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The impact of data aggregation on the measurement of vertical price transmission: Evidence from German food prices

Stephan von Cramon-Taubadel, Jens-Peter Loy and Jochen Meyer[1]

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Abstract

The impact of cross sectional aggregation over individual retail stores on the estimation and testing of vertical price transmission is investigated using a unique data set of individual retail prices. 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 results based on aggregated data generally cannot be used to draw conclusions about price transmission behaviour at the level of the individual data that underlies aggregates.

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Contact: *Stephan v. Cramon-Taubadel, Institute of Agricultural Economics, University of Göttingen, Platz der Göttinger Sieben 5, 37073 Göttingen, Germany, phone: +49551394859, Fax: +49551399866, e-mail: scramon@gwdg.de.*

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[1] The authors are professor, interim professor, and research assistant at the Institute of Agricultural Economics, University of Göttingen, Germany, respectively.

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 over recent decades. Numerous studies have estimated long-run relationships and 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. 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 behaviour. 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 behaviour.

The general problems connected with 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). Because disaggregated data have rarely been available, the significance of these problems in the real world is still unknown. Therefore, we investigate the diversity of individual behaviour and its impact on the estimation and interpretation of aggregated price series for the price transmission between selected wholesale and retail food prices in Germany.

The data set employed consists of weekly grocery prices for frozen chicken and lettuce in Germany. The were collected by reporters in roughly 1500 grocery stores across Germany between 1995 and 2000. The selection of grocery stores is a representative sample of the different types of stores in all regions of Germany. Wholesale prices are collected from various regional markets in Germany.

We proceed as follows. In the next two sections (2 and 3) we provide a brief overview of the theory of cross sectional aggregation and review the relevant literature in the field of vertical price transmission on food markets over the last two decades. In section 4 we estimate the relationship between average wholesale and average retail prices for frozen chicken and lettuce, respectively. Then we use the same model specification (lags, functional form etc.) to estimate the relationships between the average wholesale price and each of the individual retail prices. We compare results from these two procedures to quantify the extent of the bias and the loss of information that is caused by aggregation. Section 5 closes with an intuitive explanation for our results and some implications for the interpretation of aggregate estimates.

2. Theory on data aggregation

Following Shumway and Davis (2001, p. 161): "Consistent aggregation ensures that behavioural 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). In the case of two consumers who individually rank two alternatives in the same order, he shows that 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 either products or individuals at a given point in time. While temporal aggregation can give rise to interesting problems of consistency and interpretation[3], in this study we only address the impact of cross sectional data aggregation on the measurement of vertical price transmission. In the case at hand, the products are individual food items – such as lettuce or frozen chicken – and the individuals 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 behaviour of individual agents and test whether it is consistent with assumptions such as profit maximisation, perhaps constrained by considerations such as psychological pricing, menu costs, etc. At the aggregate level one might be more interested in price transmission on the market as a whole; for instance, to what extent does an average consumer benefit from a reduction in wholesale prices. The first intuition which many authors seem to follow – at least implicitly – is that the empirical answers to these questions are independent of data aggregation. Most studies of vertical price transmission make use of average prices at different levels of the marketing chain, such as wholesale and retail. The question of interest is whether or to what extent price transmission relations that are estimated using aggregated retail price data cast light on price transmission at the individual level.

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

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

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) separability[4] or fixed 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 (1995) 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.

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

$$\ln p_t^i = a_i + b_i \ln p_t^* + \varepsilon_t^i . \tag{1}$$

The error term e is white noise. In this case the aggregate model based on the average retail price is:

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

Summing (1) over all i:

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

and dividing by n leads to:

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

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

Thus, the estimate of the price transmission elasticity B in (2) will equal the average of the individual price transmission elasticities b_i (see also Pesaran, 2003). If the individual retail prices satisfy the CCT, then all b_i will be equal and aggregation will be consistent in the sense that the reactions to aggregate prices will exactly reflect reactions to individual prices. If the b_i differ, the aggregate estimate will – for correctly specified models - still reflect individual behaviour on average.[5]

Two points should be noted, however. First, the variance of e_t^i in (1) will not equal the variance of $E_t^i = \frac{1}{n}\sum_i e_t^i$ in (2); the latter will be smaller unless the e_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 carry out inference regarding the b_i using estimates of B and its variance.

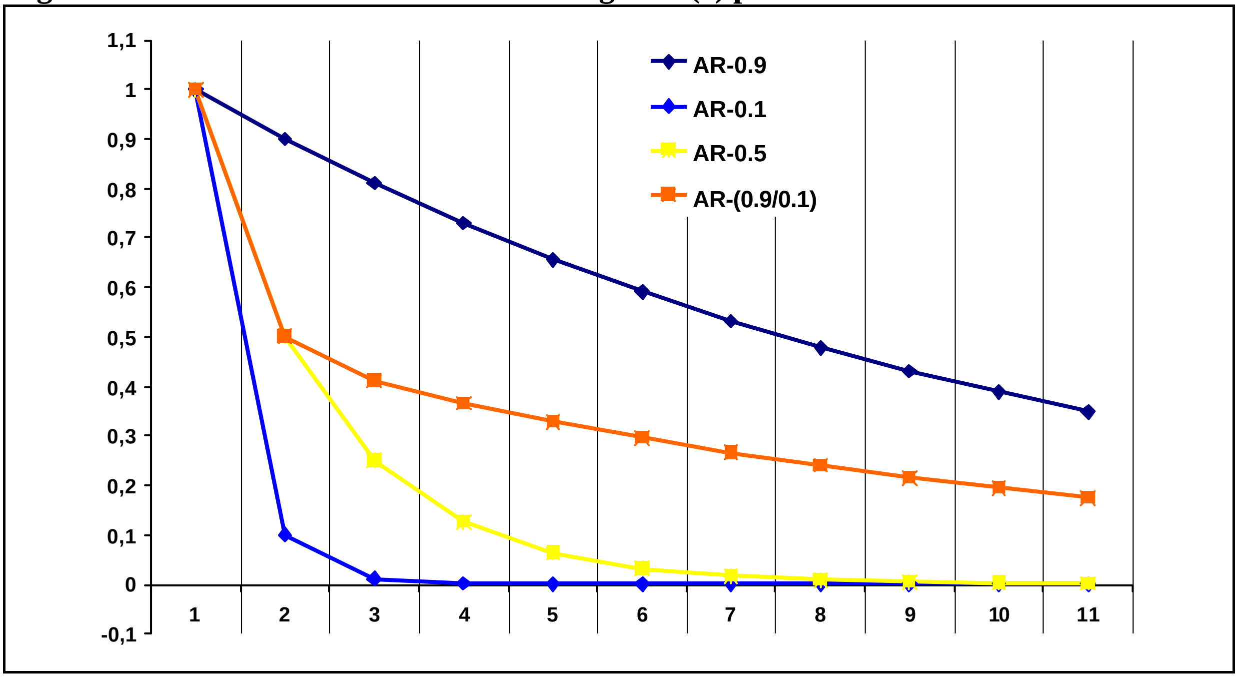
Second, the simple example above does not include any dynamic elements. In essence, (1) and (2) model the long run equilibrium relationship between wholesale and (disaggregated or aggregated) retail prices. Hence, whatever insights the estimation of (2) using aggregated data provides regarding the individual behaviour in (1), they will be restricted to long price transmission. If the individual retail store transmission equation (1) includes dynamic elements (lagged retail and/or wholesale prices), then the coefficients in the corresponding aggregate model will be biased.

To illustrate this phenomenon, consider the response of deterministic AR(1)-processes 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 and we set the unconditional mean at zero. Thus, following a common shock both processes return to zero asymptotically at different rates. These processes are analogous to the disaggregated 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 behaviour of an AR(1) process with

[5] Note that if the 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 of the slope coefficients to be one.

a coefficient of 0.5 differs considerably from the behaviour of the process that results from the aggregation of the two individual processes (labelled 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 responses. Furthermore, the time series properties of this aggregated process differ, as it does not display AR(1) behaviour. Instead, as Gourieroux and Monfort (1997), Granger (1980), and Linden (1999) have shown, such aggregation leads to fractionally integrated (long memory) processes.

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



Source: Own calculations.

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: 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 behaviour at the individual level, and it will only provide a basis for statistical inference on the parameters underlying this behaviour under restrictive conditions. Furthermore, whatever insights it does provide will be apply solely to long run price transmission relationships; 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 behaviour that differs fundamentally from that of the individual series from which it is derived.

3. Review of the empirical literature on vertical price transmission

The last two decades have seen many publications on vertical price transmission. In Table 1 a selection of recent empirical analyses is presented. In all of these studies, an attempt is made to quantify linkages between the farm, wholesale and/or retail prices, and to examine the dynamic patterns of adjustment of prices at one level to changes in prices at others. The existence of asymmetric price transmission (whether price transmission differs according to the direction of an exogenous shock or disturbance) has been a common theme in most studies of price transmission, as it has interesting implications for theory and policy (Peltzman, 2000). From Table 1 it can be seen that a wide range of products has been studied, over different periods and with different data frequencies.[6]

Table 1: Selection of empirical analysis of vertical price transmission

Authors	Year	Journal	Product	Data frequency	Data period	Results
Kinnucan and Forker	1987	AJAE	milk products	monthly	1971 - 1981	asymmetry
Schroeder	1988	AB	pork	weekly	1983 - 1986	asymmetry/symmetry
Boyd and Brorsen	1988	NCJAE	pork	weekly	1974 - 1981	symmetry
Pick et al.	1990	AB	fruit	weekly	1985 - 1987	asymmetry/symmetry
Griffith and Piggott	1994	AE	meat	monthly	1971 - 1988	asymmetry/symmetry
Powers	1995	AB	lettuce	weekly	1986 - 1992	asymmetry/symmetry
Zhang et al.	1995	AB	peanut	monthly	1984 - 1992	asymmetry/symmetry
Schertz Willet et at.	1997	AB	apples	monthly	1975 - 1990	asymmetry/symmetry
Brooker et al.	1997	JFDR	vegetables	weekly	1988 - 1993	asymmetry
v. Cramon	1998	ERAE	pork	weekly	1990 - 1993	asymmetry
Worth	1999	ERS	vegetables	monthly	1980 - 1999	asymmetry/symmetry
Peltzman	2000	JPE	diff.	monthly	1978 - 1996	asymmetry/symmetry
Goodwin and Harper	2000	JAAE	pork	weekly	1987 - 1999	asymmetry/symmetry
Miller and Hayenga	2001	AJAE	pork	weekly	1981 - 1995	asymmetry/symmetry
Aguiar and Santana	2002	AB	diff.	monthly	1987 - 1998	asymmetry/symmetry

AB (Agribusiness) AE (Agricultural Economics) AJAE (American Journal of Agricultural Economics) ERAE (European Review of Agricultural Economics) ERS (Economic Research Service) JAAE (Journal of Agriculture and Applied Economics) JPE (Journal of Political Economics) NCJAE (North Central Journal of Agricultural Economics)

In most analyses of vertical price transmission, reference is made implicitly or explicitly to individual actors. Boyd and Brorsen (1988) refer to pork producers who perceive that packers or retailers pass on price increases but not price reductions. Related statements can be found in Pick et al. (1990), Griffith and Piggott (1994) and Powers (1995). On the demand side, individual consumers are shown to face search costs and therefore prefer one-stop shopping,

[6] Meyer and von Cramon-Taubadel (2002) review these and other studies of asymmetric transmission in greater detail, pointing out that there is as of yet no unified theory of the causes of asymmetric price transmission. Furthermore, a wide variety of empirical tests for asymmetry exist, but there is no clear consensus over what tests are appropriate under what conditions, and whether it is possible to draw inferences regarding the causes of asymmetry from test results.

which might also lead to imperfect price transmission (Chang and Griffith, 1998). At the retail level, price rigidities are often explained with reference to menu costs that make price changes expensive for individual retailers. Price rigidities may also arise at the individual retail level because retailers are fearful that price changes may lead to a loss of consumers' goodwill (see Schroeder, 1988; Brooker et al. 1997; Worth, 1999; Miller and Hayenga, 2001).

Hence, in almost all studies the process of price transmission is explained with reference to the behaviour of individual actors such as farmers, consumers or the managers of retail outlets. Nevertheless, almost all studies rely on aggregated price data – for example average farm gate or retail prices – to empirically test hypotheses regarding price transmission. In other words, most if not all past studies are based on the (implicit) assumption that aggregation is consistent – i.e. that studying empirical relationships between aggregated price series provides insights into the relationships between individual prices and thus into the behaviour of individual actors on the markets in question.

Among the few exceptions, Schwartz and Schertz Willett (1994) mention that the data collection process may influence measured price transmission, briefly referring to the level of aggregation and whether or not price specials are captured in the data as important issues. In his extensive analysis of asymmetric price transmission, Peltzman (2000) also considers price data for products in individual supermarkets in the Chicago area. He reports a sharp contrast between the results obtained at the supermarket level and at the aggregated level. Specifically, price transmission appears to be much stronger if individual retail prices are considered. Schroeder (1988) analyses the price transmission process for individual pork cuts and also mentions variability in the wholesale-retail price linkage across individual grocery stores.

Vertical price transmission on the market for lettuce is analysed by Powers. Using city-level retail prices for 12 US cities, he finds that prices at the retail level adjust more rapidly to changes at the wholesale level than has been found in studies that rely on national retail data (Powers 1995). The same point is repeated in Worth (1999). Without going into details, Powers links his results to the level of aggregation (city vs. national).

In the following we make use of a unique data set on retail food prices in Germany to systematically study the impact of price aggregation on attempts to model price transmission processes.

4. The transmission for aggregated German food prices

To illustrate the effects of aggregation on measures of price transmission we analyse the vertical price transmission between wholesale and retail prices for chicken and lettuce in Germany at different levels of aggregation. We conduct our analysis using weekly prices between May 1995 and December 2000 (296 weeks) for both products. At the retail level we have information on prices in individual stores throughout Germany collected by the Zentrale Markt- und Preisberichtstelle (ZMP).[7] These prices are collected on a weekly basis by a network of reporters who are given strict instructions on a list of standardised products for which they are to record prices. For chicken (lettuce) we have prices over the entire period from 246 (250) retail stores.[8] Average retail prices are calculated as the simple unweighted arithmetic means of all individual retail prices in the sample. For each product, an average wholesale price for all of Germany is employed.[9] For chicken and lettuce, respectively, Figures 2 and 3 show the wholesale price, the average retail price and two randomly selected individual retail prices.

In both figures, important differences between the average 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 average 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 price and the average retail price for chicken are I(1). A test for cointegration confirms that wholesale and retail prices are cointegrated. We therefore use an error correction model (ECM) to estimate price transmission between wholesale and average retail prices. For lettuce, both wholesale and average retail prices are found to be stationary. We nevertheless – for purposes of comparability – also use an ECM in the case of lettuce.

[7] We gratefully acknowledge the ZMP's generosity in making this data available.

[8] Only stores for which less than 5% of the weekly observations are missing are included in the sample. Missing values are filled using the observed value in the following week.

[9] Clearly this average wholesale price is also an aggregated series that will 'hide' variation between individual wholesalers. For simplicity we focus on aggregation at one stage in the vertical chain, but future work could certainly explore the implications of simultaneous aggregation at two or more stages.

Figure 2: Wholesale and selected retail prices in Germany for chicken

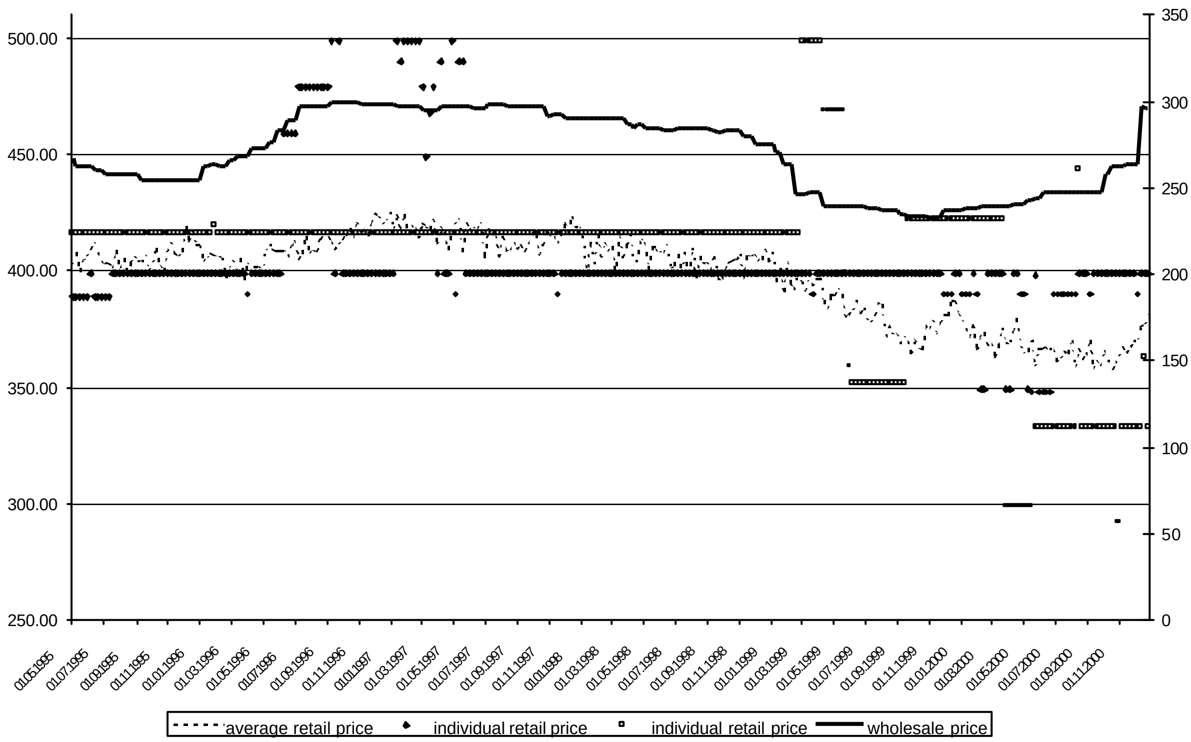
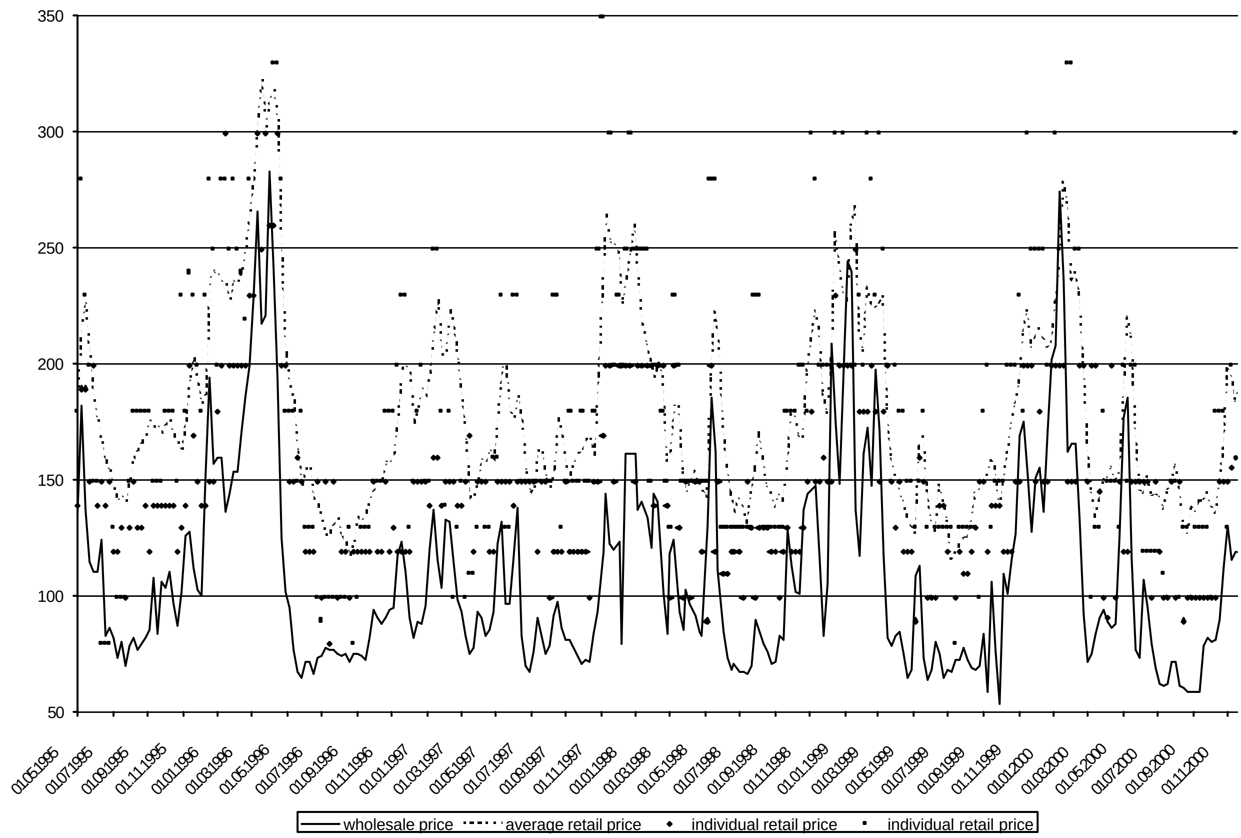


Figure 3: Wholesale and selected retail prices in Germany for lettuce



In line with most studies, we assume that wholesale prices lead retail prices.[10] The specification of the ECM with symmetric adjustment to deviations from the long-term equilibrium is given in equations (5) and (6):

$$p_t^R = f_0 + f_1 p_t^W + e_t^i \tag{5}$$

$$\Delta p_t^R = const + \sum_{n=0}^{k} a_n \Delta p_{t-n}^W + \sum_{n=1}^{l} b_n \Delta p_{t-n}^R + l\,ECT_{t-1} + u_t^i \tag{6}$$

where the superscripts R and W indicate 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). l measures adjustments to deviations from the long-term equilibrium, while short-term dynamics are measured by the a_k and b_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-term equilibrium (von Cramon-Taubadel, 1998). Asymmetry is concluded if l^+ differs significantly from l^-.

$$\Delta p_t^R = const + \sum_{n=0}^{k} a_n \Delta p_{t-n}^W + \sum_{n=1}^{l} b_n \Delta p_{t-n}^R + l^+ ECT_{t-1}^+ + l^- ECT_{t-1}^- + u_t^i \tag{6}$$

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 product. The Breusch-Godfrey test fails to reject the null hypothesis of no autocorrelation in both (6) or (7) for chicken as well as for lettuce. Using a White test, we find that homoskedasticity can only be rejected in equation (6) for lettuce. Estimated coefficients of the price adjustment processes for chicken and lettuce based on average retail and wholesale prices are presented in the first two columns of Tables 2 and 3, respectively.

In the second step of our analysis we use the same models (same specifications and lag-lengths for chicken on the one hand, and lettuce on the other) to estimate the price transmission process between each individual retail price and the corresponding wholesale

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10 Other studies that make this assumption are Kinnucan and Forker (1987), Boyd and Brorsen (1988), Pick et al. (1990), Griffith and Piggott (1994), Powers (1995), Brooker et al. (1997), and Worth (1999).

price. In other words, p_t^R in equations (5), (6) and (7) is no longer the average price over all individual retail outlets but rather becomes p_t^{Ri}, with i indexing the individual outlets. Thus in the case of chicken (lettuce) we estimate 246 (250) individual regressions. The resulting sets of estimated transmission coefficients for the individual retail prices (summarised in the form of means and standard errors in columns three and four of Tables 2 and 3) are then compared with those estimated for the average adjustment.

Table 2: Estimated error correction models of price adjustment for chicken

	estimation for the average retail price				**estimation with the individual retail price**			
	symmetry		**asymmetry**		**symmetry**		**asymmetry**	
	estimated coefficients	standard error	estimated coefficients	standard error	mean of the estimated coefficients	significant coefficients	mean of the estimated coefficients	significant coefficients
phi0	3.47		3.47		3.47		3.47	
phi1	0.45		0.45		0.45		0.45	
constant	0.006	(0.002)	0.006	(0.002)	0.013	31%	0.007	28%
alpha0	0.115	(0.076)	0.104	(0.076)	0.054	7%	0.051	6%
alpha1	-0.048	(0.080)	-0.061	(0.081)	-0.249	6%	-0.241	7%
alpha2	0.031	(0.080)	0.022	(0.081)	-0.153	5%	-0.135	7%
alpha3	-0.119	(0.106)	-0.123	(0.106)	-0.272	8%	-0.260	8%
beta1	-0.556	(0.062)	-0.557	(0.062)	-0.223	66%	-0.204	61%
beta2	-0.284	(0.067)	-0.290	(0.067)	-0.143	49%	-0.133	47%
beta3	-0.180	(0.057)	-0.184	(0.057)	-0.067	25%	-0.062	22%
lambda0	-0.164	(0.041)			-0.493	97%		
lambda1			-0.125	(0.059)			-0.417	77%
lambda2			-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	
DW	2.034		2.031					
p-value(BG)	0.53		0.59					
p-value(W)	0.34		0.42					

Source: own calculations

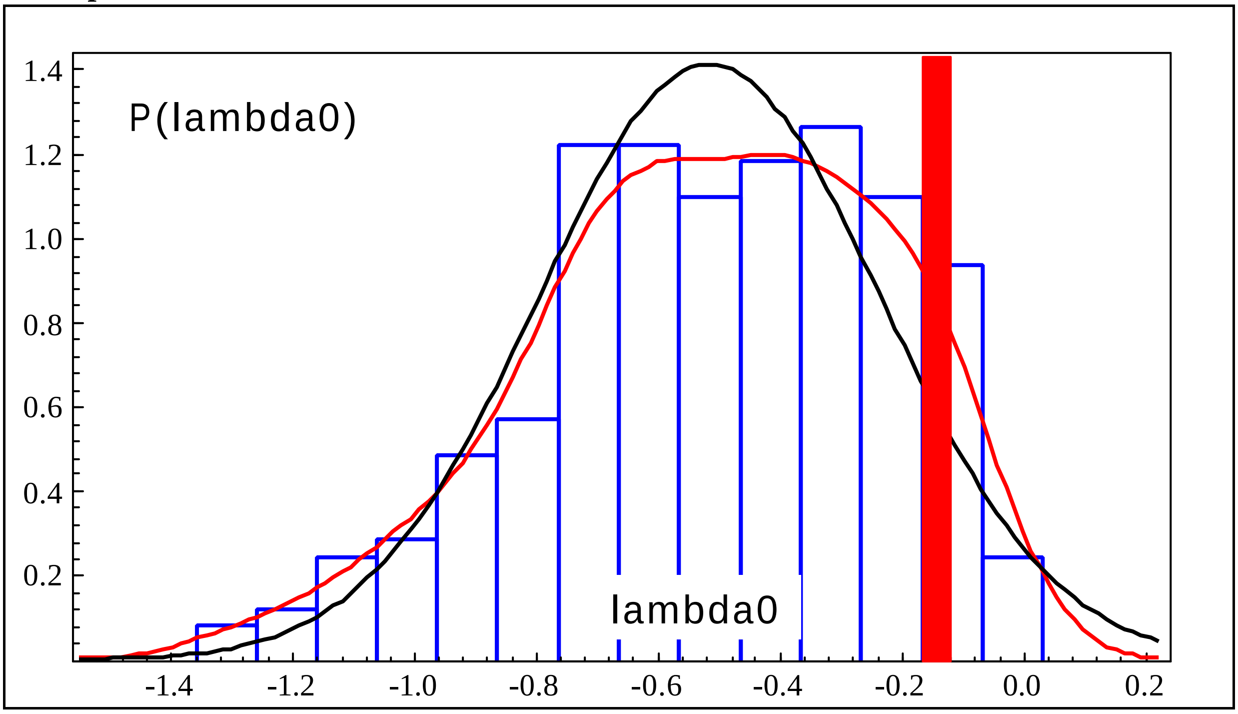
Table 3: Estimated error correction models of price adjustment for lettuce

	estimation with the average retail price				**estimation with the individual retail price**			
	symmetry		**asymmetry**		**symmetry**		**asymmetry**	
	estimated coefficients	standard error	estimated coefficients	standard error	mean of the estimated coefficients	significant coefficients	mean of the estimated coefficients	significant coefficients
phi0	2.68		2.68		2.68		2.68	
phi1	0.53		0.53		0.53		0.53	
constant	-0.0001	(0.0027)	-0.005	(0.004)	-0.00002	0%	-0.016	14%
alpha0	0.182	(0.015)	0.182	(0.015)	0.169	64%	0.171	65%
alpha1	0.220	(0.022)	0.218	(0.022)	0.125	46%	0.125	44%
alpha2	0.090	(0.022)	0.087	(0.022)	0.129	49%	0.125	46%
beta1	0.044	(0.056)	0.052	(0.056)	-0.176	68%	-0.165	62%
beta2	-0.019	(0.039)	-0.021	(0.039)	-0.070	22%	-0.067	21%
lambda0	-0.139	(0.031)			-0.480	100%		
lambda1			-0.086	(0.049)			-0.385	90%
lambda2			-0.195	(0.050)			-0.564	99%
R^2	0.696		0.698		0.396		0.402	
DW	1.999		2.004					
p-value(BG)	0.93		0.83					
p-value(W)	0.05		0.18					

Source: own calculations

The estimated adjustment coefficients in Tables 2 and 3 show large differences between the price transmission coefficients for the average 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 *l*-coefficients (adjustment to the long-term equilibrium). For example, according to the results estimated using the average retail price for chicken, deviations from the long-term equilibrium are corrected by a factor of 16.4% per week (Table 2, column 1). However, the average correction over the 246 estimates based on individual retail prices is 49.3% per week (Table 2, column 3). These results are summarised in Figure 4 which shows the estimated long-term adjustment coefficient for the aggregated retail price and the distribution of the estimated corresponding individual coefficients.

Figure 4: Estimated long-term adjustment coefficients for aggregated and disaggregated retail prices.



Source: Own calculations.

Another important difference emerges in the tests for asymmetric price transmission. In the case of price transmission estimated on the basis of average retail prices, no significant asymmetry is found for either chicken or lettuce. Positive deviations of the average retail price from the long-term equilibrium for chicken are reduced by 12.5% per week, while negative deviations are reduced by 19.8% per week, the difference being insignificant at the 5% level. The same is true for adjustment between the average retail price for lettuce and the corresponding wholesale price, where positive and negative deviations are corrected by 8.6% and 19.5% per week, respectively. If price transmission is estimated on the basis of individual retail prices, however, 28% (23%) of all individual retailers are found to display significantly asymmetric pricing behaviour for chicken (lettuce).

Finally, the results in the first rows of Tables 2 and 3 confirm that the estimation of the long-run relationship 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 already provided 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 average processes appear to 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 simply example illustrates, this is indeed the case. In equations (8) and (9) we consider two simple ECMs, each relating changes in a retail price to changes in a common wholesale price as well as to an (unrestricted) ECT. Equation (10) is then the average of these two ECMs, illustrating what happens when changes in the average retail price are related to the same variables;

$$\Delta p_t^{R1} = a_0^1 + a_1^1 p_{t-1}^{R1} + b_1^1 p_{t-1}^W + b_0^1 \Delta p_t^W + e_t^1 \tag{8}$$

$$\Delta p_t^{R2} = a_0^2 + a_1^2 p_{t-1}^{R2} + b_1^2 p_{t-1}^W + b_0^2 \Delta p_t^W + e_t^2 \tag{9}$$

$$\frac{1}{2}\sum_{i=1}^{2} \Delta p_t^{Ri} = \frac{1}{2}\sum_{i=1}^{2} a_0^i + \frac{1}{2}\sum_{i=1}^{2} a_1^i p_{t-1}^{Ri} + (\frac{1}{2}\sum_{i=1}^{2} b_1^i) p_{t-1}^W + (\frac{1}{2}\sum_{i=1}^{2} b_0^i) \Delta p_t^W + \frac{1}{2}\sum_{i=1}^{2} e_t^i \tag{10}$$

We see that when average data is used in (10), the coefficient on the lag endogenous term p_{t-1}^{Ri} is not the average of the two corresponding coefficients in (8) and (9). As a result, the long-run adjustment term estimated using average prices will differ from the average of the corresponding terms estimated using individual prices. As outlined above, the former will point to slower adjustment than the latter.

To quantify this effect, we have run some simulations of unrestricted ECMs. In a scenario in which a_1^i and b_1^i are drawn at random from a uniform distribution between 0 and 1 in repeated samples, we find a bias of about 0.2 for the long-run adjustment coefficient. This accounts for roughly 50% 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 simulations.

6. Implications

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 ‘neighbourhood 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 behaviour, 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 highly filtered and distorted view of what is going on at the level of individual behaviour.

7. References

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