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PRICE TRANSMISSIONS IN THE FINNISH FOOD CHAIN

A NONLINEAR ARDL ANALYSIS FOR 8 COICOP CATEGORIES

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Price transmissions in the Finnish food chain - A nonlinear ARDL analysis for 8 COICOP categories

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Abstract

This study investigates asymmetric price transmission (APT) in the Finnish food retail sector using a nonlinear autoregressive distributed lag (NARDL) model. Monthly wholesale and retail price data from 2017 to 2023 are analyzed across eight food categories defined by the COICOP classification. The results indicate significant differences in price transmission elasticities and adjustment speeds across product categories. For instance, long-run asymmetries are substantial in *Cereals and Bread* and *Fruits and Berries*, while short-run asymmetries are pronounced in *Fish* and *Milk, Cheese, and Eggs*. Adjustment speeds vary from *Meat* adjusting within four months to *Fish* taking up to thirteen months.

Keywords: Asymmetric price transmission, Nonlinear ARDL, Finnish food chain, Price transmission elasticity

JEL: C32, L13, L40, L66, Q18.

1 Introduction

Asymmetric price transmission (APT) in vertical markets refers to situations where positive and negative price changes are not transmitted equally along the supply chain. According to Meyer and von Cramon-Taubadel (2004)[24], asymmetry can occur in either the speed or the magnitude of price adjustments, and can be classified as positive (if increases are transmitted more fully or rapidly) or negative (if decreases are).

APT is often interpreted as a potential indicator of market inefficiencies and power imbalances along the supply chain. In particular, when price increases are passed on more quickly or fully than price decreases, it may suggest that one or more actors have the ability to influence outcomes to their advantage. In the Finnish food market, where retail is highly concentrated, such asymmetries could reflect unequal bargaining power or limited competition. While these explanations are commonly proposed in the literature, the precise mechanisms behind APT often remain difficult to isolate empirically.

This study examines APT in the Finnish food supply chain using detailed data covering eight COICOP food categories: *Cereals and Bread, Meat, Fish, Milk, Cheese and Eggs, Fruits and Berries, Vegetables, Food Products*, and *Non-Alcoholic Beverages*. We apply a nonlinear autoregressive distributed lag (NARDL) model to estimate both short-run and long-run price transmission elasticities between wholesale and retail levels.

Using monthly average price data aggregated at the three-digit COICOP level, this study provides a broad and systematic comparison of price transmission across food categories in the Finnish grocery market. The dataset covers all major retail chains, offering a rare opportunity to examine differences between product groups within a single, highly concentrated market. While earlier studies have often focused on specific commodities or used more narrowly defined market segments, this research enables category-level analysis within a comprehensive and sector wide context.

The remainder of this paper is structured as follows. Section 2 reviews recent literature on APT, with a focus on food sector studies using the NARDL approach, alongside key theoretical perspectives, empirical methods, and product-specific findings. Section 3 describes the data, product categorization, aggregation strategy, and implementation of the NARDL model, including tests for stationarity and cointegration. Section 4 presents empirical NARDL estimation results, including diagnostic tests, elasticity estimates, asymmetry tests, and adjustment dynamics for each COICOP category. Section 5 discusses the findings in light of earlier research, and provides conclusions and suggestions for future studies.

2 Literature review

2.1 Theoretical background: price transmission and market efficiency

In the ideal of a perfectly competitive market, prices adjust instantly and proportionally to cost changes at all stages of the supply chain. This ensures that resources are allocated efficiently—meaning that firms operate at marginal cost, price differences reflect only transaction costs, and consumers face prices that convey accurate economic signals. Symmetric price transmission is one manifestation of this allocative efficiency and reflects what is commonly referred to as the law of one price [26][24].

Asymmetric price transmission (APT) occurs when this condition is violated—typically when prices rise faster than they fall. Various theoretical explanations have been proposed. Menu cost models suggest that firms are more likely to adjust prices upwards due to higher marginal incentives, while downward adjustments are delayed because of fixed costs associated with repricing[3]. Even in the absence of market power, such frictions can lead to persistent asymmetries.

Market structure is another key factor. In concentrated downstream markets, retailers may exploit their position by passing through input price increases quickly while delaying the pass-through of decreases[2]. Similar arguments apply to supply chains characterized by differentiated products and vertical contractual arrangements[23]. As Gopinath (2010)[15] note, price adjustment frequency itself can shape the timing and completeness of pass-through, particularly when pricing decisions are infrequent and strategic.

From a policy perspective, the existence of APT has raised concerns about consumer welfare, pricing transparency, and the responsiveness of markets to shocks[34]. Consequently, empirical identification of asymmetries is often used as an indicator of inefficiency or distorted power relations in the supply chain.

2.2 Empirical approaches to asymmetric price transmission

A wide range of empirical methods has been applied to investigate asymmetric price transmission (APT) in agri-food markets. Early studies were often based on linear cointegration and error correction frameworks, following the Engle-Granger two-step procedure or Johansen's system-based approach. These models typically assume symmetry in price adjustments, but can be adapted to test for asymmetries by modifying the error correction terms.

To address the limitations of linear models, threshold cointegration techniques were introduced. Threshold autoregressive (TAR) and momentum-threshold autoregressive (M-TAR) models allow the speed of adjustment to differ depending on the direction or magnitude of price changes. Goodwin and Harper (2000)[14], for instance, applied a threshold vector error correction model (TVECM) to pork prices in the United States and found evidence of adjustment asymmetries.

Another important development has been the use of smooth transition regression (STR) models, which enable gradual, non-linear switching between regimes. Gervais (2011)[13] applied a smooth transition cointegration model to U.S. pork retail prices and found long-run asymmetry, although short-run dynamics appeared symmetric.

Copula-based models have also gained traction in recent years, offering a flexible, nonparametric way to analyze dependence structures without relying on linearity or normality assumptions. Qiu and Goodwin (2012)[29] and Emmanoulides and Fousekis (2014)[11] employed copulas to study the dynamic relationship between farm, wholesale, and retail pork prices, capturing complex forms of asymmetry over time and across markets.

A further stream of literature has drawn on the New Empirical Industrial Organization (NEIO) framework to explore how market structure and firm behavior shape price transmission patterns. For instance, Cavicchioli (2018)[8] and Liu et al. (2022)[22] consider the role of retailer and processor market power in creating or amplifying asymmetries in fish and aquaculture markets.

The nonlinear autoregressive distributed lag (NARDL) model introduced by Shin et al. (2014)[32] offers yet another approach. It allows for both short-run and long-run asymmetries and is suitable for small samples with mixed integration orders. Compared to threshold models or copulas, NARDL is more accessible in applied settings, and has become a popular tool in recent studies of food markets (e.g. Abdallah et al[5]., Rezitis[31], Panagiotou[25]).

Each of these approaches captures different aspects of asymmetric adjustment. Threshold models are well suited to identifying regime shifts, while copulas excel at modeling dependence structures. NARDL provides an intuitive framework for decomposing and quantifying asymmetries over time. Taken together, these methods illustrate the growing complexity and methodological diversification of the APT literature.

2.3 Empirical findings across product categories and markets

2.3.1 Dairy products

The dairy sector has received considerable attention in APT research, given its structural features and the importance of vertical coordination. Several studies have documented both short-run and long-run asymmetries in farm-retail or wholesale-retail price transmission for milk and processed dairy products.

In Hungary, Abdallah et al. (2020)[5] found positive asymmetry in long-run price transmission from raw milk to products like butter, sour cream, and cheese. They attributed this to the strong market power of processors and limited competition. In Finland, Rezitis (2019)[31] observed significant long-run asymmetries between farm and retail prices for various dairy products, including blue cheese and low-fat milk, and linked these to retailer market power and adjustment costs.

Studies in Turkey (Bor et al., 2021[6]) and Sweden (Lindström, 2021[21]) have also reported asymmetries in both directions, although the results vary depending on the product type and market structure. Notably, Lindström found clear asymmetries for regular milk but not for organic milk, suggesting that product differentiation and supply contracts may mediate transmission patterns.

2.3.2 Meat and fish products

APT has also been widely examined in the context of meat and fish supply chains. These sectors often feature multi-stage value chains, seasonal demand fluctuations, and product perishability—all of which can influence price transmission dynamics.

Fousekis et al. (2016)[12] investigated the U.S. beef sector and found significant asymmetries in both speed and magnitude between farm, wholesale, and retail levels. Their results suggest that both processors and retailers may have the ability to delay or amplify price responses depending on the direction of the change. Similarly, Panagiotou (2021)[25] found short-run and long-run asymmetries in pork markets, emphasizing the role of downstream market concentration in shaping transmission patterns.

Fish markets have also drawn attention, particularly due to their varying structures across countries. Bronnmann and Bittmann (2019)[7] analyzed cod and herring prices in Germany and found that both transmission speed and magnitude varied across retail formats such as supermarkets, discounters, and fishmongers. Liu et al. (2022)[22] studied freshwater carp markets in China, where wholesalers hold substantial bargaining power. Despite this structural contrast, they too found positive asymmetry, supporting the idea that APT may be a general feature of vertically organized food markets, even under differing institutional settings.

2.3.3 Grain, fruits, and vegetable products

In markets for fruits, vegetables, and cereals, APT has often been linked to perishability, storage constraints, and seasonal price volatility. These product characteristics can introduce asymmetries in how costs and supply shocks are transmitted to retail prices.

Harshana and Ratnasiri (2023)[18] examined fruits and vegetables in Sri Lankan wholesale–retail markets and found substantial asymmetries in the magnitude of price transmission. Although their study focused exclusively on perishable products, they concluded that storage limitations and product lifespan may explain part of the uneven adjustment patterns.

Rahman et al. (2022)[30] studied rice markets in Bangladesh using a multi-stage model (farm → wholesale → retail) and found evidence of asymmetric price transmission, particularly in the downstream segments. They also included consumer demand estimation, allowing them to quantify welfare losses due to asymmetries—estimated at up to ninety million dollars per month. Their findings highlight the importance of supply chain transparency and price responsiveness, especially for staple goods.

While cereal products in high-income countries are generally less perishable, they are not exempt from transmission asymmetries. Policy-driven mechanisms such as stockholding, export restrictions, or contractual pricing can lead to delayed or incomplete price adjustments. However, empirical evidence in this product category remains more limited.

2.3.4 Institutional and market structure influences

Beyond product characteristics, market structure and institutional settings have been identified as key factors influencing the presence and form of asymmetric price transmission. These include the degree of concentration at different levels of the supply chain, the use of vertical coordination mechanisms, and national regulatory environments.

Several studies emphasize the role of downstream concentration in enabling retailers to exercise pricing power. For example, Panagiotou (2021)[25] links observed asymmetries in U.S. pork markets to the bargaining power of retailers over wholesalers. In the Chinese freshwater fish market, Liu et al. (2022)[22] describe a markedly different structure, where wholesalers dominate and retailers have limited influence. Despite these contrasts, both studies find persistent asymmetries—suggesting that power imbalances at any level of the chain can distort transmission.

Policy environments also shape transmission outcomes. In Hungary, Abdallah et al. (2020)[5] suggest that milk quotas may explain short-run asymmetries in dairy prices. Liu et al.(2002)[22] propose open-access pricing platforms and producer cooperatives as potential tools for reducing asymmetry. In highly regulated staple markets like rice in Bangladesh, Rahman et al. (2022)[30] highlight the need for improved price transparency and supply chain monitoring to mitigate consumer welfare losses.

In general, these studies suggest that while market concentration is a recurrent theme, institutional and policy differences can reinforce or mitigate asymmetries depending on how they affect pricing behavior and power relations among market participants.

2.4 Summary and research gap

Empirical research on asymmetric price transmission has expanded significantly in recent decades, covering a wide range of products, market contexts, and methodological approaches. Studies across dairy, meat, fish, grain, and produce markets consistently highlight the influence of product perishability, vertical coordination, and supply chain power imbalances on transmission dynamics. Additionally, institutional factors such as policy interventions, regulatory frameworks, and pricing mechanisms further shape asymmetry patterns in country-specific ways.

While this literature has advanced our understanding of APT, many studies focus on single product types or market stages, limiting opportunities for cross-category comparisons. Furthermore, methodological fragmentation—ranging from threshold models to copula-based and structural approaches—complicates the synthesis of findings across contexts.

Related evidence from inflation research highlights the importance of disaggregation in price analysis. Williams (2024)[36] finds that aggregate producer price indices (PPI) poorly predict consumer prices, while disaggregated components, such as fuels, metals and paper, have strong leading effects. Although the context differs, the implication is similar: aggregate indicators can mask important category-specific dynamics. This supports the use of disaggregated data when analyzing price transmission in retail markets.

This study contributes to the existing literature by applying a unified nonlinear framework to a broad set of food categories using harmonized retail data. It provides a rare opportunity to examine variation in speed, magnitude, and asymmetry of price transmission across multiple product groups within a single, highly concentrated national retail market.

3 Data and methodology

3.1 Data

The data for this study comprise monthly product- and chain-specific sales and price data from the Finnish retail sector, covering the period of January 2017 to April 2023[1]. The dataset, sourced from Kesko, S-Group, and Lidl, which together account for approximately 92 percent[2] of the Finnish market, includes product-specific identifiers (EAN codes), supplier details, quantities sold, and average monthly wholesale and retail prices, disaggregated by retail chain. Product characteristics such as categories, brand names, and packaging sizes are also included. A thorough description of the data is given in Heinonen et al.|(2024)[19].

For the purpose of product group comparisons, the dataset has been classified according to the COICOP classification (Classification of Individual Consumption According to Purpose)[33]. COICOP is a widely used system for categorizing consumption purposes, including in the calculation of the Consumer Price Index. This study utilizes the three-digit level COICOP food categories, except for the categories *Oils and Fats* and *Sugar, Jams, Honey, Chocolate, and Confectionery*, which were omitted as they represent a relatively small share of food expenditure and were not central to the study's analytical objectives. Additionally, the two-digit level category *Non-Alcoholic Beverages* has been included as a single category.

Three methods were employed for data aggregation, each with well-founded justifications. First, the monthly product category price was derived by weighting individual product prices with their sales volumes. This enables the examination of the groceries' (as a level in the food chain) ability to transfer average purchase price changes at the product category level to sales prices. Second, each product was weighted by its sales value share within the product group over the entire observation period. This adjustment aimed to standardize product weights, reducing the risk of over- or under-representation, and account for seasonal fluctuations. For instance, in the meat product category, December sales differ from other months in both sales volumes and product assortments. Therefore, explaining January sales prices with December's (sales and) purchase prices could lead to misinterpretation. Thirdly, the monthly price of each product was weighted by its sales value share

[1] This time period generates 76 observations.

[2] According to the Finnish Grocery Trade Association´s annual publication in 2024 S-Group had a market share of 48,3 percent, Kesko´s market share was 34,3 percent and Lidl had a 9,6 percent market share.

in the product group for that specific year. The justifications for this are the same as above, but in addition, this approach better accounts for structural shifts in consumption patterns, such as the introduction of new products. All three aggregation methods yielded reasonably similar estimates. For simplicity, the first method was employed.

In table 1 is given an overall view of the price changes of different COICOP categories. Across all price series, price increases outnumber price decreases. Average percentual price changes are biggest in categories with perishable and/or seasonal products, such as *Fish, Fruits and Berries* and *Vegetables*.

Table 1: Number of price changes and their average amounts

Coicop category	**Buying price increases**	**Buying price decreases**	**Selling price increases**	**Selling price decreases**
Cereals and bread	45 2.54%	31 -2.45%	48 2.33%	28 -2.35%
Meat	47 1.79%	29 -1.47%	46 2.00%	30 -1.78%
Fish	44 4.67%	32 -4.52%	41 5.30%	35 -4.50%
Milk, cheese and eggs	46 1.83%	30 -1.30%	44 2.03%	32 -1.43%
Fruits and berries	38 5.61%	38 -4.13%	44 3.73%	32 -3.64%
Vegetables	42 3.99%	34 -3.78%	46 3.27%	30 -3.70%
Food products	47 1.90%	29 -1.88%	46 2.33%	30 -2.34%
Non-alcoholic beverages	43 2.18%	33 -1.74%	51 1.90%	25 -2.38%

Figure 1 presents the log-level time series of retail and wholesale prices for the COICOP categories examined. Structural breaks are indicated where the `xtbreak` module in Stata identifies statistically significant shifts in the intercept of the relationship between the wholesale and retail price series[3]. Only those breakpoints that were found to be statistically significant regressors in the subsequent NARDL models—explaining retail prices using wholesale prices—are shown in the figure. The most common time for structural break was March 2021[4], it was present in half of the COICOP categories, four out of eight.

[3] Breakpoints were estimated using the `xtbreak estimate` command with a maximum of five breaks, based on the methodology by Bai and Perron (2003)[1]. The optimal number and location of breaks were selected using a sequential F-test, implemented internally in the module according to hypothesis 3 as described by Ditzen et al.(2021)[9].

[4] At that time, the corona restrictions in Finland were at their peak. Gatherings of more than ten people had to be avoided, leisure activities were generally on hold, and schools largely switched to distance learning.

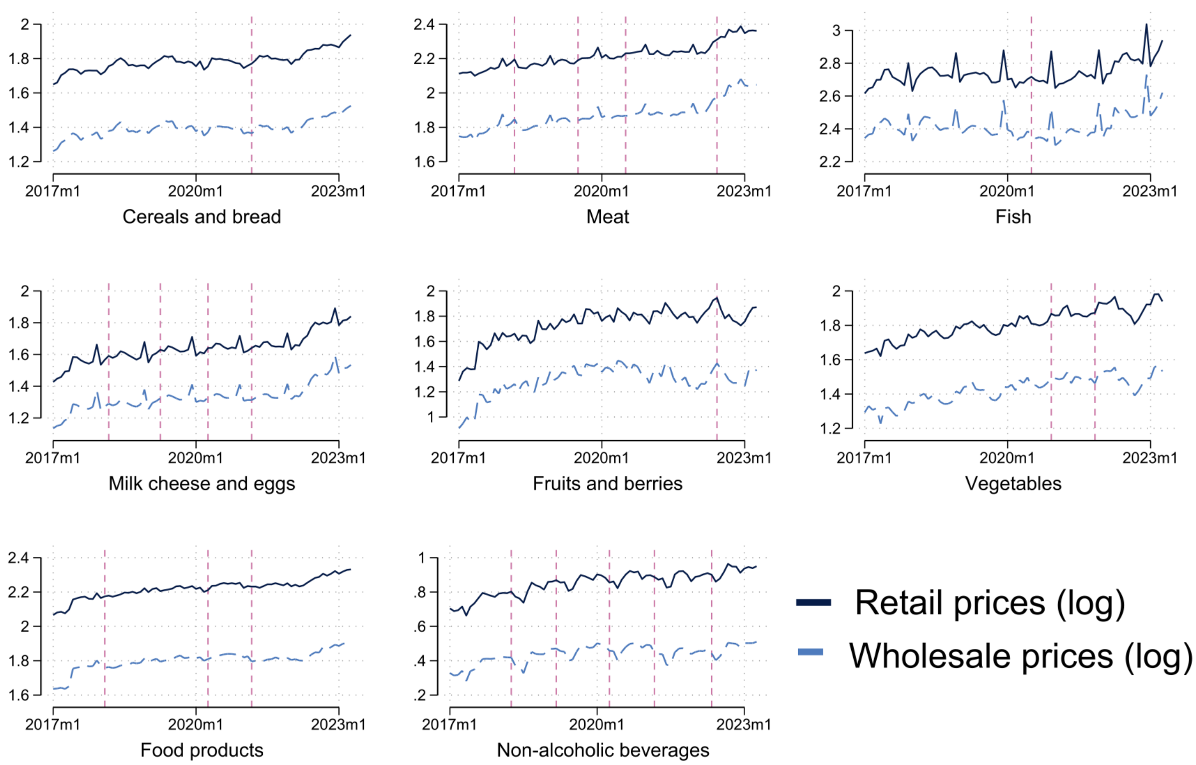

Figure 1: Retail and wholesale price series for coicop categories

3.2 Empirical model

To investigate the relationship between retail and wholesale prices, this study employs the bounds testing approach for level relationships developed by Pesaran et al. (2001)[28]. It utilizes an autoregressive distributed lag framework of Pesaran and Shin (1999)[27] which is further advanced to nonlinear ARDL model in Shin et al. (2014)[32].

The trend represents the long-term structure of the time series. If a time series lacks a trend, it is stationary, meaning its statistical parameters (mean and standard deviation) do not change over time. A time series has a unit root if it is non-stationary. If the coefficient β in the equation 1 equals one, the time series y_t is said to have a unit root, and the model is considered a random walk model. For the time series to be stationary, it must hold that $|\beta| < 1$.

$$y_t = \beta y_{t-1} + \varepsilon_t \tag{1}$$

Non-stationarity in a time series can lead to spurious correlations in analysis (Granger and Newbold, 1974)[16]. If a non-stationary time series is differenced once by subtracting the value of the previous period from the current observation and the differenced series becomes stationary, the time series is said to be integrated of order 1, denoted as I(1). Similarly, a time series that becomes stationary after differencing X times is integrated of order X, denoted as I(X).

The NARDL model employed in this study is suitable for use if the time series are integrated at either I(0) or I(1). To test this, an Augmented Dickey-Fuller and Phillips-Perron unit root tests were conducted for all price series. The null hypothesis of the tests state that the variable being tested has a unit root, indicating non-stationarity. According to the alternative hypothesis, the time series being tested does not have a unit root and is stationary. Table 2 presents the results, confirming that all tested time series are integrated at either I(0) or I(1), making them suitable for NARDL analysis.

In order to model asymmetry, regressor x_t is decomposed into positive and negative partial sums:

$$x_t = x_0 + x_t^+ + x_t^- \tag{2}$$

where the decomposed series are sums of respective changes. Thus, the asymmetric long-run relationship between dependent variable y_t and independent variable x_t can be expressed as:

$$y_t = \alpha + \beta^+ x_t^+ + \beta^- x_t^- + \varepsilon_t \tag{3}$$

where β coefficients represents the long-run parameters for changes in x_t. While the series x_t and y_t are logarithmic, the β coefficients can be referred to as price transmission elasticities. If positive price transmission elasticity is bigger than negative, the APT is said to be positive in the long-run.

Table 2: ADF and PP test results for price series

Coicop category	Series	ADF Test	PP Test	Order of integration
Cereals and bread	Retail 1st diff.	-8.284 .000	-8.294 .000	I(1)
	Wholesale 1st diff.	-9.710 .000	-9.753 .000	I(1)
Meat	Retail 1st diff.	-12.757 .000	-13.491 .000	I(1)
	Wholesale 1st diff.	-12.481 .000	-13.158 .000	I(1)
Fish	Retail level	-5.517 .000	-5.598 .000	I(0)
	Wholesale level	-5.383 .000	-5.467 .000	I(0)
Milk, cheese and eggs	Retail 1st diff.	-14.207 .000	-16.681 .000	I(1)
	Wholesale 1st diff.	-13.784 .000	-15.944 .000	I(1)
Fruits and berries	Retail level	-3.462 .009	-3.616 .005	I(0)
	Wholesale level	-3.551 .007	-3.569 .006	I(0)
Vegetables	Retail 1st diff.	-9.542 .000	-9.618 .000	I(1)
	Wholesale 1st diff.	-10.953 .000	-10.951 .000	I(1)
Food products	Retail 1st diff.	-10.350 .000	-10.330 .000	I(1)
	Wholesale 1st diff.	-9.361 .000	-9.336 .000	I(1)
Non-alcoholic beverages	Retail 1st diff.	-8.504 .000	-8.671 .000	I(1)
	Wholesale 1st diff.	-8.289 .000	-8.317 .000	I(1)

Respectively, APT is negative if negative price transmission elasticity is bigger. While $\beta^+ = \beta^-$ price transmission is symmetric.

Cointegrating relationship between y_t and x_t may be defined between partial sums of y and x with different signs, which Granger and Yoon (2002)[17] call hidden cointegration. If we consider the error correction term z_t to be

$$z_t = \rho_0 y_t + {\beta_1}^+ x_t^+ + {\beta_1}^- x_t^- \tag{4}$$

and if z_t is stationary then y_t and x_t are asymmetrically cointegrated. Furthermore, as a special case if $\beta^+ = \beta^-$ the underlying cointegration relation is linear. From the error correction presentation it follows that the long-run parameters are $\beta^+ = -\beta_1^+/\rho_0$ and $\beta^- = -\beta_1^-/\rho_0$.

As described in Shin et al. (2014)[32] we obtain following form NARDL(p,q) model:

$$y_t = \alpha + \sum_{j=1}^{p} +\Phi_j y_{t-j} + \sum_{j=0}^{q} (\Theta_j^+ x_{t-j}^+ + \Theta_j^- x_{t-j}^-) + \varepsilon_t \tag{5}$$

where the first part of the right-hand side depicts autoregression of dependent variable and the latter part represents distributed lags of the regressor[5]. Arguments p and q are the optimal lags for dependent and independent variables[6]. Shin et al. (2014)[32] also show that equation 5 can be rewritten in an error correction form as

$$\Delta y_t = \alpha + \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{j=1}^{p-1} \gamma_j \Delta y_{t-j} + \sum_{j=0}^{q-1} \phi_j^+ \Delta x_{t-j}^+ + \sum_{j=0}^{q-1} \phi_j^- \Delta x_{t-j}^- + \varepsilon_t \tag{6}$$

where the outcome variable is the change in y_t and the acquired model is linear in all the parameters. In this case a standard OLS estimates are reliably usable. Nonlinearity in the model is captured trough the asymmetric dynamic multipliers

$$m_h^+ = \sum_{i=0}^{h} \frac{\delta y_{t+j}}{\delta x_t^+}, m_h^- = \sum_{i=0}^{h} \frac{\delta y_{t+j}}{\delta x_t^-}, h = 0,1,2.. \tag{7}$$

While $h \to \infty$, $m_h^+ \to \theta^+$ and $m_h^- \to \theta^-$, i.e. dynamic multipliers approach to their respectful long term relationship parameters. In the empirical model applied, additional regressors are added to

[5] In this study, the dependent variable Y_t represents the monthly average retail price (lnpr) for each COICOP category, while the independent variable X_t denotes the corresponding average wholesale price (lnpw). Both price series are expressed in natural logarithms.

[6] Optimal lags are computed using varsoc (Stata 16.1) pre-estimation, Akaike´s information criterion (AIC). The minimum lag order for NARDL model is 2.

equation 6 when deemed necessary. Those are structural breaks [9], quantities sold and ”change of year” dummy[7].

4 Results

4.1 Model testing results

Regression results were tested with four diagnostic tests. With Portmanteau test for white noise it can be confirmed that the residuals are uncorrelated. It can also help to adjust the model for optimal lag selection. The heteroscedasticity of residuals was tested with Breusch-Pagan test. Ramsay RESET (Regression equation specification test) is a model specification error test. Normality of residuals was tested with Jarque-Bera test.[8] Test results are shown in table 3. All the tests are formulated so that the test statistics presents evidence against the null hypotheses of problems in the model. In this case, it can be concluded that the phenomenon being tested is not problematic for the model if the p-value is greater than 0.05. In five test cases out of thirty two, it can not be ruled out that there is a problem in the model. Given the model’s robust explanatory power (R-squared ranging from 0.94 to 0.99) and the absence of systematic issues in the residual analysis, it can be concluded that the model is a good fit.

Table 3: NARDL model diagnostic tests

Coicop category	**Portmanteau**		**Breusch/Pagan**		**Ramsay reset**		**Jarque-Bera**	
	stat	p-value	stat	p-value	stat	p-value	stat	p-value
Cereals and bread	59.34	.006	2.27	.132	3.53	.020	.050	.976
Meat	38.33	.279	5.70	.017	0.69	.565	.319	.852
Fish	35.14	.414	0.23	.635	0.57	.639	.040	.980
Milk, cheese and eggs	45.27	.094	0.36	.546	0.13	.944	.738	.419
Fruits and berries	41.37	.180	1.14	.287	0.37	.777	.058	.971
Vegetables	40.68	.234	1.04	.309	1.08	.366	15.6	.000
Food products	26.90	.835	0.03	.856	0.65	.583	.290	.525
Non-alcoholic beverages	48.47	.051	5.33	.021	1.30	.285	.283	.118

Since the estimated equation in NARDL model is nonlinear by nature, there is no reason to test for linear cointegration. Instead, nonlinear cointegration is tested with t-test developed in Banerjee et al (1998)[4] and F-test developed in Pesaran et al (2001)[28]. Critical bounds were taken from case (iii)[9] in Shin et al (2014)[32]. Table 4. presents bounds-testing results for nonlinear cointe-

[7] Structural breaks are estimated with xtbreak (Stata 16.1) and change of year dummy is used when necessary to take into account the effect of Christmas sales.

[8] All tests were carried out in Stata 16.1 using nardl command by Marco Sunder.

[9] Case (iii) refers to a model with unrestricted intercept term and no trend.

gration between the retail and wholesale prices at one percent significance level. Value of k after COICOP category name indicates the number of regressors. While F-test statistics is bigger than the upper critical bound I(1), the price series are cointegrated. Similarly with t-test, if test statistics are smaller than I(1) then the null hypotheses of $\rho_0 = 0$ from equation 4 is rejected and there is a long-run relationship between the price series. Both tests confirm that retail and wholesale prices are cointegrated for all COICOP categories[10].

Table 4: Cointegration test

Coicop category	F_{PSS}	**I(0)**	**I(1)**	t_{BDM}	**I(0)**	**I(1)**
Cereals and bread (k=2)	15.248	5.407	6.783	-6.715	-3.430	-4.100
Meat (k=5)	22.088	3.725	5.163	-7.820	-3.430	-4.790
Fish (k=2)	10.939	5.407	6.783	-4.974	-3.430	-4.100
Milk, cheese and eggs (k=5)	15.148	3.725	5.163	-5.355	-3.430	-4.790
Fruits and berries (k=2)	9.658	5.407	6.783	-5.130	-3.430	-4.100
Vegetables (k=2)	18.024	5.407	6.783	-6.604	-3.430	-4.100
Food products (k=5)	28.842	3.725	5.163	-8.873	-3.430	-4.790
Non-alcoholic beverages (k=5)	18.168	3.725	5.163	-5.202	-3.430	-4.790

4.2 Estimation results

Table 5 shows the estimation results from NARDL model for COICOP categories. Overall, estimated parameters tend to be statistically significant. For some categories the estimated model used more lags than two although the table shows only parameters up to two lags. As explained in equations 4 and 6, the long-run price transmission elasticities are obtained from the estimated values of $lnpr_{t-1}$, $lnpw^{+}_{t-1}$ and $lnpw^{-}_{t-1}$[11]. The greater the autoregressive coefficient of the dependent variable is relative to the first lag of the independent variable, the smaller is the corresponding price transmission elasticity. The intuition behind this is simple - if retail prices of a given period are strongly affected by the retail prices of the previous period, then the price transmissions from the wholesale prices are inelastic.

[10] Tests were carried out using pssbounds. See details in Jordan and Philips[20]

[11] $lnpr_{t-1}$ refers to the first lag of log retail price, and accordingly $lnpw^{+}_{t-1}$ to the wholesale price. Superscripts $^{+}$ and $-$ refer to positive and negative cumulative changes in wholesale prices, respectively.

Table 5: Estimates from NARDL model

Variable	Cereals and bread	Meat	Fish	Milk, cheese and eggs	Fruits and berries	Vegetables	Food products	Non-alcoholic beverages
Constant	1.602*** (0.217)	2.410*** (0.336)	1.124*** (0.404)	1.171*** (0.220)	1.592*** (0.463)	0.911*** (0.137)	2.602*** (0.283)	0.597*** (0.112)
$lnpr_{t-1}$	-0.687*** (0.102)	-0.982*** (0.126)	-0.710*** (0.143)	-0.817*** (0.152)	-0.623*** (0.212)	-0.542*** (0.082)	-0.963*** (0.109)	-0.834*** (0.160)
$lnpw^{+}_{t-1}$	0.652*** (0.10)	0.641*** (0.092)	0.764*** (0.135)	0.737*** (0.139)	0.464*** (0.105)	0.427*** (0.076)	0.828*** (0.091)	0.625*** (0.133)
$lnpw^{-}_{t-1}$	0.628*** (0.098)	0.669*** (0.096)	0.756*** (0.132)	0.747*** (0.135)	0.373*** (0.092)	0.413*** (0.076)	0.817*** (0.091)	0.623*** (0.115)
$\Delta lnpr_{t-1}$	0.565*** (0.108)	0.051 (0.111)	0.239* (0.131)	0.099 (0.126)	-0.072 (0.122)	0.076 (0.097)	0.191** (0.084)	0.015 (0.112)
Δlnw^{+}	0.803*** (0.058)	0.771*** (0.044)	0.792*** (0.041)	0.983*** (0.026)	0.940*** (0.084)	0.965*** (0.061)	0.832*** (0.043)	0.969*** (0.062)
Δlnw^{+}_{t-1}	-0.536*** (0.118)	0.037 (0.102)	-0.324*** (0.115)	0.029 (0.131)	0.167 (0.141)	-0.092 (0.102)	-0.090 (0.063)	0.078 (0.106)
Δlnw^{-}	0.763*** (0.056)	0.757*** (0.065)	1.063*** (0.087)	0.825*** (0.124)	0.714*** (0.123)	0.769*** (0.061)	0.957*** (0.081)	0.923*** (0.060)
Δlnw^{-}_{t-1}	-0.460*** (0.089)	0.025 (0.106)	-0.366** (0.158)	-0.028 (0.131)	0.099 (0.162)	-0.097 (0.098)	-0.032 (0.094)	0.230** (0.106)
Structural breaks	0.010*** (0.003) 2021m3	0.019*** (0.004) 2018m2 0.016*** (0.003) 2019m7 0.015*** (0.003) 2020m7 0.018*** (0.005) 2022m6	0.014** (0.007) 2020m7	0.013*** (0.001) 2018m3 0.006* (0.003) 2019m4 0.010*** (0.003) 2020m4 0.012*** (0.003) 2021m3	-0.047*** (0.012) 2022m6	0.012*** (0.004) 2020m12 0.016*** (0.005) 2021m1	0.020*** (0.003) 2018m2 0.006*** (0.002) 2020m4 0.018*** (0.003) 2021m3	0.025*** (0.004) 2018m4 0.017*** (0.004) 2019m3 0.010** (0.004) 2020m4 0.019*** (0.005) 2021m3 0.010** (004) 2022m5
lnq	-0.028*** (0.006)	-0.021** (0.009)	0.054*** (0.015)	0.028** (0.013)	-0.046* (0.025)		-0.039*** (0.025)	
Observations (N)	74	73	72	72	73	74	74	72
R^2	0.9427	0.9599	0.9867	0.9945	0.8865	0.9283	0.9414	0.9672

In table 6 is presented the price transmission elasticities and p-values of both long-run and short-run asymmetries. Overall, the price transmissions are quite elastic, elasticities ranging from 0.6 (negative from *Fruits and berries*) to 1.1 (positive for *Fish*). Standard errors, given in parenthesis, are bigger for negative elasticities. This is natural, since as can be seen in table 1, there are fewer observations for price decreases compared to price increases. All elasticities are statistically significant at 1 percent level. In the long-run, asymmetries in price transmission elasticities are confirmed for COICOP categories *Cereals and bread* and *Fruits and berries*. In the short-run, asymmetries in adjustment paths are confirmed (at 5 percent) for COICOP categories *Fish* and *Milk, cheese and eggs*.

Table 6: Price transmission elasticities and asymmetry

Coicop category	**Positive elasticity**	**Negative elasticity**	**P-value of long-run asymmetry**	**P-value of Short run asymmetry**
Cereals and bread	0.949 (.026)	-0.914 (.032)	0.001	0.796
Meat	0.653 (.037)	-0.682 (.046)	0.128	0.443
Fish	1.076 (.084)	-1.064 (.091)	0.248	0.000
Milk, cheese and eggs	0.902 (.025)	-0.914 (.044)	0.604	0.045
Fruits and berries	0.744 (.053)	-0.599 (.062)	0.000	0.355
Vegetables	0.785 (.052)	-0.762 (.068)	0.330	0.958
Food products	0.859 (.023)	-0.848 (.050)	0.722	0.069
Non-alcoholic beverages	0.750 (.049)	-0.747 (.066)	0.955	0.530

The adjustment paths following a one percent increase and decrease in wholesale prices leading towards long-run price transmission elasticities are shown in figure 2. The upper dotted line represents the values of dynamic cumulative multipliers for up to 10 periods following a positive price shock in the wholesale prices. Similarly, the lower dotted line marks the adjustment path for retail prices following a decrease in the wholesale prices. The line in between represents their difference and the shaded area around it denotes a 95 percent confidence interval. Therefore, if the zero line is visible from beneath the shaded area, there is asymmetry in price transmissions at the five percent significance level.

In empirical applications of NARDL model, APT in speed is typically assessed either by visually inspecting plots such as those in figure 2 or by testing the equality of positive and negative dynamic multipliers in equation 7. Figure 3 presents an alternative and straightforward way of comparing the speed of positive and negative price transmissions. First, adjustment paths are converted into distances from respective price transmission elasticities. Then, the number of periods it takes for the distance to permanently fall below a chosen threshold is evaluated. In figure 3 the dark blue line depicts the distance between the positive dynamic multiplier and β^+, the light blue line depicts the

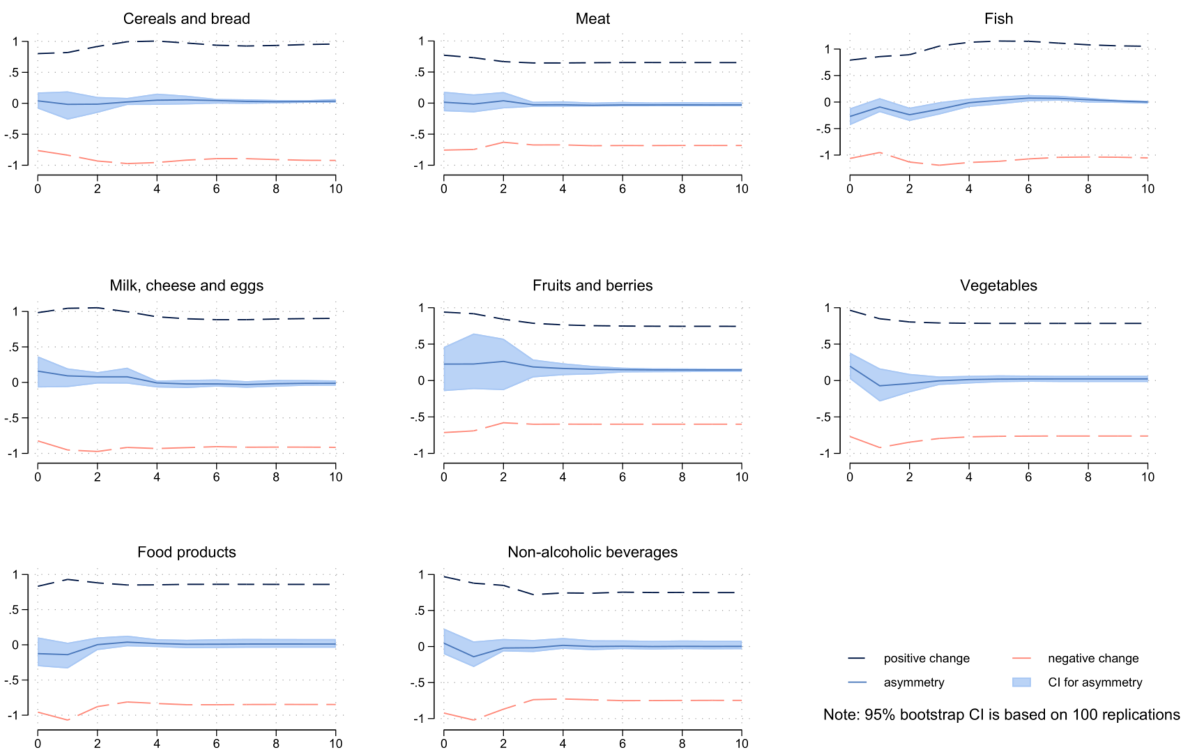

Figure 2: Dynamic multipliers for retail price adjustment

distance between negative dynamic multipliers and β^-, and the light red line represents the chosen threshold of 0.01 percentage point.

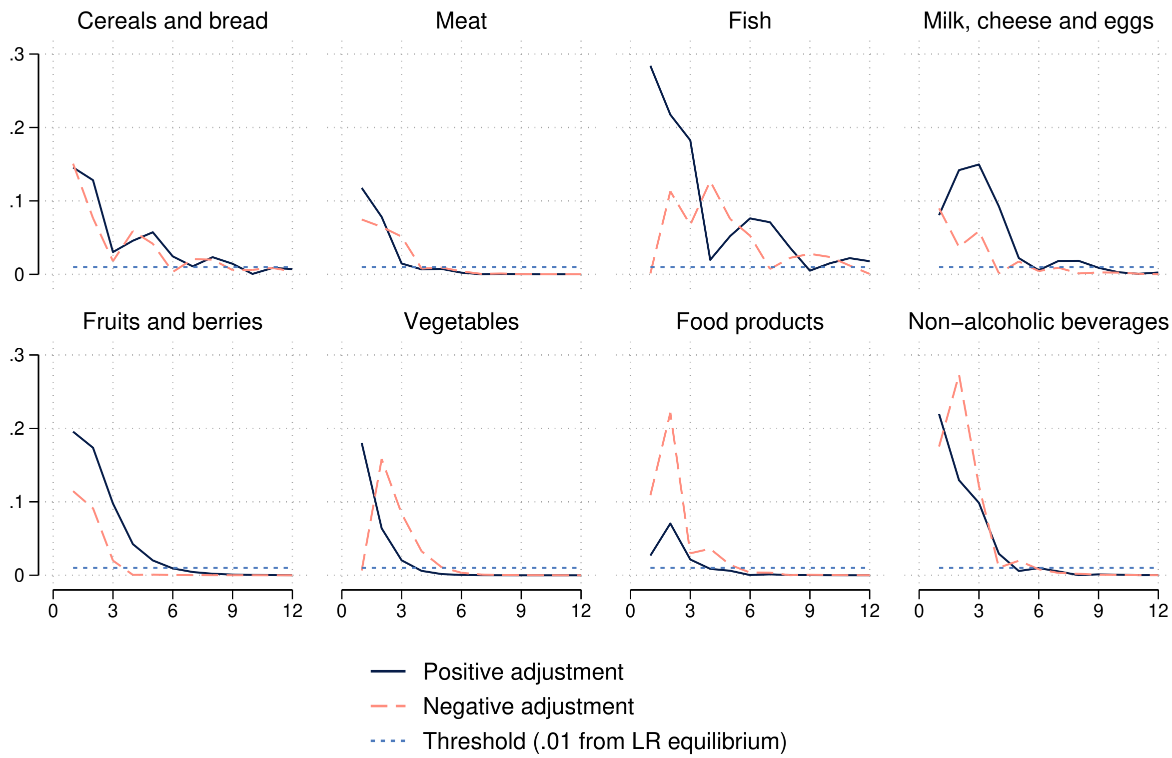

Figure 3: Speed of adjustment after price shocks for coicop categories

In the NARDL model, the short-run asymmetries are tested by comparing the equality of positive and negative dynamic multipliers. In addition to examining the adjustment paths, this study suggests a simple metric for assessing the speed of price transmission - the number of months it takes from adjustment to reach a given distance threshold from the long-run relation that the adjustment has reached. The chosen threshold in this study was 0.01 percentage points. The speeds of positive and negative price transmissions (in months) are given in table 7.

5 Discussion and conclusion

This study examined the asymmetries of price transmissions at the grocery level in the Finnish food chain. The analysis was based on aggregated data at the three-digit COICOP category level. There are both advantages and disadvantages of using aggregated data. On one hand, it can be argued that grocers are not particularly interested in the markups of a single product and do not necessarily base their pricing decisions on the level or changes in wholesale prices of a single product[10][35]. Thus,

Table 7: Speed of adjustment

Coicop category	Positive	Negative
Cereals and bread	10	9
Meat	4	4
Fish	13	12
Milk, cheese and eggs	9	6
Fruits and berries	6	4
Vegetables	4	6
Food products	4	6
Non-alcoholic beverages	5	6

category-level aggregation can provide a realistic view of how price changes are transmitted at the retail level as a whole. On the other hand, aggregation may obscure category-internal dynamics and product-specific pricing strategies that influence how prices adjust within narrower product markets. It is difficult to attribute that the market structure causes results when the level of aggregation does not match any meaningful market definition[12].

A key strength of the NARDL model lies in its ability to estimate both short- and long-run asymmetries within a unified framework. The underlying assumption is that faster, more complete, and more symmetric price transmission reflects a more efficient vertical supply chain. By comparing results across product categories, we can assess whether price adjustments differ in ways that suggest inefficiencies or structural frictions. In this study, the lowest transmission elasticities were observed in the *Meat* category ($\beta^+ = 0.65$ and $\beta^- = 0.68$), while the highest were found in *Fish* ($\beta^+ = 1.08$ and $\beta^- = 1.06$). This notable difference is unlikely to result from variation in competitive conditions, as the retail environment is largely consistent across categories. Overall, the results indicate that retailers are generally able to pass changes in their purchase prices through to consumer prices.

The results also reveal clear differences in the speed of price transmission across product categories. Adjustments were fastest in the *Meat* category, where both positive and negative shocks reached their long-run equilibrium within four months (defined as the point where the cumulative difference in β falls below 0.01). In contrast, price transmission in the *Fish* category was markedly slower, taking thirteen months after a positive shock and twelve months after a negative one. The results indicate that categories with higher price transmission elasticity do not necessarily exhibit faster adjustment speeds.

This contrast highlights that speed and magnitude of adjustment are not mechanically linked, but may reflect different structural or behavioral dynamics. Faster adjustments in *Meat* prices may be driven by high turnover rates, stable demand, or automated pricing practices, whereas slower

[12] In that case disaggregation would improve the analysis[36].

but more complete adjustments in *Fish* may result from higher price volatility, perishability, or more conservative pricing strategies. These differences emphasize the importance of analyzing both dimensions of price transmission separately.

The largest asymmetry in adjustment speed was observed in the *Milk, cheese and eggs* category: the effect of wholesale price increases took nine months to be fully transmitted, while decreases adjusted in six months.

These findings partly diverge from earlier NARDL-based studies on asymmetric price transmission in food markets. While the magnitudes of price transmissions are quite similar, we found less asymmetry than expected. Fousekis et al. (2016)[12] found asymmetries in both speed and magnitude in the U.S. beef sector, while Bronnmann and Bittmann (2019)[7] observed heterogeneous adjustment dynamics across fish species in Germany. Rezitis (2019)[31], in turn, documented long-run asymmetries in the Finnish dairy sector. Compared to previous literature, the present study covers a wider set of food categories within a single retail market, which allows for within-country comparisons that are rare in APT literature.

This study revealed clear differences in both the speed and magnitude of price transmission across product categories. While asymmetry in magnitude was substantial only in the *Fruits and Berries* category, smaller differences were observed elsewhere as well. These results suggest that category-specific factors, such as perishability, inventory dynamics, and pricing strategies, may play a role in shaping the dynamics of price adjustment, even within a uniform retail environment. The dataset also enables future analysis of APT across levels of aggregation. For example, comparing private label and branded products, or examining store size variation, could help clarify the underlying mechanisms that drive asymmetric price responses in retail pricing.

One notable result is the relatively low long-run elasticity observed in the *Meat* category, despite fast adjustment speeds. This finding raises questions about pricing behavior within that category and suggests a need for more detailed analysis at the product level—distinguishing, for example, between broiler, pork, and beef.

In conclusion, this study finds that price transmission in the Finnish grocery sector is category-specific. While the general retail environment is similar across product groups, the observed differences in both speed and magnitude of adjustment suggest that supply chain dynamics and pricing behavior vary by category. Although the current framework does not allow for causal inference, the possibility that structural frictions or pricing power contribute to these patterns cannot be ruled out.

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