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Data aggregation and vertical price transmission: An experiment with German food prices

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Data aggregation and vertical price transmission: An experiment with German food prices

Abstract

The impact of cross sectional aggregation over individual retail stores on the estimation and testing of vertical price transmission between the wholesale and retail levels is investigated using a unique data set of individual retail prices in Germany. Systematic differences between the results of estimations using aggregated data on the one hand, and disaggregated data on the other, are discussed theoretically and confirmed empirically. The results suggest that estimation with aggregated data generates misleading conclusions about price transmission behavior at the level of the individual units (i.e. retail stores) that underlie these aggregates.

1 Introduction

Measuring vertical price relationships along the food chain from producers to consumers has become a popular means of evaluating the efficiency and the degree of competition in food processing and marketing. Numerous studies have estimated long-run relationships and the short-run impulse-response dynamics between prices at different stages of the marketing chain for various food products and countries. For lack of alternatives, most of these studies have employed aggregated data (e.g. average retail prices for a number of stores in a region or country). Perhaps as a result, most studies have also at least implicitly assumed that empirical results derived using this aggregated data are representative of – at least average – individual behavior. We propose to investigate whether this assumption is valid and, by extension, whether aggregate results can be used as a basis for statistical inference on individual behavior.

The information loss and bias that can result from aggregation have been investigated theoretically by many well known econometricians, such as Hicks (1936), Leontief (1936), Theil (1964), Green (1964), Granger (1980), or Pesaran (2003). With few exceptions, however, there has been little attempt to analyze these issues using actual data.¹ Using selected retail and wholesale food prices in Germany, we investigate the diversity of vertical price transmission behavior at the disaggregated level (the individual store) and compare this with vertical price transmission behavior estimated using the corresponding aggregates.

¹ These exceptions include Lyon and Thompson (1993) and Blank and Schmiesing (1990). The latter consider temporal and not cross sectional aggregation.

The data set employed consists of weekly grocery prices for frozen chicken and lettuce in Germany. Frozen chicken and lettuce were chosen as they are relatively homogenous products that are widely available in all types of grocery stores. Prices were collected by reporters in a representative sample of roughly 1300 grocery stores across Germany between 1995 and 2000. Wholesale prices are collected from various regional markets in Germany.

We proceed as follows. In the next section we provide a brief overview of the theory of spatial aggregation. Then in section 3 we present the data for our experiment. In section 4 we estimate the relationship between average wholesale and average retail prices for chicken. Then we use the same model specification (lags, functional form etc.) to estimate the n relationships between the average wholesale price and each of the n retail prices individually. We compare the results from these two procedures to quantify the extent of the bias and loss of information that is caused by aggregation. Section 5 closes with an intuitive explanation of our results and some implications for the interpretation of price transmission estimates based on spatially aggregated data.

2 Theory on data aggregation

Following Shumway and Davis (2001, p. 161): “Consistent aggregation ensures that behavioral properties which apply to the disaggregate relationships apply also to the aggregate relationships”. There are many situations in economics in which this is not the case. An intuitive example for bias resulting from aggregation is presented by Kirman (1992, p. 125), who shows how given two consumers who individually rank two alternatives in the same order, aggregation can lead to a reverse ranking. Another intuitively appealing example is provided by Caplin and Spulber (1987) who show that menu cost pricing and the associated price rigidities at the firm level can nevertheless be consistent with aggregate price flexibility.²

Data can be aggregated over time as well as in cross section, where cross section refers to products or economic agents at a given point in time.³ While temporal aggregation can give

² If differences in menu costs lead to differences in the timing of price adjustments between firms, aggregated prices might indicate price adjustments in every period. This example is cited in Caballero (1992, p. 1279).

³ Cross sectional aggregation will be spatial in nature if the units of observation that are being aggregated are spatially dispersed. It is, however, possible to imagine cases of cross sectional aggregation for which

rise to interesting problems of consistency and interpretation⁴, in this study we focus on the impact of cross sectional data aggregation on the measurement of vertical price transmission. In the case at hand, the products are food items (lettuce and frozen chicken) and the economic agents are individual retailers (grocery stores and supermarkets) in Germany.

Price transmission can be studied at both the individual and the aggregate level. At the individual level one can study the pricing behavior of economic agents and test whether it is consistent with assumptions such as profit maximization, perhaps constrained by menu costs, etc. At the aggregate level one might be interested in price transmission on the market as a whole; for instance, to what extent a reduction in wholesale prices is passed on to consumers by the retail sector. Many authors assume – at least implicitly – that the empirical answers to these questions are independent of data aggregation. Most studies of vertical price transmission use cross sectional aggregated prices at different levels of the marketing chain (i.e. regional or national average wholesale and/or retail prices). The question of interest is to what extent price transmission relations that are estimated using cross sectional aggregated price data cast light on price transmission behavior at the level of individual agents such as retail stores.

We begin by drawing on insights that have emerged from the study of aggregation in the field of demand analysis. To estimate demand systems it is necessary to aggregate over products and individuals. For consistent aggregation over products one must assume (weak) separability⁵ or constant ratios between product prices over time. The latter condition is called the composite commodity theorem (CCT) and dates to the work of Hicks (1936) and Leontief (1936). Under the CCT, commodity bundles display all the properties of their constituent parts, and in a two- (or multiple-) stage budgeting process, consumers can be assumed to treat these bundles as individual goods. Lewbel (1996) shows that the CCT can be relaxed in the sense that the ratios between the prices of the goods in a bundle do not have to be strictly constant over time, but variations in these ratios must be independent of the aggregate price level. Following Asche et al. (1999, p. 570) this generalised composite commodity theorem (GCCT) is equivalent to the statistical property of cointegration between the (logarithms of the) prices in question, with the cointegration coefficient (long run elasticity) equal to one.

the spatial dimension is not relevant or at least negligible. An example might be aggregation across a sample of households drawn from a single city or region.

⁴ See, for example, Weiss (1984) and Granger and Siklos (1995).

⁵ For a detailed discussion see Deaton and Muelbauer (1980: 119 ff.).

Consider a simple case in which p_t^i is the price of the i -th ($i = 1, 2, \dots, n$) retail store at time t ($t = 1, 2, \dots, \tau$) and p_t^* is the corresponding wholesale price. The following condition is assumed to hold for each retail store i :

$$\ln p_t^i = a_i + b_i \ln p_t^* + \varepsilon_t^i. \quad (1)$$

where a_i and b_i are transition parameters to be estimated and ε is a white noise error term. In this case the aggregate model based on the average retail price is:

$$\frac{1}{n} \sum_i \ln p_t^i = A + B \ln p_t^* + E_t. \quad (2)$$

where A and B are parameters of the aggregate price transmission relation corresponding to a_i and b_i in (1), and E_t corresponds to ε_t^i .

Summing (1) over all i :

$$\sum_i \ln p_t^i = \sum_i (a_i + b_i \ln p_t^* + \varepsilon_t^i) = \sum_i a_i + \sum_i b_i \ln p_t^* + \sum_i \varepsilon_t^i \quad (3)$$

and dividing by n leads to:

$$\frac{1}{n} \sum_i \ln p_t^i = \frac{1}{n} \sum_i a_i + \left(\frac{1}{n} \sum_i b_i \right) \ln p_t^* + \frac{1}{n} \sum_i \varepsilon_t^i \quad (4)$$

Thus, the estimate of the price transmission elasticity B in (2) will equal the average of the individual price transmission elasticities b_i in (1) (see also Pesaran, 2003). If the individual retail prices satisfy the CCT, then all b_i will be equal⁶ and aggregation will be consistent in the sense that the transmission of aggregated prices will exactly reflect the transmission of

⁶ To see this, note that if p_t^1 and p_t^2 satisfy the CCT, then $\frac{p_t^1}{p_t^2} = \alpha$ (a constant) and

$\ln p_t^1 - \ln p_t^2 = \ln \alpha$ or $\ln p_t^1 = \ln p_t^2 + \ln \alpha$. Hence, if $\ln p_t^1 = a_1 + b_1 \ln p_t^*$, then $\ln p_t^2 = a_1 - \ln \alpha + b_1 \ln p_t^*$, in other words p_t^1 and p_t^2 are linked to p_t^* by the same coefficient b .

individual prices. If the b_i differ, the aggregate estimate will – for correctly specified models - still reflect individual behavior on average.⁷

Two points should be noted, however. First, the variance of ε_t^i in (1) will not equal the variance of $E_t^i = \frac{1}{n} \sum_i \varepsilon_t^i$ in (2); the latter will be smaller unless the ε_t^i in (1) are positively correlated across retail outlets (Garrett, 2002, p. 6). As a result, the standard errors of b_i and B will differ, and it will, in general, not be possible to draw statistical inferences on the b_i using estimates of B and its variance.

Second, the simple example above does not include any dynamic elements. Thus, (1) and (2) model the long run equilibrium relationship between wholesale and (disaggregated or aggregated) retail prices. Hence, whatever insights the estimation of (2) using aggregated data provides regarding the individual behavior in (1), these insights will be limited to long-run price transmission. If dynamic elements (lagged retail and/or wholesale prices) are included in (1) and (2), then the coefficients of the aggregate model (2) will not necessarily equal the average values of the corresponding coefficients of the disaggregated equations (1).

To illustrate this phenomenon, consider how deterministic AR(1)-processes respond to a common shock. Assume that the autoregressive parameter is 0.9 in one process, and 0.1 in the other (Figure 1). These processes are stationary, their unconditional means are assumed to equal zero. Thus, following a common shock both processes return to zero asymptotically at different rates. These processes are analogous to the individual retail store prices considered above. If the response to a common shock (i.e. a wholesale price change) is estimated separately for each process, coefficients of 0.9 and 0.1 will result and the average coefficient will clearly equal 0.5. Note, however, that the behavior of an AR(1) process with a coefficient of 0.5 differs considerably from the behavior of the process that results from the aggregation (average) of the two individual processes (labeled AR 0.9/0.1 in Figure 1). Specifically, this aggregated process lies exactly between the two individual processes and its adjustment is slower than that of the process based on the average of the individual response parameters. Furthermore, the time series properties of this aggregated process differ, as it does not display

⁷ Note that if all prices are integrated, then (abstracting from factors that might lead to a non-stationary margin) individual retail prices should be cointegrated with the wholesale price and, by extension among themselves. In this case the individual retail prices will satisfy the GCCT if we add the restriction that the slope coefficients equal one.

AR(1) behavior. Instead, as Gouriéroux and Monfort (1997), Granger (1980), and Linden (1999) show, such aggregation leads to fractionally integrated (long memory) processes.

Insert Figure 1 here

Analogous phenomena can be demonstrated for autoregressive distributed lag or error correction models (Pesaran, 2003; Lippi, 1988). Following Granger (1990), Lewbel (1994), and Lippi (1988, p. 584) aggregation “turns out to be a source of dynamics”, and simple dynamics at the individual level will lead to complex lag structures at the aggregated level.

Hence, estimation of the aggregate price transmission relationship will, at best, provide information on average price transmission behavior at the individual level, and it will only provide a basis for statistical inference on the parameters underlying this behavior under restrictive conditions. Furthermore, whatever insights it does provide will be limited to long run price transmission; aggregate estimates will generally provide biased estimates of the parameters underlying the short run dynamics of price transmission, reflecting the fact that aggregated data will display time series behavior that differs fundamentally from that of the individual series from which it is derived.

3 Data⁸

The data used for this study have been provided by the “Zentrale Markt- und Preisberichtsstelle” (ZMP) in Bonn, Germany. The ZMP is an independent organisation that has a mandate from the German Government to collect and disseminate, among other things, representative consumer price data. The purpose of this mandate is to keep all participants on agricultural and food markets informed about market developments. To inform consumers and retailers about developments in retail food prices, the ZMP has set up a weekly price reporting system. The ZMP maintains a network of about 450 so-called ‘Melder’ (*melden* = to report in German) who visit about 1300 retail food stores in Germany on a weekly basis and collect price data for a variety of standard fresh foods. The sample is designed to be representative of the geographic regions and types of retail store in Germany, conditional on their population and market shares, respectively. For this purpose, Germany is divided into 8 geographic regions, and 6 types of retail store are considered. These are: small supermarkets (primarily food; less than 400 square meter shopping area); big supermarkets (primarily food; more than 400 but less than 800 square meter shopping area); combined supermarkets (food

⁸ We gratefully acknowledge the ZMP’s generosity in making this data available.

and other items; more than 800 square meter shopping area); discounters (primarily food with self service); butchers; and fruit and vegetable markets. Each Melder is told how many stores of each particular type he/she is to visit, but is free to choose the specific stores visited in accordance with these directions.

Price data are collected for 56 fresh food products. To ensure the comparability of the reported prices, the Melder are given detailed instructions on the quality of the product and the definition of the price to be recorded (e.g. per piece or per kg). Each Melder is free to choose the day of the week on which he or she visits the stores in question. Special offers are to be considered. The Melder fills out a standard sheet that is send back to the ZMP once per week. For our study we select one of the 56 food products in the ZMP panel. We choose frozen chicken as a very homogenous product that is sold year-round and in most of the stores. We consider only those stores for which prices were reported over the entire period from May 1995 to December 2000 and for which there are observations for at least 92 % of the weeks in this period ($n = 296$). If an observation p_t^i for store i in week t is missing, it is replaced with p_{t-1}^i . This selection process reduces the number of stores from about 1300 to 250. Prices are reported in German cent per kilogram.

Wholesale prices for chicken were also collected by the ZMP by interviewing major suppliers. The individual data underlying these average wholesale prices were not provided to us. Therefore, we must assume the law of one price without empirical support. As the validity of the law of one price has been confirmed for wholesale prices in many studies, this assumption is reasonable.

4 The transmission for aggregated German food prices

Figures 2 presents the wholesale price, the aggregated retail price and two randomly selected individual retail prices for chicken and lettuce, respectively.

Important differences between the aggregated retail price and the underlying individual retail prices are clearly visible. The average retail price varies from period to period (first differences are never equal to 0), whereas the individual retail prices are rigid (most first differences equal 0). Another characteristic of the individual retail prices is psychological pricing, i.e. the prevalence of 9 -type prices. Clearly, neither the CCT nor the GCCT hold for these prices.

We first test both wholesale and aggregated retail prices for a unit-root using Kwiatowski et al. (1992) (KPSS) and augmented Dickey-Fuller (1981) (ADF) tests. Both tests confirm that the wholesale and the aggregated retail prices for chicken are I(1). A test for cointegration confirms that wholesale and aggregated retail prices are also cointegrated. We therefore use an error correction model (ECM) to estimate price transmission between wholesale and aggregated retail prices.

Insert Figures 2 here

In line with most studies, we assume that wholesale prices lead retail prices.⁹ The specification of the ECM with symmetric adjustment to deviations from the long-term equilibrium is given in equations (5) and (6):

$$p_t^R = \phi_0 + \phi_1 p_t^W + \varepsilon_t^i \quad (5)$$

$$\Delta p_t^R = const + \sum_{n=0}^k \alpha_n \Delta p_{t-n}^W + \sum_{n=1}^l \beta_n \Delta p_{t-n}^R + \lambda ECT_{t-1} + \nu_t^i \quad (6)$$

where the superscripts R and W indicate aggregated retail and wholesale prices, respectively. According to the Granger two-step approach, the long-term relationship between retail and wholesale prices in equation (5) is estimated first. The lagged residuals from (5) are then used as the error correction term (ECT) to estimate (6). λ measures adjustments to deviations from the long-run equilibrium, while short-run dynamics are measured by the α_k and β_l coefficients. To allow for asymmetric price adjustment we also estimate the ECM in (7) in which the ECT is segmented into positive (ECT^+) and negative (ECT^-) deviations from the long-run equilibrium (von Cramon-Taubadel, 1998). Asymmetry is concluded if λ^+ differs significantly from λ^- (F-test).

$$\Delta p_t^R = const + \sum_{n=0}^k \alpha_n \Delta p_{t-n}^W + \sum_{n=1}^l \beta_n \Delta p_{t-n}^R + \lambda^+ ECT_{t-1}^+ + \lambda^- ECT_{t-1}^- + \nu_t^i \quad (7)$$

The lag-lengths k and l are determined by the Akaike Information Criteria. In the case of chicken $k = l = 3$, and for lettuce $k = l = 2$. A trend is also found to have a significant impact on the price transmission process for chicken and is therefore included in (6) and (7) for this

⁹ Other studies that make this assumption are Kinnucan and Forker (1987), Boyd and Brorsen (1988), Pick et al. (1990), and Griffith and Piggott (1994).

product. The Breusch-Godfrey test fails to reject the null hypothesis of no autocorrelation in both (6) or (7). Using a White test, we find that homoskedasticity can not be rejected for both in equations (6) and (7). The estimated coefficients of the price adjustment processes for chicken based on aggregated retail and wholesale prices are presented in the first two columns of Tables 1.

In the second step of our analysis we use the same specifications and lag-lengths to estimate the price transmission process between each individual retail price and the corresponding wholesale price. In other words, p_t^R in equations (5), (6) and (7) is substituted by p_t^{Ri} , with i indexing the individual retail stores. We estimate 246 individual regressions. The resulting sets of estimated transmission coefficients for the individual retail prices (summarised in the form of means and shares of significant coefficients in columns three and four of Tables 1 can be compared with those estimated using the aggregated retail prices.

Insert Table 1 here

The estimated adjustment coefficients in Tables 1 reveal large differences between price transmission coefficients for the aggregated retail price on the one hand, and the average of the price transmission coefficients for the individual retail prices on the other. The most pronounced differences are found for the λ -coefficients (adjustment to the long-run equilibrium). For example, according to the results estimated using the aggregated retail price for chicken, deviations from the long-run equilibrium are corrected by a factor of 16.4% per week (Table 1, column 1). However, the average correction over the 246 estimates using individual retail prices is 49.3% per week (Table 1, column 3).

These results are summarized in Figure 3 which shows the distribution of the estimated long-run adjustment coefficient for the individual series, the average of this distribution, and for the long-run adjustment coefficient estimated using the aggregated retail price. Figure 3 illustrates that the coefficient estimated using the aggregated retail price is not representative for coefficients estimated using individual retail prices.

Insert Figure 3 here

Another important difference emerges in the tests for asymmetric price transmission. In the case of price transmission estimated on the basis of aggregated retail prices, no significant asymmetry is found for either chicken or lettuce. Positive deviations of the average retail price from the long-run equilibrium are reduced by 12.5% per week, while negative

deviations are reduced by 19.8% per week (Table 1, column 2), the difference being insignificant at the 5% level. When price transmission is estimated on the basis of individual retail prices, however, 28% of all individual retailers are found to display significantly asymmetric pricing behavior.

Finally, the results in the first rows of Tables 1 confirm that the estimation of the long run relationship (i.e. coefficients ϕ_0 and ϕ_1) between wholesale and retail prices using the average retail price (columns 1 and 2) produces an unbiased estimate of the average relationship over all individual retailers (columns 3 and 4).

5 A possible explanation

In section 2 we have proposed an intuitive explanation for the aggregation bias observed above, using the example of AR(1) processes. Both the simple AR(1) example and our empirical results illustrate that aggregate processes adjust less rapidly than the underlying individual processes do on average. It would seem reasonable to assume that the same logic applies to the long run adjustment term in an error correction model, and as the following simple example illustrates, this is indeed the case. In equations (8) and (9) we consider two simple ECMs, each relating changes in an individual retail price to changes in a common wholesale price as well as an unrestricted ECT. In equation (10) we add these two ECMs and divide by 2:

$$\Delta p_t^{R1} = \alpha_0^1 + \alpha_1^1 p_{t-1}^{R1} + \beta_1^1 p_{t-1}^W + \beta_0^1 \Delta p_t^W + \varepsilon_t^1 \quad (8)$$

$$\Delta p_t^{R2} = \alpha_0^2 + \alpha_1^2 p_{t-1}^{R2} + \beta_1^2 p_{t-1}^W + \beta_0^2 \Delta p_t^W + \varepsilon_t^2 \quad (9)$$

$$\frac{1}{2} \sum_{i=1}^2 \Delta p_t^{Ri} = \frac{1}{2} \sum_{i=1}^2 \alpha_0^i + \frac{1}{2} \sum_{i=1}^2 \alpha_1^i p_{t-1}^{Ri} + \left(\frac{1}{2} \sum_{i=1}^2 \beta_1^i \right) p_{t-1}^W + \left(\frac{1}{2} \sum_{i=1}^2 \beta_0^i \right) \Delta p_t^W + \frac{1}{2} \sum_{i=1}^2 \varepsilon_t^i \quad (10)$$

We see that the second term on the RHS of (10) is not equivalent to a coefficient multiplied with the average of the two lagged individual retail prices p_{t-1}^{R1} and p_{t-1}^{R2} (i.e., $\frac{1}{2} \sum_{i=1}^2 p_{t-1}^{Ri}$). If we estimate an ECM in which the change in the aggregated retail price (LHS of (10)) is a function of the average lagged retail price, there is no reason to expect that the corresponding coefficient will equal the average of the coefficients α_1^1 and α_1^2 .

To quantify this effect, we run some simulations of unrestricted ECMs. Using (8) and (9) we generate artificial retail price series, with α_1^i (β_1^i) drawn from a uniform random distribution between 0 and -1 (0 and 1). α_0^i is set equal to zero and β_2^i equal to 0.5 for $i=1,2$. Each sample contains 250 price series with 300 observations. In repeated samples, we find that the long-run adjustment coefficient (α_1^i) estimated using the aggregated retail price lies roughly 0,25 below the average of the corresponding coefficients estimated using the individual (artificial) prices. This accounts for roughly 75% of the bias observed empirically in Tables 2 and 3 and Figure 4 above. Future work could be aimed at identifying the causes of the remaining observed bias, perhaps by refining the simulation.

6 Conclusions

As Shumway and Davis (2001: 190) note, the problems associated with aggregation are not independent of the research task: “It also is important to emphasize and warn that any effort to decrease specification errors (because of aggregation) cannot be taken to an extreme. It is useful here to think in terms of a ‘neighborhood aggregation invariance principle’ because the level of aggregation should be dictated by the question of interest.”

Hence, while our analysis would appear to point to a systematic problem associated with using aggregated data to draw conclusions about individual price transmission behavior, our empirical results are context-specific. Further work is needed to establish what general conclusions, if any, can be reached. It would appear, however, that empirical results generated with average price data provide a distorted view of what is going on at the level of individual behavior.

7 References

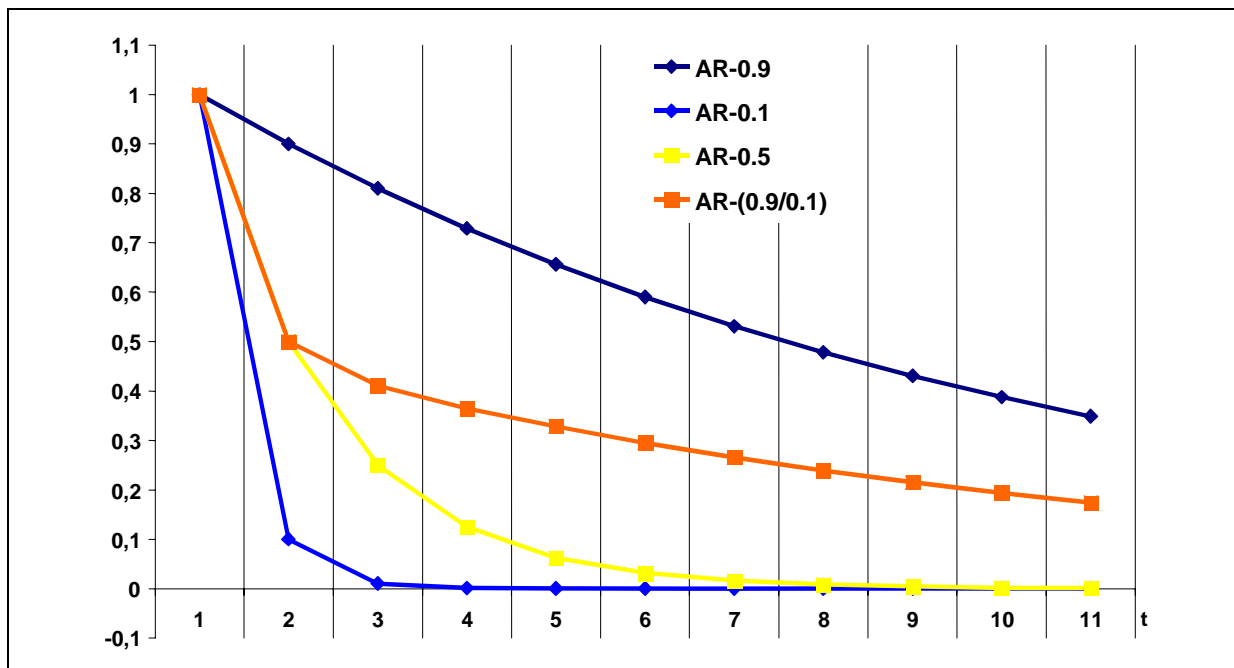
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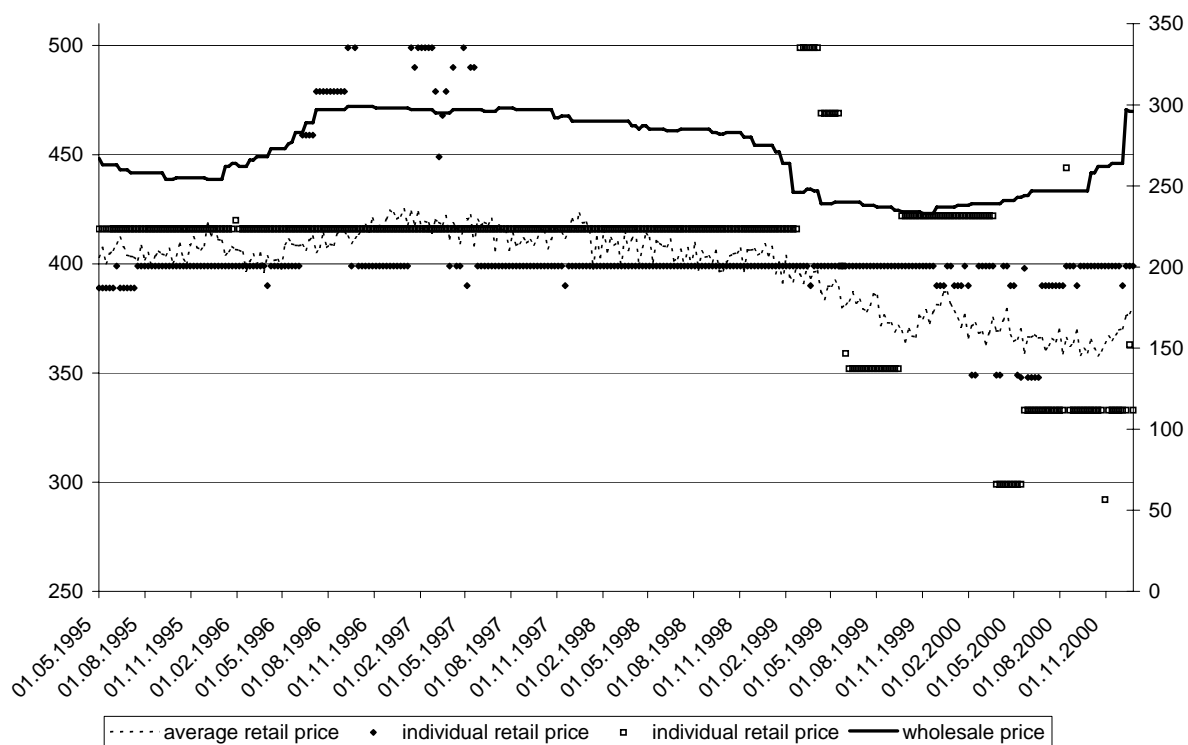
Tables and Figures

Figure 1: Simulation of individual and average AR (1) processes



Source: Own calculations.

Figure 2: Wholesale and selected retail prices for chicken in Germany (cents/kg)



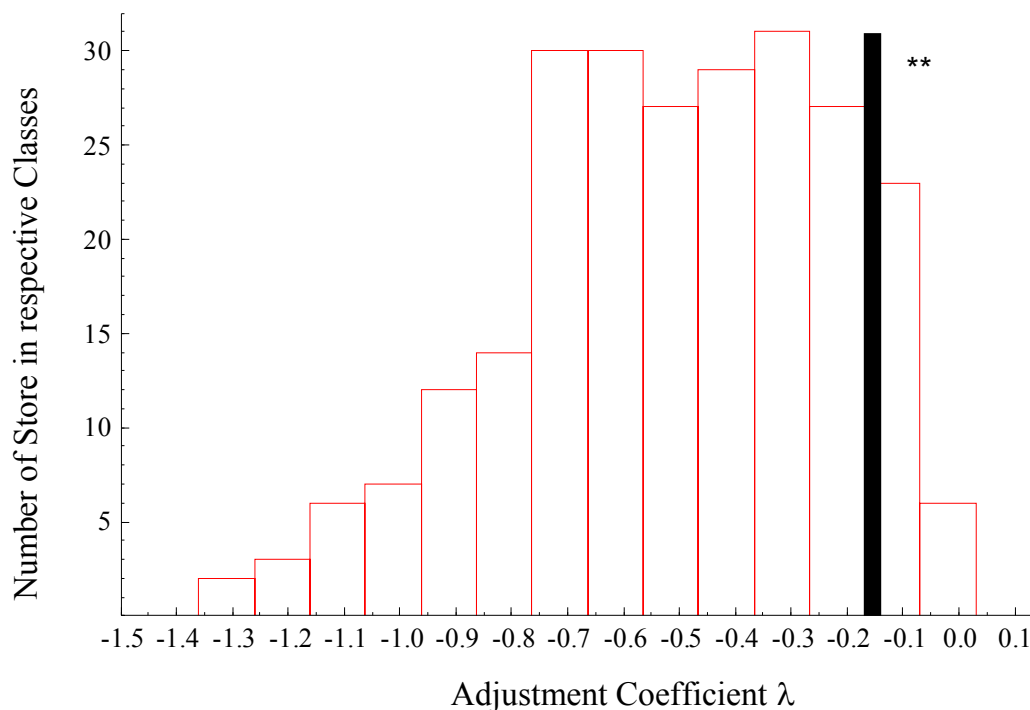
Source: Data from ZMP, 2001.

Table 1: Estimated error correction models of price adjustment for chicken

	Estimation with the aggregated retail price				Estimation with the individual retail price			
	1) Symmetry		2) Asymmetry		3) Symmetry		4) Asymmetry	
	Estimated coefficients	Standard error	Estimated coefficients	Standard error	Mean of the estimated coefficients	Significant coefficients	Mean of the estimated coefficients	Significant coefficients
ϕ_0	3.47		3.47		3.47		3.47	
ϕ_1	0.45		0.45		0.45		0.45	
constant	0.006	(0.002)	0.006	(0.002)	0.013	31%	0.007	28%
α_0	0.115	(0.076)	0.104	(0.076)	0.054	7%	0.051	6%
α_1	-0.048	(0.080)	-0.061	(0.081)	-0.249	6%	-0.241	7%
α_2	0.031	(0.080)	0.022	(0.081)	-0.153	5%	-0.135	7%
α_3	-0.119	(0.106)	-0.123	(0.106)	-0.272	8%	-0.260	8%
β_1	-0.556	(0.062)	-0.557	(0.062)	-0.223	66%	-0.204	61%
β_2	-0.284	(0.067)	-0.290	(0.067)	-0.143	49%	-0.133	47%
β_3	-0.180	(0.057)	-0.184	(0.057)	-0.067	25%	-0.062	22%
λ_0	-0.164	(0.041)			-0.493	97%		
λ_1			-0.125	(0.059)			-0.417	77%
λ_2			-0.198	(0.055)			-0.539	87%
trend	-0.00005	(0.00001)	-0.000005	(0.00001)	-0.00008	38%	-0.00009	40%
R^2	0.371		0.373		0.368		0.376	
p-value (Breusch-Godfrey)	0.53		0.59		p-value < 0.05 24.8%		p-value < 0.05 24.4%	
p-value (White)	0.34		0.42		43.9%		43.1%	

Source: Own calculations

Figure 3: Estimated long-term adjustment coefficients for aggregated and disaggregated retail prices.



** The solid bar marks the estimate for the adjustment coefficient from the aggregated retail price Source:

Own calculations.