Price Passthrough without Intertemporal Substitution: Evidence from Germany's Temporary VAT Cut

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Abstract

We evaluate the effectiveness of an unconventional fiscal policy implemented during the first wave of the Covid-19 pandemic in Germany, where VAT was temporarily cut from July 2020 to January 2021. We estimate the causal effects of the policy on consumer prices and quantities purchased using granular scanner data, covering both durable and non-durable goods with over 100 million transactions. Using other European countries as control groups for Germany, together with a complementary research design that analyzes shifts in the product-level distribution of price changes over time within Germany, we find sizable pass-through of the VAT changes to retail prices: 65 percent for durables and 91 percent for non-durables. However, we do not observe significant quantity responses for either durable or non-durable goods. We find that even in a short time window around the policy shock, there is little change in quantities purchased even for durable goods, despite strong price incentives to delay consumption for these goods. Using a simple model, we show that the empirical estimates imply a tight upper bound on the elasticity of intertemporal substitution (EIS). Our baseline specification rules out an EIS above 0.08.

Keywords: value-added taxes, incidence, asymmetry, tax pass-through, unconventional fiscal policy

JEL classification: H20, H22, H24, H30

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1 Introduction

During severe economic crises, when monetary policy is constrained by the zero lower bound, governments around the world increasingly consider so-called unconventional fiscal policies to stimulate demand, as seen for instance during the Covid-19 pandemic. Temporary VAT reductions are a prime example of such policies and were used by several countries during the pandemic, including Germany, which reduced its standard VAT rate from 19 percent to 16 percent between July and December 2020.

In principle, temporary VAT changes can stimulate the economy if two conditions hold: price pass-through must be sufficiently high, and consumers' elasticity of intertemporal substitution must be large enough for them to pull forward expenditures in anticipation of future price increases (Shapiro, 1991, Feldstein, 2002, Hall, 2011, Correia et al., 2013). While a growing literature has characterized the price effects of temporary VAT policies (e.g., Blundell, 2009, Montag et al., 2023, Fuest et al., 2025), the effectiveness of temporary VAT changes in stimulating the economy remains debated. Indeed, owing to data limitations, evidence on quantity responses remains scarce, particularly for durable goods.

In this paper, we leverage a new multi-country scanner database covering both durable and non-durable goods, with barcode-level information on prices paid and quantities purchased. The data, sourced from YouGov (for fast-moving consumer goods, FMCG) and NielsenIQ (for slow-moving consumer goods, SMCG), comprise well over 100 million transactions in Germany and control-group countries during the period under review. The data cover purchases in all relevant offline retail formats (supermarkets, discounters, electronics retailers) as well as online stores, and record actual transaction prices rather than posted dealer prices. Using quasi-experimental methods, we estimate the impact of the temporary VAT cut in Germany on prices and quantities and infer the implied consumer elasticity of intertemporal substitution. Our analysis proceeds in three steps.

In the first part of the analysis, we estimate the response of prices. Using the Netherlands and other European countries as a control group in a difference-in-differences specification around the implementation of Germany's temporary VAT policy, we find sizable pass-through rates of 65 percent for durables and 91 percent for non-durables. To address potential concerns about unobserved country-specific shocks that could confound these estimates, we complement the difference-in-differences analysis with an examination of the product-level distribution of price changes. We show that in all months, there is a large mass at zero price changes, except around the policy implementation date in Germany, when this mass shifts to -2.5 percent, confirming a high pass-through rate.

For durable goods, pass-through is slightly asymmetric, with a smaller price increase at the end of the temporary VAT reduction period, whereas pass-through is symmetric for non-durables. When weighting by expenditure shares, the average price pass-through across all products is 76 percent. The pass-through estimates imply that the temporary tax cut provided meaningful short-term income relief to households across the income distribution, including lower-income households, whose consumption baskets are concentrated in non-durable goods subject to high pass-through.

In the second part of the analysis, we use the same difference-in-differences research design to study quantity responses. We do not find statistically significant effects on quantities. Depending on the product category considered, the estimated quantity response changes sign but remains statistically insignificant. Relative to the emerging literature on the quantity responses to temporary VAT policies (Bachmann et al., 2026, Koeniger and Kress, 2024), a key advantage of our approach is that we can conduct the analysis at a high frequency, studying price and quantity dynamics jointly. We show that even in a short time window around the policy change, there is little change in quantities despite strong price incentives to delay consumption. This evidence allows us to provide tight bounds on the elasticity of intertemporal substitution (EIS).

In the third part of the analysis, we develop a simple model, following Orchard et al. (2025), to interpret our reduced-form estimates and derive bounds on the EIS of durable goods. In the model, the estimated quantity response is the product of the EIS, a term capturing user costs, and potential adjustment frictions. Across a wide range of parameter values, we consistently obtain a low EIS, even when considering the upper bound of the (relatively noisy) estimated quantity responses implied by the 95 percent confidence intervals.

Intuitively, durable goods provide strong incentives for intertemporal substitution. Yet we observe only small changes in the quantities of durable goods purchased, even in a short time window around the policy change, implying that the elasticity of substitution must be low. Specifically, in our baseline specification mostly using the same parameters as Orchard et al. (2025) but adjusted for the durability of the goods in our sample, we can rule out EIS values greater than 0.0023 in the frictionless version of the model. In the version with frictions, we can rule out an EIS above 0.08.

Taken together, these findings suggest that temporary VAT reductions are unlikely to provide a strong demand stimulus through intertemporal substitution. While consumers benefit from an income effect through lower prices, they do not appear to respond meaningfully to intertemporal price incentives. Moreover, this income effect arises from an untargeted transfer, in contrast to other stimulus tools that can target high-marginal-propensity-to-consume agents or directly raise MPCs (Boehm et al., 2025).

Related literature. Our analysis relates to several strands of the literature.

First, the empirical literature has focused primarily on the price effects of VAT changes. Specifically, there is a growing literature on the price pass-through of either temporary changes (Crossley et al., 2014, Montag et al., 2023, Benzarti, Garriga, et al., 2024, Koeniger and Kress, 2024, Bernardino et al., 2025, Fuest et al., 2025) or permanent changes (Besley and Rosen, 1999, Benedek et al., 2020, Benzarti, Carloni, et al., 2020, Carbonnier, 2007, Buettner and Madzharova, 2021, Kosonen, 2015) in VAT or sales taxes. Our data allow us to estimate price passthrough for durable goods and, most importantly, to go beyond the price margin and jointly estimate quantity responses, which is essential for assessing the effectiveness of the policy as a demand stimulus.

To the best of our knowledge, only two papers empirically investigate the quantity or expenditure effects of temporary VAT cuts (Bachmann et al., 2026, Koeniger and Kress, 2024).[1]

[1] In addition, there are a few related studies analyzing the effect of short-lived sales tax holidays in the U.S. on

Both studies exploit the 2020 VAT cut in Germany, but differ in the methodology and data employed. Bachmann et al. (2026) rely on two cross-sectional surveys within Germany, comparing the behavior of individuals who report they are more or less informed about the VAT tax cut. Their approach suggests the quantity response was very large. Koeniger and Kress (2024) study the same policy using credit card transactions data in a difference-in-differences approach across countries. They find more modest but still meaningful quantity responses effects. In contrast, we estimate a small response. Relative to Bachmann et al. (2026), our approach provides direct evidence on quantity responses at a high frequency, obviating the need to leverage self-reported policy awareness. In contrast to Koeniger and Kress (2024), we do not restrict our analysis to the subpopulation of credit-card users and we can disentangle prices and quantities. More broadly, by pooling multiple control-group countries, we can directly test the sensitivity of our estimates to country-specific pandemic dynamics. The high-frequency approach we take for the analysis of quantities makes it possible to show clear graphical evidence that quantities changed very little relative to the strong price incentives to delay consumption in the short run.

Finally, we contribute to the literature estimating the EIS. Several studies estimate intertemporal substitution responses to preannounced permanent VAT changes, providing the closest precedents for our EIS analysis. Buettner and Madzharova (2021) studies the impact of 33 (32 permanent) VAT changes in a panel of European countries using microdata on household appliances, finding an anticipatory quantity response just before the tax change that is more than offset by decreases when the tax change was implemented. D'Acunto et al. (2022) analyze the 3-pp. increase in the German VAT in 2007 using France as their counterfactual, showing that the preannounced VAT increase resulted in higher inflation expectations and increased plans to buy durable goods in survey data. Cashin and Unayama (2016) investigate the 1997 VAT increase in Japan and estimate a low EIS of 0.21, which is not significantly different from zero.

Our paper advances this prior work by estimating the EIS from a *temporary* VAT change — a setting that is arguably most favorable to detecting intertemporal substitution, since the price incentive operates over the entire six-month window of reduced rates and consumers face two salient price changes (down in July 2020, up in January 2021). Using our reduced-form quantity estimates within a structural framework following Orchard et al. (2025), we can bound the EIS tightly. In a model with or without friction, we obtain upper bounds for the EIS that are very close to zero. This result offers a tighter upper bound on EIS compared to prior work, while being broadly consistent with the very low EIS estimated in Best et al. (2020), who estimate an EIS of around 0.1 using mortgage notches in the UK, and with the bias-corrected mean of micro estimates reported in the meta-analysis of Havránek (2015).

Outline. The remainder of the paper is structured as follows. Sections 2 and 3 present a description of the data and research design. Empirical results on the price and quantity effects of the temporary VAT cut are presented in Section 4. In Section 5, we discuss our estimates and a simple model to provide tight bounds on the elasticity of intertemporal substitution. Section 6 concludes.

expenditures and consumption (Agarwal et al., 2017, Baker, Kueng, et al., 2019, Baker, Johnson, et al., 2021). (Crossley et al., 2014) also study purchase responses to the temporary VAT reduction in the UK in 2008-9.

2 Data

Our analysis leverages a very rich set of scanner data from the research marketing companies YouGov (FMCG) and NielsenIQ (SMCG) which has not been used for macro-oriented research of the type we conduct so far.[2] This data set has several characteristics making it particularly well suited to address the main questions of our analysis.

One of the major strengths of the data used is that we not only have information on FMCG transactions but for the first time purchase data for SMCG transactions. The response of SMCG purchases are of particular importance for the intended macroeconomic stabilization effects, which are supposed to result from a forward shifting of the purchases of durable consumer goods from the future into 2020.

A second virtue of the data is that we observe purchases of data in all relevant online and "offline" markets (especially supermarkets and discounters), which in Germany still make up the vast majority of grocery purchases, as well as purchases in online supermarkets.

Thirdly, we have available the data not only for Germany but also for neighboring countries. Given that we can define homogeneous product groups across countries, this allows us to form control groups. In particular, we use Dutch, Italian and Austrian data to construct control groups for both the FMCG- and SMCG-data based analysis.

As indicated, we obtain our data from two different sources. The FMCG data come from the YouGov household panel for Germany (and the corresponding YouGov household panels for Austria, Italy and the Netherlands). The YouGov household panel for Germany comprises around 30,000 households, which largely constitute a representative sample of the population of German households. The underlying FMCG data sample begins in January 2020 and ends in March 2021. Data from 2019 is also used for robustness purposes. The participating households record their purchases on a continuous basis. The data set includes information not only about the amount of products purchased and the price paid, but also about the (socio-economic) characteristics of the households and is therefore very well suited for analyzing the question of the extent to which different household groups participate in benefit to varying degrees from VAT.

The second data source is the NielsenIQ POS panel (POS = point of sale) for Germany (and again for Austria, Italy and the Netherlands). The POS Panel is a regular, comprehensive survey to monitor sales of SMCG. In detail, products from 23 sectors are recorded in the POS panel, which are divided into 78 categories (see table in the appendix for an overview of the sectors). The purchases recorded include both in-store and online purchases. The data set spans a period from January 2020 to the end of March 2021. Data from 2019 is also added for robustness analyses.

Data preparation The scanner dataset offers granular transaction-level data on both prices and quantities at weekly (SMCG) or even daily (FMCG) frequencies. Each record provides the quantity purchased and the price paid for a specific barcode at a given retailer. To facilitate meaningful analysis, we aggregate this data to a monthly frequency by calculating unit values and total units purchased at the barcode-retailer level within each country. This level of aggregation

[2] Throughout the paper, we use the terms FMCG and non-durables, and SMCG and durables synonymously.

captures price and quantity dynamics without losing too much variation.

Although the scanner data from GfK for both FMCG and SMCG is of high quality and has been shown to closely track official price indices (see Beck and Jaravel (2020); Beck, Carstensen, et al. (2024)), occasional recording errors or unwanted transactions can still appear. To address these, we implement several filters, guided by the relevant literature.

First, we apply a plausibility filter to retain only transactions with positive price and quantity values. This eliminates records involving returns (negative quantities) or free product promotions. Next, we exclude transactions with prices greater than four times or less than one-quarter of the median price, as well as quantities more than 25 times the median quantity purchased. These filters are applied at the retailer-barcode level, following the methodology of Redding and Weinstein (2020)

For the FMCG dataset, we include only households with at least one purchase in each quarter of 2019 (pre-treatment period) to ensure a consistent sample over time, allowing for occasional absences (e.g., holidays). This step mitigates the potential bias introduced by household entry and exit. This issue does not arise in the SMCG dataset, which collects data from a fixed set of retailers weekly.

To address outliers in price changes, we discard observations with month-over-month price changes exceeding 10% at the retailer-barcode level. This threshold is justified, as large price jumps are rare and any month-over-month change greater than 10% cannot be attributed to the VAT effect, where even full pass-through would only result in a price change of about 2.5%.

Finally, we exclude highly seasonal product categories from the analysis based on two criteria: (i) a product category must have at least 10 distinct retailer-barcode combinations, and (ii) it must not exhibit excessively high price index volatility. Applying these filters, we exclude seasonal items like Christmas gifts and gardening tools from the dataset to ensure more stable and generalizable findings.

3 Empirical Strategy

In this section, we present the empirical strategy to identify the causal effect of the change in the VAT rate on consumer prices and quantities. Subsection 3.1 presents our general research design, which boils down to a difference-in-differences model. In Subsection 3.2, we use the diff-in-diff design to provide first pieces of evidence of the reform effects using raw data. In Subsection 3.3, we spell out the main empirical specifications.

3.1 Research Design

Estimating the causal effects of changes in the VAT on prices and quantities is challenging for two main reasons. First, the VAT rate cut was implemented nationally; hence, it is difficult to identify a suitable control group that represents Germany's counterfactual outcomes in the absence of the VAT change. Second, prices and even more so quantities are very volatile: on the one hand, product-specific shocks happen frequently but irregularly, for instance, fluctuations in energy prices, wheat production, or scarcity of certain inputs. On the other hand, there is strong seasonality in purchases. Moreover, product life cycles, particularly for durables, are relatively short (Buettner and Madzharova, 2021).

We propose a differences-in-differences research design to address these challenges. We compare prices and quantities in Germany over time with those of a set of control-group countries, accounting for seasonality and other COVID-specific shocks. The identifying assumption is that the evolution of outcomes in counterfactual Germany, without VAT changes, is identical to that observed in the control group after controlling for country-specific potential confounders, such as seasonality or COVID dynamics.

Treatment. Germany is the treatment country, and there are two treatments. The first treatment occurs with the reduction of VAT rates on July 1, 2020. The second treatment is the re-raise of VAT rates to pre-reform levels. Hence, from July 1, 2020, until December 31, 2020, the standard VAT rate was reduced from 19% to 16%, and the reduced rate on necessities was reduced from 7% to 5%.

The temporary VAT rate cuts, with an estimated cost of 20 billion euros, were the central and most salient component of a 60 billion euro economic stimulus program. The program was announced on June 3, 2020. A stimulus program was anticipated, but the temporary VAT rate cuts came as a surprise to the public. The stimulus was explicitly grounded in economic arguments about unconventional fiscal policy at the zero lower bound, a view endorsed by several close economic advisors to the chancellor. Borrowing from the language of comics — and in contrast to his usual style of communication — the German Chancellor referred to the program as "BOOOM" (German: WUMMS), underscoring both its intended scale and the expectations placed on it to stimulate the German economy, which was suffering under the COVID-19 pandemic.

Other measures in the package included a one-time child bonus payment of 5 billion euros; the remaining funds were allocated primarily to short-term liquidity stabilization for firms and municipalities. The overall package totaled 130 billion euros, including 50 billion euros for a "Future Package" of medium-term, partly relabeled, investment measures focused on climate policy and digitalization, and 20 billion euros for energy-related measures.

Control-Group Countries. Germany forms the treatment group. A suitable control country should resemble Germany in terms of market structures for durable and non-durable goods and should have experienced a similar pandemic trajectory, including policy responses, except for the change in VAT. The NielsenIQ data allows for the selection from a large set of European countries, for which scanner data on durable and non-durable goods are available.

There are several ex-ante reasons to think that the Netherlands, Austria, and Italy provide useful comparison groups, which we use as as control groups individually or collectively in robustness analyses.

First, the Netherlands closely resembles Germany in terms of retail market structure for both SMCG and FMCG, with a high degree of overlap in product assortments, brands, and pricing strategies captured in the NielsenIQ data. In addition, the Netherlands is a highly open economy with strong trade integration with Germany, implying exposure to similar external demand conditions and common upstream cost shocks. Geographic proximity further ensures comparable seasonal patterns and macroeconomic conditions, making the Netherlands the closest observable proxy for Germany's counterfactual evolution of prices and quantities.[3] Lastly, the pandemic trajectory is similar, as shown in Appendix Figure A.1.

Another country of interest is Austria, another direct neighbor, which has also been used in Fuest et al. (2025) and Koeniger and Kress (2024). Austria provides a closely comparable institutional and economic environment, with similar income levels, consumption patterns, and regulatory frameworks, as well as a comparable VAT system. Retail markets are highly similar and covered consistently in the NielsenIQ data. As a neighboring country, Austria is exposed to similar seasonal patterns and macroeconomic shocks, making it a natural benchmark for Germany's counterfactual dynamics.

Third, Italy provides another instructive comparison point, deliberately more distant. Unlike the neighboring countries, Italy is less tightly integrated with Germany's retail and cross-border consumption markets, limiting the scope for direct spillovers of the German VAT reform. At the same time, Italy shares key institutional features, such as EU single-market integration, comparable VAT systems, and coverage by the same NielsenIQ retail data, ensuring consistency in measurement. Its different pandemic trajectory and economic environment, therefore, provide a useful robustness check, allowing us to verify that our results are not driven by COVID-specific shocks or cross-border spillovers.

Adjusting for Seasonality. Given the strong and country-specific seasonality in many productions and consumption patterns, we always specify outcomes relative to the same time unit (week or month) in the same country in the previous year (one-year lag).

3.2 Graphical Evidence based on Raw Data

In this subsection, we present simple graphical evidence based on minimal data processing. We aim to detect changes in price and quantity in the raw data. In light of the relatively small VAT rate changes from 19 to 16% (and 7 to 5% for necessities), this exercise is challenging. Perfect pass-through would imply a price change around July 1, 2020, of $-0.025 = 1.16/1.19 - 1$ for standard products and a change of -0.019 for necessities. Price changes of this or larger magnitudes are routinely observed in price change distributions at the weekly or monthly level.

Prices. Figure 1 shows the weekly price change distribution for durables in Germany and the Netherlands for two selected weeks in 2020 and 2019. Week 20 (May 13-19,2019; May 11-17, 2020) precedes the German government's announcement of the VAT rate cut. Week 27 (July 1-7, 2019; June 29-July 5, 2020) is the week of the 2020 reform implementation. The figure clearly shows that, for many goods, prices do not change from one week to the next. There is a large stable part of the weekly inflation distribution at all times in both countries, with one exception: Only in Germany during the reform week (the blue line in panel (d)), we observe negative price

[3]While this close integration raises the possibility of cross-border spillovers of the German VAT reform, any such spillovers would attenuate estimated treatment effects. The fact that we obtain sizable and robust estimates despite this potential attenuation therefore strengthens the interpretation of our results.

changes between 2.5% and 2.0% in the normally stable part of the weekly inflation distribution. This is the first clear indication of price reactions to the VAT rate cut.

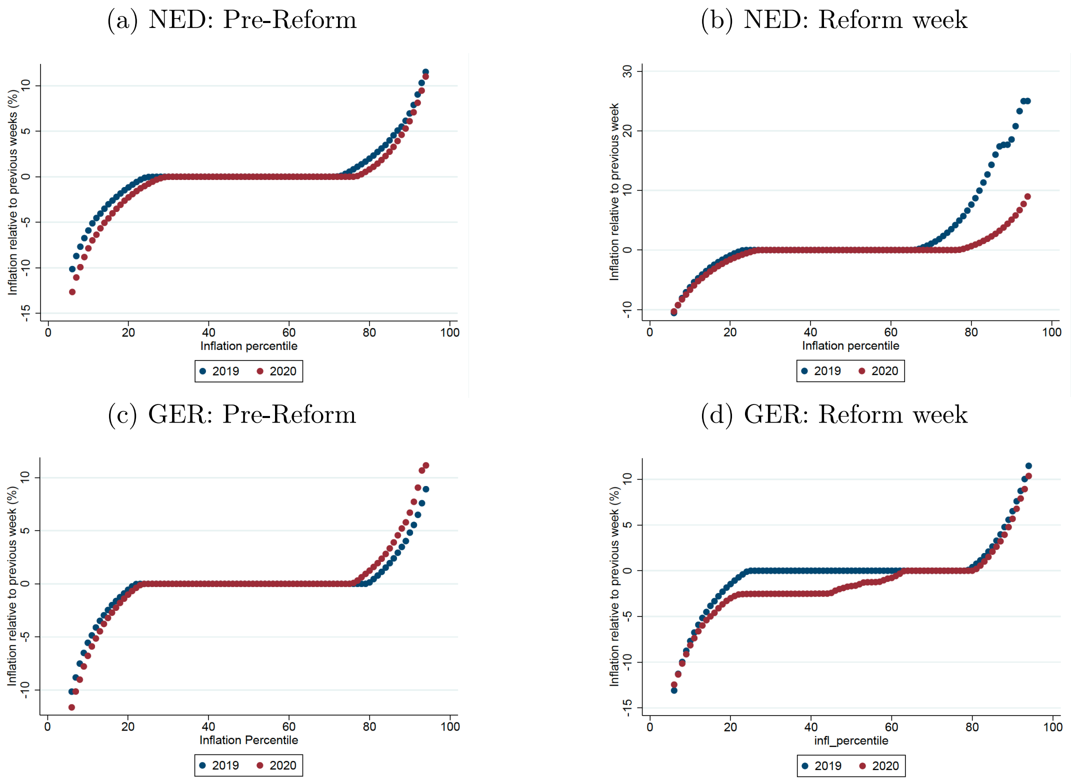
Using insights from Figure 1, we take the analysis at the monthly level. We identify the stable part of the price change distribution in Germany and the Netherlands pre-reform to be between the 40th and the 60th percentile of the monthly inflation distribution. We focus on this portion of the distribution and plot monthly price changes for Germany and the Netherlands. To adjust for seasonality as discussed in Subsection 3.1, we subtract the monthly price changes from the previous year for each product.

Figure 2 presents the results. For the Netherlands, we see that price changes are sharply centered around zero for both durables and non-durables (top panels) across all months considered. In contrast, for Germany, we clearly see that the price distribution for durables in July 2020, when VAT rates were cut, is shifted to the left and centered at -0.025. In January 2021, when rates increased to pre-reform levels, we detected a symmetric pattern: the price change distribution was shifted to the right and centered around 0.025. In all other months, price changes are sharply centered around zero. The pattern suggests that durable goods prices respond to changes in VAT rates with near-instant, symmetric effects.

For non-durables, we see a similar pattern. The price distribution shifts leftward in July 2020. In 2021, prices did not increase as sharply. In contrast to durable goods, the price distribution is shifted again to the right in January, but the distribution for February 2021 also displays a shift to the right, even though this is less pronounced. In March 2021, the price change distribution is again centered at zero.

Quantities. In principle, we could conduct the same analysis for quantities. However, the weekly and monthly quantity distributions do not exhibit a stable component. The higher volatility in quantity changes is a challenge we will discuss further in the following sections, when presenting the triple difference estimates.

Figure 1: Weekly price change distributions in GER and NED in selected weeks



(a) NED: Pre-Reform

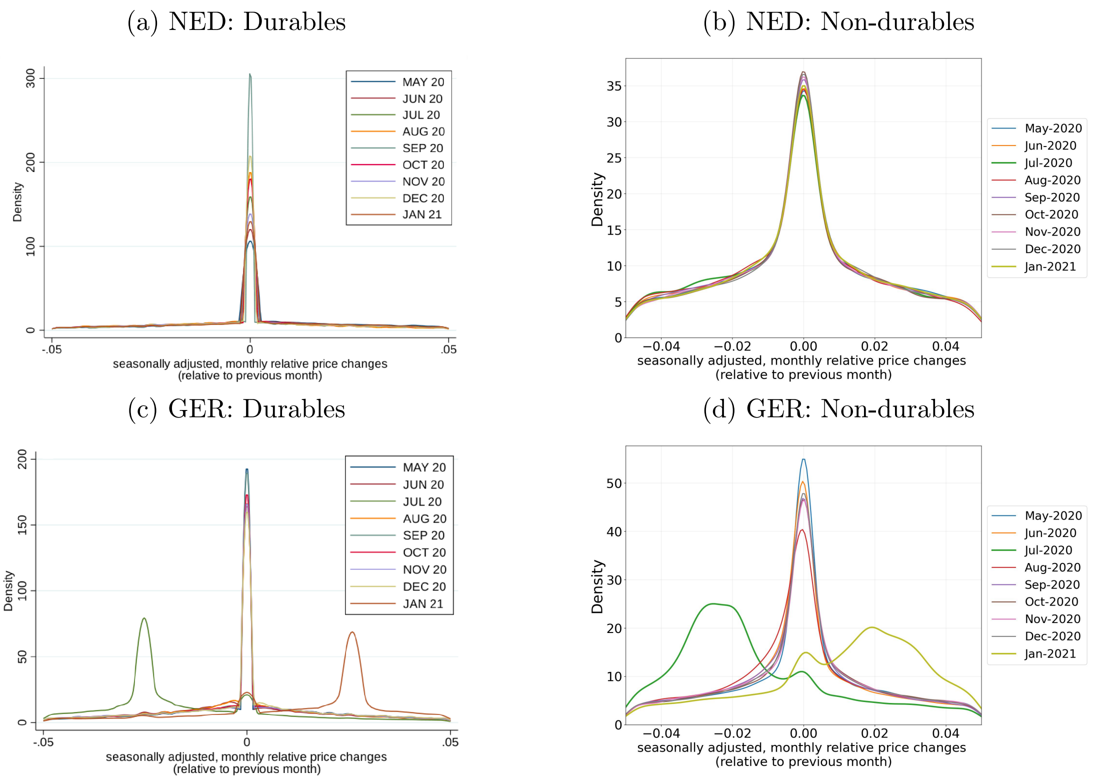
(b) NED: Reform week

(c) GER: Pre-Reform

(d) GER: Reform week

Notes: Source: Own calculations based on . *Notes:* The four panels of this figure show the weekly price changes for Germany (GER) and the Netherlands (NED) in two selected weeks in 2020 (blue lines) and 2019 (red lines). Week 20 in 2020 is before the German government announced the VAT rate cut from 19% to 16% for the standard rate and from 7% to 5% for the reduced rate. Week 27 in 2020 is the week of the implementation of the reform, which came into effect on July 1, 2020.

Figure 2: Monthly price change distributions in GER and NED, 2020 and 2021



Notes: Source: Own calculations based on . *Notes:* The four panels of this figure shows the monthly price changes for durables (left panels) and non-durables (right panels) for Germany (lower panels) and the Netherlands (upper panels) for 2020 and parts of 2021.

3.3 Empirical model

In this subsection, we translate the general identification strategy from section 3.1 into an empirical model.

In the first step, we compute Tornqvist price and quantity indices for a highly granular, *country-specific* product category c at time t, where t is a month in the baseline, but can be week, quarter, or half-year :

$$Y_{c,t} = \prod_{i \in \Omega_{c,t,t-1}} \left(\frac{y_{ic,t}}{y_{ic,t-1}}\right)^{\frac{s_{ic,t}+z_{ic,t-1}}{2}}. \tag{1}$$

Outcome $Y_{c,t}$ is either the price index $P_{c,t}$ or the quantity index $Q_{c,t}$. $y_{ic,t}$ denotes the average price ($y_{ic,t} = p_{ic,t}$) or quantity ($y_{ic,t} = q_{ic,t}$) of product i in country-specific product category c, sold at time t. Products i are defined at the retailer-barcode level. $\Omega_{c,t,t-1} = \Omega_{c,t} \cap \Omega_{c,t-1}$ refers to the basket of all goods that are available across *adjacent* periods $t-1$ and t in category c. $s_{ic,t}$ and $z_{ic,t-q}$ are the weights of the Tornqvist index, which is the average expenditure share of the product in the two periods:

$$s_{ic,t} = \frac{p_{ic,t}q_{ic,t}}{\sum_{i\in\Omega_{c,t,t-1}} p_{ic,t}q_{ic,t}}, \tag{2}$$

$$z_{ic,t-1} = \frac{p_{ic,t-1}q_{ic,t-1}}{\sum_{i\in\Omega_{c,t,t-1}} p_{ic,t-1}q_{ic,t-1}}. \tag{3}$$

The Tornqvist is attractive as it provides a second-order approximation to exact price indices for any standard utility function.

As durable and non-durable scanner data come from different countries, employing their own product categorization system, harmonization is essential to enable cross-country comparisons. To address this, we manually assign FMCG products across all countries to harmonized categories that match the 10-digit granularity of the German COICOP. For slow-moving consumer goods (SMCG), NielsenIQ already categorizes products into groups that roughly correspond to the German COICOP 10-digit level; therefore, no additional harmonization is required.

Given outcome $Y_{c,t} \in [P_{c,t}, Q_{c,t}]$, we estimate the following differences-in-difference model at the product category-time level with monthly baseline periodicity:

$$\ln \Delta Y_{c,t} = \sum\nolimits_m \beta_m \left(\mathbb{1}\{j = \text{Germany}\} \cdot \mathbb{1}\{t = m\}\right) + \gamma\, X_{j(c),t} + \mu_{j(c)} + \rho_t + \epsilon_{c,t}. \tag{4}$$

where Δ represents the difference of the the outcome in product category c and month t to the outcome twelve months ago. The one-year difference, accounts for country-specific seasonality.

The first difference of the difference-in-differences approach is given by dummy variable ($\mathbb{1}\{j = \text{Germany}\}$), which is equal to one if product category c is sold on the German market. The second difference is captured by a set of months dummies ($\sum_m \mathbb{1}\{t = m\}$) before and after the reform, which allow assessing dynamic (pre-)treatment effects as in an event-study design. The coefficients β^t capture the dynamic diff-in-diff estimates of a VAT rate changes in Germany on prices and quantities. Operator Δ differences out country-specific category c fixed effects, ρ_t are month-by-year fixed effects.

Identification. The main remaining threat to identification is that β's do not only capture the effects of the VAT reform, but pick up other country-specific (COVID) dynamics. For this reason, we add country-specific time trends $\mu_{j(c)}$. Moreover, we test the sensitivity of our results to including direct measures of COVID dynamics, such as total COVID deaths and the stringency of national containment policies, which are captured in $X_{j(c),t}$. Last, we assess the sensitivity with regard to the choice of the control group countries.

Estimation. We estimate the above equation using a weighted least squares where the weights are defined to be inversely proportional to the volatility of the category level index.

4 Empirical Results: Price and Quantity Responses to Temporary VAT Cut

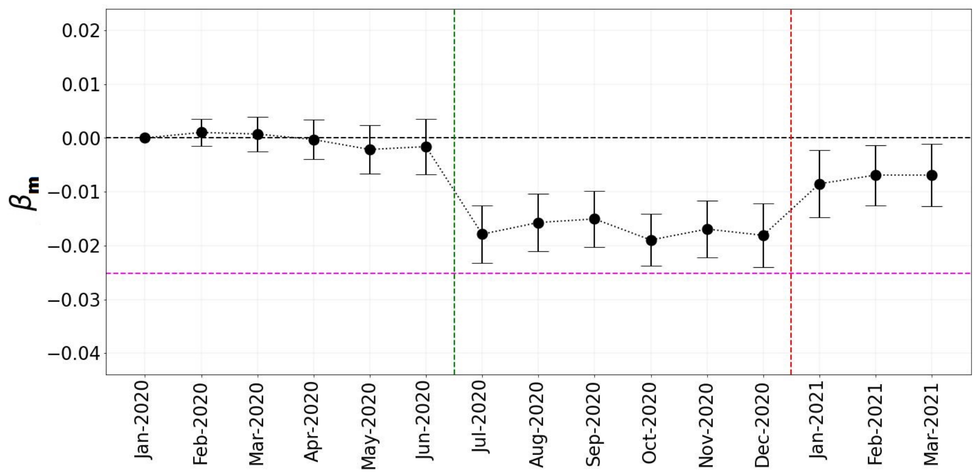
In this section, we present empirical results of the causal effect of the temporary VAT cut on prices (Subsection 4.1) and quantities (Subsection 4.2) based on the empirical model, presented in Section 3.3.

4.1 Price Effects

Durables. Figure 3 plots the dynamic (pre-)treatment effects of the temporary VAT cut on prices of durable goods, following Equation (4). The figure presents our baseline specification, which includes all control-group countries (the Netherlands, Austria, and Italy) and includes only fixed effects, excluding other control variables ($X_{j(c),t}$). The horizontal magenta line denotes the full pass-through benchmark for durable goods, which is around -2.5% as the standard VAT rate applies to most durable goods.

In line with the graphical evidence presented in Section 3.2, Figure 3 shows a sharp drop in prices for durable goods in Germany in the month of the VAT cut (July 2020) and a similarly strong rebound when tax rates are re-raised to pre-reform levels in January 2021. During the period of reduced VAT rates, prices are stable at a level about 1.63% lower, implying a pass-through of 65%.

Figure 3: Price pass-through for Durables

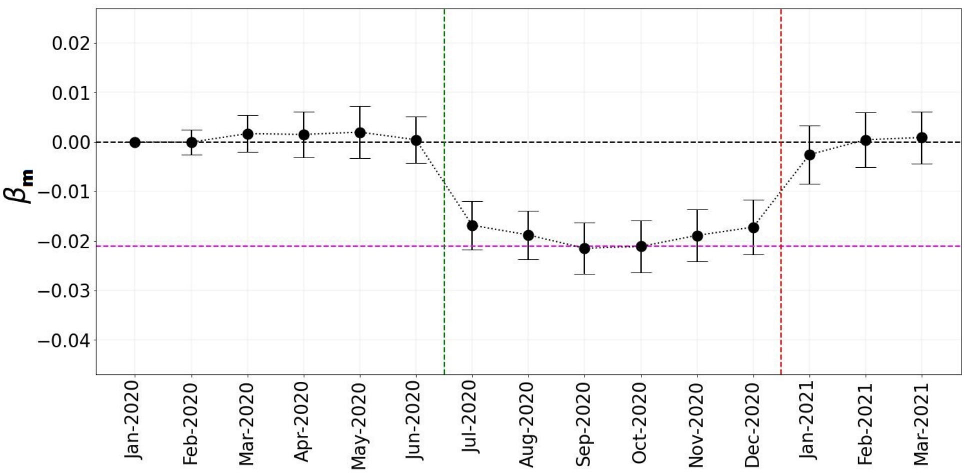


Notes: This graph plots the effect of the temporary VAT cut in Germany on the price index for durable consumption goods with 95% confidence bands. The underlying econometric model is given in Equation (4). The baseline model excludes control variables ($X_{j(c),t}$). The sample comprises product categories of durable goods in Germany, the Netherlands, Austria, and Italy from January 2020 to March 2021. The horizontal line indicates the full price pass-through benchmark. The first vertical line indicates the temporary cut in VAT rates; the second vertical line indicates the subsequent increase in VAT rates to pre-reform levels. Source: Own illustration based on data from the NielsenIQ.

Non-Durables. Figure 4 presents the analogous results for prices of non-durable consumption goods. We detect similarly sharp price responses in the months when German VAT rates change.

Again, prices from July to December 2020 are relatively stable, 1.9% below pre-reform levels. Compared to the full-passthrough benchmark, we estimate a pass-through of 91%.[4] In the case of non-durables, we find symmetric price responses.

Figure 4: Price pass-through for Non-Durables



Notes: This graph plots the effect of the temporary VAT cut in Germany on the price index for non-durable consumption goods with 95% confidence bands. The underlying econometric model is given in Equation (4). The baseline model excludes the control variables ($X_{j(c),t}$). The sample comprises product categories of durable goods in Germany, the Netherlands, Austria, and Italy from January 2020 to March 2021. The horizontal line indicates the full price pass-through benchmark. The first vertical line indicates the temporary cut in VAT rates; the second vertical line indicates the subsequent increase in VAT rates to pre-reform levels. Source: Own illustration based on data from the NielsenIQ.

Overall, our price effects suggest roughly symmetric price responses to VAT rate changes, with high implied pass-through rates of 65 to 91%. Quantitatively, the estimates are in line with other microdata studies by Fuest et al. (2025) and Montag et al. (2023) or studies relying on more aggregated data Koeniger and Kress (2024). Fuest et al. (2025) compare posted prices across two supermarket chains in Germany and Austria, respectively, and find a pass-through of 70%. Montag et al. (2023) investigate the pass-through to fuel prices, and find pass-through rates of 40% for E5 gasoline, 61% for E10 gasoline, and 81% for diesel. Using aggregate price indices Koeniger and Kress, 2024 conclude that the pass-through was 57% for durables, 49% for semi-durables, and 85% for non-durables.

The symmetric responses are in contrast to Benzarti, Carloni, et al. (2020), who find that tax increases show higher passthrough rates than decreases. There are various possible reasons for the different patterns. First, we study the impact on prices of durable and non-durable goods, whereas the first piece of evidence of Benzarti, Carloni, et al. (2020) is based on the prices of Finnish hairdressers, hence the service sector. In fact, the different pass-through rates and patterns we obtain for the two types of goods suggest that price responses should be sector and good-specific in line with economic theory. Second, we study a preannounced temporary VAT cut, whereas the second piece of evidence presented by Benzarti, Carloni, et al. (2020) is based

[4]Note that the full pass-through benchmark is lower than for durables as the reduced VAT rate applies to a majority of non-durable goods.

Table 1: Robustness: Price Effects, Durables

Specification	**Pre-Treatment**	**Treatment**	**Post-Treatment**
Baseline	-0.0002	-0.0163	-0.0074
	(0.0015)	(0.0024)	(0.0027)
+ Covid Death	-0.0003	-0.0163	-0.0072
	(0.0015)	(0.0024)	(0.0028)
+ Containment	-0.0021	-0.0189	-0.0100
	(0.0016)	(0.0025)	(0.0027)
+ Covid Death and Containment	-0.0020	-0.0208	-0.0140
	(0.0017)	(0.0028)	(0.0031)
- Austria	-0.0005	-0.0165	-0.0080
	(0.0016)	(0.0024)	(0.0027)
- Italy	0.0005	-0.0143	-0.0053
	(0.0015)	(0.0026)	(0.0029)
- Netherlands	0.0017	-0.0107	-0.0093
	(0.0022)	(0.0041)	(0.0039)

on preannounced permanent VAT reforms across Europe. Hence, the fact that consumers are aware that tax rates return to old levels might impede firms from passing on the tax burden asymmetrically. Note that Buettner and Madzharova (2021) finds symmetric passthrough even for mostly permanent tax changes using microdata.

In other related work, Benzarti, Garriga, et al. (2024) and Bernardino et al. (2025) study temporary reductions of VAT on food in Argentina and Portugal, respectively. The former study finds an asymmetric passthrough of 50% for the decrease and 90% for the increase; the latter a symmetric full passthrough.

Our heterogeneous pass-through estimates are broadly consistent with the literature on the pass-through of *permanent* VAT changes (Benedek et al., 2020, Benzarti, Carloni, et al., 2020, Carbonnier, 2007, Buettner and Madzharova, 2021, Kosonen, 2015). While these studies typically cannot reject a full pass-through of tax increases on consumer durables, they have also shown heterogeneity in pass-through rates across products and services, and lower pass-through rates for rate decreases.

Robustness. We conduct several tests to assess whether we can uphold the causal interpretation of our estimates. As stressed in Subsection 3.3, the main concern is that treatment effects are confounded by other country-specific (COVID) dynamics that are not accounted for by the linear country-specific time trends $\mu_{j(c)}$. To test the sensitivity, we conduct two types of tests.

In the first test, we directly control for country-specific COVID dynamics. We can conduct this test since our baseline specification includes more than one control-group country. We add the number of (i) COVID deaths per country and months, (ii) the monthly severity of COVID containment measures, and (iii) both COVID-related variables to our baseline specification and assess whether (pre)-treatment effects change. Tables 1 and 2 show the results for durables and

Table 2: Robustness: Price Effects, Non-Durables

Specification	**Pre-Treatment**	**Treatment**	**Post-Treatment**
Baseline	0.0011	-0.0190	-0.0003
	(0.0019)	(0.0025)	(0.0027)
+ Covid Death	0.0012	-0.0191	-0.0006
	(0.0018)	(0.0025)	(0.0028)
+ Containment	0.0015	-0.0185	-0.0000
	(0.0019)	(0.0025)	(0.0027)
+ Covid Death and Containment	0.0015	-0.0185	-0.0000
	(0.0019)	(0.0027)	(0.0030)
- Austria	0.0019	-0.0176	-0.0001
	(0.0018)	(0.0025)	(0.0028)
- Italy	0.0013	-0.0196	-0.0016
	(0.0019)	(0.0026)	(0.0032)
- Netherlands	0.0050	-0.0154	0.0011
	(0.0019)	(0.0029)	(0.0037)

non-durables, respectively. The tables show that results do not change relative to the baseline effects, which are reproduced in the first line of the tables.

In the second test, we assess whether our results are driven by the inclusion of a particular control-group country that may have experienced a highly specific evolution during the pandemic. In our baseline, the control group consists of the Netherlands, Austria, and Italy. To test the sensitivity, we exclude Austria or Italy. Results hardly change (cf. Tables 1 and 2).

Overall pass-through. Combining the pass-through estimate of 65% for durables and 91% for non-durables, the expenditure-share weighted, overall price pass-through of the temporary VAT cut was 76%.

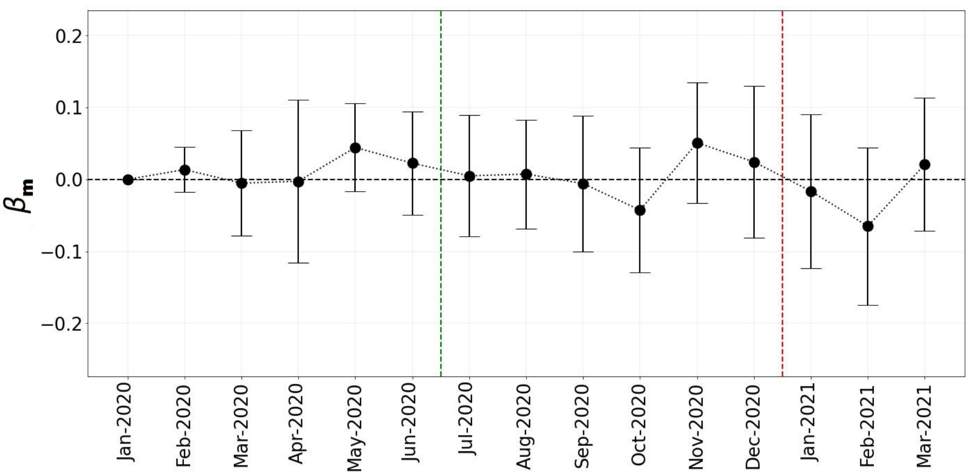
4.2 Quantity effects

In this subsection, we extend our analysis to estimate the quantity responses that were induced by these price changes. We apply the same approach as done for prices presented in the previous Subsection 4.1, and replace category-level price indices with category-level quantity indices.

Durables. Figure 3 displays the dynamic (pre-)treatment effects of a temporary VAT cut on quantities for durable consumption goods. The graph reveals that we do not detect quantity responses that are statistically different from zero, while point estimates are quite noisy. Taken at face value, quantities increased slightly from July to December 2020 by 0.0065 (0.0410). The implied semi-elasticity for a one percentage point increase in the VAT rate is -0.22 (1.367).

In Section 5, we assess what this quantity response implies for the elasticity of intertemporal substitution.

Figure 5: Quantity Effects for Durables



Notes: This graph plots the effect of the temporary VAT cut in Germany on the quantity index for durable consumption goods with 95% confidence bands. The underlying econometric model is given in Equation (4). The baseline model excludes control variables ($X_{j(c),t}$). The sample comprises product categories of durable goods in Germany, the Netherlands, Austria, and Italy from January 2020 to March 2021. The horizontal line indicates the full price pass-through benchmark. The first vertical line indicates the temporary cut in VAT rates; the second vertical line indicates the subsequent increase in VAT rates to pre-reform levels. Source: Own illustration based on data from the NielsenIQ.

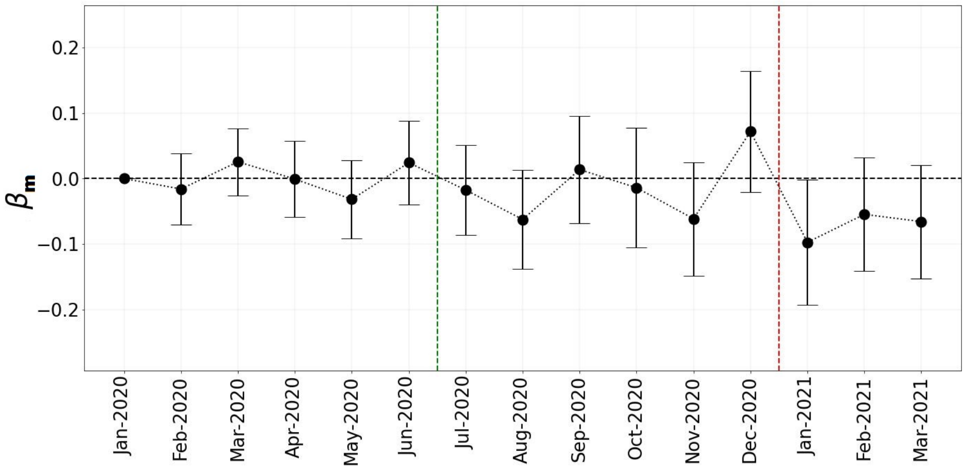
Non-Durables. Turning to the quantity responses of non-durable consumption goods, Figure 6 reveals a similar pattern. Again, we do not detect any significant quantity responses. The average treatment effect from July to December 2020 is even slightly negative $-0.012\,(0.039)$, with an implied semi-elasticity of $0.50\,(1.68)$.

Our findings of a limited quantity response stands in contrast with some results in the recent literature. Bachmann et al. (2026) rely on two cross-sectional surveys within Germany. First, before the VAT cut took effect, they show that individuals who are more informed about the tax cut (treatment group) plan to spend more on durables relative to those less informed (control group). Second, after the temporary VAT cut expired, their results indicate that survey respondents who perceived a high pass-through (treatment group) spent more on durables than individuals who perceived a low or zero pass-through (control group). Estimates suggest sizable effects: A reduction of the VAT by 1 PP. increased durable goods expenditures among individuals who perceived a positive pass-through by over 12%, and an average effect of about 8%. Evaluating these estimates through the lens of a HANK model, their estimates suggest that the temporary VAT cut had a large stimulus effect of 4.4 percent % in total consumption.

Koeniger and Kress (2024) study the same policy but find more modest quantity effects. Their research design relies on transactional expenditure data from credit card records and on a difference-in-differences approach, with Austria as the control group. They find that a 1-pp. temporary reduction in the VAT rate resulted in a 2-pp. increase in durable goods expenditures.

Several advantages of our approach compared to these studies are worth noting. First, we avoid leveraging self-reported policy awareness (Bachmann et al., 2026) and do not restrict the analysis to the subpopulation of credit-card users (Koeniger and Kress, 2024). Furthermore, by

Figure 6: Quantity effects for Non-Durables



Notes: This graph plots the effect of the temporary VAT cut in Germany on the quantity index for non-durable consumption goods with 95% confidence bands. The underlying econometric model is given in Equation (4). The baseline model excludes the control variables ($X_{j(c),t}$). The sample comprises product categories of durable goods in Germany, the Netherlands, Austria, and Italy from January 2020 to March 2021. The horizontal line indicates the full price pass-through benchmark. The first vertical line indicates the temporary cut in VAT rates; the second vertical line indicates the subsequent increase in VAT rates to pre-reform levels. Source: Own illustration based on data from the NielsenIQ.

focusing on the price and quantity responses estimated at high frequency, we obtain tight bounds on the elasticity of intertemporal substitution, which we present in the next section.

5 Bounding the Elasticity of Intertemporal Substitution

We now interpret our empirical findings in the context of a simple dynamic model of consumer behavior. Using the framework of Orchard et al. (2025), we distinguish durable and non-durable consumption and model durable goods adjustment by introducing a Calvo-type friction. This approach is consistent with microdata evidence on the importance of lumpy adjustment costs and is a convenient way to map these frictions into aggregate consumption dynamics. The analysis illustrates how the total quantity response depends on the EIS, the user cost, and adjustment frictions.

We assume that, of a continuum of households with measure one, in each period only a fraction $1-\theta$ adjusts their durable goods stock. The parameter θ can thus be regarded as a measure of adjustment frictions. The household utility function is

$$U = \sum_{t=0}^{\infty} \beta^t \left[\frac{c_t^{1-\frac{1}{\sigma}} - 1}{1-\frac{1}{\sigma}} + \psi \frac{d_t\,(i)^{1-\frac{1}{\sigma}} - 1}{1-\frac{1}{\sigma}} \right],$$

with $\psi > 0$, and where c_t is consumption of non-durable goods and $d_t\,(i)$ is the durable stock of the household i, which generates a proportional flow of services. The utility curvature parameter σ corresponds to the intertemporal elasticity of substitution. In principle, one could allow this parameter to differ between durables and non-durables. However, our focus here is to exploit the frictions in durable goods adjustment which allows us to increase the precision of our estimate of the EIS. The stock of durables is indexed by household, since, due to the Calvo-type adjustment, the stocks differ by household. Households form a family that provides insurance across household members so that non-durable consumption is equalized $c_t(i) = c_t \ \forall i$. Integrating across households, the family utility function is

$$U = \sum_{t=0}^{\infty} \beta^t \left[\frac{c_t^{1-\frac{1}{\sigma}} - 1}{1 - \frac{1}{\sigma}} + \psi \frac{\int_0^1 d_t(i)^{1-\frac{1}{\sigma}} - 1}{1 - \frac{1}{\sigma}} \right]. \tag{5}$$

We focus only on the consumption decision and do not explicitly model labor supply, but assume that households receive an exogenous income y_t in each period. This abstracts from propagation mechanisms and general equilibrium effects, which can increase or attenuate the original impact of the consumption response. This is reasonable given the small changes in consumption we estimate. The period budget constraint is

$$c_{n,t} + p_t x_t + a_t = y_t + (1 + r_{t-1}) \left(\frac{1 + \tau_{t-1}}{1 + \tau_t} \right) a_{t-1}, \tag{6}$$

where x_t are purchases of durable goods, p_t is the tax-exclusive price of durables, τ_t is the value-added tax rate (VAT) and r_{t-1} is the gross interest rate on bond holdings. We take this rate as exogenously given and do not explicitly model monetary policy, reflecting that Germany cannot independently set its monetary policy, which is conducted by the ECB for the entire Euro Area. The tax-exclusive price of non-durables is set to one, so that the tax-inclusive prices are $1 + \tau_t$ and $p_t(1 + \tau_t)$, respectively. We abstract from inflation, and from changes in relative prices, so that price changes are driven only by changes in VAT rates, i.e., the inflation rate amounts to $(1 + \tau_t) / (1 + \tau_{t-1})$. Note that this assumes full pass-through, but, for the interpretation of our empirical results, we adjust for deviations from it below. Moreover, we do not include durables' operating costs since these are negligible for the type of durables included in our data. Finally, $(1 + \tau_t) a_t$ are nominal bond holdings, and households start with an original bond endowment of $(1 + \tau_{-1}) a_{-1}$. The budget constraint shows that an increase in the VAT rate has the same effect as a reduction in the real interest rate.

The family chooses an optimal sequence $\{c_t, a_t, d_t\}_{t=0}^{\infty}$ to maximize family utility. For non-durable good consumption optimality implies

$$\Delta ln\, c_t = const. + \sigma\, ln\, (1 + r_{t-1}) - \sigma \kappa_n \Delta ln\, (1 + \tau_t), \tag{7}$$

where Δ denotes the difference operator, κ_n denotes the pass-through rate for non-durables.

Purchases of durable goods relate to the durable stock by $x_t = d_t - (1 - \delta) d_{t-1}$, where δ is the depreciation rate. Moreover, as shown by Orchard et al. (2025), the Calvo-type friction not only mechanically limits the extensive margin of durable goods adjustment but also reduces the sensitivity of the intensive margin response to changes in the real interest rate. The optimal

Table 3: Model parameters and baseline calibration

Parameter	Value	Description
β	0.997	discount factor
r	0.001	interest rate
δ	varies	depreciation of durables
r	0.001	interest rate
σ	inferred	Utility curvature/EIS
θ	varies	Calvo frictions parameter for durables' adjustment
ψ	.	Weight on durables' services
κ_n	0.91	VAT pass-through nondurables (own estimate)
κ_d	0.65	VAT pass-through durables (own estimate)
d	.	durable goods stock
x	.	durable goods purchases
c	.	nondurables consumption
p	.	price of durables
τ	.	VAT rate
a	.	bond holdings

adjustment by the reoptimizing fraction of households implies that

$$\Delta ln\, x_t \approx const. + \sigma\Phi ln\ (1 + r_{t-1}) - \sigma\kappa_d\Phi\Delta ln\,(1 + \tau_t)\,, \tag{8}$$

where $\Phi \equiv \left[\frac{1-\theta(1-\delta)}{\delta}\right]\left[\frac{(1-\delta)[1-\beta\theta(1-\delta)]}{[r+\delta]}\right]$, and $\kappa_d \equiv \frac{\Delta ln\, p}{\Delta ln\,(1+\tau_t)}$ is the pass-through rate for durables. The response to an increase in the VAT rate is increasing in durability (lower δ) but decreasing in θ, the share of inactive households.

The framework now allows a direct interpretation of our estimates, and we can assess the range of values for the EIS compatible with our estimates with increased precision. As a first step to determine the value of Φ, we calculate the expenditure-weighted average lifetime of the durable goods in our sample as 6.38 years. This translates into a monthly depreciation factor of $\delta = 0.025$.[5] Second, our point estimate from the durable goods price equation of 0.0163 corresponds to a pass-through for durables of $\hat{\kappa}_d = 0.65$. For the other parameters, we follow Orchard et al. (2025), who calibrate their model to monthly data for the US. Setting $r = 0.001$, $\beta = 0.997$, and $\theta = 0.85$ in our baseline yields $\Phi \approx 45$ and $\hat{\kappa}_d\Phi \approx 29$.[6] Next, our quantity estimate[7] of 0.01155 corresponds to an empirical elasticity $\frac{\Delta ln\, x_t}{\Delta ln\,(1+\tau_t)} \approx -0.46$. Similarly, we can calculate the lower bound of the empirical elasticity from the confidence intervals as -2.27. This implies a point estimate of the EIS of 0.016 and an upper bound of 0.08 (in absolute value), see Table (4) for an overview of this baseline case and various sensitivity checks. In the absence of adjustment frictions ($\theta = 0$), $\Phi = 1500$ and $\hat{\kappa}_d\Phi = 975$, which imply a point estimate of 0.00047 for the EIS and an upper bound of 0.0023. Thus, without frictions, this allows excluding values of the EIS larger than 0.0023. With frictions, values of the EIS larger than 0.08 can be ruled

[5] We follow the BEA practice for durable goods and divide 1.65 by the lifetime to derive the annual depreciation factor, which we then convert into a monthly depreciation factor.

[6] The interest rate parameter is not set exogenously in Orchard et al., 2025.

[7] This is the average of the differences between the coefficients estimated for July and June 2020, and December 2020 and January 2021, respectively.

Table 4: Implied upper bounds on elasticity of intertemporal substitution by model parameters

Case	Frictions θ	Depreciation δ	Φ	$\hat{\sigma}$	Upper bound $\hat{\sigma}$
No frictions	0	0.025	1500	0.00047	0.0023
Baseline	0.85	0.025	45	0.016	0.08
Orchard et al. (2025)	0.85	0.015	110	0.006	0.032
Ext. margin response	0.7	0.025	152	0.005	0.02

out.

Alternatively, we can use the monthly depreciation rate of $\delta = 0.015$ from Orchard et al. (2025). Keeping frictions constant ($\theta = 0.85$), this results in an adjustment factor $\hat{\kappa}_d \Phi \approx 72$. With these parameters, our point estimate corresponds to $\hat{\sigma}_d = 0.006$, and we can rule out values of the EIS larger than $\hat{\sigma}_d = 0.032$. Similarly, the extensive margin may respond to the tax reduction. Given that our durable goods point of sale data does not allow us to investigate the durable goods purchase activity of individual households, we consider an ad hoc sensitivity check to the extensive margin. Doubling the monthly share of households actively readjusting their durable goods stock to 30%, so that $\theta = 0.7$, and keeping the depreciation rate at $\delta = .025$, implies a point estimate of the EIS of 0.005 and an upper bound for the EIS of 0.023. Intuitively, any extensive margin response reduces frictions, which for a given empirical quantity response to the tax change, further reduces the implied EIS. Thus, both sensitivity adjustments imply an even lower bound on the EIS relative to our baseline.

6 Conclusion

In this paper, we have studied the effects of Germany's temporary VAT reduction during the Covid-19 pandemic using comprehensive scanner data covering both durable and non-durable goods. We documented substantial pass-through of the tax cut to consumer prices, particularly for non-durables, but found no corresponding increase in quantities purchased. Interpreting these findings through a simple model, we showed that the implied elasticity of intertemporal substitution is close to zero.

Taken together, our results suggest that temporary VAT reductions are unlikely to be an effective tool for stimulating demand through intertemporal substitution. While such policies generate an income effect via lower prices, they do not appear to meaningfully alter the timing of consumption, highlighting important limits of untargeted, price-based fiscal stimuli during economic downturns.

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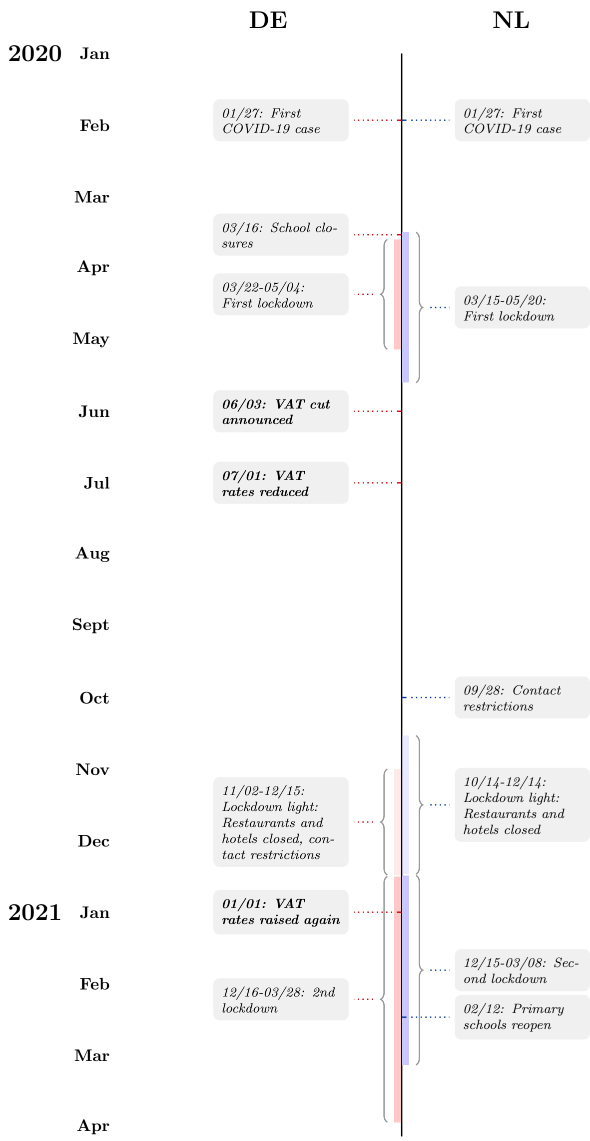
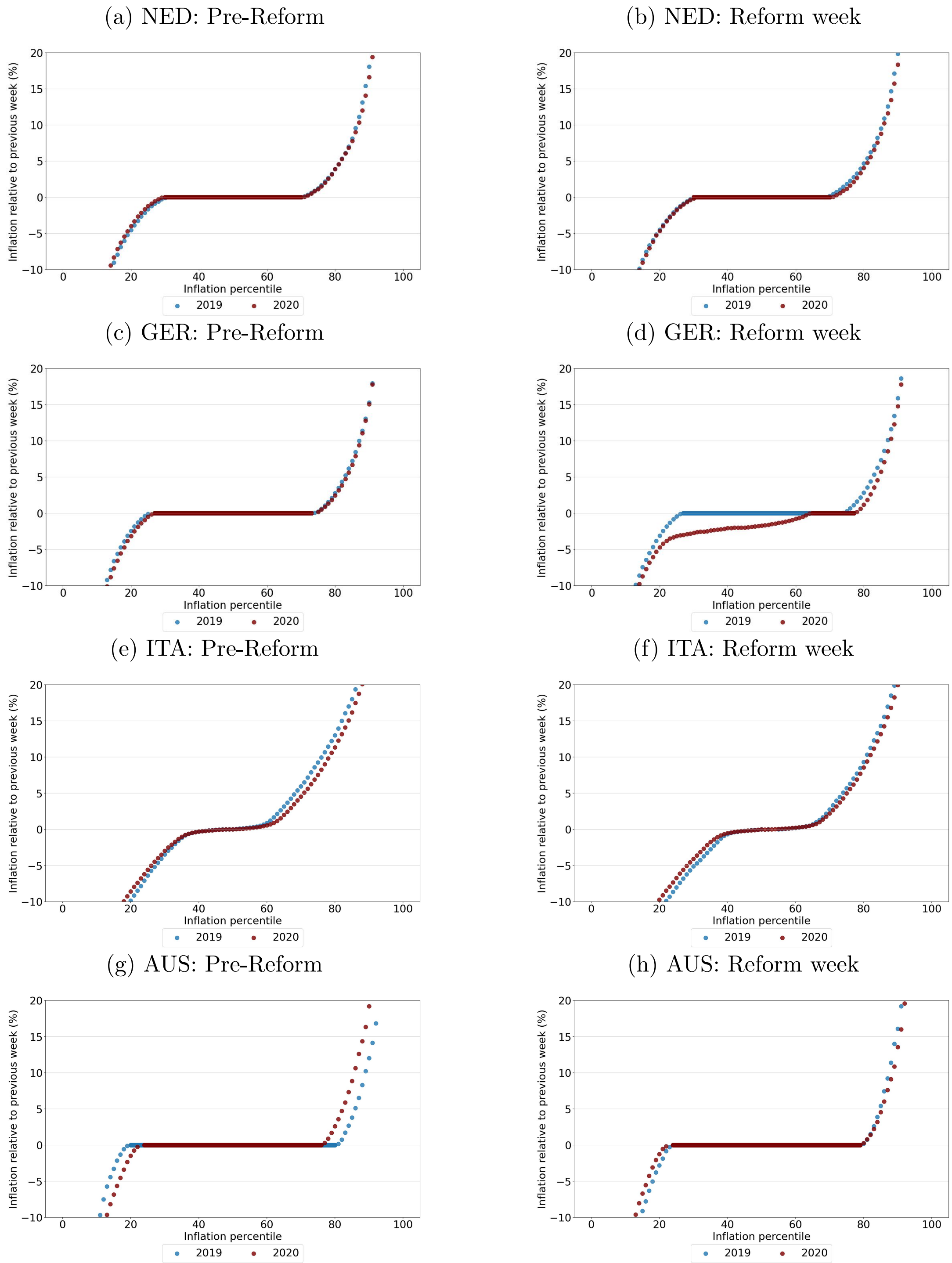
A Additional Figures

Figure A.1: Timeline of the pandemic development and induced policy measures in Germany and the Netherlands



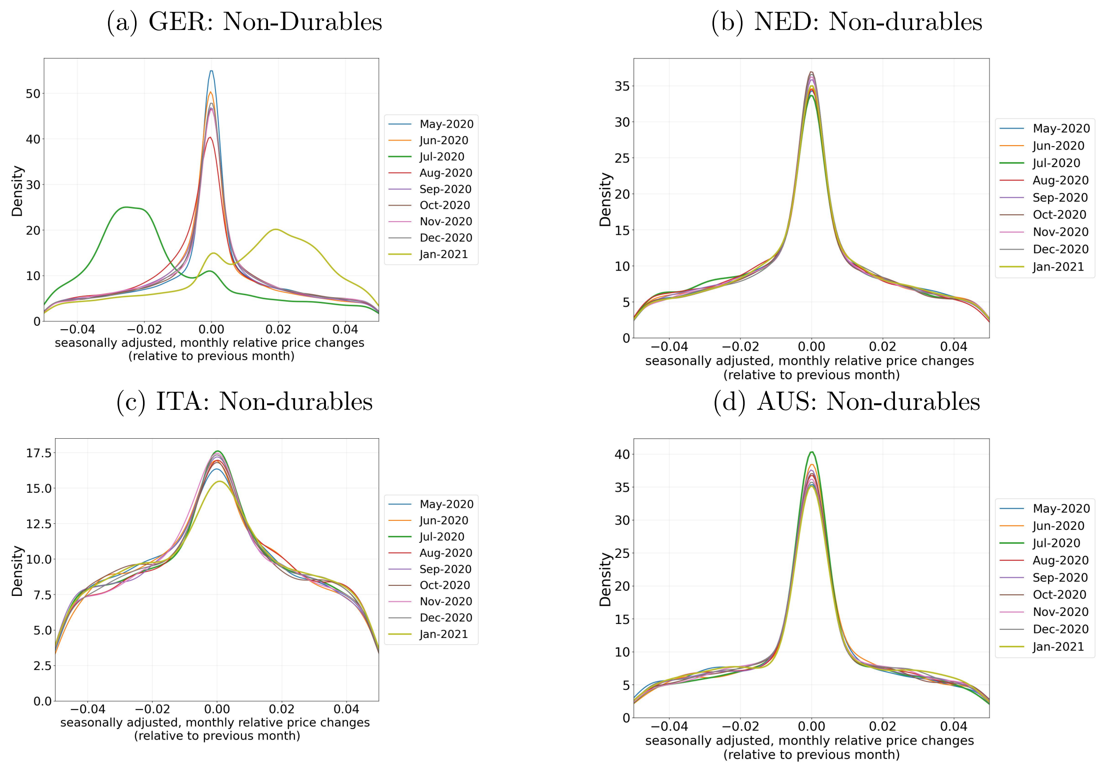
Notes: The figure plots a timeline of major pandemic events and induced policy measures in Germany and the Netherlands starting in January 2020.

Figure A.2: Weekly price change distributions of non-durable in sample countries in selected weeks



Notes: Source: Own calculations based on . *Notes:* The four panels of this figure show the weekly price changes for Germany (GER), Netherlands (NED), Italy (ITA), and Austria (AUS) in two selected weeks in 2020 (blue lines) and 2019 (red lines). Week 20 in 2020 is before the German government announced the VAT rate cut from 19% to 16% for the standard rate and from 7% to 5% for the reduced rate. Week 27 in 2020 is the week of the implementation of the reform, which came into effect on July 1, 2020.

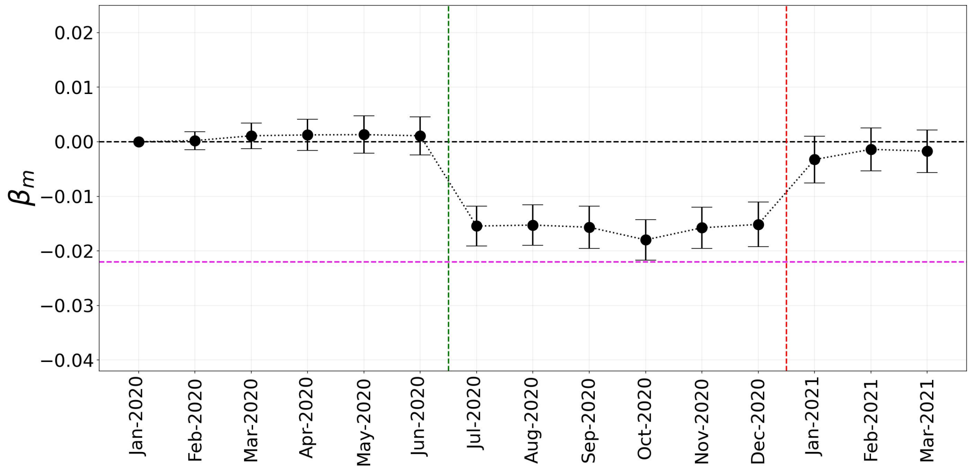
Figure A.3: Monthly price change distributions in sample countries, 2020 and 2021



Notes: Source: Own calculations based on . *Notes:* The four panels of this figure shows the monthly price changes for non-durables for Germany (upper left panel) and the other control countries for 2020 and parts of 2021.

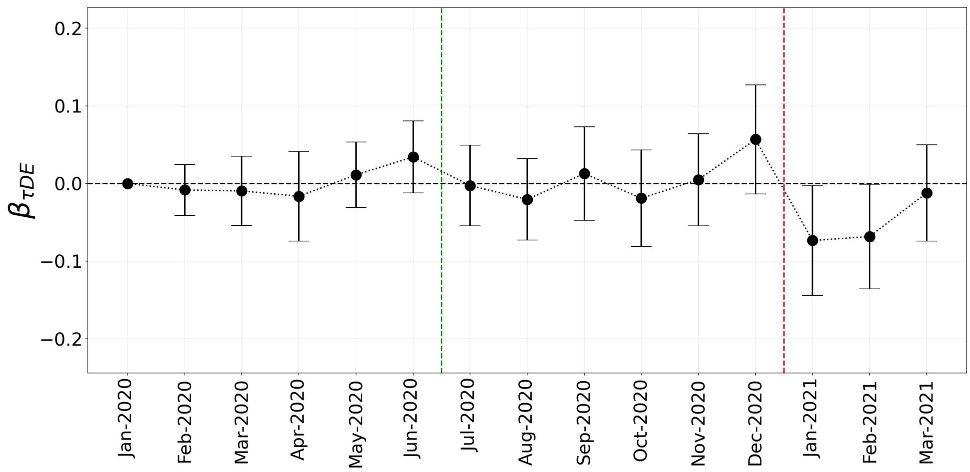
A.1 Analysis of Durables and Non-Durables Combined

Figure A.4: Price pass-through for durables and non-durables combined



Notes: This graph plots the effect of the temporary VAT cut in Germany on the price index for durable and non-durable consumption goods with 95% confidence bands. The plot is similar to Figures 3 and 4, with the only exception that the data used was pooled from both durables and non-durables. Source: Own illustration based on data from the YouGov and NielsenIQ.

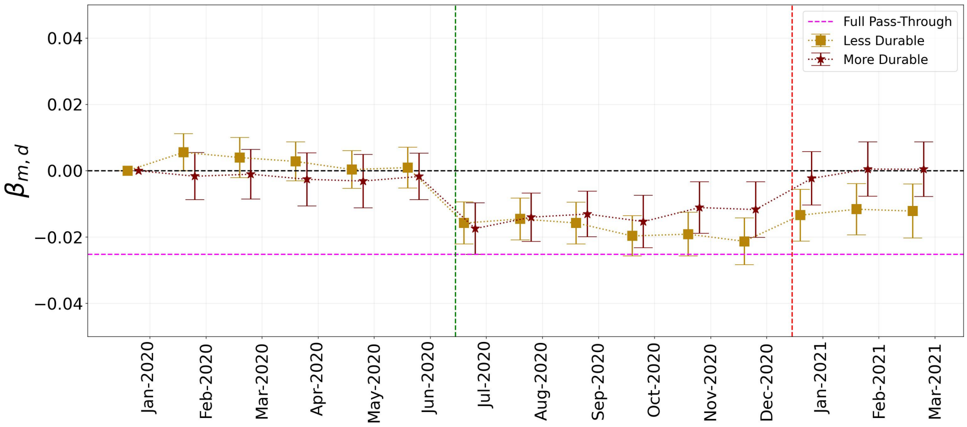
Figure A.5: Quantity effects for durables and non-durables combined



Notes: This graph plots the effect of the temporary VAT cut in Germany on the quantity index for durable and non-durable consumption goods with 95% confidence bands. The plot is similar to Figures 5 and 6, with the only exception that the data used was pooled from both durables and non-durables. Source: Own illustration based on data from YouGov and NielsenIQ.

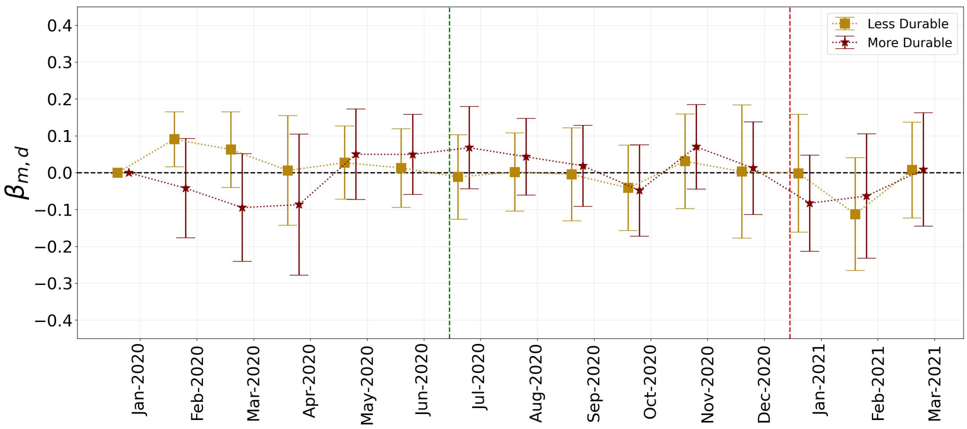
A.2 Durability Analysis

Figure A.6: Price pass-through for durables by varying durability



Notes: This graph plots the effect of the temporary VAT cut in Germany on the price index for durable consumption goods with 95% confidence bands with varying durability.

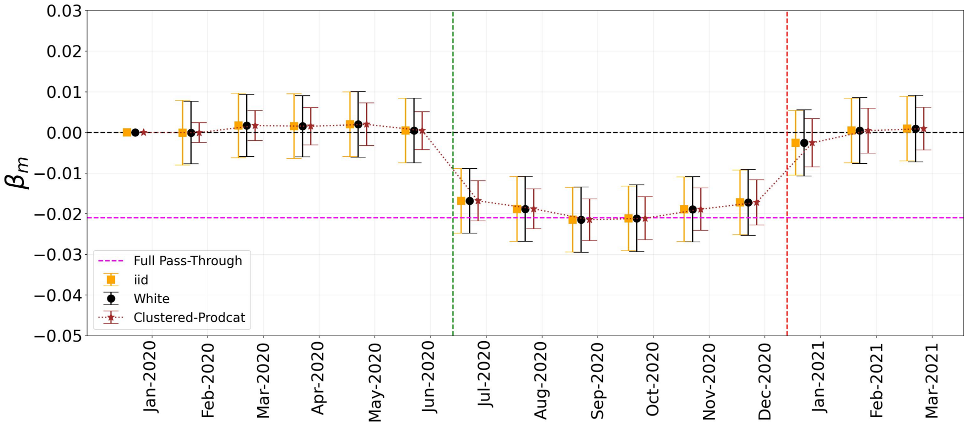
Figure A.7: Quantity effects for durables by varying durability



Notes: This graph plots the effect of the temporary VAT cut in Germany on the quantity index for durable consumption goods with 95% confidence bands for varying durability.

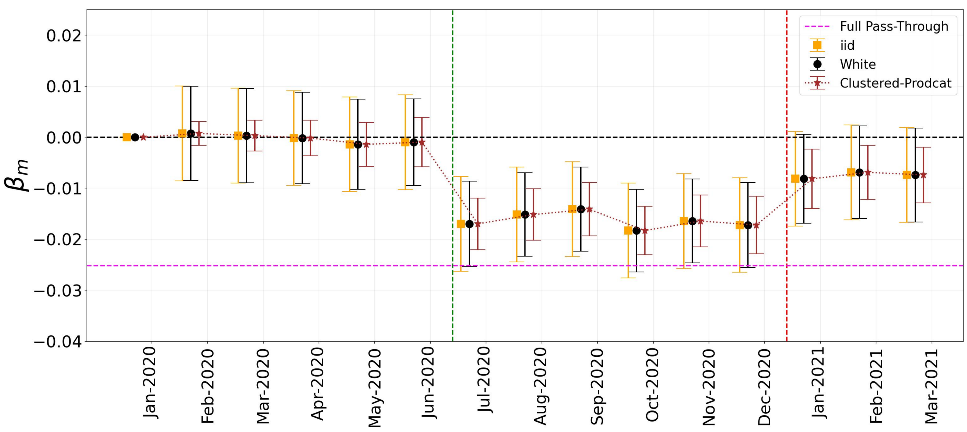
A.3 Standard Errors Analysis

Figure A.8: Different standard errors for non-durables price pass-through



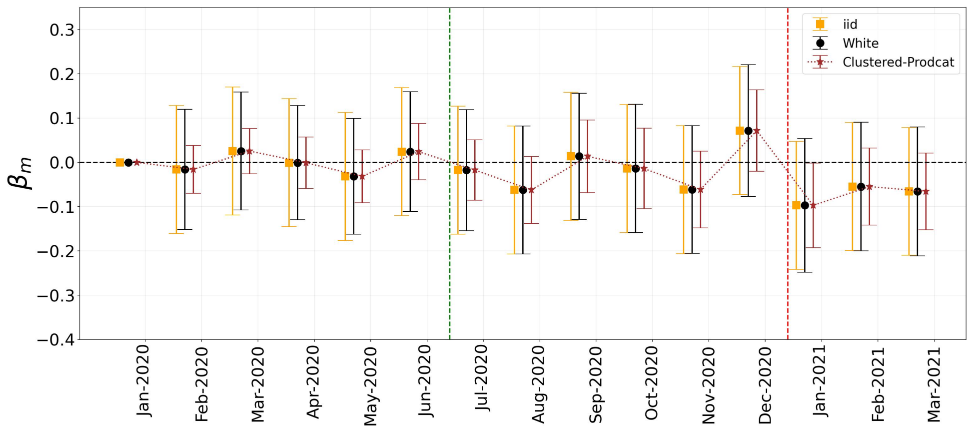
Source: Own calculations based on Scanner data. To provide a benchmark for standard errors, we report iid and heteroskedasticity-robust White standard errors. Clustered-prodcat refers to standard errors clustered at the product category level.

Figure A.9: Different standard errors for non-durables price pass-through



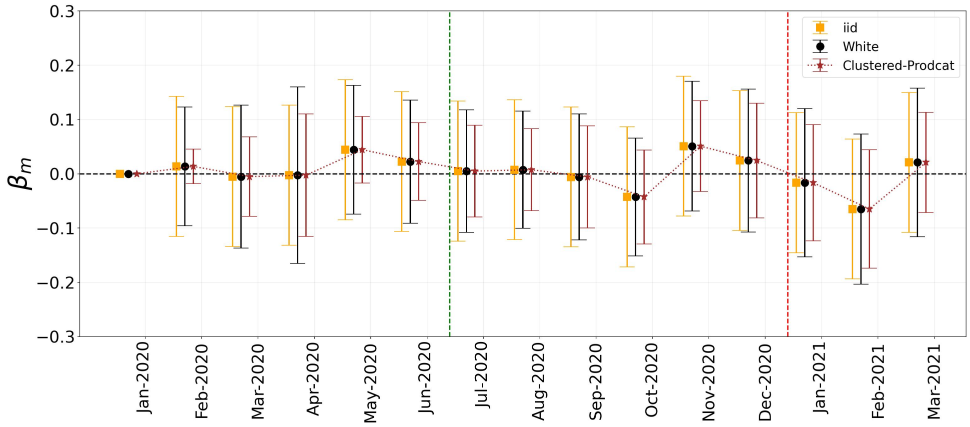
Source: Own calculations based on Scanner data. To provide a benchmark for standard errors, we report iid and heteroskedasticity-robust White standard errors. Clustered-prodcat refers to standard errors clustered at the product category level.

Figure A.10: Different standard errors for non-durables quantity effects



Source: Own calculations based on Scanner data. To provide a benchmark for standard errors, we report iid and heteroskedasticity-robust White standard errors. Clustered-prodcat refers to standard errors clustered at the product category level.

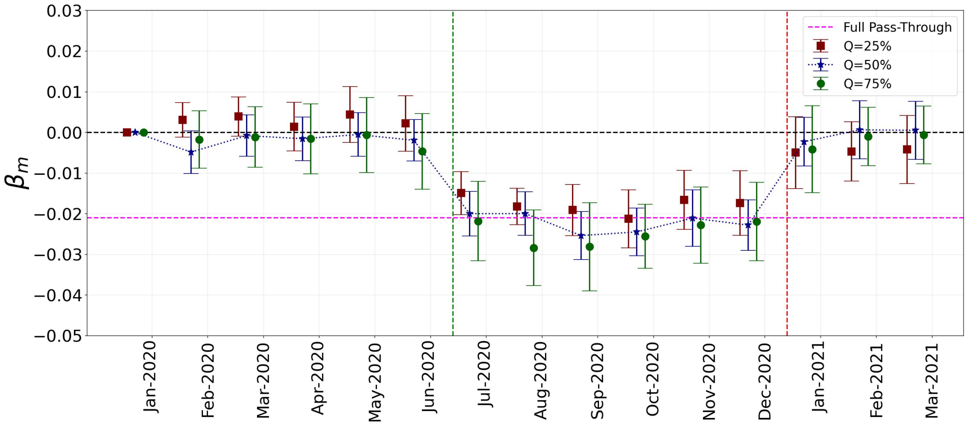
Figure A.11: Different standard errors for durables quantity effects



Source: Own calculations based on Scanner data. To provide a benchmark for standard errors, we report iid and heteroskedasticity-robust White standard errors. Clustered-prodcat refers to standard errors clustered at the product category level.

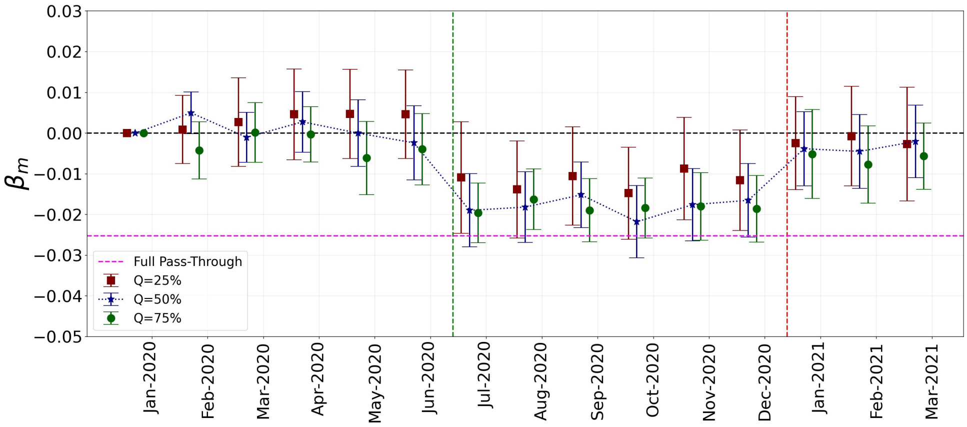
A.4 Quantile Regressions

Figure A.12: Quantile regressions for non-durables price pass-through



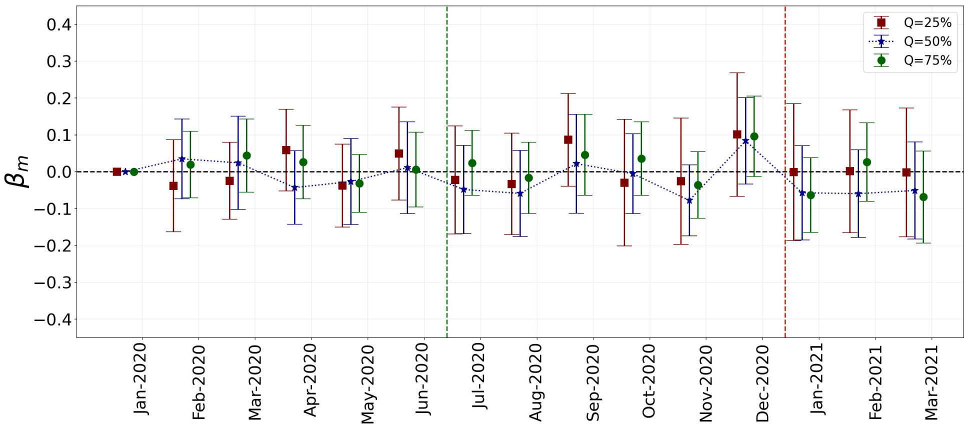
Note: This graph plots the effect of the temporary VAT cut in Germany on the price index for non-durable consumption goods with 95confidence bands using quantile regression with varying quantiles.

Figure A.13: Quantile regressions for non-durables price pass-through



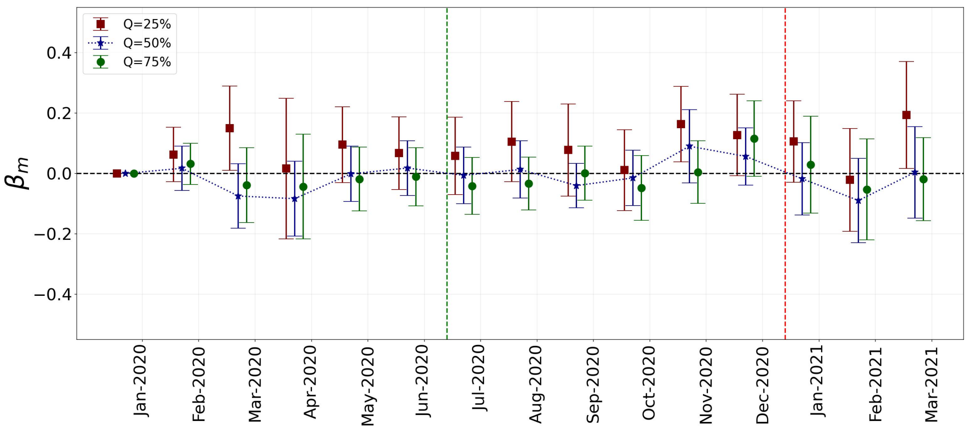
Note: This graph plots the effect of the temporary VAT cut in Germany on the price index for non-durable consumption goods with 95confidence bands using quantile regression with varying quantiles.

Figure A.14: Quantile regressions for non-durables quantity effects



Note: This graph plots the effect of the temporary VAT cut in Germany on the price index for non-durable consumption goods with 95confidence bands using quantile regression with varying quantiles.

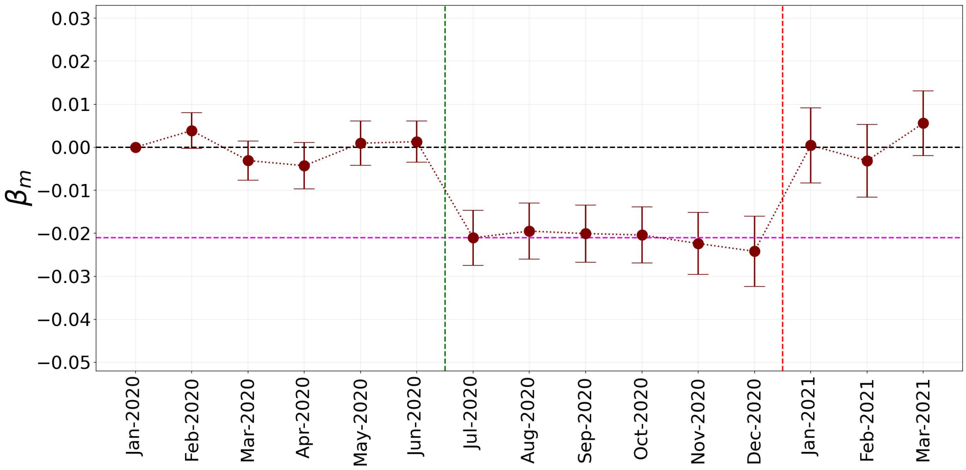
Figure A.15: Quantile regressions for durables quantity effects



Note: This graph plots the effect of the temporary VAT cut in Germany on the price index for non-durable consumption goods with 95confidence bands using quantile regression with varying quantiles.

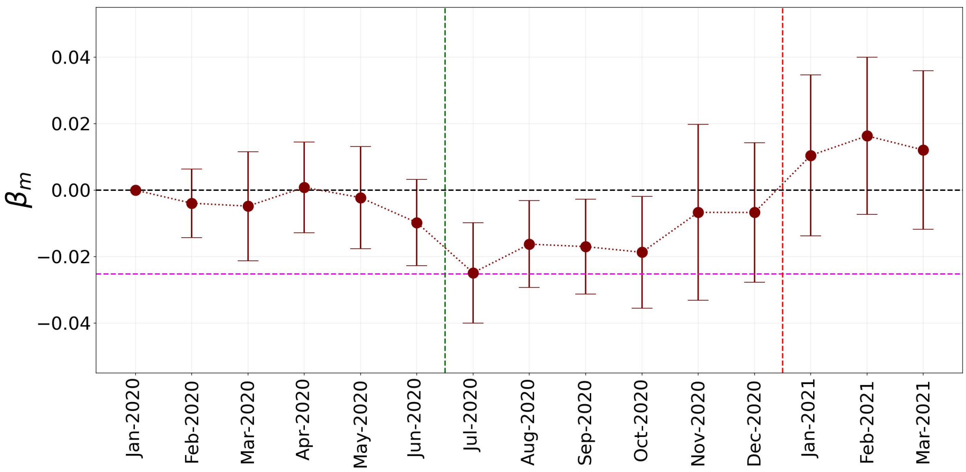
A.5 Comparison with HICP Price Indices

Figure A.16: Price pass-through for non-durables using HICP indices



Note: This graph plots the effect of the temporary VAT cut in Germany on the price index for non-durable consumption goods with 95confidence bands using HICP data (source: Eurostat). The indices used are COICOP 5-digit level (63 categories) and were chosen to closely match the non-durable universe of the scanner data available to the authors. The underlying methodology is the same as is used to compute the baseline plots using the scanner data.

Figure A.17: Price pass-through for durables using HICP indices



Note: This graph plots the effect of the temporary VAT cut in Germany on the price index for durable consumption goods with 95confidence bands using HICP data (source: Eurostat). The indices used are COICOP 5-digit level (24 categories) and were chosen to closely match the durable universe of the scanner data available to the authors. The underlying methodology is the same as is used to compute the baseline plots using the scanner data.

B Additional Tables

B.1 Analysis of Durables and Non-Durables Combined

Table B.1: Robustness: Price Pass-Through, Durables and Non-Durables Combined

Specification	Pre-Treatment	Treatment	Post-Treatment
Baseline Non-Durables	0.0011	-0.0190	-0.0003
	(0.0019)	(0.0025)	(0.0027)
Baseline Durables	-0.0002	-0.0163	-0.0074
	(0.0015)	(0.0024)	(0.0027)
Non-Durables + Durables	0.0009	-0.0158	-0.0021
	(0.0012)	(0.0018)	(0.0019)

Table B.2: Robustness: Quantity Effects, Durables and Non-Durables Combined

Specification	Pre-Treatment	Treatment	Post-Treatment
Baseline Non-Durables	0.0002	-0.0116	-0.0724
	(0.0253)	(0.0387)	(0.0427)
Baseline Durables	0.0146	0.0065	-0.0201
	(0.0303)	(0.0410)	(0.0482)
Non-Durables + Durables	0.0022	0.0054	-0.0512
	(0.0190)	(0.0276)	(0.0313)

B.2 Durability Analysis

Table B.3: Robustness: Price Pass-Through, Durables

Specification	Pre-Treatment	Treatment	Post-Treatment
Baseline	-0.0002	-0.0163	-0.0074
	(0.0015)	(0.0024)	(0.0027)
Less Durable	0.0027	-0.0177	-0.0124
	(0.0026)	(0.0031)	(0.0039)
More Durable	-0.0020	-0.0138	-0.0005
	(0.0037)	(0.0036)	(0.0040)

Table B.4: Robustness: Quantity Effects, Durables

Specification	Pre-Treatment	Treatment	Post-Treatment
Baseline	0.0146	0.0065	-0.0201
	(0.0303)	(0.0410)	(0.0482)
Less Durable	0.0400	-0.0035	-0.0354
	(0.0477)	(0.0594)	(0.0698)
More Durable	-0.0246	0.0274	-0.0456
	(0.0616)	(0.0527)	(0.0668)

Table B.5: Sample of Categories by Classified as Less Durable

Nr	Product Category Name	Durability Type
1	Contact Lenses	Less Durable
2	Care Products	Less Durable
3	Dental Care	Less Durable
4	Dry Batteries	Less Durable
5	Fertilizers	Less Durable
6	Inkjet Cartridge	Less Durable
7	DIY-Adhesive Tapes	Less Durable
8	DIY Adhesives	Less Durable
9	Household Insecticides	Less Durable
10	Office Adhesives	Less Durable

Notes: This table lists sample product categories classified as less durable. The main sources used for the classification of durability are Lifespan database for Vehicles, Equipment, and Structures: LiVES database and product lifespan reports from European Environment Agency.

Table B.6: Sample of Categories by Classified as More Durable

Nr	Product Category Name	Durability Type
1	Car Audio	More Durable
2	Car Speakers	More Durable
3	Powered Chain Saws	More Durable
4	Cooling/Refrigerators	More Durable
5	Dishwashers	More Durable
6	Electric Saws	More Durable
7	Garden Hand Shears	More Durable
8	Freezers	More Durable
9	Hand Lawnmowers	More Durable
10	Washing Machines	More Durable

Notes: This table lists sample product categories classified as more durable. The main sources used for the classification of durability are Lifespan database for Vehicles, Equipment, and Structures: LiVES database and product lifespan reports from European Environment Agency.

B.3 Quantile Regressions

Table B.7: Robustness: Price Effects, Non-Durables, Quantile Regressions

Specification	**Pre-Treatment**	**Treatment**	**Post-Treatment**
Baseline	0.0011	-0.0190	-0.0003
	(0.0019)	(0.0025)	(0.0027)
Q=0.25	0.0030	-0.0179	-0.0024
	(0.0024)	(0.0026)	(0.0037)
Q=0.5	-0.0019	-0.0222	0.0007
	(0.0022)	(0.0025)	(0.0032)
Q=0.75	-0.0019	-0.0247	-0.0004
	(0.0038)	(0.0043)	(0.0038)

Table B.8: Robustness: Price Effects, Durables, Quantile Regressions

Specification	**Pre-Treatment**	**Treatment**	**Post-Treatment**
Baseline	-0.0002	-0.0163	-0.0074
	(0.0015)	(0.0024)	(0.0027)
Q=0.25	0.0035	-0.0117	-0.0025
	(0.0046)	(0.0054)	(0.0060)
Q=0.5	0.0008	-0.0180	-0.0030
	(0.0030)	(0.0041)	(0.0043)
Q=0.75	-0.0029	-0.0183	-0.0059
	(0.0028)	(0.0036)	(0.0042)

B.4 Comparison with HICP Price Indices

Table B.9: Price Effects, HICP vs Scanner Data

Specification	**Pre-Treatment**	**Treatment**	**Post-Treatment**
Price PT Scanner (ND)	0.0011	-0.0190	-0.0003
	(0.0019)	(0.0025)	(0.0027)
Price PT HICP (ND)	-0.0002	-0.0212	0.0009
	(0.0020)	(0.0032)	(0.0037)
Price PT Scanner (D)	-0.0002	-0.0163	- 0.0074
	(0.0015)	(0.0024)	(0.0027)
Price PT HICP (D)	-0.0039	-0.0150	0.0129
	(0.0058)	(0.0082)	(0.0115)

Table B.10: Details of HICP-COICOP indices used for price pass-through comparison

Category	HICP-COICOP
Non-durables	CP01111, CP01112, CP01113, CP01114, CP01115, CP01119, CP01122, CP011221, CP011222, CP011224, CP01123, CP01125, CP01131, CP01132, CP01133, CP01141, CP01143, CP01145, CP01146, CP01147, CP01148, CP01151, CP01152, CP01153, CP01161, CP01162, CP01163, CP01164, CP01165, CP01167, CP01169, CP01171, CP01172, CP01174, CP01175, CP01176, CP01178, CP01179, CP01181, CP01182, CP01183, CP01185, CP01186, CP01189, CP01191, CP01192, CP01193, CP01194, CP01199, CP01210, CP01220, CP01230, CP01250, CP01260, CP02110, CP02121, CP02130, CP02190, CP05611, CP05619, CP09312, CP09322, CP13120
Durables	CP05112, CP05311, CP05313, CP05314, CP05321, CP05322, CP05329, CP05403, CP06123, CP06132, CP07213, CP08110, CP08120, CP08131, CP08132, CP08140, CP08150, CP09221, CP09222, CP09311, CP09510, CP09520, CP13111, CP13291

Notes: This table lists the indices that were used to compute the price pass-through with official HICP data. The data was collected via web-scraping from the official Eurostat website. To ensure consistency, only those 5/6-digit categories were kept that are also present in the scanner data. Also, some categories were dropped due to unavailability of the series in one of sample countries.

Table B.11: 5-digit ECOICOP categories with available scanner data, spending per 1000 euros

ID	**(E)COICOP category**	**5-digit subcategories**						**Major source**
		#	Weight: all	# goods only	Weight: goods only	# cov-ered	Weight cov-ered	
1	Food and non-alcoholic beverages	61	113.42	61	113.42	61	113.42	FMCG
2	Alcoholic beverages, tobacco and narcotics	14	42.06	14	42.06	13	42.06	FMCG
3	Clothing and footwear	12	51.39	10	50.2	0	0	SMCG
4	Housing, water, electricity, gas and other fuels	25	233.06	9	48.74	2	7.04	SMCG
5	Furnishings, household equipment and routine household maintenance	40	56.93	29	51.41	21	26.33	SMCG
6	Health	14	53.83	6	21.85	1	1.5	SMCG
7	Transport	28	152.19	12	88.45	4	8	SMCG
8	Communications	11	29.59	8	2.92	8	27.16	SMCG
9	Recreation and culture	53	114.19	39	57.86	18	31.71	SMCG
10	Education	6	9.31	0	0	0	0	
11	Restaurants and hotels	6	57.67	2	23.82	0	0	
12	Miscellaneous goods and services	33	86.36	9	19.91	8	32.3	SMCG

The table provides an overview of 5-digit subcategories with available scanner data, taking into account both the fast-moving consumer goods (FMCG) scanner data and the slow-moving consumer good (SMCG) scanner data. Entries in the "Goods only" columns refer to the number (and relative importance) of 5-digit ECOICOP subcategories composed of goods only. For illustration, ECOICOP weights for Germany for the year 2020 are provided.

C Extensive derivation of durable goods dynamics

Our approach directly builds on Orchard et al., 2025. The problem of a household which adjusts its durable goods stock in a given period is

$$\begin{aligned} max_{d_t(i)} \sum_{s=0}^{\infty} (\beta\theta)^s \psi \frac{\left[(1-\delta)^s d_t(i)\right]^{1-\frac{1}{\sigma}} - 1}{1-\frac{1}{\sigma}} - \lambda_t p_t d_t(i) \\ + \sum \beta^s \theta^{s-1} (1-\theta) \lambda_{t+s} p_{t+s} (1-\delta)^s d_t(i). \end{aligned} \tag{C.1}$$

The first order condition is

$$\psi \sum_{s=0}^{\infty} \left(\beta\theta (1-\delta)^{1-\frac{1}{\sigma_d}}\right)^s d_t^{-\frac{1}{\sigma}} = \lambda_t p_t - (1-\theta)\beta(1-\delta) \sum_{s=1}^{\infty} \left[\beta\theta(1-\delta)\right]^{s-1} p_{t+s}\lambda_{t+s}. \tag{C.2}$$

The optimal reset level of households that can adjust in a given period d_t^* is

$$d_t^* = \left[\frac{\psi \sum_{s=0}^{\infty} \left(\beta\theta(1-\delta)^{1-\frac{1}{\sigma}}\right)^s}{\lambda_t p_t - (1-\theta)\beta(1-\delta)\sum_{s=1}^{\infty}\left[\beta\theta(1-\delta)\right]^{s-1} p_{t+s}\lambda_{t+s}}\right]^{\sigma}. \tag{C.3}$$

Note that the development of the VAT rate only enters the optimal adjustment decision via λ_t. Following Orchard et al., 2025 the optimal durable goods level of an adjusting household can be written in recursive form

$$d_t^* = \left(\frac{\Omega_{1t}}{\Omega_{2t}}\right)^{\sigma}, \text{where} \tag{C.4}$$

$$\Omega_{1t} = \psi + \beta\theta(1-\delta)^{1-\frac{1}{\sigma}} \Omega_{1,t+1}$$

$$\begin{aligned} \Omega_{2t} &= p_t\lambda_t - \beta(1-\delta) p_{t+1}\lambda_{t+1} + \beta\theta(1-\delta)\Omega_{2,t+1} \\ &= \lambda_t \left[p_t - \frac{(1-\delta)(1+\tau_{t+1}) p_{t+1}}{(1+r_t)(1+\tau_t)}\right] + \beta\theta(1-\delta)\Omega_{2,t+1}, \end{aligned}$$

where the latter made use of the first order condition $\lambda_{t+1} = \frac{1+\tau_{t+1}}{\beta(1+r_t)(1+\tau_t)}\lambda_t$. In the aggregate we have

$$d_t = (1-\delta) d_{t-1} + x_t \text{ or } x_t = d_t - (1-\delta) d_{t-1}, \tag{C.5}$$

whereas durable goods purchases are determined by those households who are reoptimizing, so that

$$x_t = (1-\theta)\left[d_t^* - (1-\delta) d_{t-1}\right]. \tag{C.6}$$

Note, for further reference, that (C.5) and (C.6) imply

$$(1-\theta)\left[d_t^* - (1-\delta) d_{t-1}\right] = d_t - (1-\delta) d_{t-1}. \tag{C.7}$$

In the long run, $d_t = d_{t-1} = \bar{d}$, so that (C.7) can be written as

$$\bar{d}_t^* = \frac{\left[1-\theta\left(1-\delta\right)\right]\bar{d}}{1-\theta} \text{ or } \bar{d} = \frac{1-\theta}{1-\theta\left(1-\delta\right)}\bar{d}_t^*. \tag{C.8}$$

The elasticity of durable goods with respect to the VAT rate can be decomposed as $\frac{d\ln x}{d\ln(1+\tau)} = \frac{dlnx}{d\ln d^*}\frac{d\ln d^*}{d\ln(1+\tau)}$, which allows calculating it by its two components. Consider first $\frac{d\ln x}{d\ln d^*}$. Taking logs and approximating both sides of equation (C.6) around the reference values (indicated by an upper bar) and setting $d_{t-1} = \bar{d}$ gives

$$\frac{x_t - \bar{x}}{\bar{x}} = \frac{1}{\bar{d}_t^* - \left(1-\delta\right)\bar{d}}\left(d_t^* - \bar{d}_t^*\right).$$

Using (C.8) this can be restated as

$$\frac{x_t - \bar{x}}{\bar{x}} = \frac{1-\theta\left(1-\delta\right)}{\delta}\frac{d_t^* - \bar{d}_t^*}{\bar{d}_t^*}, \text{ which implies}$$

$$\frac{d\ln x_t}{d\ln d^*} \approx \frac{1-\theta\left(1-\delta\right)}{\delta}. \tag{C.9}$$

Turn now to $\frac{d\ln d^*}{d\ln(1+\tau)}$. From (C.4) and taking logs

$$\ln d_t^* = \sigma\ln\Omega_{1t} - \sigma\ln\Omega_{2t}. \tag{C.10}$$

A first oder approximation of the LHS of (C.10) is $\ln d_t^* \approx \ln\bar{d}^* + \frac{d^*-\bar{d}^*}{d^*}$. The approximation of the RHS of (C.10) gives

$$\sigma\ln\Omega_{1t} - \sigma_d\ln\Omega_{2t} \approx \sigma_d\ln\bar{\Omega}_1 - \sigma\ln\bar{\Omega}_2 - \sigma\frac{\frac{\bar{\lambda}(1-\delta)\bar{p}}{(1+\bar{r})(1+\bar{\tau})}}{\bar{\lambda}\left[\bar{p} - \frac{(1-\delta)(1+\bar{\tau})\bar{p}}{(1+\bar{r})(1+\bar{\tau})}\right] + \beta\theta\left(1-\delta\right)\overline{\Omega}_{2,t+1}}\left[(1+\tau_t) - (1+\bar{\tau})\right],$$

where $\bar{\Omega}_1$ and $\bar{\Omega}_2$ are the respective expressions evaluated at the reference values. Setting $\bar{p} = 1$ and using the property of the geometric series

$$\sigma\ln\Omega_{1t} - \sigma\ln\Omega_{2t} \approx \sigma\ln\bar{\Omega}_1 - \sigma\ln\bar{\Omega}_2 - \sigma\frac{\left(1-\delta\right)\left[1-\beta\theta\left(1-\delta\right)\right]}{\bar{r}+\delta}\frac{(1+\tau_t)-(1+\bar{\tau})}{1+\bar{\tau}}$$

Bringing together the approximations of the LHS and the RHS and taking into account that $log\bar{d}^* = \sigma\ln\bar{\Omega}_1 - \sigma\ln\bar{\Omega}_2$

$$\frac{d^* - \bar{d}^*}{\bar{d}^*} \approx -\sigma\frac{\left(1-\delta\right)\left[1-\beta\theta\left(1-\delta\right)\right]}{\bar{r}+\delta}\frac{(1+\tau_t)-(1+\bar{\tau})}{1+\bar{\tau}}, \text{ which implies}$$

$$\frac{d\ln d_t^*}{d\ln\left(1+\tau_t\right)} \approx -\sigma\frac{\left(1-\delta\right)\left[1-\beta\theta\left(1-\delta\right)\right]}{\bar{r}+\delta}. \tag{C.11}$$

Combining (C.9) and (C.11)

$$
\begin{aligned}
\frac{d\ln x}{d\ln(1+\tau)} &= \frac{d\ln x}{d\ln d^{*}}\frac{d\ln d^{*}}{d\ln(1+\tau)} \\
&\approx \frac{1-\theta\left(1-\delta\right)}{\delta}\left(-\sigma\frac{\left(1-\delta\right)\left[1-\beta\theta\left(1-\delta\right)\right]}{\bar{r}+\delta}\right) \\
&= -\sigma\left[\frac{1-\theta\left(1-\delta\right)}{\delta}\right]\left[\frac{\left(1-\delta\right)\left[1-\beta\theta\left(1-\delta\right)\right]}{\bar{r}+\delta}\right].
\end{aligned}
$$