UNIVERSITÀ CATTOLICA del Sacro Cuore

DIPARTIMENTO DI SCIENZE ECONOMICHE E SOCIALI

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ABSTRACT

We investigate the impact of retailers' strategies on dairy price dynamics. Using high frequency Italian scanner data for different dairy products, we compute a weekly drift-free price index, specific for product category, chain, and type of store. Exploiting the (unbalanced) panel data structure to control for unobservable strategies by chain, time, and type of store, we test if unobservables are statistically significant in influencing the inflation rate on each of the products covered by our analysis. In general chain and type-of-store specific unobservables have a significant role in controlling price dynamics. Moreover, we identify the role of some observable strategic variables in controlling or in stimulating price inflation rates. Results show that the growth of Private Label (*PL*) market shares tend to slow down the upward price trend, while price promotions tend to be more effective if applied to National Brands (*NB*s). Policy implications for the potential role of retailers in controlling food inflation are drawn.

Keywords: food price dynamics; GEKS index; retailers' strategies; ECM.

JEL classification: C23; C43; E31; L11.

1. INTRODUCTION

According to Eurostat, after a period of relatively stable consumer prices during the 90's, at the beginning of the last decade the European Union (EU) has been affected by a price inflation of about 2% per year. In 2008 the price inflation sharply increased to 3.7%. In 2009, following a decline in food prices, the inflation rate stood at 1.0% to accelerate again in 2010 (2.1%) and 2011 (3.1%), while slowing down progressively in the following years (2.6% in 2012, 1.5% in 2013, and 0.5% in 2014). Food prices are an important driver of the Consumer Price Index (*CPI*): food, alcohol, and tobacco weigh almost 20% in the EU *CPI* basket, thus price inflation largely depends on food prices (BernsteinResearch, 2011).

As food is an essential good, every consumer is affected by its price changes. However, changes in food retail prices will impact differently on consumers' purchasing power depending on income levels and on the share of budget committed to food items. Since lower income consumers spend most of their income on food, they are most likely affected by rising food prices than high-income consumers. Thus, an increase in food prices can have a direct effect on food security, poverty rates, and social equality, especially in periods when the economy shrinks, as shown by a recent study on poverty in Italy (ISTAT, 2014).

The agricultural commodity and energy price rise in 2007-08 has been transmitted at the retail level, increasing food prices during the same time period. As food prices peaked, Government agencies renewed their interest in understanding how volatility in commodity prices affects food prices at the retail level. Irz et al. (2013) analyzed the impact of cost shifters, such as energy, on food prices in Finland during the agricultural commodity crisis of 2006-08. They found that such cost shifters have an important role in determining the final market prices. Other sources of variation in food price dynamics can be searched on the competitive environment and on retailer's marketing strategies. In this paper we focus our attention on the latter, since we analyze whether retailers' strategies are affecting the average price paid by consumers.

Through store and chain marketing strategies, retailers are somehow able to influence consumer choices. "Understanding retailer market power, pricing practice, and marketing strategies is critical for many reasons. Most obvious is the impact that retailer behavior can have on consumer and producer welfare" (Li et al., 2006). For instance, Chevalier and Kashyap (2011) showed how retailers use promotion activities to charge different prices to consumers, influencing their reservation price and "thus, how consumers update reservation prices for individual goods becomes a critical factor affecting inflation".

Broda et al. (2009), using household scanner data, showed that "poor households systematically pay less than rich households for identical goods". Different explanations on why a richer person might pay more can be proposed. First, poor people might be willing to invest more time in comparing prices among stores, looking for the one which offers deeper discounts. Second, stores in richer neighborhoods might face higher rent costs (Broda et al., 2009), reflecting in higher prices. Last, different stores' characteristics might be a source of differentiation between two goods that otherwise would be identical, meaning the same good may have different value if purchased at different stores because of the related shopping experience (Betancourt and Gautschi, 1992 and 1993; Broda et al., 2009).

Previous literature has found that the presence of Private Labels (*PL*s) and their line extension have an impact on National Brands (*NB*s) prices (Gabrielsen et al., 2002; Ward et al., 2002; Bonfrer and Chintagunta, 2004; Bontemps et al., 2005 and 2008; Sckokai and Soregaroli, 2008). Although findings about the impact of *PL*s on *NB*s' prices are still mixed, the case of an increase in *NB*s' prices due to price discrimination seems to be the most supported (Ward et al., 2002; Bontemps et al., 2005), thus showing a sort of perverse effect of *PL*s on food inflation.

Furthermore, product heterogeneity and promotional sales have been found to be key strategies in terms of impact on retail prices. Nijs et al. (2001) have found a strong association between the successful introduction of new products and a permanent increase of the category demand, while the frequency in price promotion mainly correspond to short-run, rather than long-run, effects on consumer sensitivity to prices. Foremost, a higher number of products in the stores can be related to an increase of the money spent by consumers (Richards and Hamilton, 2006). Since consumers show a strong preference for variety and assortment depth, retailers have incentives to increase their margins when offering higher assortment. Specifically, studying the

U.S. market, Richards and Hamilton (2013) have found that retailers tend to charge consumers for the higher variety offered by their store, subsidizing suppliers to enter their "networks". This might lead to observe an increase in prices when variety deepens. As Richards and Hamilton (2006) pointed out, under the assumption of a retailer acting as local monopolist (Slade, 1995), the effect of an increase in variety can help retailers to implement a "portfolio" pricing strategy and extract multiproduct monopoly rents. Rooderkerk et al. (2013) have shown how choosing optimal assortment by retailers have a considerable impact on their profitability. However, an increase of the retailer product variety can promote price competition (Richards and Hamilton, 2009); in this case we might observe a downward trend in prices. Further, Richards (2006), studying the perishable food market, found that the depth of promotion (percentage reduction in price) has a stronger impact than its breadth (number of items on sales) in generating store level sales revenue, and that price levels are the critical factors in determining market shares. Hansen and Singh (2009), analyzing a consumer panel from a large Midwestern U.S. city, where households are observed to make purchases across three store types (high-end grocery store, traditional supermarket, and large everyday low pricing), show "strong correlations between the marketing mix sensitivities, store format preference, and unobserved brand attributes". Therefore, failure to account for retail format effects can substantially bias our understanding of the functioning of the market.

Although there is a rich marketing literature analyzing the consumer response to retailers' strategies, to our knowledge no study has yet analyzed its effect on aggregate food price indexes. This work mainly focuses on determining the impact of the retailers' marketing mix, such as promotion, assortment, and the presence of *PL*s, on food inflation. In particular, focusing on the Italian dairy market, we try to identify how some observable retailers' strategy variables may affect dairy inflation rates. Moreover, we try to test whether the retail chain and/or the type of store play a role in influencing the dairy price dynamics.

Price dynamics in dairy products is measured by resorting to the drift-free Gini-Eltetö-Köves-Szulc (*GEKS*) index proposed by Ivancic et al. (2011). After computing the GEKS index for each product and for each chain-type of store combination, we use a semi-logarithmic model specification to estimate the effect of observed retailers' strategies. Estimation is carried out by means of the three-way Error

Component Model (*ECM*) estimator (Davis, 2002), which allows to capture the effect of unobservables due to chain, time, and type of store variation. The remainder of the paper gives a description of the data considered, discusses the use of the price indexes, the econometric methodology, and the results. Policy implications are drawn along with the conclusions.

2. DATA AND VARIABLE DEFINITIONS

A SymphonyIRI scanner dataset is used to compute price indexes and to measure retailers' strategies by chain and type of store. This dataset provides brand level weekly prices and sales, with and without promotion, for 400 points of sales belonging to 14 retailing chains along 156 weeks, from January 2009 to January 2012. All points of sales of the sample are located in Italy, but we do not observe their geographical location. For each point of sales, we observe the retailing chain it belongs to and its store format (hypermarket, supermarket, or minimarket[1]). More details are provided in Table 1.

Table 1. Distribution of the point of sales in the sample by retail chain and store format

Retail Chain	Hypermarket	Supermarket	Minimarket	Total
A	-	10	4	14
B	8	8	-	16
C	16	22	4	42
D	12	26	4	42
E	16	29	5	50
F	-	30	5	35
G	10	10	-	20
H	16	35	4	55
I	10	8	-	18
L	-	8	4	12
M	-	8	4	12
N	12	28	6	46
O	-	20	6	26
P	-	8	4	12
Total	**100**	**250**	**50**	**400**

Source: Own elaboration on SimphonyIRI data

[1] SimphonyIRI defines minimarkets as stores with a sales area lower than 400 square meters, supermarkets as stores with sales area between 400 and 2,500 square meters, and hypermarkets as stores with a sales area larger than 2,500 square meters. Discount stores are not included in the sample.

Furthermore, in the dataset retail chains, manufacturers and brands (except the indication of *PL*s), are blinded by letter codes for confidentiality. In this way we can distinguish different chains, manufacturers, and brands but we are not able to link them to real market entities.

The data cover seven different dairy product categories: refrigerated and ultra-high temperature (UHT) liquid milk, butter, cheese[2], mozzarella cheese, UHT cream, and yogurt. Since we do not observe the Universal Product Code (*UPC*), we define a "product" as the interaction of segment, manufacturer, brand, and packaging attributes. For instance, any product in the UHT milk category will be defined by the interaction of 4 different segments (whole, semi-skimmed, skimmed, and vitamin enriched), 27 different manufacturers, 122 brands, and 2 attributes related to product packaging, leading to a total of 261 products.

Table 2. Number of Segments[3], Manufacturers, Brands, Packaging types and Brand Units for each product category

	Segments	Manufacturers	Brands	Packaging types	Brand Units
Butter	3	45	118	5	251
Cheese	2	23	54	4	65
Milk (refrigerated)	7	30	139	2	364
Mozzarella cheese	4	39	163	7	315
UHT cream	5	33	84	1	121
UHT milk	4	27	122	2	261
Yogurt	15	36	199	11	739

Source: Our elaboration on IRI data

[2] Processed spreadable cheese and cheese flakes.

[3] For each of the product listed in Table 2 the SymphonyIRI database provides information on the following segments. (1) Butter: normal, salty, other types. (2) Cheese: processed spreadable, cheese flakes. (3) Refrigerated milk: high digestibility, high quality, enriched, whole, skim, semi-skim, micro-filtered. (4) Mozzarella cheese: buffalo mozzarella, cow mozzarella, light, mixed. (5) UHT cream: cream for salty dishes, to be whipped, whipped cream, cream from vegetable fat. (6) UHT milk: skim, semi skim, whole, with vitamins added or health benefits. (7) Yogurt: functional reducing cholesterol, functional improving intestinal transit, functional pro immune system, functional with other benefits, with fruit snacks, with other snacks, drinkable with package of 250 gr or less, drinkable with package bigger than 250 gr, whole with pieces of fruit, whole with fruit flavor, whole white, whole other flavors, skim with pieces of fruit, skim with fruit flavors, white skim, skim with other flavors.

We define such elementary unit of analysis as brand unit (*BU*)[4]. Within dairy product categories, the variability in terms of product differentiation is quite high. For instance, the yogurt category is the most differentiated one with 739 different *BUs*, while in other product categories the number of *BUs* ranges from 65 for cheese to 364 for refrigerated milk (see Table 2).

2.1 Price Dynamics

The use of scanner data in measuring inflation has been proposed since the late 90's. Boskin et al. (1998) recommended their use as a possible way to reduce the bias carried by the standard *CPI* in assessing the cost of living. In this context, the use of scanner data is appealing for four main reasons. First, the cost for collecting them is relatively cheap compared to other types of data. Second, their use can facilitate the computation of a flexible basket index, whose product composition can be updated period by period. Third, scanner data record the actual purchasing consumer decision, so they implicitly embody the effects of marketing activities on consumer choices, allowing their evaluation when accounting for substitution patterns among different products. Fourth, the availability of both price and quantity purchased of all items allows the construction of many types of price indexes.

However, at the same time, some potential negative implications may arise: in particular, the high volatility of prices and quantities due to retailers' sales would generate drifts in the *CPI* estimation, producing the so-called "price and quantity bouncing" bias (de Haan and van der Grient, 2011)[5].

A rather new literature has focused on analyzing different approaches to the computation of price indexes using scanner data, and on establishing the effect of time and store aggregation as well as the drift bias on inflation measurement. Ivancic et al. (2011) showed that the level of data aggregation across time and points of sale becomes relevant when high frequency scanner data are used to estimate price

[4] Even if we do not observe the *UPC* code, the way we define *BU* should approximate the *UPC* with fairly high precision.

[5] The "price and quantity bouncing" bias effect is linked to retailers sales because households tend to stock up during sale periods and consume from inventories when products are not on sale.

changes through the computation of the *CPI*. Evidence of a "price bouncing" bias when estimating price indexes was also found by de Haan and van der Grient (2011) using Dutch data. Similarly, Nakamura et al. (2011), using U.S. scanner data, compared price indexes computed using either all prices or only "regular prices", i.e. excluding "sale prices", and confirmed the insurgence of a chain drift problem. Their suggestion was that "averaging within chains will ameliorate the chain drift problem", although it cannot be the sole solution.

A more promising approach is to resort to drift-free multilateral indexes, such as the *GEKS* index proposed by Ivancic et al. (2011). They showed how the conventional superlative indexes, such as the Fisher index, even calculated at a level of aggregation that seems to minimize the drift bias, "show a troubling degree of volatility when high-frequency data are used". Differently, the *GEKS* index provides drift-free estimates. In their empirical tests, de Haan and van der Grient (2011) confirmed the superiority of *GEKS* indexes with respect to the Dutch method, based on monthly-chained Jevons indexes[6], when dealing with high frequency scanner data.

The *GEKS* is a multilateral index, often used in international trade to compare several entities. For example, consider P_{ij} to be the Fisher index between entities i and j ($j = 1, \dots, M$) and P_{kj} to be the Fisher index between entities k and j. The *GEKS* index between i and k will be the geometric mean of the two Fisher indexes.

Ivancic et al. (2011) proposed to use the *GEKS* index to make comparison among T different time periods, $t = 1, \dots, T$. Considering the reference time period $t = 0$, the *GEKS* price index between 0 and t will be:

$$GEKS_{0,t} = \prod_{l=0}^{T} \left(\frac{P_{0l}}{P_{tl}}\right)^{\frac{1}{T+1}} = \prod_{l=1}^{T} \left(\frac{P_{0l}}{P_{tl}}\right)^{\frac{1}{T}} = \prod_{\tau=1}^{t} GEKS_{\tau-1,\tau}. \quad (1)$$

As it is clear from equation (1), and differently from other bilateral indexes, multilateral indexes satisfy the Fisher's circularity test (Fisher, 1922) which allows to directly compare entities among each other, or through their relationship with a third one. The circularity property allows to write the *GEKS* index between time

[6] The Jevons index is the unweighted geometric average of the price in the current period relative to the price in the base period.

period 0 and t ($GEKS_{0,t}$) as a period-to-period chain index: $\prod_{\tau=1}^{t} GEKS_{\tau-1,\tau}$.

In addition, the *GEKS* index is free of chain drift bias, as it satisfies by construction the multi-period identity test proposed by Walsh (1901) and Szulc (1983)[7]. Finally, it can accomodate a flexible basket over time. Thus, the *GEKS* index is a good candidate for *CPI* computation using high frequency data, since scanner data are characterized by high heterogeneity in product assortment over time.

In this paper, weekly GEKS price indexes are computed using data for all points of sales in the sample, distinguishing by dairy product categories, chains and type of store. The final dataset includes indexes measured in each of the 156 weeks for the available 33 chain-type of store combinations; this gives a total of 5,148 observations for each of the 7 product categories. In order to explore the absolute differences among chains and types of store, the *GEKS* price index is multiplied by the average price level in the first week.

2.2 Retailers' Strategies

Proxies for the intensity of some retailers' strategies are constructed at the product category level. Six variables are considered, related to the assortment, the breadth of promotion, the market share of *PL*s, the *PL* line extension within each category, and the intensity of promotion for both *PL*s and *NB*s (see Table 3).

The assortment is measured by first computing the number of BU at each point of sale in a given week and product category, and then averaging across the points of sales of the same chain and type. Product heterogeneity has a crucial role in determining retailer's price and assortment strategies (Richards and Hamilton, 2006). Previous studies have found two opposite effects. First, product heterogeneity may generate an upward trend in prices due to portfolio strategies by the retailer (Richards and Hamilton, 2006) or extra charge to

[7] Given elementary price indexes computed among all different time periods, the price index formula will not suffer from chain drift bias if the product of indexes among all possible time combinations is equal to one For example, in the case of a three-time period, given the price indexes between periods 1 and 2, $p(p_1, p_2, q_1, q_2)$, between periods 2 and 3, $p(p_2, p_3, q_2, q_3)$, and between periods 3 and 1, $p(p_3, p_1, q_3, q_1)$, if the product of the three indexes is equal to one, the price index formula is not affected by drift chain bias.

consumer for entering a richer "network" (Richards and Hamilton, 2013). Second, higher product heterogeneity may lead to higher competition among *BU*s, thus decreasing prices (Richards and Hamilton, 2009).

Table 3. Definition of the explanatory variables

Variable	Computation	Rationale
$\mathbf{Assortment}_{itj}$	Average weekly number of BU in the points of sales of the same chain and type .	The variable aims to capture the assortment strategy for each type of store and chain over time.
$\mathbf{Breadth\ of\ promotion}_{itj}$	Average weekly number of BU in promotion in the points of sales of the same chain and type .	The variable aims to capture the breadth of promotion, defined as the number of items on sales, for each type of store and chain over time
$\boldsymbol{PL}$ $\mathbf{share}_{itj}$	Average weekly *PL* market share in value in the points of sales of the same chain and type.	The variable aims to capture the *PL* market competitiveness over time, with respect to the other brands.
$\boldsymbol{PL}$ $\mathbf{line\ extension}_{itj}$	Average weekly share of the segments where the *PL*s are present in the points of sales of the same chain and type. The elementary shares are computed as number of segments where the *PL*s are present over all segments in a given point of sale.	The variable aims to measure the *PL* line extension in each type of store and chain over time, measured by the number of segments in which they are present
$\boldsymbol{PL}$ $\mathbf{promotion}_{itj}$ $\boldsymbol{NB}$ $\mathbf{promotion}_{itj}$	Weekly average of the *PL*/*NB* value share sold under promotion in the points of sales of the same chain and type. The elementary shares are computed as value of *PL/NB* sold under promotion over the total value sales of *PL*/*NB* in a given point of sale.	The two variables aim to capture the intensity on promotion activity by *PL*/*NB* in each type of store and chain over time.

In order to account for the breadth of promotion, we measure the number of items on sales for a given product and week, again averaging across the points of sales of the same chain and type. In this regard, Richards (2006) has shown that the breadth of promotion has an important role in food marketing strategies and may have an important impact on prices, since it typically works as complement, rather than substitute, of the depth of promotion (i.e. the number of products on sale in a given category tends to increase with the percentage reduction in their price).

The share in value of *PL* sales on total sales is computed as a proxy for their market competitiveness with respect to other brands. This measure has been widely used in the literature (Ward et al., 2002; Bontemps et al., 2005 and 2008; Sckokai and Soregaroli, 2008) in order to analyze its impact on *NB* prices. As mentioned in the introduction, results on this issue are mixed and not conclusive.

Furthermore, to capture the *PL* line extension, the ratio between the number of market segments where *PL*s are present and the total number of segments for a given product category is computed. For example, within the UHT milk category, where we observe four different market segments (whole, semi-skimmed, skimmed, and vitamin enriched), the presence of *PL*s in two of the four market segments in a given point of sale and in a given week will correspond to a *PL* line extension of 50%.

Finally, the intensity of promotion activities for *PL*s and *NB*s is measured through the corresponding shares in value term (i.e. *NB* sales in promotion over total *NB* sales and *PL* sales in promotion over total *PL* sales).

Descriptive statistics in Table 4 show that the marketing mix strongly differs among product categories. The yogurt market is characterized not only by a larger assortment, but also by a high variability across chains, types of stores and over time, with a standard deviation of more than 40 *BU*s. UHT milk and mozzarella also show a rather large assortment, with an average number of *BU*s higher than 20, while the remaining categories range from 12 to 15 units.

Significant differences across product categories can be found also for the *PL* share and its line extension. Butter is the category with the higher *PL* share (28.2%), followed by UHT cream (20.6%), mozzarella (19.3%), UHT milk (16.3%), and refrigerated milk (11%), while yogurt and cheese have an average *PL* share below 10% (8.6% and 2.6% respectively).

Table 4. Descriptive Statistics for the retailers' strategy variables

	Mean	Std Dev	Minimum	Maximum
		Butter		
Assortment	15.3	7.7	2.8	40.1
Breadth of promotion	2.0	1.7	0.0	19.2
PL share	28.2	14.5	0.7	70.6
PL line extension	39.9	17.0	0.0	100.0
PL promotion	17.2	23.1	0.0	100.0
NB promotion	23.0	14.7	0.0	88.1
		Cheese		
Assortment	12.6	7.0	2.6	37.1
Breadth of promotion	2.3	1.8	0.0	11.6
PL share	2.6	4.2	0.0	29.2
PL line extension	29.7	24.6	0.0	50.0
PL promotion	15.1	29.0	0.0	100.0
NB promotion	32.2	17.4	0.0	88.4
		Milk (refrigerated)		
Assortment	15.9	5.0	6.3	28.7
Breadth of promotion	0.9	1.2	0.0	14.6
PL share	11.0	11.3	0.0	46.7
PL line extension	28.3	19.3	0.0	57.1
PL promotion	11.8	23.1	0.0	100.0
NB promotion	3.7	7.2	0.0	70.6
		Mozzarella		
Assortment	23.5	13.5	1.5	57.4
Breadth of promotion	4.9	4.2	0.0	27.6
PL share	19.3	12.4	0.0	63.5
PL line extension	41.2	15.2	0.0	50.0
PL promotion	23.1	23.9	0.0	100.0
NB promotion	31.7	16.8	0.0	80.6
		UHT Milk		
Assortment	26.5	8.3	9.9	50.3
Breadth of promotion	4.5	2.9	0.0	24.1
PL share	16.3	11.2	0.0	62.0
PL line extension	69.6	16.0	0.0	100.0
PL promotion	21.9	22.6	0.0	99.9
NB promotion	33.0	16.1	0.0	84.1
		UHT Cream		
Assortment	13.2	5.6	4.5	28.2
Breadth of promotion	2.0	1.5	0.0	13.8
PL share	20.6	9.1	0.0	60.1
PL line extension	40.0	19.2	0.0	100.0
PL promotion	18.8	26.4	0.0	100.0
NB promotion	19.2	13.4	0.0	83.2
		Yogurt		
Assortment	86.7	40.7	29.3	207.1
Breadth of promotion	16.7	13.0	0.0	85.7
PL share	8.6	6.1	0.0	35.0
PL line extension	58.1	18.6	0.0	85.7
PL promotion	21.6	22.2	0.0	100.0
NB promotion	26.4	12.5	0.0	76.2

Source: Our elaboration on IRI info-scan database

The average line extension is around 30% for cheese, refrigerated milk, and UHT milk, while it reaches 40% for butter, mozzarella cheese, and UHT cream, and 58.2% for yogurt.

The intensity of *NB* promotion activities is quite high in almost all categories, ranging from 19.2% to 33% in value terms; only refrigerated milk strongly differs from the other products with a 3.7% share of *NB*s sold in promotion. Consistently, in refrigerated milk, also *PL*s show a rather low promotion share, while in the other categories the share of *PL*s sold under promotion ranges from 15.1% for cheese to 23.1% for mozzarella. Overall, the share of *NB*s sold under promotion is higher than the corresponding share of *PL*s, with the only exception of refrigerated milk. Also the breadth of promotion is rather variable across categories: on average, within the refrigerated milk category we observe around one item on sale, compared to two items for butter and UHT cream, almost five for UHT milk and mozzarella cheese and more than sixteen items for yogurt.

3. Estimation and Results

In order to preliminarily investigate the source of variation in the *GEKS* indexes for each product category, we implement a variance decomposition using a three-way ANOVA, which accounts for chain, type of store, and time. Results (see Table 5) show how the ANOVA model sum of squares over the total sum of squares ranges from around 30% in UHT milk and UHT cream to over 60% in refrigerated milk, thus indicating strong variability among different product categories. This might be due to different marketing strategies and different competitive interactions among manufactures, but also to the intrinsic characteristics of the products, like the shelf life, and to their degree of differentiation. This analysis suggests that accounting for the variability among chains, types of store, and time periods can be a good estimation strategy to identify the contribution of retailers' marketing activities.

Table 5. Results of the three-way ANOVA on the *GEKS* indexes for each product category

	Butter		**Cheese**		**Milk (refrigerated)**		**Mozzarella**		**UHT Cream**		**UHT Milk**		**Yogurt**	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Model	**23.1**	**53.90%**	**19.7**	**34.40%**	**8.9**	**61.80%**	**16.4**	**43.00%**	**7.4**	**30.30%**	**6.4**	**30.10%**	**7**	**50.90%**
Chain	5.9	13.60%	10.3	18.10%	5	34.50%	13	34.10%	3.8	15.70%	2.8	13.30%	3.8	27.90%
Type of store	3.4	7.90%	1.7	3.00%	0.9	6.00%	0.4	1.10%	0.4	1.50%	1.3	6.10%	1.6	11.90%
Time	13.9	32.30%	7.6	13.30%	3.1	21.30%	3	7.80%	3.2	13.10%	2.3	10.70%	1.5	11.10%
Residual	**19.8**	**46.10%**	**37.5**	**65.60%**	**5.5**	**38.20%**	**21.7**	**57.00%**	**17**	**69.70%**	**14.8**	**69.90%**	**6.7**	**49.10%**
Total	**43**		**57.2**		**14.4**		**38.2**		**24.4**		**21.2**		**13.7**	
Observations	5148		5148		5148		5148		5148		5148		5148	
R-squared	0.54		0.34		0.62		0.43		0.3		0.3		0.51	

(a) sum of squares and (b) percentage contribution to the total variance

In order to evaluate the role of retailers' strategies on the behavior of dairy prices the following semi-logarithmic three-way *ECM* is estimated (Davis, 2002):

$$y_{itj} = \mathbf{x}'_{itj}\boldsymbol{\beta} + \mu_i + \nu_t + \lambda_j + u_{itj} = \mathbf{x}'_{itj}\boldsymbol{\beta} + \varepsilon_{itj}, \qquad (2)$$

where the dependent variable y_{itj} is given by the natural logarithm of the *GEKS* index multiplied by the chain and type-of-store specific average price at time $t = 1$, $\mathbf{x}_{itj}$ is a k vector of the explanatory variables[8], which describes the retailers' marketing mix, $\boldsymbol{\beta}$ is a k vector of parameters, μ_i is the chain-specific effect (indexed $i = 1, \dots, N$), ν_t the time-specific effect (indexed $t = 1, \dots, T$), λ_j the type of store-specific effect (indexed $j = 1, \dots, L$), u_{itj} the remainder error term, and ε_{itj} the composite error term. More details on the estimated econometric model are given in Appendix A.1.

Using the *LM* test we check for the significance of chain and type of store unobservables on food price dynamics (see Appendix A.2). The null hypothesis $\bar{\boldsymbol{\vartheta}} = (0,0,0,\sigma_{OLS}^2)'$ has been checked vs. various alternatives: the two one-way models for chain $\boldsymbol{\vartheta} = (\sigma_\mu^2, 0,0,\sigma_u^2)'$ and type of store $\boldsymbol{\vartheta} = (0,0,\sigma_\lambda^2,\sigma_u^2)'$, the two-way model for chain and type of store $\boldsymbol{\vartheta} = (\sigma_\mu^2, 0, \sigma_\lambda^2, \sigma_u^2)'$, and the three-way model $\boldsymbol{\vartheta} = (\sigma_\mu^2, \sigma_\nu^2, \sigma_\lambda^2, \sigma_u^2)'$. In all these tests we reject the null hypothesis of plain OLS (see Table 6). This suggests the existence of significant differences in unobservable retailers' strategy effects among chains, types of stores, and weeks for all product categories.

Table 6. Results of the specification tests

	***LM* test**[a] $H_0: \bar{\boldsymbol{\vartheta}} = (0,0,0,\sigma_{OLS}^2)'$ $H_1: \boldsymbol{\vartheta} =$				**Hausman test**[b] H_0: $E(\varepsilon_{itj} \mid \boldsymbol{x}_{itj}) = 0$	**Modified Wald test**[c] $H_0: \psi_i = \sigma_u^2$
	$(\sigma_\mu^2, 0,0,\sigma_u^2)'$	$(0,0,\sigma_\lambda^2,\sigma_u^2)'$	$(\sigma_\mu^2, 0, \sigma_\lambda^2, \sigma_u^2)'$	$(\sigma_\mu^2, \sigma_\nu^2, \sigma_\lambda^2, \sigma_u^2)'$		
Butter	99819.559*	1318.424*	100355.980*	104154.489*	39.235*	0.001
Cheese	75721.703*	1577.567*	75864.109*	76370.065*	97.211*	0.002
Milk (refrigerated)	173604.224*	1833.769*	174878.521*	175319.275*	38.898*	9.235
Mozzarella	80765.477*	8.792*	83372.830*	83444.222*	30.167*	0.003
UHT Cream	142622.051*	4.493*	147481.275*	147485.077*	33.800*	0.092
UHT Milk	66652.366*	54.559*	68383.751*	68516.814*	30.751*	0.997
Yogurt	78257.662*	4.467*	80867.134*	80879.698*	40.738*	0.002

a See Appendix A2; **b** See Appendix A3 ($\chi_{k,0.05}^2 = \chi_6^2 = 12.59$); **c** See Appendix A4 ($\chi_{N,0.05}^2 = \chi_{14}^2 = 23.68$)
*H_0 is rejected at the 5% level of significance

We estimated equation (2) using both the fixed effect (*FE*) within estimator and the random effect (*RE*) *GLS* estimator. The Hausman

[8] Throughout the paper, all vectors and matrices are in boldface.

test statistic carried out for all product categories (see Appendix A.3) confirms that, while the within estimator $\widehat{\boldsymbol{\beta}}^{W}$ is unbiased and consistent, the *GLS* estimator $\widehat{\boldsymbol{\beta}}^{GLS}$ is biased and inconsistent (See Table 6). Hence, as suggested by these results, we focus the reminder of the analysis only on the *FE* three-way model.

Another problem that may affect our estimation is heteroskedasticity, since in model (2) observations on the dependent variable are likely to depend on individual specific characteristics (in our case, chain specific characteristics). In Appendix A.4 the heteroskedastic variances ψ_i on the remainder error terms u_{itj} are obtained in equation (A.20). Appendix A.4 presents also the modified Wald test statistic defined in equation (A.22) as derived by Baum (2001). The null hypothesis that $\psi_i = \sigma_u^2$ is accepted for all products (see Table 6), which means that the remainder error term u_{itj} is homoskedastic.

Estimation results for the *FE* model are presented in Table 7. Most of the estimated parameters are significant, although their sign is not always consistent across the seven models. For example, we found mixed effects of the assortment level for different product categories. In fact, we may think of two different effects on prices related with the level of assortment. First, more *BU*s can lead to stronger price competition among brands, pushing prices downward, while, at the same time, a larger assortment is an extra service that retailers offer to consumers, leading to higher costs and higher retail prices. The first effect prevails for yogurt and UHT cream, while the second is more important for refrigerated milk and mozzarella. The assortment mix does not seem to have any effect on price dynamics in the butter, cheese, and UHT milk categories.

The number of items on sale (breadth of promotion) does not influence price dynamics within the UHT cream and UHT milk categories, while it slightly pushes prices upward for all the other products, with the exception of refrigerated milk. This result might be explained considering that premium price items on sale may compete with the lower price ones. This might result in the cannibalization of purchases from low to premium items.

Table 7. Estimated Parameters under FE Three-Way ECM (*n*=5,148 for all products)

	Butter	Cheese	Milk (refrigerated)	Mozzarella	UHT Cream	UHT Milk	Yogurt
Assortment	0.0002 (0.0004)	-0.0001 (0.0005)	0.0053*** (0.0003)	0.0009** (0.0004)	-0.0023*** (0.0008)	-0.0004 (0.0004)	-0.0007*** (0.0001)
Breath of promotion	0.0029*** (0.0011)	0.0045*** (0.0013)	-0.0063*** (0.0009)	0.0027*** (0.0007)	-0.0005 (0.0017)	0.0009 (0.0007)	0.0009*** (0.0002)
***PL* share**	-0.0764*** (0.0141)	-0.1734*** (0.0450)	-0.2366*** (0.0194)	-0.2946*** (0.0169)	-0.1247*** (0.0229)	-0.0411*** (0.0158)	-0.6018*** (0.0274)
***PL* line extension**	0.1324*** (0.0111)	0.0822*** (0.0089)	0.0831*** (0.0075)	0.0787*** (0.0110)	0.0435*** (0.0148)	0.0798*** (0.0073)	0.0568*** (0.0077)
***PL* promotion**	-0.0687*** (0.0049)	0.0064 (0.0049)	-0.0025 (0.0033)	-0.0097 (0.0059)	-0.0144** (0.0057)	-0.0321*** (0.0048)	0.0163*** (0.0039)
***NB* promotion**	-0.1937*** (0.0082)	-0.3425*** (0.0088)	-0.0523*** (0.0127)	-0.3302*** (0.0108)	-0.2721*** (0.0145)	-0.2754*** (0.0084)	-0.3670*** (0.0104)
SSR	18.9862	28.2933	7.8854	28.7842	35.7221	18.8622	12.9840
R^2	0.6708	0.6747	0.7531	0.5063	0.5591	0.6624	0.6593
σ_u^2	0.0038	0.0057	0.0016	0.0058	0.0072	0.0038	0.0026

Standard errors in brackets; *** 1% significance, ** 5% significance, * 10% significance

Higher *PL* shares tend to decrease the category price index. This result is consistent across all products, although with different magnitudes. Specifically, a unit (i.e., 1%) increase of the *PL* share contributes to significantly reduce the average price of 0.1-0.6%, depending on the product (yogurt is the most sensitive , butter and UHT milk are the least sensitive).

Furthermore, the *FE* estimation results show that the development of *PLs* in different market segments (*PL* line extension) for a given product category is related to an upward trend in prices. This result may be explained with the development of the *PL* product lines in "premium" segments of the market. The introduction of a *PL* might cause a reduction in prices of the premium segment where the introduction takes place. This reduction in prices might induce consumers to shift their consumption from relatively cheaper to more expensive products.

The impact of *PL* sales is not significant or less intense than *NB* sales, as shown by the magnitude of the coefficients on *PL* promotion, which range from 0.02% (UHT cream and Yogurt) to 0.07% (butter). Differently, the effect of the *PL* promotion intensity seems to be not significantly different from zero in the cheese, mozzarella, and refrigerated milk categories.

As expected, we found that the intensity of sales on *NB* products significantly reduces the *GEKS* index for all products categories. The refrigerated milk category is the one with the least intense effect, since a unit increase in the share of *NB* products sold under promotion contributes to a 0.05%decrease in its average price, while for yogurt such reduction is 3.6% .

A common feature of the above results is that, while significant, most of the impacts of retailers' strategies on price trends tend to be quite small. This general finding seems to suggest that retailers tend to use their strategies mostly as intra-chain competition tools, in order to attract more consumers and increase store sales, since strategies addressed to increase store traffic may not necessary lead to a strong average price reduction. The only exception is the impact of the *PL* share, which is quite sizeable and consistently negative. This evidence is in line with the stream of literature in which the price reducing role of PLs seems to prevail on the *NB* price discrimination strategies (Bonfrer and Chintagunta, 2004; Sckokai and Soregaroli, 2008).

4. Discussion and Conclusion

The EU has been affected by an increasing rate of food inflation, starting from the last decade, with a sharp increase during 2007-08. Many explanations for this increase in prices along the food supply chain have been proposed. While the increase in input costs, such as agricultural raw materials and energy, may be one of the factors contributing to the food price increase, other phenomena can determine the upward food inflation rate. For instance, retailers using specific marketing strategies may accelerate or slow down the inflation trend.

In this paper we use high frequency scanner data to empirically explore the contribution of some observed retailers' strategies on 7 dairy product categories. Moreover, we test if the unobserved heterogeneity among chains and types of stores (hypermarket, supermarket, and minimarket) gives a significantly different contribution to dairy inflation rates.

The first novelty of this paper is in the research design. To our knowledge, no empirical study has previously analyzed how retailers' marketing activities influence the food inflation rate using scanner data. For each of the observed dairy product categories, chains, and types of store we compute a weekly price index free of drift chain bias, as proposed by Ivancic et al. (2011). After computing the *GEKS* index for each product and chain-type of store combination, we use a three-way *ECM* estimator (Davis, 2002) to capture unobservable effects due to chain, time, and type-of-store heterogeneity. Moreover, for each product, we estimate the impact of observed retailers' marketing strategies, such as retailers' assortment, breadth of promotion, *PL* share, *PL* line extension, and promotional activities, on the price index.

Results show that, while higher *PL* shares help in slowing down an upward dairy inflation rate, higher *PL* line extension tends to accelerate it. Sales activities, as expected, alleviate the burden of a general increase in prices; however, *PL* sales have an effect on reducing the price inflation rate which is proportionally smaller than the overall average. This means that sales on *PL*s may be less effective than sales on *NB*s in alleviating a generalized upward price trend. Finally, assortment activities and the number of items on sales have mixed effects depending on the competition environment of the market we refer to. In general, the impact of retailers strategies is quite small, with the only exception of the impact of the *PL* market share, which is quite sizeable and consistently negative. In addition, *NB* promotional activities, which are typically agreed by retailers and manufacturers through their bargaining activities, seem to be more effective than those on *PL*s.

These results, if confirmed by other studies on different products and different countries, may have important policy implications on the issue of food price trends. In general, the potential role of retailers' strategies as price-moderator tools should not be overemphasized, while a key role may be played by the growth of the *PL* market share and by the promotional activities agreed between retailers and their suppliers. This means that food and competition policies should mainly focus on guaranteeing fair trading practices along the chain, as emphasized also in the recent report published by the *High Level Forum for a Better Functioning Food Supply Chain* (European Commission, 2014).

The research structure applied in this study may be further developed and used to explore smaller segments of the market within the same product categories. Moreover, having a geographic identifier of the points of sales, it would be interesting to explore the spatial dimension of our research issue, i.e. how retailers' strategies differ from rich to poor neighborhoods and their influence on the price differentials. In general, we believe that high frequency scanner data may give important insights in exploring food inflation rates, as well as the specific contribution of the various supply chain actors, especially retailers and manufacturers.

APPENDIX: THE ECONOMETRIC MODEL

A.1 The Three-way Error Component Model

Defining the $n \times N$ matrix $\mathbf{\Delta}_\mu$, the $n \times T$ matrix $\mathbf{\Delta}_\nu$, and the $n \times L$ matrix $\mathbf{\Delta}_\lambda$, where n is the total number of observations, using matrix notation it is possible to write the equation (2) as:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{\Delta}_\mu\boldsymbol{\mu} + \mathbf{\Delta}_\nu\boldsymbol{\nu} + \mathbf{\Delta}_\lambda\boldsymbol{\lambda} + \mathbf{u} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \qquad \text{(A.1)}$$

where $\mathbf{X}$ is a $n \times k$ matrix of explanatory variables, $\boldsymbol{\mu}$ the $N \times 1$ vector of chain-specific effects, $\boldsymbol{\nu}$ the $T \times 1$ vector of time-specific effects, $\boldsymbol{\lambda}$ the $L \times 1$ vector of format-specific effects, $\mathbf{u}$ the $n \times 1$ vector of residual disturbances, and $\boldsymbol{\varepsilon}$ the $n \times 1$ vector of composite error terms.

Davis (2002) develops simple matrix algebra techniques that simplify and unify much of the previous literature on estimating *ECM*s. In fact, the simple analytic results provided by Davis (2002) are useful for analyzing a very broad set of models with complex error structures (multi-way *ECM*s).

The within (*W*) transformation of the three-way *ECM* is based on:

$$\mathbf{Q}_{\Delta_{3\mathrm{w}}} = \mathbf{Q}_A - \mathbf{P}_B - \mathbf{P}_C \tag{A.2}$$

with

$$\begin{aligned}
\mathbf{P}_A &= \boldsymbol{\Delta}_\mu \boldsymbol{\Delta}_N^{-1} \boldsymbol{\Delta}'_\mu \rightarrow \mathbf{Q}_A = \mathbf{I}_n - \mathbf{P}_A \\
\mathbf{P}_B &= \mathbf{Q}_A \boldsymbol{\Delta}_\nu (\boldsymbol{\Delta}'_\nu \mathbf{Q}_A \boldsymbol{\Delta}_\nu)^- \boldsymbol{\Delta}'_\nu \mathbf{Q}_A = \mathbf{Q}_A \boldsymbol{\Delta}_\nu \mathbf{Q}_{2\mathrm{w}}^- \boldsymbol{\Delta}'_\nu \mathbf{Q}_A \rightarrow \mathbf{Q}_B = \mathbf{I}_n - \mathbf{P}_B \\
\mathbf{P}_C &= \mathbf{Q}_A \mathbf{Q}_B \boldsymbol{\Delta}_\lambda (\boldsymbol{\Delta}'_\lambda (\mathbf{Q}_A \mathbf{Q}_B) \boldsymbol{\Delta}_\lambda)^- \boldsymbol{\Delta}'_\lambda \mathbf{Q}_A \mathbf{Q}_B = \\
&= (\mathbf{Q}_A - \mathbf{Q}_A \boldsymbol{\Delta}_\nu \mathbf{Q}_{2\mathrm{w}}^- \boldsymbol{\Delta}'_\nu \mathbf{Q}_A) \boldsymbol{\Delta}_\lambda \mathbf{Q}_{3\mathrm{w}}^- \boldsymbol{\Delta}'_\lambda (\mathbf{Q}_A - \mathbf{Q}_A \boldsymbol{\Delta}_\nu \mathbf{Q}_{2\mathrm{w}}^- \boldsymbol{\Delta}'_\nu \mathbf{Q}_A)
\end{aligned} \tag{A.3}$$

where $\boldsymbol{\Delta}_N = \boldsymbol{\Delta}'_\mu \boldsymbol{\Delta}_\mu$, $\mathbf{I}_n$ is the identity matrix of dimension n, and $\mathbf{Q}_A \mathbf{Q}_B = \mathbf{I}_n - \mathbf{P}_A - \mathbf{P}_B = \mathbf{Q}_A - \mathbf{P}_B$ (see Davis, 2002). Therefore the *W* or fixed effect (*FE*) estimator is:

$$\widehat{\boldsymbol{\beta}}^W = \left(\mathbf{X}' \mathbf{Q}_{\Delta_{3\mathrm{w}}} \mathbf{X}\right)^{-1} \mathbf{X}' \mathbf{Q}_{\Delta_{3\mathrm{w}}} \mathbf{y}, \tag{A.4}$$

where μ_i, ν_t, and λ_j are assumed to be fixed parameters and $u_{itj} \sim (0, \sigma_u^2)$.

In the three-way random effect (*RE*) model all error components are random variables: $\mu_i \sim \left(0, \sigma_\mu^2\right)$, $\nu_t \sim (0, \sigma_\nu^2)$, $\lambda_j \sim \left(0, \sigma_\lambda^2\right)$, and $u_{itj} \sim (0, \sigma_u^2)$. The covariance matrix of the composite error ε_{itj} is:

$$\begin{aligned}
\boldsymbol{\Omega}_{3\mathrm{w}} &= E(\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}') \\
&= \sigma_\varepsilon^2 \cdot \mathbf{I}_n + \sigma_\mu^2 \cdot \boldsymbol{\Delta}_\mu \boldsymbol{\Delta}'_\mu + \sigma_\nu^2 \cdot \boldsymbol{\Delta}_\nu \boldsymbol{\Delta}'_\nu + \sigma_\lambda^2 \cdot \boldsymbol{\Delta}_\lambda \boldsymbol{\Delta}'_\lambda.
\end{aligned} \tag{A.5}$$

Following Davis (2002), the following matrices are defined:

$$\begin{aligned}
&\mathbf{V}_N = \mathbf{I}_n - \boldsymbol{\Delta}_\mu \left(\boldsymbol{\Delta}_N + \frac{\sigma_u^2}{\sigma_\mu^2} \cdot \mathbf{I}_N\right)^{-1} \boldsymbol{\Delta}'_\mu && \rightarrow \boldsymbol{\Omega}_{1\mathrm{w}}^{-1} = \frac{1}{\sigma_u^2} \cdot \mathbf{V}_N \\
&\begin{cases} \mathbf{W}_{TN} = \dfrac{\sigma_u^2}{\sigma_\nu^2} \cdot \mathbf{I}_T + \boldsymbol{\Delta}'_\nu \mathbf{V}_N \boldsymbol{\Delta}_\nu \\ \mathbf{V}_{TN} = \mathbf{V}_N - \mathbf{V}_N \boldsymbol{\Delta}_\nu \mathbf{W}_{TN}^{-1} \boldsymbol{\Delta}'_\nu \mathbf{V}_N \end{cases} && \rightarrow \boldsymbol{\Omega}_{2\mathrm{w}}^{-1} = \frac{1}{\sigma_u^2} \cdot \mathbf{V}_{TN} \\
&\begin{cases} \mathbf{W}_{LTN} = \dfrac{\sigma_u^2}{\sigma_\lambda^2} \cdot \mathbf{I}_L + \boldsymbol{\Delta}'_\lambda \mathbf{V}_{TN} \boldsymbol{\Delta}_\lambda \\ \mathbf{V}_{LTN} = \mathbf{V}_{TN} - \mathbf{V}_{TN} \boldsymbol{\Delta}_\lambda \mathbf{W}_{LTN}^{-1} \boldsymbol{\Delta}'_\lambda \mathbf{V}_{TN} \end{cases} && \rightarrow \boldsymbol{\Omega}_{3\mathrm{w}}^{-1} = \frac{1}{\sigma_u^2} \cdot \mathbf{V}_{LTN},
\end{aligned} \tag{A.6}$$

where $\mathbf{I}_N$ is the identity matrix of dimension N, $\mathbf{I}_T$ the identity matrix of dimension T, and $\mathbf{I}_L$ the identity matrix of dimension L. Then the *GLS* estimator is:

$$\widehat{\boldsymbol{\beta}}^{GLS} = (\mathbf{X}_C'\boldsymbol{\Omega}_{3\mathrm{w}}^{-1}\mathbf{X}_C)^{-1}\mathbf{X}_C'\boldsymbol{\Omega}_{3\mathrm{w}}^{-1}\mathbf{y}, \tag{A.7}$$

where $\mathbf{X}_C$ is the $n \times (k+1)$ matrix of explanatory variables with the constant term.

The Quadratic Unbiased Estimators (*QUE*s) for σ_u^2, σ_μ^2, σ_ν^2, and σ_λ^2 are derived using the *FE* residuals averaged over chains, periods, and type of stores. Because a constant term is considered, with the *FE* residuals $\mathbf{e} \equiv \mathbf{y} - \mathbf{X}\boldsymbol{\beta}^W$ and with $\mathbf{f} \equiv \mathbf{E}_\mathrm{n}\mathbf{e} = \mathbf{e} - \bar{e}$, where $\mathbf{E}_n = \mathbf{I}_n - \bar{\mathbf{J}}_n$, $\bar{\mathbf{J}}_n = \mathbf{J}_n/n$, and $\mathbf{J}_n$ a matrix of ones of dimension n, we equate:

$$\begin{aligned} q_n &= \mathbf{f}'\mathbf{Q}_{\Delta_{3\mathrm{w}}}\mathbf{f} \\ q_N &= \mathbf{f}'\boldsymbol{\Delta}_\mu\boldsymbol{\Delta}_N^{-1}\boldsymbol{\Delta}_\mu'\mathbf{f} \\ q_T &= \mathbf{f}'\boldsymbol{\Delta}_\nu\boldsymbol{\Delta}_T^{-1}\boldsymbol{\Delta}_\nu'\mathbf{f} \\ q_L &= \mathbf{f}'\boldsymbol{\Delta}_\lambda\boldsymbol{\Delta}_L^{-1}\boldsymbol{\Delta}_\lambda'\mathbf{f} \end{aligned} \tag{A.8}$$

with $\boldsymbol{\Delta}_T = \boldsymbol{\Delta}_\nu'\boldsymbol{\Delta}_\nu$ and $\boldsymbol{\Delta}_L = \boldsymbol{\Delta}_\lambda'\boldsymbol{\Delta}_\lambda$, to their expected values:

$$\begin{aligned} \mathrm{E}(q_n) = \quad & (n - N - (T-1) - (L-1) - k)\cdot\sigma_u^2 \\ \mathrm{E}(q_N) = \quad & (N + k_N - k_0 - 1)\cdot\sigma_u^2 + (n - \lambda_N)\cdot\sigma_\mu^2 \\ & +(k_{NT} - \lambda_T)\cdot\sigma_\nu^2 + (k_{NL} - \lambda_L)\cdot\sigma_\lambda^2 \\ \mathrm{E}(q_T) = \quad & (T + k_T - k_0 - 1)\cdot\sigma_u^2 + (k_{TN} - \lambda_N)\cdot\sigma_\mu^2 \\ & +(n - \lambda_T)\cdot\sigma_\nu^2 + (k_{TL} - \lambda_L)\cdot\sigma_\lambda^2 \\ \mathrm{E}(q_T) = \quad & (L + k_L - k_0 - 1)\cdot\sigma_u^2 + (k_{LN} - \lambda_N)\cdot\sigma_\mu^2 \\ & +(k_{LT} - \lambda_T)\cdot\sigma_\nu^2 + (n - \lambda_L)\cdot\sigma_\lambda^2, \end{aligned} \tag{A.9}$$

where $k_N \equiv \mathrm{tr}\left(\left(\mathbf{X}'\mathbf{Q}_{\Delta_{3\mathrm{w}}}\mathbf{X}\right)^{-1}\mathbf{X}'\boldsymbol{\Delta}_\mu\boldsymbol{\Delta}_N^{-1}\boldsymbol{\Delta}_\mu'\mathbf{X}\right)$, $k_T \equiv \mathrm{tr}((\mathbf{X}'\mathbf{Q}_{\Delta_{3\mathrm{w}}}\mathbf{X})^{-1}$ $\mathbf{X}'\boldsymbol{\Delta}_\nu\boldsymbol{\Delta}_T^{-1}\boldsymbol{\Delta}_\nu'\mathbf{X})$, $k_L \equiv \mathrm{tr}\left(\left(\mathbf{X}'\mathbf{Q}_{\Delta_{3\mathrm{w}}}\mathbf{X}\right)^{-1}\mathbf{X}'\boldsymbol{\Delta}_\lambda\boldsymbol{\Delta}_L^{-1}\boldsymbol{\Delta}_\lambda'\mathbf{X}\right)$, $k_0 \equiv \left(\boldsymbol{\iota}_n'\mathbf{X}\left(\mathbf{X}'\mathbf{Q}_{\Delta_{3\mathrm{w}}}\mathbf{X}\right)^{-1}\mathbf{X}'\boldsymbol{\iota}_n\right)/n$, $\lambda_N \equiv \left(\boldsymbol{\iota}_n'\boldsymbol{\Delta}_\mu\boldsymbol{\Delta}_\mu'\boldsymbol{\iota}_n\right)/n$, $\lambda_T \equiv (\boldsymbol{\iota}_n'\boldsymbol{\Delta}_\nu\boldsymbol{\Delta}_\nu'\boldsymbol{\iota}_n)/n$, and $\lambda_L \equiv (\boldsymbol{\iota}_n'\boldsymbol{\Delta}_\lambda\boldsymbol{\Delta}_\lambda'\boldsymbol{\iota}_n)/n$. Moreover, $k_{NT} \equiv \mathrm{tr}(\boldsymbol{\Delta}_{TN}\boldsymbol{\Delta}_N^{-1}\boldsymbol{\Delta}_{TN}')$ and $k_{NL} \equiv \mathrm{tr}(\boldsymbol{\Delta}_{LN}\boldsymbol{\Delta}_N^{-1}\boldsymbol{\Delta}_{LN}')$, with $\boldsymbol{\Delta}_{TN} = \boldsymbol{\Delta}_\nu'\boldsymbol{\Delta}_\mu$ and $\boldsymbol{\Delta}_{LN} = \boldsymbol{\Delta}_\lambda'\boldsymbol{\Delta}_\mu$, $k_{TN} \equiv \mathrm{tr}(\boldsymbol{\Delta}_{TN}'\boldsymbol{\Delta}_T^{-1}\boldsymbol{\Delta}_{TN})$ and $k_{TL} \equiv \mathrm{tr}(\boldsymbol{\Delta}_{LT}\boldsymbol{\Delta}_T^{-1}\boldsymbol{\Delta}_{LT}')$, with $\boldsymbol{\Delta}_{LT} = \boldsymbol{\Delta}_3'\boldsymbol{\Delta}_2$, and $k_{LN} \equiv \mathrm{tr}(\boldsymbol{\Delta}_{LN}'\boldsymbol{\Delta}_L^{-1}\boldsymbol{\Delta}_{LN})$ and $k_{LT} \equiv \mathrm{tr}(\boldsymbol{\Delta}_{LT}'\boldsymbol{\Delta}_L^{-1}\boldsymbol{\Delta}_{LT})$.

A.2 The Lagrange Multiplier Test

To check for the validity of assumptions made on the structure of the three-way *ECM,* the Lagrange Multiplier (*LM*) test statistic based on components of the loglikelihood evaluated at parameters estimates is applied (Boumahdi et al., 2004). The loglikelihood function under normality of the disturbances is:

$$L = constant - \frac{1}{2} \cdot \log|\mathbf{\Omega}_{3\mathrm{w}}| - \frac{1}{2} \cdot \mathbf{e}'\mathbf{\Omega}_{3\mathrm{w}}^{-1}\mathbf{e}, \qquad \text{(A.10)}$$

where $\boldsymbol{\vartheta} = \left(\sigma_\mu^2, \sigma_\nu^2, \sigma_\lambda^2, \sigma_u^2\right)'$. Under H_0, $\boldsymbol{\vartheta} = \bar{\boldsymbol{\vartheta}} = (0,0,0,\sigma_{OLS}^2)'$, where σ_{OLS}^2 is the variance of the *OLS* residuals $\mathbf{e}_{OLS}$. Then the restricted score vector is computed as:

$$\mathbf{D}(\boldsymbol{\vartheta}) = -\frac{n}{2 \cdot \sigma_{OLS}^2} \cdot \bar{\mathbf{D}}(\boldsymbol{\vartheta}) = -\frac{n}{2 \cdot \sigma_{OLS}^2} \cdot \begin{bmatrix} 1 - \dfrac{\mathbf{e}_{OLS}'\mathbf{\Delta}_\mu\mathbf{\Delta}_\mu'\mathbf{e}_{OLS}}{\mathbf{e}_{OLS}'\mathbf{e}_{OLS}} \\ 1 - \dfrac{\mathbf{e}_{OLS}'\mathbf{\Delta}_\nu\mathbf{\Delta}_\nu'\mathbf{e}_{OLS}}{\mathbf{e}_{OLS}'\mathbf{e}_{OLS}} \\ 1 - \dfrac{\mathbf{e}_{OLS}'\mathbf{\Delta}_\lambda\mathbf{\Delta}_\lambda'\mathbf{e}_{OLS}}{\mathbf{e}_{OLS}'\mathbf{e}_{OLS}} \\ 0 \end{bmatrix} \qquad \text{(A.11)}$$

and the information matrix is:

$$\begin{aligned} \mathbf{J}(\boldsymbol{\vartheta}) &= \frac{1}{2 \cdot \sigma_{OLS}^4} \cdot \bar{\mathbf{J}}(\boldsymbol{\vartheta}) \\ &= \frac{1}{2 \cdot \sigma_{OLS}^4} \cdot \begin{bmatrix} \mathrm{tr}\left(\mathbf{\Delta}_\mu\mathbf{\Delta}_\mu'\mathbf{\Delta}_\mu\mathbf{\Delta}_\mu'\right) & \mathrm{tr}\left(\mathbf{\Delta}_\mu\mathbf{\Delta}_\mu'\mathbf{\Delta}_\nu\mathbf{\Delta}_\nu'\right) & \mathrm{tr}\left(\mathbf{\Delta}_\mu\mathbf{\Delta}_\mu'\mathbf{\Delta}_\lambda\mathbf{\Delta}_\lambda'\right) & n \\ & \mathrm{tr}(\mathbf{\Delta}_\nu\mathbf{\Delta}_\nu'\mathbf{\Delta}_\nu\mathbf{\Delta}_\nu') & \mathrm{tr}(\mathbf{\Delta}_\nu\mathbf{\Delta}_\nu'\mathbf{\Delta}_\lambda\mathbf{\Delta}_\lambda') & n \\ & & \mathrm{tr}(\mathbf{\Delta}_\lambda\mathbf{\Delta}_\lambda'\mathbf{\Delta}_\lambda\mathbf{\Delta}_\lambda') & n \\ & & & n \end{bmatrix} \end{aligned} \qquad \text{(A.12)}$$

with $\mathbf{J}(\boldsymbol{\vartheta}) = E(\partial^2 L/\partial\boldsymbol{\vartheta}\partial\boldsymbol{\vartheta}') = [\mathbf{J}_{rs}]$ and $\mathbf{J}_{rs} = E(-\partial^2 L/\partial\vartheta_r\partial\vartheta_s)$. Hence the *LM* statistic under H_0 $\boldsymbol{\vartheta} = \bar{\boldsymbol{\vartheta}}$ is given by

$$\begin{aligned} LM &= \mathbf{D}(\boldsymbol{\vartheta})'\mathbf{J}(\boldsymbol{\vartheta})^{-1}\mathbf{D}(\boldsymbol{\vartheta}) \\ &= \left(-\frac{n}{2 \cdot \sigma_{OLS}^2} \cdot \bar{\mathbf{D}}(\boldsymbol{\vartheta})'\right) \cdot \left(2 \cdot \sigma_{OLS}^4 \cdot \bar{\mathbf{J}}(\boldsymbol{\vartheta})^{-1}\right) \cdot \left(-\frac{n}{2 \cdot \sigma_{OLS}^2} \cdot \bar{\mathbf{D}}(\boldsymbol{\vartheta})\right) \\ &= \frac{n^2}{2} \cdot \bar{\mathbf{D}}(\boldsymbol{\vartheta})'\bar{\mathbf{J}}(\boldsymbol{\vartheta})^{-1}\bar{\mathbf{D}}(\boldsymbol{\vartheta}) \end{aligned} \qquad \text{(A.13)}$$

which, under H_0, is asymptotically distributed as χ_{DF}^2. To test for the validity of the error component specification, the *LM* test statistic can be easily computed under various assumptions on null variances in the alternative hypothesis[9] (Boumahdi et al., 2004).

A.3 The Hausman Test

A critical assumption in the *ECM* is that $E\left(\varepsilon_{itj} \middle| \mathbf{x}_{itj}\right) = 0$. When $E\left(\varepsilon_{itj} \middle| \mathbf{x}_{itj}\right) \neq 0$, while the *GLS* estimator $\widehat{\boldsymbol{\beta}}^{GLS}$ becomes biased and inconsistent for $\boldsymbol{\beta}$, the within estimator $\widehat{\boldsymbol{\beta}}^{W}$ remains unbiased and consistent for $\boldsymbol{\beta}$ (see Baltagi, 2005). Hausman (1978) suggests comparing $\widehat{\boldsymbol{\beta}}^{GLS}$ and $\widehat{\boldsymbol{\beta}}^{W}$, both of which are consistent under the null hypothesis $H_0: E\left(\varepsilon_{itj} \middle| \mathbf{x}_{itj}\right) = 0$, but which will have different probability limits if H_0 is not true. In fact, $\widehat{\boldsymbol{\beta}}^{W}$ is consistent whether H_0 is true or not, while $\widehat{\boldsymbol{\beta}}^{GLS}$ is BLUE, consistent, and asymptotically efficient under H_0, but is inconsistent when H_0 is false (see Baltagi, 2005).

A natural test statistic would be based on:

$$\mathbf{q} = \widehat{\boldsymbol{\beta}}^{GLS} - \widehat{\boldsymbol{\beta}}^{W}, \tag{A.14}$$

where $\widehat{\boldsymbol{\beta}}^{GLS}$ is the *GLS* estimator without the constant term. Under H_0, $plim\ \mathbf{q} = 0$ and $cov\left(\mathbf{q}, \widehat{\boldsymbol{\beta}}^{GLS}\right) = 0$.

Using the fact that $\widehat{\boldsymbol{\beta}}^{W} = \widehat{\boldsymbol{\beta}}^{GLS} - \mathbf{q}$, since $cov\left(\mathbf{q}, \widehat{\boldsymbol{\beta}}^{GLS}\right) = 0$ one gets:

$$var\left(\widehat{\boldsymbol{\beta}}^{W}\right) = var\left(\widehat{\boldsymbol{\beta}}^{GLS}\right) + var(\mathbf{q}). \tag{A.15}$$

Therefore

$$\begin{aligned} var(\mathbf{q}) &= var\left(\widehat{\boldsymbol{\beta}}^{W}\right) - var\left(\widehat{\boldsymbol{\beta}}^{GLS}\right) \\ &= \sigma_u^2 \cdot \left(\mathbf{X}'\mathbf{Q}_{\Delta_{3\mathrm{w}}}\mathbf{X}\right)^{-1} - (\mathbf{X}'\boldsymbol{\Omega}_{3\mathrm{w}}^{-1}\mathbf{X})^{-1}, \end{aligned} \tag{A.16}$$

where $\mathbf{X}'\boldsymbol{\Omega}_{3\mathrm{w}}^{-1}\mathbf{X}$ is computed considering the $n \times k$ matrix of explanatory variables without the constant term $\mathbf{X}$. Hence, the Hausman test statistic is given by:

$$\mathbf{m} = \mathbf{q}'\left(var(\mathbf{q})\right)^{-1}\mathbf{q} \tag{A.17}$$

which under H_0 is asymptotically distributed as χ_k^2.

[9] The DF is the number of variances assumed to be equal to zero.

A.4 The Modified Wald Test

Heteroskedasticity placed on the remainder error term implies $u_{itj} \sim (0, \psi_i)$. The adapted *QUE*s for ψ_i can be derived from:

$$
\begin{aligned}
q_i &= \underset{1\times n}{\mathbf{f}'} \underset{n\times n}{\mathbf{Q}_{\Delta_{3\mathrm{w}}}} \underset{n\times n_i}{\mathbf{H}_i'} \underset{n_i\times n}{\mathbf{H}_i} \underset{n\times n}{\mathbf{Q}_{\Delta_{3\mathrm{w}}}} \underset{n\times 1}{\mathbf{f}} \\
&\rightarrow \sum_{i=1}^{N} q_i = q_n ,
\end{aligned}
\tag{A.18}
$$

where $\mathbf{H}_i$ is the matrix obtained from the identity matrix $\mathbf{I}_n$ by omitting the rows referring to observations not related to chain i and with $n_i = \sum_{t\in T^i} L_{it}$ the number of observations related to chain i, where T^i is the set of weeks the chain i is observed and L_{it} is the number of types of store with which the chain i is on the market in the week t. The adapted *QUE*s is obtained by equating the q_i's in (A.18) to their expected values:

$$
\begin{aligned}
\mathrm{E}(q_i) &= \mathrm{E}\left(\underset{1\times n}{\mathbf{f}'} \underset{n\times n}{\mathbf{Q}_{\Delta_{3\mathrm{w}}}} \underset{n\times n_i}{\mathbf{H}_i'} \underset{n_i\times n}{\mathbf{H}_i} \underset{n\times n}{\mathbf{Q}_{\Delta_{3\mathrm{w}}}} \underset{n\times 1}{\mathbf{f}} \right) \\
&= \mathrm{trE}\left(\underset{n_i\times n}{\mathbf{H}_i} \underset{n\times n}{\mathbf{Q}_{\Delta_{3\mathrm{w}}}} \underset{n\times 1}{\mathbf{f}} \underset{1\times n}{\mathbf{f}'} \underset{n\times n}{\mathbf{Q}_{\Delta_{3\mathrm{w}}}} \underset{n\times n_i}{\mathbf{H}_i'} \right) \\
&= \mathrm{tr}\left(\underset{n_i\times n}{\mathbf{H}_i} \underset{n\times n}{\mathbf{Q}_{\Delta_{3\mathrm{w}}}} \underset{n\times n}{\mathbf{E}_{\mathrm{n}}} \underset{n\times n}{\mathbf{M}} \underset{n\times n}{\mathbf{\Omega}} \underset{n\times n}{\mathbf{M}'} \underset{n\times n}{\mathbf{E}_{\mathrm{n}}} \underset{n\times n}{\mathbf{Q}_{\Delta_{3\mathrm{w}}}} \underset{n\times n_i}{\mathbf{H}_i'} \right) \\
&= \mathrm{tr}\left(\underset{n_i\times n}{\mathbf{H}_i} \underset{n\times n}{\mathbf{Q}_{\Delta_{3\mathrm{w}}}} \underset{n\times n}{\mathbf{M}} \underset{n\times n}{\mathbf{\Omega}} \underset{n\times n}{\mathbf{M}'} \underset{n\times n}{\mathbf{Q}_{\Delta_{3\mathrm{w}}}} \underset{n\times n_i}{\mathbf{H}_i'} \right) \\
&= \left(n_i - 1 - k_{\psi_i}\right) \cdot \psi_i - k_i \cdot \sigma_u^2 ,
\end{aligned}
\tag{A.19}
$$

where $k_{\psi_i} \equiv n_i - 1 - \mathrm{tr}\left(\mathbf{H}_i \mathbf{Q}_{\Delta_{3\mathrm{w}}} \mathbf{H}_i'\right)$, with $\sum_{i=1}^{N} k_{\psi_i} = (T-1) + (L-1)$, and $k_i \equiv \mathrm{tr}\left(\left(\mathbf{X}'\mathbf{Q}_{\Delta_{3\mathrm{w}}}\mathbf{X}\right)^{-1} \mathbf{X}'\mathbf{Q}_{\Delta_{3\mathrm{w}}}\mathbf{H}_i'\mathbf{H}_i\mathbf{Q}_{\Delta_{3\mathrm{w}}}\mathbf{X}\right)$. Hence, the estimator of ψ_i is:

$$
\hat{\psi}_i = \frac{q_i + k_i \cdot \hat{\sigma}_u^2}{n_i - 1 - k_{\psi_i}}. \tag{A.20}
$$

As in Baum (2001), the estimated variance of $\hat{\psi}_i$ is:

$$
V_i = \frac{\sum_{t\in T^i} \sum_{j\in L^{it}} \left(e_{itj}^2 - \hat{\psi}_i\right)^2}{n_i \cdot (n_i - 1)}, \tag{A.21}
$$

where L^{it} is the set of types of store with which the chain i is on the market in the week t. The modified Wald statistic, defined as

$$W = \sum_{i=1}^{N} \frac{\left(\hat{\psi}_i - \hat{\sigma}_u^2\right)^2}{V_i}, \tag{A.22}$$

will be distributed as χ_N^2 under the null hypothesis that $\psi_i = \sigma_u^2$.

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