have been due to firms trying to mask potential price increases to increase margins after the announcement. A limitation still remains in that anticipation effects could have existed before April 2015, even if the VAT cut was unannounced. For instance, expectation of further cuts may have formed following the cut on bakeries introduced in 2013. Unfortunately, this is something which we are unable to address, if present, and we acknowledge that there is a possibility of this causing minor bias in our estimate.

Finally, we note that the pre-treatment month-by-month estimates in Figure 4, are all indistinguishable from zero at the 5% significance level, pointing towards the SDID algorithm successfully constructing a counterfactual following a similar trend to Romania. In addition, prices remain significantly lower in Romania throughout the post-treatment period, thus pointing towards the policy effect persisting.

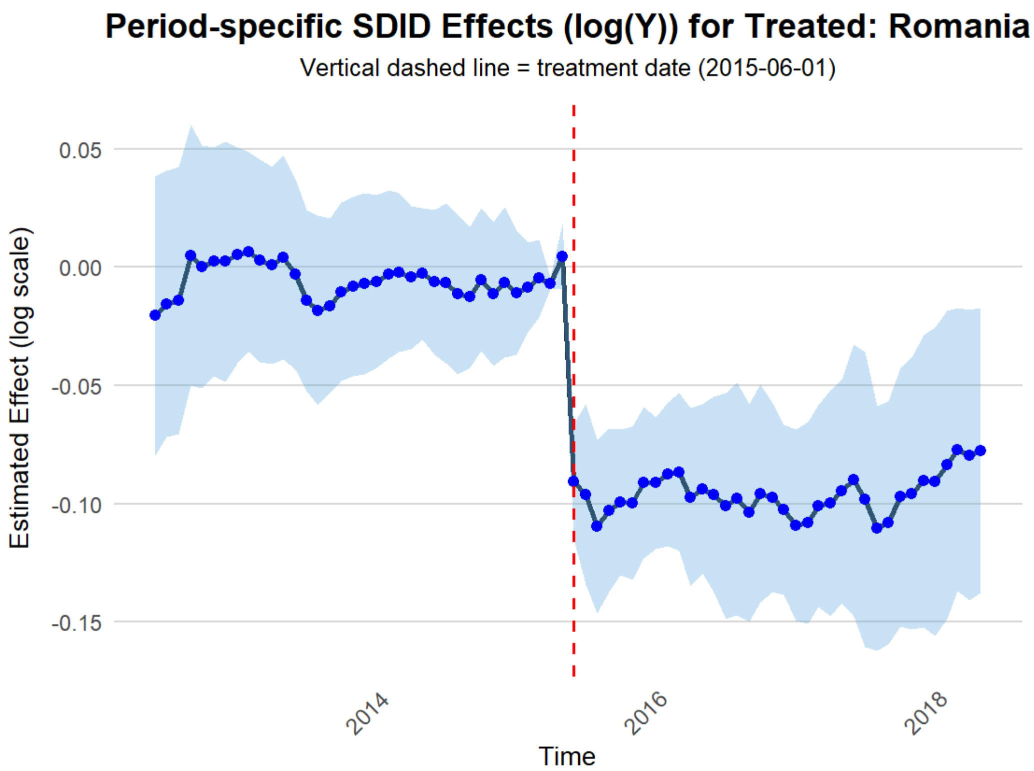

Figure 3. Month-by-month SDID estimates with 2015-06-01 as the treatment date and log(price index) as the outcome. The red dashed line shows the treatment date assigned, the blue dots are the estimated effects, and the blue area marks the 95% confidence intervals.

Source: Authors' own calculations using data extracted from Eurostat (2025c).

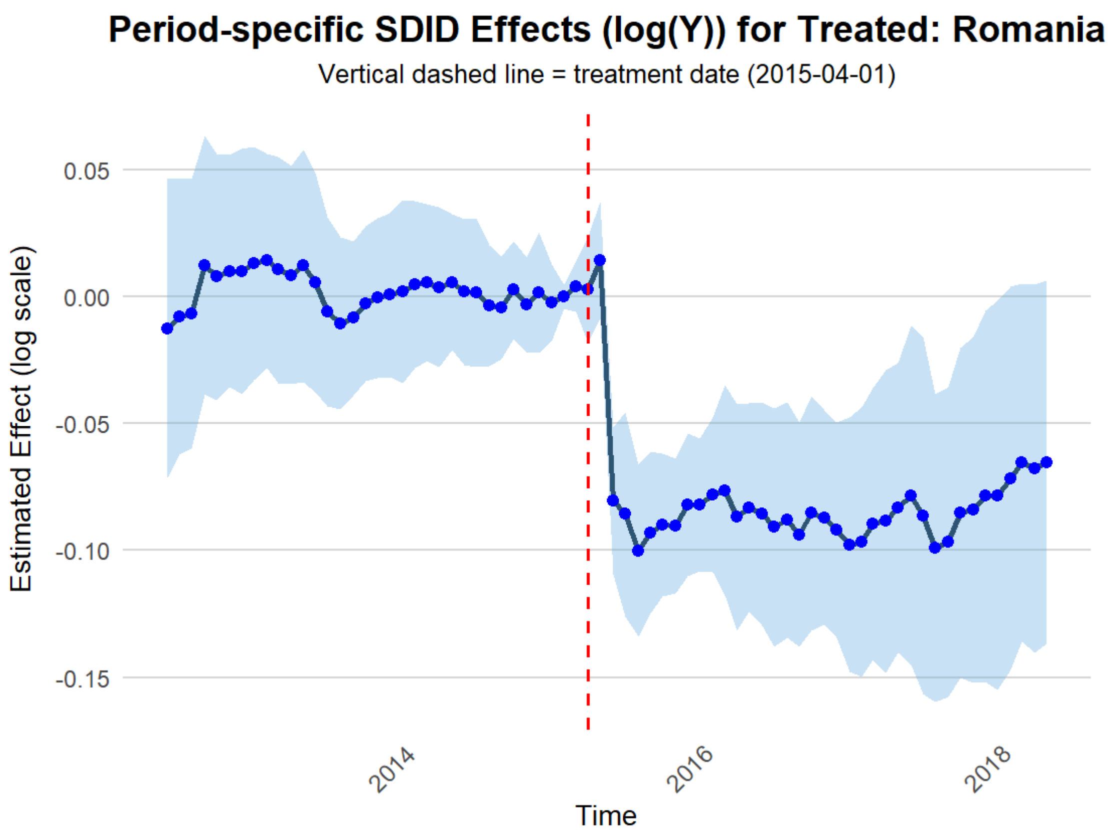

Figure 4. Month-by-month SDID estimates with 2015-04-01 as the treatment date and log(price index) as the outcome. The red dashed line shows the treatment date assigned, the blue dots are the estimated effects, and the blue area marks the 95% confidence intervals.

Source: Authors' own calculations using data extracted from Eurostat (2025c).

6.2 Placebo Testing

To test whether our SDID estimates are robust, we present placebo average treatment effects obtained by assuming that the treated unit in Eq(4) is one of the top 10 highest weighted countries from the donor pool (Refer to Table A.1 for weights), instead of Romania. The idea is that we want further confirmation that the results found in Romania are not due to randomness, rather that they systematically differ from other countries due to the policy intervention. In fact, we find from Figure 5 that the estimates are only significant for Romania at the 5% significance level, with the estimated magnitude of the effect clearly being stronger than for all the countries. As such, we are able to further argue for the robustness of our identification strategy.

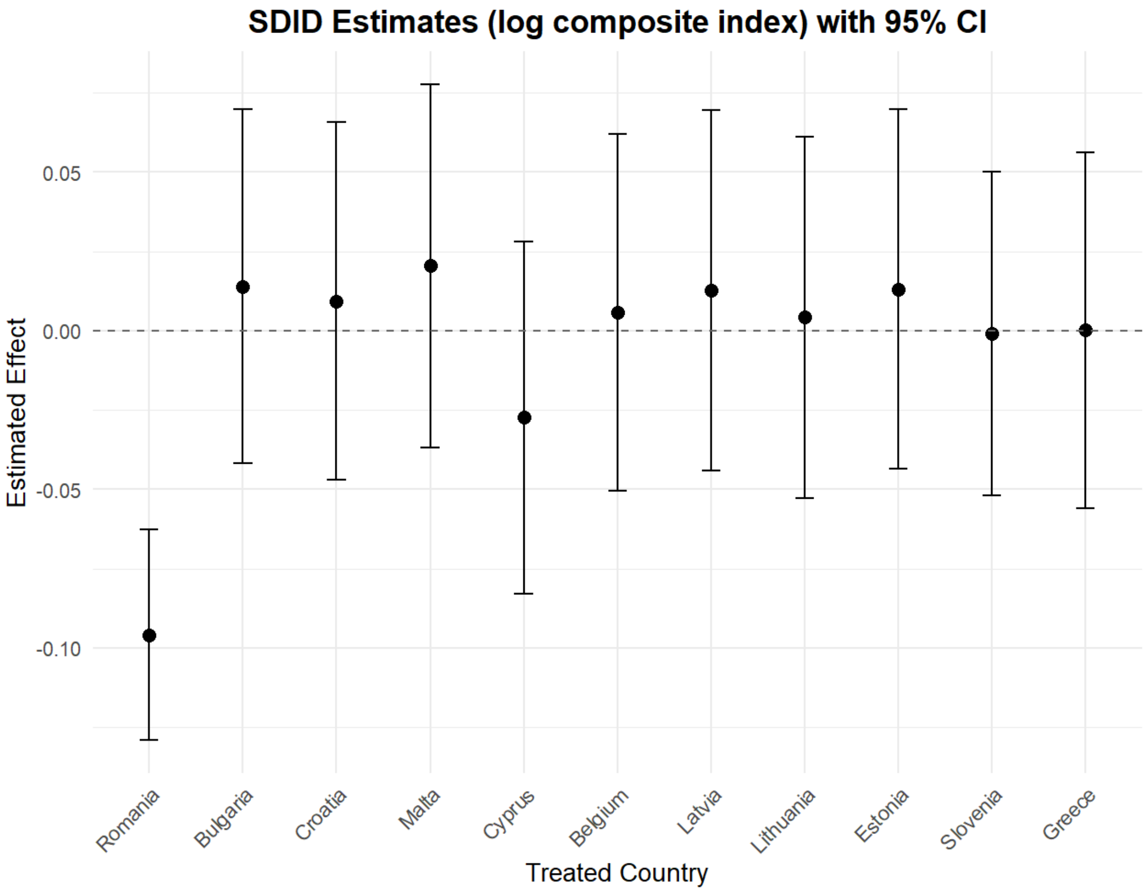

Figure 5. Placebo results showing the SDID estimates and corresponding 95% confidence interval, when switching treated country from Romania to a set of listed countries that were attributed the greatest weight, when running the SDID regression Eq (4).

Source: Authors' own calculations using data extracted from Eurostat (2025c).

6.3 Sensitivity To Donor Pool Composition

Given how the SDID algorithm functions, which creates a "Doppelgänger" based on the available countries in the donor pool, our pass-through estimates in Section 5.2 are sensitive to which countries we choose as possible controls. Therefore, we re-run Eq (4) with three different country compositions in the donor pool, each with their own set of discussed issues: currency effects, differing market dynamics related to EU membership and, finally, effects from cross-border shopping. The first composition change involves only using non-Eurozone countries. These are countries that neither adopt the Euro currency or peg their own currency to the Euro. Second, we test excluding the United Kingdom and Croatia from our sample. Lastly, we evaluate adding Hungary, a country bordering Romania, to the original donor pool. In each case, our estimates remain consistent with findings in Section 5.2.

Excluding Eurozone countries.

By running the SDID regression with only non-Eurozone countries (Romania, Poland, United Kingdom, Czechia and Sweden), we can examine whether currency effects may have biased our results. Such effects could be especially troublesome for our estimates, considering that the agricultural market in Europe commonly denotes prices in Euro, which most of our control countries adopt, while Romania uses the RON. Thus, if the Euro were to strengthen (weaken) in value during the study period, the relative price of food in non-Eurozone countries would increase (decrease), thus creating an upward (downward) bias and a violation of the parallel trends assumption discussed in Section 4.2. When, in turn, running our regression without Eurozone countries, we find that our estimate is in line with prior results (price decrease of 9.41% versus our main result of 9.14%), suggesting modest to no impact of Romania not being part of the Eurozone on our results. Exact results when removing eurozone countries are found in Figure A.1 (SDID plot) and Tables A.9-A.10**,** showing SDID estimates and corresponding country and time weights.

Removing Croatia and the United Kingdom.

In our initial donor pool selection, we excluded Hungary due to large-scale VAT cuts in 2016 which would interfere with the parallel trends assumption. Likewise, Croatia and the United Kingdom, are countries which arguably could be removed from the donor pool for similar reasons. Croatia was accepted as an EU member in 2011, but formally accepted in 2013, thus after our pre-period starts. Meanwhile, the United Kingdom took a significant step away from the internal market in 2016 through its Brexit referendum, which could have affected the food market through, for example, a reduction in imports. Moreover, both these countries are considerable contributors to our original donor pool, where Croatia receives a weighting of 13.10%, second behind Bulgaria, while the United Kingdom receives a 1.56% weighting. Consequently, it is reasonable to assume that they are able to shift results. However, when we remove these two countries we, once again, find results well in line with prior estimates, where the price decrease estimate is 9.18% as opposed to 9.14% in our main result. For the new SDID plot with this donor pool, refer to Figure A.2. In addition, Tables A.11-A.12 report exact SDID estimates as well as country and month weight when excluding Croatia and the UK.

Possible effects of cross-border shopping.

Finally, we assess whether including Hungary in the donor pool has an effect on the pass-through estimates. As is established in Section 4.1, we exclude Hungary from our sample due to VAT-cuts on food in 2016, thus violating parallel trends. However, another possible problem that Hungary could present comes from cross-border shopping, where Hungarian residents can make considerable savings from making purchases in Romania. A report from the European Commission (2017) estimated price savings of up to 19.5% for Hungarians traveling across the border in 2015, thus pointing to a potential for arbitrage. In turn, if cross border shopping would have increased due to the VAT cut as Romanian prices fell, we would expect demand in Hungary to decrease, in turn affecting Hungarian prices. Effectively, this would have implied that Hungary was treated by the VAT reduction in Romania, in turn biasing our estimates. The direction of such bias for pass-through would likely be downwards, where a drop in Hungarian prices makes the drop in Romania relatively smaller to its counterfactual. Our results when thus including Hungary in the donor pool reveal a weighting of 7.51%, suggesting similarity to Romania. However, our estimate is virtually unchanged with a price drop of 9.19% as opposed to 9.14% in our main regression, suggesting no effect of cross-border shopping on our estimate. An SDID plot is shown in Figure A.3, as well as estimates and weights in Table A.13-A.14, when Hungary is included.

In conclusion, we find little to no impact on our results due to sensitivity to the choice of donor pool, where estimates under new specifications are virtually identical to in Section 5.2, finding a pass-through of 75%. In turn, this points to the robustness of our results relating to issues around the composition of the donor pool.

7. Discussion

By using monthly data on food prices from EU countries, we studied the pass-through of a large and permanent VAT reduction implemented for all foodstuffs in Romania in 2015. Using a Difference-in-Differences approach, our estimate reveals 73.39% pass-through, growing to 75.77% when we use the SDID estimator introduced by Arkhangelsky et al. (2021). These point estimates stay at the same level when we change specifications and are notably lower than what was forecast by the government at a price drop of around twelve percent, which would have corresponded to near full pass-through (Chiriac, 2015). In addition, this pass-through estimate is also lower than what is found by most recently published empirical papers on VAT cuts to the food basket. These papers include, for example Gaarder (2019) who studies a large and permanent reduction in Norway, as well as several papers on temporary cuts introduced by EU members in response to high inflation.[4] The following section seeks to explain what sets the Romanian example apart from these examples by setting our pass-through estimates in relation to suggestive evidence on, for instance, differences in retail competition and food consumption growth. As a baseline for this discussion, we use the mechanisms introduced in Section 2 to which prior literature has attributed pass-through of VAT reforms, namely, the relative elasticity of demand, market structure, menu costs and policy and product visibility.

Under the standard theoretical model of perfect competition, where pass-through is determined solely by the relative elasticity of demand, there is strong reason to believe that the Romanian example should be characterized by lower pass-through. While we do not observe demand or supply curves, there are clear indications that this VAT reduction had a greater impact on demand than in prior empirical examples. In terms of volume, both seasonally and calendar adjusted, retail sales of food rose by 11.4% in the first month following the cut and remained at a higher level throughout the year (Eurostat, 2025d). By contrast, Norwegian sales volume increased by 0.6% in July 2001 following its large and permanent VAT cut on foodstuff, for which Gaarder (2019) finds full pass-through (Eurostat, 2025d). Intuitively, if food quantities in Romania respond more to a VAT cut due to higher demand elasticity, this can explain a smaller decrease in prices, assuming similar elasticity of supply in both cases. Such an explanation is also feasible given the Romanian situation, where food and non-alcoholic beverages took up 31% of the consumer portfolio prior to the cut, highest in the EU and more than double that of Norway at 14% in 2001 (Eurostat,

[4] See, e.g., Bernardino et al. (2025), Forteza et al. (2025) and Jaworski and Olipra (2025)

2025a). Effectively, this cut should thus have had a relatively larger effect on consumer purchasing power than in recent empirical examples finding full pass-through, both with regards to Norway in 2001 and, especially, to cuts post Covid, where their temporary nature implies smaller effects on income. In turn, both direct income effects and substitution effects, where consumers increase spending on more luxurious foods, are likely.

At the same time, multiple reasons exist for why this explanatory framework under perfect competition alone is insufficient. First, as described in Section 3, the Romanian retail market at the time was moderately concentrated, with an HHI score of 1880 in 2012 (European Commission, 2014). While this measure, derived by retailer market shares, is far from perfect, a smaller number of competitors has been shown to reduce pass-through by, for instance, Dimitrakopoulou et al. (2024). Second, it is difficult to find a clear connection between product growth in demand and our observed heterogeneity in pass-through, which is reported in Table 3. BMI Research (2016) reports sales growth rates of between 8.7% and 10.0% in 2015 in every product category for which we measure pass-through, except for *Fresh and preserved fruit* and *Coffee, teas and other hot drinks*, for which sales grew by 5.7% 13.1% respectively. Our estimates in Table 3 reveal 54.8% pass-through for *fruit*, for which we are not able to reject zero pass-through, and 95.6% for *Non-alcoholic beverages*. While these category definitions are not one to one and supply elasticities may differ, they indicate that growth in demand alone cannot explain variations in pass-through. Third, the arguably most important indicator that relative demand elasticity by itself fails to explain incomplete and heterogeneous pass-through, comes from the evolution of retailer margins in 2015. A report by Stoenescu (2017) reveals 131% profit growth, on average, for Romania's 14 largest international retailers in 2015, compared to turnover growth of 13%. Based on findings from, for instance, Copestake and Bellon (2022), higher margins following a VAT cut is indicative of imperfect competition.

With this noted, it is also difficult to find a clear reason for why the Romanian retail market would be less competitive than markets in prior empirical examples. The European retail market, in general, faces high levels of concentration, with Romania ranking below average in 2012 (European Commission, 2014). Moreover, looking into product heterogeneity, some of the product markets with the highest concentration as per HHI score, are *Oils and fats*, *Fish* and *Non-alcoholic beverages* (European Commission, 2021). In our results, these are the categories in which we find the highest level of pass-through, reported in Table 3. Meanwhile, markets for *Meat*, *Dairy*, *Fruit* and *Vegetables* see substantially lower market concentration as per HHI score, despite us finding incomplete shifting in these categories (European Commission, 2021).

One mechanism which could create differences between our examples and recent empirical examples of VAT cuts in high-inflation environments, is menu costs. As is mentioned by Fuest et al. (2025), menu costs should be lower for a permanent VAT change, such as the one in Romania, than for a temporary one where firms have to bear the cost of adjusting prices twice. While we find lower pass-through than multiple recent empirical examples on temporary cuts, it is difficult to analyze this mechanism more in-depth. Fuest et al. (2025)

find higher pass-through after Germany's temporary VAT cut for private label brands, consistent with theory on a retailer's cost of changing prices being higher for independent brands. In our case, we do not observe such product-level characteristics. However, a noteworthy characteristic of the Romanian retail market is that it had the lowest private label share out of 14 EU members analyzed, at 4.56%, compared to over 30% in Germany, Spain and Portugal (European Commission, 2014). Given general growth in private labels since, this would likely have made discrepancy in private labels even larger between Romania in 2015 and recent examples of cuts in 2022 and 2023.

Another mechanism, elaborated on in Section 2, which has facilitated full or near full pass-through in previous papers, is salience, where more attentive consumers put pressures on retailers to pass a VAT cut through to food prices. For instance, both Jaworski and Olipra (2025) and Bernardino et al. (2025) argue that measures that mandated stores to increase transparency for consumers facilitated near full pass-through. In this regard, the Romanian case is notably different, where retailers had managed to block the implementation of the government approved "Price Monitor" and where the Competition Council's ability to intervene against unjust price setting was severely questioned (see Section 3). Even though the cut received widespread media attention and retailers received threats of sanctions, it is probable that a lack of enforcement credibility along with pricing intransparency at the point of sale reduced consumer salience and thus pass-through.

A notable difference that may also make recent temporary VAT cuts more salient than Romania's, is the economic conditions in which they were implemented, characterized by high inflation. Jaworski and Olipra (2025) acknowledge that their results are in line with theoretical reasoning by Bénabou and Gertner (1993), stating that inflationary noise can lead consumers to seek additional information on prices, thus increasing policy salience. In Romania, inflation in the year leading up to the VAT cut was 1.1% (World Bank Group, 2025) and thus considerably lower than levels of up to over 10% present in empirical examples of Poland, Spain and Portugal in 2022 and 2023. In turn, this could further reduce the observed pass-through rate.

Similar arguments on costs of searching can also be made for product pass-through heterogeneity in Romania. As is observed by for example Frey and Haucap (2024) and Politi and Mattos (2011), pass-through is lower for products with lower weights in the consumer portfolio. For these, the cost of searching may outweigh the benefit of finding lower prices, thus resulting in lower consumer awareness and in turn pass-through. By analyzing our results from Table 3 on food category heterogeneity in relation to each product category's weight in the consumer portfolio, we can conduct a similar analysis. In 2015, the three categories with the largest weights relative to total *Food and non-alcoholic beverages* purchases in Romania, were *Meat* (29.6%), *Milk, cheese and eggs* (16.5%) and *Vegetables* (12.7%) Eurostat (2025a). Meanwhile, *Food products n.e.c*, *Fish and seafood* and *Oils and fats* were the most insignificant items at 1.9%, 2.6% and 3.0% respectively. Interestingly, a similar pattern to Politi and Mattos (2011) is not visible in our results, where the three smallest categories in the Romanian consumer portfolio are among the four for which we observe the highest pass-through.

Limitations.

From these findings also emerges a clear limitation of our study, where we find a high degree of product heterogeneity in Romania, but cannot identify a clear pattern explaining its nature. In our results, there is no relationship between pass-through and market concentration, sales growth or portfolio weight, however, it is possible that these mechanisms still explain heterogeneity although we do not observe it due to method and data limitations.

While a benefit of the HICP data which we use is comparability facilitated by harmonization across EU members, a clear disadvantage is that each category is broad and thus incorporates products that likely share different economic characteristics. For instance, the category "Meat" incorporates both pork chops and filet mignon. While pork is one of the most commonly consumed foods in Romania and arguably a necessity, filet mignon is a luxury. For the latter, we would thus expect higher demand elasticity and, in turn, reduced pass-through as per, for example, Browning and Crossley (2000). In turn, this makes it significantly harder to connect product characteristics to pass-through while also introducing a large amount of noise, with enhanced standard errors. Jaworski and Olipra (2025), who also use Eurostat HICP data for food prices and analyze a 2022 VAT cut in Poland, acknowledge mention that within-category variation inflates standard errors, in their case to a point where they fail to find significant pass-through for most categories. In our case, we do see pass-throughs significantly different from zero. However, the problem of inflated standard errors is made worse due to EU members only reporting prices at the four-digit COICOP level in 2015, where product categories are more broadly defined than at the current standard. With more granularly reported categories and, in turn, lower standard errors, we would also have been able to make a better assessment of the degree to which pass-through was incomplete. Although our estimates suggest a pass-through rate of around 75% over both regular DiD and SDID, full pass-through is at the upper limit of the 95% confidence interval for the latter.

Another limitation of this approach comes from our method and current data alone not allowing us to disentangle the contribution from each mechanism to the overall pass-through of the VAT rate reduction. By instead using regionalized HICP data, we would have been able to conduct analysis similar to what Alm et al. (2009) and Dimitrakopoulou et al. (2024) do for gas stations, finding lower pass-through in more rural areas where the intensity of competition is smaller. Moreover, with access to the product-level price data collected by the National Institute of Statistics from retail stores across all of Romania, laying the foundation for the aggregated HICP which we observe, we would be able to analyze pass-through heterogeneity for additional characteristics. These are not only limited to product weight in the consumer portfolio, but also include pass-through discrepancies between high-end and private label brands, or based on a product's number of available brands. The latter of these could plausibly be used as a proxy for competition, whereas private label brands are more likely to be characterized by lower menu costs and inelastic demand (Fuest et al., 2025).

The third limitation, also complicating conclusions, is that the HICP data we use only incorporates legal purchases. When introducing a VAT cut on bakery goods in 2013, Romanian PM Ponta cited a need for reducing tax evasion in the sector (Chiriac, 2013). There is good reason to believe that the 2015 VAT cut would have affected tax evasion too and thus, part of the observed increase in sold quantities following the cut may merely be an increase in legal purchases. In turn, conclusions around demand elasticity in Romania could be wrongly informed, where part of observed changes stem from previously unobserved purchases being reflected in the data.

Contribution and Implications for Future Research.
In this thesis, we set the objective to estimate the pass-through of a large and permanent VAT cut on food in Romania, examining heterogeneity across products and the mechanisms driving these effects. Using the SDID estimator and comparing Romanian food prices to other EU countries, we find an aggregate pass-through of 75.77% and considerable variation between product categories. While disentangling the contributions of individual mechanisms remains beyond the scope of this study, we make two main contributions. First, the cross-country application of the SDID estimator is novel in a VAT pass-through context, offering a robust approach where within-country controls comparing products are likely to suffer from endogeneity. This method can be applied more broadly, as Eurostat HICP data harmonizes inflation across foods and other goods and services. Second, we provide evidence from an understudied context: a lower-income Eastern European country, extending insights beyond the Western and Central European settings typical in the literature. Our estimate, indicating incomplete pass-through, is plausibly a result of stronger demand effects and imperfect competition, which is likely to generalize to similar environments such as Bulgaria or EU candidate countries. This suggests a need for caution for policymakers implementing VAT cuts on food to reduce consumer prices, rather than assuming full pass-through based on estimates in past empirical literature. Finally, it also presents opportunities for future research, in which the SDID approach could be applied to countries characterized by lower income, where similar demand effects are likely, such as for the VAT cut introduced on basic foods in North Macedonia in 2022. In turn, this would provide clearer understanding on the relevant determinants of pass-through in middle- and lower-income contexts.

8. Conclusion

By 1 June 2015, the Romanian government reduced VAT rates on all foods and non-alcoholic beverages in an attempt to reduce the high impact of food prices on family budgets. This intervention imposed significant costs to the government budget, reaching over 5 billion RON (1.12 billion euros) annually. To test to the extent that this intervention managed to reduce consumer prices, we implemented the SDID method introduced by Arkhangelsky et al. (2021) to create a Doppelgänger Romania based on HICP data from other EU countries. Our conclusions are as follows. First, our results reveal that 75.77% of the reduction was passed through to consumer prices. Second, PM Ponta's argument that prices "should almost entirely be reflected in lower prices", as well as government forecasts of prices falling by near the full amount of the VAT cut, did seemingly not come into fruition. Third, unlike a growing set of recent literature on pass-through of VAT rate cuts on food, we do not find a point estimate of full or near full pass-through. Suggestive evidence points toward this difference being driven primarily by two factors: a sharper rise in demand for food than in prior examples in the Romanian case and an absence of price transparency and visibility to consumers. Fourth, our estimates reveal large degrees of variation in pass-through between product groups, although we are not able to identify product characteristics predicting higher pass-through, leaving a gap for future research.

In conclusion, our thesis indicates incomplete pass-through for a VAT cut on food, thus contrasting a growing set of literature on both temporary and permanent cuts finding full pass-through. This estimated pass-through is not universally applicable for every environment in which a VAT reduction may be implemented for foods. The Romanian example is characterized by certain distinguishing characteristics. At the same time, our estimates highlight a need for caution for policymakers considering implementation of VAT cuts with the goal of relieving households of pressures from high prices. The ability of a VAT cut to pass through fully to consumer prices cannot be assumed by default. Instead, effective implementation, even for a necessity such as food, requires active design, monitoring and timing to succeed.

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10. Appendix

Appendix A: Tables and Figures

See Tables A.1–A.14 and Figures A.1–A.3 below. Contents include: estimates for regular DiD (with and without log transformed outcome variable, as well as, equivalent fixed effects model), estimates and plots for SDID (both regular and log-transformed price index, as well as, with changes to the donor pool), time- and country weights from SDID and finally SDID month-by-estimates estimates.

Table A.1 Time and country weights obtained from our main SDID regression Eq (4). The left side shows country weights and time weights for the SDID regression when the dependent variable is regular price index, while the right side shows corresponding results for the case where the outcome variable is log(price index).

SDID Country Weights

	Control Countries	
Rank	**Country**	**Weight**
1	Bulgaria	0.1456
2	Croatia	0.1419
3	Malta	0.0796
4	Belgium	0.0739
5	Latvia	0.0706
6	Lithuania	0.0688
7	Cyprus	0.0637
8	Estonia	0.0521
9	Slovenia	0.0473
10	Finland	0.0399
11	Poland	0.0342
12	Netherlands	0.0324
13	Czechia	0.0308
14	Greece	0.0282
15	Ireland	0.0249
16	Slovakia	0.0176
17	France	0.0174
18	United Kingdom	0.0126
19	Italy	0.0105
20	Germany	0.0048
21	Austria	0.0021
22	Spain	0.0011
23	Denmark	0.0000

SDID Country Weights (log Price Index)

	Control Countries	
Rank	**Country**	**Weight**
1	Bulgaria	0.1407
2	Croatia	0.1310
3	Malta	0.0790
4	Belgium	0.0715
5	Latvia	0.0680
6	Lithuania	0.0679
7	Cyprus	0.0661
8	Estonia	0.0482
9	Slovenia	0.0445
10	Finland	0.0376
11	Netherlands	0.0342
12	Poland	0.0338
13	Greece	0.0334
14	Ireland	0.0309
15	Czechia	0.0268
16	France	0.0226
17	United Kingdom	0.0156
18	Slovakia	0.0154
19	Italy	0.0138
20	Austria	0.0069
21	Germany	0.0044
22	Denmark	0.0040
23	Spain	0.0038
24	Iceland	0.0000

SDID Time Weights

Time Period	Weight
2015-05	0.5921
2015-04	0.4079

SDID Time Weights (log Price Index)

Time Period	Weight
2015-05	0.6116
2015-04	0.3884

Source: Authors' own calculations using data extracted from Eurostat (2025c).

Table A.2 Regression estimates from Eq(1) with regular standard errors. The outcome variable is the regular price index and the treatment date is 2015-06-01.

Difference-in-Differences Regression: Price Index

	(1)
Intercept	99.138***
	(0.051)
Treated (Romania)	5.906***
	(0.278)
Post-Treatment	3.097***
	(0.072)
Treated × Post	-9.496***
	(0.393)
Num.Obs.	19440
R2	0.101

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Authors' own calculations using data extracted from Eurostat (2025c).

Table A.3 Regression estimates from Eq(1) and using clustered standard errors on the country level. The dependent variable is the regular price index and the treatment date is 2015-06-01.

Difference-in-Differences Regression: Price Index (Clustered SE)

	Clustered SE Model
Intercept	99.138***
	(0.294)
Treated (Romania)	5.906***
	(0.294)
Post-Treatment	3.097***
	(0.485)
Treated × Post	-9.496***
	(0.485)
Num.Obs.	19440
R2	0.101

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Authors' own calculations using data extracted from Eurostat (2025c)

Table A.4 Regression estimates from Eq(2) with regular standard errors. The dependent variable is the log price index and the treatment date is 2015-06-01.

Difference-in-Differences Regression: Log(Price Index)

	(1)
Intercept	4.595***
	(0.000)
Treated (Romania)	0.058***
	(0.003)
Post-Treatment	0.031***
	(0.001)
Treated × Post	-0.093***
	(0.004)
Num.Obs.	19440
R2	0.101

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Source: Authors' own calculations using data extracted from Eurostat (2025c)

Table A.5 Regression estimate using a fixed effects model, which includes both country and month fixed effects. The dependent variable is the log price index and the treatment date is 2015-06-01.

Difference-in-Differences with Full Fixed Effects and Log(Price Index) (Clustered SE)

	DiD w/ Country + Year + Month FE (Clustered SE)
Intercept	4.570***
	(0.005)
Romania (Treated)	0.061***
	(0.002)
Post-Treatment	0.002
	(0.002)
Treated × Post	-0.093***
	(0.005)
Num.Obs.	19440
R2	0.205

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Source: Authors' own calculations using data extracted from Eurostat (2025c)

Table A.6 Estimates and parameters for the Synthetic Difference-in-Difference analysis. The outcome variable is the regular price index and the treatment date is 2015-06-01.

SDID Treatment Effect Estimates, Dependant Variable is Price Index Points

	Uncertainty			Penalty Params	
Estimate	Std. Error	95% CI Lower	95% CI Upper	Unit Regularization	Time Regularization
-9.8298	1.7189	-13.1988	-6.4607	2.1006	0

Source: Authors' own calculations using data extracted from Eurostat (2025c)

Table A.7 Month-by-month SDID estimates with treatment date set to 2015-06-01. The dependent variable is the log price index.

	Period-Specific Estimates
Time	**Estimate**
2012-06-01	-0.020593
2012-07-01	-0.015533
2012-08-01	-0.014042
2012-09-01	0.004899
2012-10-01	0.000194
2012-11-01	0.002412
2012-12-01	0.002366
2013-01-01	0.005185
2013-02-01	0.006407
2013-03-01	0.002804
2013-04-01	0.000741
2013-05-01	0.003946
2013-06-01	-0.003011
2013-07-01	-0.014140
2013-08-01	-0.018402
2013-09-01	-0.016408
2013-10-01	-0.010478
2013-11-01	-0.008136
2013-12-01	-0.006934
2014-01-01	-0.006053
2014-02-01	-0.003114
2014-03-01	-0.002284
2014-04-01	-0.004409
2014-05-01	-0.002831
2014-06-01	-0.006407
2014-07-01	-0.006775
2014-08-01	-0.011435
2014-09-01	-0.012681
2014-10-01	-0.005357
2014-11-01	-0.011439
2014-12-01	-0.006442
2015-01-01	-0.010846
2015-02-01	-0.008753
2015-03-01	-0.004832
2015-04-01	-0.006875
2015-05-01	0.004365
2015-05-01	0.004365
2015-06-01	-0.090509
2015-07-01	-0.096007
2015-08-01	-0.109727
2015-09-01	-0.102748
2015-10-01	-0.099346
2015-11-01	-0.099726
2015-12-01	-0.091146
2016-01-01	-0.091176
2016-02-01	-0.087555
2016-03-01	-0.086593
2016-04-01	-0.097223
2016-05-01	-0.093629
2016-06-01	-0.096044
2016-07-01	-0.100890
2016-08-01	-0.097904
2016-09-01	-0.103853
2016-10-01	-0.095757
2016-11-01	-0.097474
2016-12-01	-0.102448
2017-01-01	-0.109022
2017-02-01	-0.108159
2017-03-01	-0.100979
2017-04-01	-0.099886
2017-05-01	-0.094744
2017-06-01	-0.090040
2017-07-01	-0.098095
2017-08-01	-0.110312
2017-09-01	-0.108111
2017-10-01	-0.097057
2017-11-01	-0.095738
2017-12-01	-0.090432
2018-01-01	-0.090594
2018-02-01	-0.083640
2018-03-01	-0.077209
2018-04-01	-0.079463
2018-05-01	-0.077496

Source: Authors' own calculations using data extracted from Eurostat (2025c)

Table A.8 Month-by-month SDID estimates with treatment date set to 2015-04-01. The dependent variable is the log price index.

	Period-Specific Estimates
Time	Estimate
2012-06-01	-0.012581
2012-07-01	-0.007755
2012-08-01	-0.006558
2012-09-01	0.012427
2012-10-01	0.007889
2012-11-01	0.010143
2012-12-01	0.009800
2013-01-01	0.013159
2013-02-01	0.014155
2013-03-01	0.010579
2013-04-01	0.008563
2013-05-01	0.012152
2013-06-01	0.005548
2013-07-01	-0.005888
2013-08-01	-0.010467
2013-09-01	-0.008435
2013-10-01	-0.002847
2013-11-01	-0.000463
2013-12-01	0.000650
2014-01-01	0.002129
2014-02-01	0.004815
2014-03-01	0.005616
2014-04-01	0.003783
2014-05-01	0.005667
2014-06-01	0.001884
2014-07-01	0.001492
2014-08-01	-0.003406
2014-09-01	-0.004482
2014-10-01	0.002786
2014-11-01	-0.003238
2014-12-01	0.001749
2015-01-01	-0.002334
2015-02-01	0.000022
2015-03-01	0.004104
2015-04-01	0.002827
2015-05-01	0.014441
2015-06-01	-0.080400
2015-07-01	-0.085701
2015-08-01	-0.100098
2015-09-01	-0.093096
2015-10-01	-0.089911
2015-11-01	-0.090493
2015-12-01	-0.081963
2016-01-01	-0.081853
2016-02-01	-0.077855
2016-03-01	-0.076329
2016-04-01	-0.086866
2016-05-01	-0.083130
2016-06-01	-0.085588
2016-07-01	-0.090785
2016-08-01	-0.088005
2016-09-01	-0.093790
2016-10-01	-0.085350
2016-11-01	-0.087018
2016-12-01	-0.091951
2017-01-01	-0.097741
2017-02-01	-0.096653
2017-03-01	-0.089680
2017-04-01	-0.088510
2017-05-01	-0.083163
2017-06-01	-0.078282
2017-07-01	-0.086233
2017-08-01	-0.098938
2017-09-01	-0.096651
2017-10-01	-0.085236
2017-11-01	-0.083944
2017-12-01	-0.078590
2018-01-01	-0.078261
2018-02-01	-0.071597
2018-03-01	-0.065374
2018-04-01	-0.067576
2018-05-01	-0.065240

Source: Authors' own calculations using data extracted from Eurostat (2025c)

Table A.9 SDID results from Eq (4) but excludes Eurozone countries from the donor pool. The dependent variable is log(price index) and the treatment date is 2015-06-01.

SDID Treatment Effect Estimates, Dependent Variable is log(Price Index)

	Uncertainty			Penalty Params	
Estimate	Std. Error	95% CI Lower	95% CI Upper	Unit Regularization	Time Regularization
-0.0988	0.0384	-0.1741	-0.0236	0.022	0

Source: Authors' own calculations using data extracted from Eurostat (2025c)

Table A.10 SDID country weights from Eq (4) but excludes Eurozone countries from the donor pool.

SDID Country Weights (log Price Index)

Country	Weight
Poland	0.3141
United Kingdom	0.2952
Czechia	0.2482
Sweden	0.1426

Source: Authors' own calculations using data extracted from Eurostat (2025c)

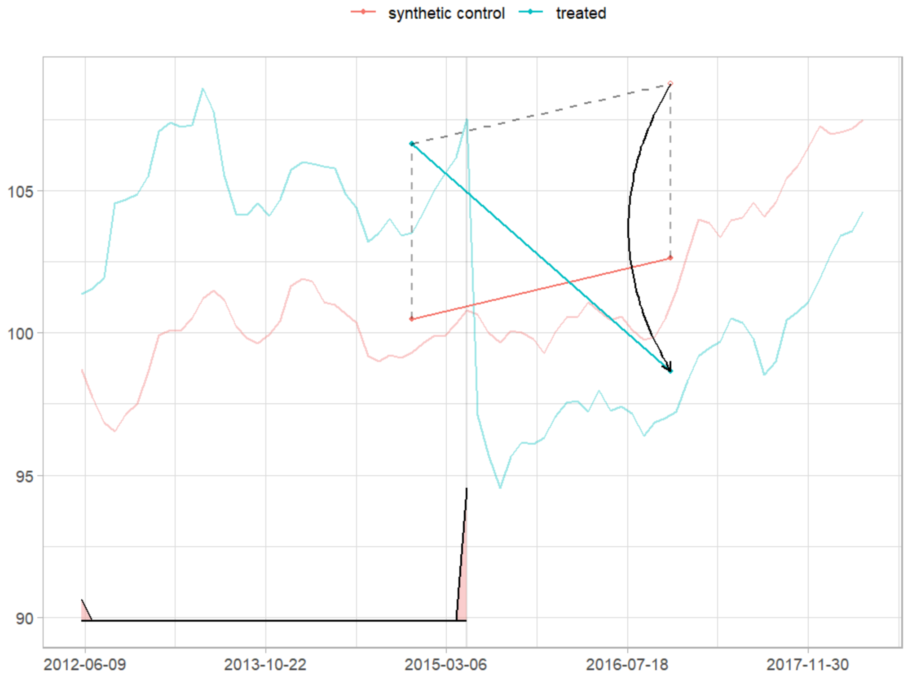

Figure A.1 SDID plot which is equivalent to Figure 2 but excludes Eurozone countries from the donor pool. The dependent variable is log(price index) and the treatment date is 2015-06-01. Moreover, the light blue line is Romania's price index trend from 2012-06-01 to 2018-05-01 while the red trend is the corresponding trend for the untreated group which only includes non-Eurozone countries. Additionally, the red line diagram at the bottom highlights time weight concentration. The thick blue arrow shows the difference in price levels between pre- and post treatment period for Romania and the red thick arrows visualizes the equivalent for the untreated group. Finally, the black curved arrow is the estimated treatment effect.

Source: Authors' own calculations using data extracted from Eurostat (2025c)

Table A.11 SDID results from Eq (4) but excludes Croatia and the United Kingdom from the donor pool. The dependent variable is log(price index) and the treatment date is 2015-06-01.

SDID Treatment Effect Estimates, Dependent Variable is log(Price Index)

	Uncertainty			Penalty Params	
Estimate	**Std. Error**	**95% CI Lower**	**95% CI Upper**	**Unit Regularization**	**Time Regularization**
-0.0963	0.0188	-0.1332	-0.0595	0.0211	0

Source: Authors' own calculations using data extracted from Eurostat (2025c)

Table A.12 SDID country weights from Eq (4) but excluding Croatia and United Kingdom in the donor pool

SDID Country Weights (log Price Index)

Country	Weight
Bulgaria	0.1647
Malta	0.0841
Belgium	0.0791
Cyprus	0.0781
Latvia	0.0731
Lithuania	0.0677
Estonia	0.0609
Slovenia	0.0569
Greece	0.0497
Poland	0.0452
Finland	0.0435
Ireland	0.0412
Netherlands	0.0386
Slovakia	0.0296
France	0.0289
Czechia	0.0202
Spain	0.0158
Italy	0.0146
Portugal	0.0061
Denmark	0.0020
Austria	0.0000
Germany	0.0000
Iceland	0.0000
Luxembourg	0.0000
Norway	0.0000
Sweden	0.0000
Switzerland	0.0000

Source: Authors' own calculations using data extracted from Eurostat (2025c)

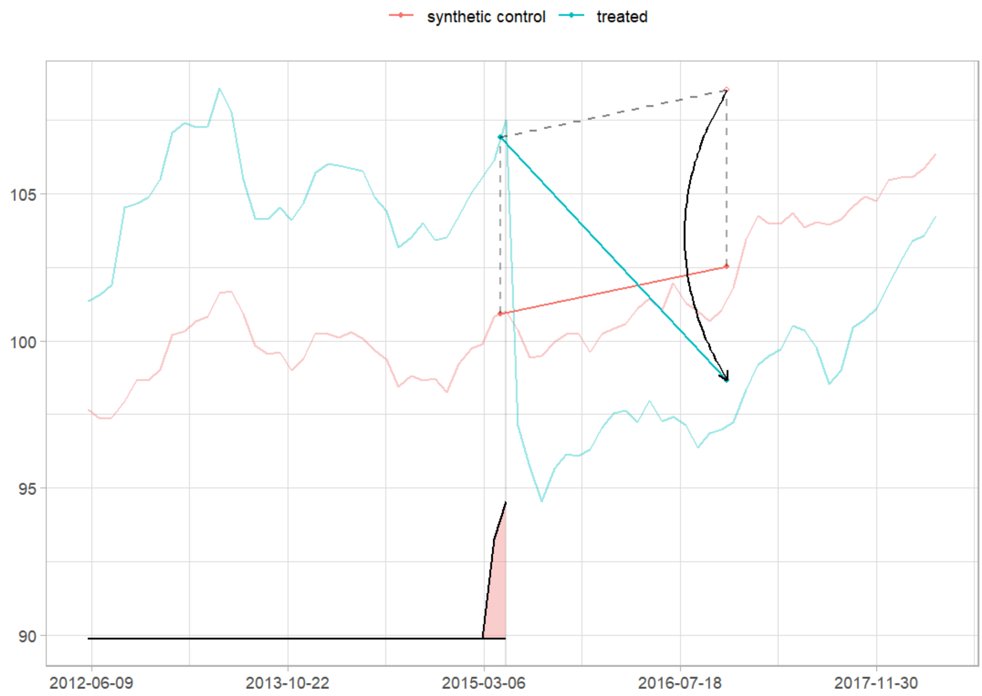

Figure A.2 SDID plot which is equivalent to Figure 2 but excludes Croatia and the United Kingdom from the donor pool. The dependent variable is log(price index) and the treatment date is 2015-06-01. Moreover, the light blue line is Romania's price index trend from 2012-06-01 to 2018-05-01 while the red trend is the corresponding trend for the untreated group which does not include Hungary, Croatia or the United Kingdom. Additionally, the red line diagram at the bottom highlights time weight concentration. The thick blue arrow shows the difference in price levels between pre- and post treatment period for Romania and the red thick arrows visualizes the equivalent for the untreated group. Finally, the black curved arrow is the estimated treatment effect.

Source: Authors' own calculations using data extracted from Eurostat (2025c)

Table A.13 results from Eq (4) but while including Hungary in the donor pool. The dependent variable is log(price index) and the treatment date is 2015-06-01.

SDID Treatment Effect Estimates, Dependent Variable is log(Price Index)

	Uncertainty			Penalty Params	
Estimate	**Std. Error**	**95% CI Lower**	**95% CI Upper**	**Unit Regularization**	**Time Regularization**
-0.0964	0.0156	-0.1269	-0.0659	0.0213	0

Source: Authors' own calculations using data extracted from Eurostat (2025c)

Table A.14 SDID country weights from Eq (4) but including Hungary in the donor pool

SDID Country Weights (log Price Index)

Country	Weight
Bulgaria	0.1348
Croatia	0.1238
Malta	0.0784
Hungary	0.0751
Belgium	0.0654
Cyprus	0.0654
Lithuania	0.0615
Latvia	0.0593
Estonia	0.0413
Finland	0.0380
Slovenia	0.0379
Netherlands	0.0314
Ireland	0.0313
Poland	0.0298
Greece	0.0288
Czechia	0.0233
France	0.0196
United Kingdom	0.0188
Italy	0.0121
Slovakia	0.0071
Austria	0.0058
Denmark	0.0041
Spain	0.0040
Germany	0.0032
Iceland	0.0000
Luxembourg	0.0000

Source: Authors' own calculations using data extracted from Eurostat (2025c)

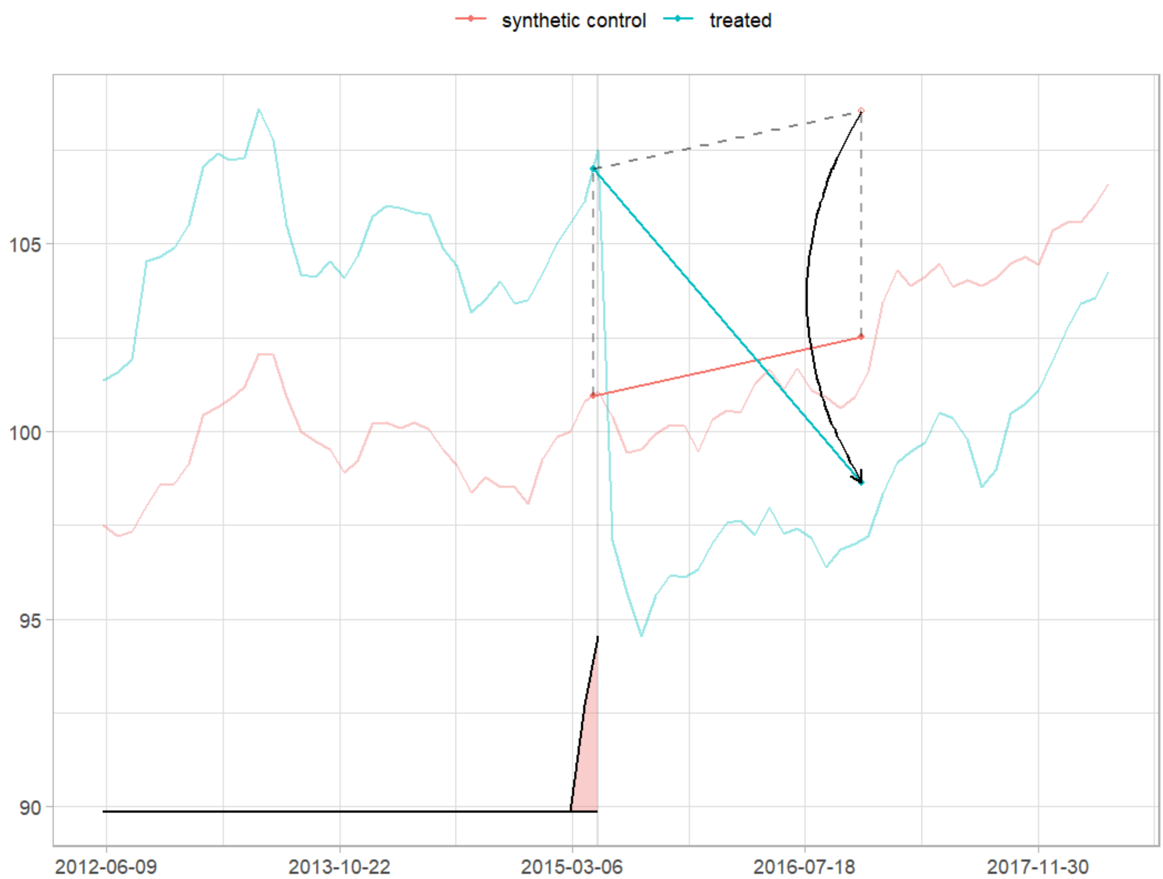

Figure A.3 SDID plot which is equivalent to Figure 2 but including Hungary in the donor pool. The dependent variable is log(price index) and the treatment date is 2015-06-01. Moreover, the light blue line is Romania's price index trend from 2012-06-01 to 2018-05-01 while the red trend is the corresponding trend for the untreated group which includes 31 European countries, counting Hungary. Additionally, the red line diagram at the bottom highlights time weight concentration. The thick blue arrow shows the difference in price levels between pre- and post treatment period for Romania and the red thick arrows visualizes the equivalent for the untreated group. Finally, the black curved arrow is the estimated treatment effect.

Source: Authors' own calculations using data extracted from Eurostat (2025c)

Appendix B: Generative AI disclosure

We have used ChatGPT to speed up our coding process in R. An example of when this has come in handy is when applying the SDID method over a variety of different products and specifications, where codes are nearly identical but somewhat different from product-to-product, requiring a lot of manual labor. We are aware of the risks, such as hallucinations, that this usage may involve and have to the best of our ability checked that our codes do what they are intended for.